UTS UNIVERSITY OF TECHNOLOGY SYDNEY

A constraints-led approach to analysing performance in team-based sport

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Certificate of Original Authorship

I, William Sheehan, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Health at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Preface

This thesis is written as per the requirements of the degree, Doctor of Philosophy and published according to the "Thesis presentation and submission" guidelines. The manuscripts included in this thesis are logically progressive in nature and form a body of work that encompasses the analysis and investigation of multiple components of performance in professional Australian Football.

The data collected during this candidature and associated research methodology has resulted in six manuscripts being accepted for publication with one more manuscript currently being reviewed by a peer-reviewed journal. The Introduction section provides a brief background of the current state of the literature in Australian football, defines the research problem, and outlines the aim and purpose of each study. As outlined in the introduction, unlike other contextually similar sports such as soccer, there are significant shortcomings with the application of tactical analysis methods in professional Australian football. Accordingly, the literature review utilises soccer as a medium to provide a synopsis of the current available literature on the current methods for analysing tactical behaviour in team-based sport. The subsequent chapter describes, in more detail, how the methods identified in the literature review will be applied in an Australian Football context and subsequently used in the ensuing studies. The next seven chapters encompass the manuscripts which are presented in a logical sequence that specifically address the research problems outlined in the Introduction. Each manuscript in chapter four to chapter ten is presented as per the guidelines of the peer-review journal in which they were submitted. Next, a General Discussion chapter provides a synopsis of the findings from the various manuscripts. Practical recommendations are provided to exemplify the real-world relevance for coaches, sport scientists and performance analysts. The limitations and delimitations of the current work is also discussed. The final chapter, Summary & Recommendations offers an interpretation of the collective findings resulting from the thesis. Finally, suggestions of future research are provided in light of the findings in this thesis.

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List of abbreviations

AFL - Australian Football League

AIC - Akaike's Information Criteria

CFI - Comparative Fit Index

CI - Confidence Interval

CV - Coefficient of Variation

FIFA - Fédération Internationale de Football Association

GNSS - Global Navigation Satellite Systems

GPS - Global Positioning System

ICC - Intraclass Correlations

IMA - Inertial Movement Analysis

IQR - Inter Quartile Range

KMO - Kaiser-Meyer-Olkin

KPI - Key Performance Indicator

LPS - Local Positioning System

OR - Odds Ratio

PCA - Principal Components Analysis

PNFI - Parsimonious Normed Fit Index

RHO - Cluster Phase

RMSEA - Root Mean Square Error

SaEn - Sample Entropy

SEM - Structural Equation Modelling

SRMR - Standardised Root Mean square Residual

SSG - Small Sided Game

TEM - Technical Error of Measurement

UEFA - Union of European Football Associations

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Abstract

While substantial information is available on the physical and technical components of Australian Football, objective methods of assessing the tactical demands have been scarcely examined. Despite enhancements in the quantity and quality of data available for assessing the technical, physical and tactical characteristics of match-play, it is not common to combine these when analysing professional sport. To overcome these shortcomings, this thesis aimed to simplify an array of physical, technical, and tactical variables utilised in Australian Football to simultaneously examine differences in successful quarters as well as specific phases-of-play.

Studies one-four reduced the dimensionality of cooperative network (*study one*), technical (*study two*), physical (*study three*), and spatiotemporal (*study four*) characteristics obtained from Australian Football League games in order to facilitate their practical use and interpretability. Principal components analyses provided simplified metrics that assisted in the reduction of complexity when analysing and interpreting multiple facets of performance while retaining a high level of variance. These metrics were subsequently used in studies *five-seven.*

Study five concurrently examined the influence of the aforementioned components on quarter margin. *Scoring opportunity* and *ball movement* had direct associations with quarter margin. Further, negative associations between *physical behaviour* and *ball movement* suggest that with less physical work, a team's collective ability to transfer possession between teammates is facilitated, offering an interesting dichotomy between skill and physical loads in Australian Football.

Study six differentiated between phase-of-play using duration, physical, and spatiotemporal properties subsequently providing new insight for coaches and providing direction for conditioning and practice design. Offensive and defensive phases presented greater *low-moderate volume*, defensive phases revealed stronger affiliations with *decelerations/impacts,* and contested phases demonstrated superior *explosiveness* and *change of direction* likely leading to lower values of synchrony and coordination. Interestingly, contested phases were strongly associated with *high-speed* metrics which may be due to players attempting to enhance positional advantage to gain possession.

Finally, *study seven* related phase duration and physical and spatiotemporal metrics with successful outcomes across various phases-of-play. Results indicated that a direct style of play with players moving erratically and unpredictability to misalign defenders or provide passing opportunities may be important for offensive success. In contrast, defensive success may be a result of players slowing movement to coordinate and synchronise movements to avoid being perturbed. The collective results from this sequence of studies provide direction for coaches and practitioners when contemplating practice design, tactical strategies, or the development of behaviour through specific training exercises.

Chapter 1

Introduction

1.1 Performance analysis in Australian Football

Australian Football is the most popular form of football in Australia and is classified as a contact, team sport.[1] The game takes place on an oval-shaped field that varies in length (149 – 175 m) and width (122 – 136 m), with two larger central posts called goal posts and two outer posts called behind posts.[1] If the ball is kicked between the two goal posts by the attacking team, a goal worth 6 points is awarded. If the ball passes between the goal posts in any other way, hits a goalpost, or passes between a goal post and a behind post, a behind worth 1 point is awarded.[2] Match play is carried out by two teams of 22 players, with 18 on the field at a time who contest play over four 20-minute quarters of 'in-play', with the clock stopping every time a goal is scored, the ball goes out of play, or play is ceased by the officiating umpires. As a result, quarter duration varies between 25-30 minutes, resulting in a total time of approximately 120 minutes.[3] Match play involves phases of ball possessions, contested play (where both teams compete for possession) and stoppages of varying durations with the physical element of the game characterised by intermittent high-speed running coupled with frequent collisions and changes of direction.[1] Additionally, competing at this level requires a high level of skill proficiency with players utilising a myriad of hand and foot skills for passing, scoring and gaining possession of the ball.[4] Teams also utilise a variety of tactical strategies depending on their own personnel, coaching philosophies, opposing team and environmental conditions during the match.[5, 6]

Collectively, players require superior physical abilities, technical skills and tactical strategies to cope with the ever-changing demands of the game.[7] Team success in Australian Football is a culmination of the aforementioned variables with superior performance allowing teams to fulfil the main objective of the game, to score the most points through goal kicking. Accordingly, applied research in this context has adopted a reductionist approach, investigating these factors (each with a wide array of variables) in isolation to derive practical applications aimed at improving a team's performance. Through the analysis of games played in the Australian Football League (AFL), the technical and physical demands of professional Australian Football have been adequately quantified using notational analysis techniques[4, 8] and microtechnology such as global navigation satellite systems (GNSS) and accelerometers.[7, 9] In contrast, only a small quantum of research exists regarding the tactical demands of the sport or, subsequently, the association of these variables with performance.

In an attempt to objectively quantify the underpinnings of successful performance, analysts have focused on identifying associated physical demands using GNSS devices.[10] Currently in the AFL, all professional teams evaluate the physical demands of game play using this technology which are capable of providing a plethora of associated variables.[7, 9] Specifically, speed-based running indices, accelerometry data and estimates of metabolic power have led to several publications that have quantified the physical components of Australian Football using a combination of these variables.[3, 11, 12] These studies found that Australian Football match-play involves higher running volumes compared to any other team sport with players performing frequent intermittent bouts of high-speed running, accelerations, decelerations, changes of direction and frequent collisions with opposing players.[1, 13] The validity and reliability of GNSS technology and a variety of subsequently derived individual measures of physical performance have been assessed and have been valuable in guiding current physical performance research.[14-16]

In other sports such as soccer, the assessment of discrete technical on-field actions such as the number of completed passes, time spent in possession of the ball, or the amount of tackles made, has endeavoured to provide reliable descriptions of the game's demands and subsequently aid in the prediction of success.[17] Technical skill counts are often provided by methods of manual notation analysis. In Australian Football, ChampionData® code all AFL matches for a myriad of technical skills.[8, 18] The most common technical skills reported in Australian Football research include the frequency of kicks, handballs, possessions, marks, ruck-contests and tackles.[9] Additionally, variables incorporating these skills such as disposal efficiency, shot efficiency, passing rate, inside 50's, marks inside 50, and contested possessions have been able to reveal particular playing styles and contribute to models predicting performance outcome.[2, 19, 20] In Australian Football, a combination of microtechnology and technical skill data present the most common methods and causal indicators of physical and technical performance constructs. The assessment of these components allows coaching and conditioning staff to develop training programs that simultaneously develop these parameters and consequentially aim to improve team performance.

While the extensive information regarding the physical and technical demands are useful, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance.[7, 18, 21-23] The excessive emphasis placed on performance outcome measures in research contexts presents an underlying issue that primarily focuses on 'who did what, when' which fails to provide a meaningful understanding of the underlying factors of successful performance in a complex team game such as Australian Football. An absence of detailed understanding exemplifies the need for a theoretical rationale that can provide insight into performance behaviours.[24, 25] Additionally, the vast dimensions of analysis in these areas has complicated interpretation limiting the practical relevance of the research. In an effort to simplify and deepen the level of understanding of match performance, notational analysis and/or a coach's subjective rating on performance have been used to audit and describe tactical behaviours of performers during different sub-phases of play, i.e., attack and defence, to provide additional information for practitioners.[26] This has typically occurred through verbal descriptions of lived experiences or game observation[27] While this process may offer valuable insight, these methods are less objective and systematic, relying on subjective impressions and procedural knowledge of expert performers.[28] Subjective analysis presents an issue, particularly when assessing performance between teams or longitudinally. Audited information perceived in this manner will be largely influenced by individual's past experiences and knowledge, subsequently making it difficult to translate or compare findings in different contexts.[28] Thereby, it is necessary to objectively assess tactical performance making it possible to assess performance in differing contexts.

1.2 Incorporating a new framework for analysis

To measure and quantify collective team behaviour, it has been suggested that technological advancements, such as an increase in sensitivity and application of GNSS devices, in conjunction with novel statistical approaches, may allow practitioners to quantitatively model, infer and predict performance outcomes in team sports, particularly during critical events in-game.[17] However, the complexity associated with the reporting of these methods, and the absence of a sound theoretical framework that can appropriately contextualise and describe behaviour, makes application difficult in a sporting context. Ecological dynamics has been considered as a viable framework as it actively focuses on the performer-environment relationship, and may provide a basis for understanding performance in team sport.[29] Utilising novel methods of tactical analysis, such as player passing interactions (cooperative networks) or team spatiotemporal measures of displacement or dispersion and inter-player levels of synchronicity and predictability, within this framework may provide an upgrade to more operational methods of analysis, acknowledging the 'how' and 'why' successful behaviours occur as opposed to just 'when' they occur.[26] Additionally, this framework has the potential to distinguish between non-expert and expert performers, the latter having an enhanced capability to achieve higher level of task outcomes, with effective and adaptive interactions between team mates.[30] Through the use of a hierarchical approach, researchers and practitioners can examine coordinative behaviour that emerges initially on a macroscopic level (between teams), followed by a mesoscopic level (intra-team) and finally on a microscopic level (player-player). This top-down form of analysis provides an all-encompassing framework that describes 'how' and 'why' certain behaviours emerge because of inter-player, intra-team, and inter-team decision-making and coordination.

From an ecological dynamics perspective, the game of Australian Football is a complex performance-environment sub-system where players and teams perceive opportunities for action which guide decision-making and subsequent actions. The perception of relevant environmental information sources allows players to self-organise into stable states of coordination that enables the achievement of task goals.[29] In this complex system, specific task-constraints, such as field dimensions and passing rules, along with specific physical and informational constraints, such as player size and opposition player movements, provide information and boundaries that guide and govern behaviour. The resultant behaviour in a complex system is the result of the interaction between its constituent components. Therefore, it is important to examine the influence of interactions and behaviour exhibited by, and between, players when analysing performance in team sports from an ecological dynamics perspective. While spatiotemporal behaviour and player interactions have been extensively researched in other football codes such as soccer there is minimal information on this topic in Australian Football.[2] Furthermore, when these cooperative networks of player behaviour and interaction were previously mapped within team sports, the interpretation was complicated due to the vast dimensions of analysis limiting the practical relevance of the research.

1.3 Statement of the Problem

Despite an increasing body of literature integrating the physical and technical parameters in Australian Football,[23, 31] there is little research that objectively examines the tactical demands of the game.[2] Further in-depth examination of this component, embedded in sound theoretical framework such as ecological dynamics, in conjunction with the physical and technical demands, may further guide coaching, conditioning and sports science staff in developing training programs where these performance elements are trained simultaneously. Integrated data of this kind which collectively examines the contribution of all performance aspects, has been deemed to have more practical significance compared to research studies where these constructs are assessed in isolation. Moreover, the conversion of match performance data into transferrable training recommendations are more probable when recommendations involve the integration of various factors relating to performance.[32]

Furthermore, the array of existing technical, physical, spatiotemporal and cooperative network variables available to analysts and practitioners makes it difficult to delineate and interpret the effect of specific variables on performance outcomes. The vast number of variables makes it difficult to interpret and identify relevant information and the consequential association with performance. Therefore, to undertake and integrate practical performance analysis in sport, analytical methods and interpretation need to be simplified. Furthermore, spatiotemporal variables, offering insight into tactical behaviour, are yet to be comprehensively examined in an Australian Football context. The simplification of the array of physical, technical, and tactical variables previously presented in the literature, embedded in a relevant theoretical framework, may make it simpler to delineate and interpret the effect of each specific component on performance outcome.

Accordingly, this project first attempted to reduce the dimensionality of commonly reported variables related to technical, physical, spatiotemporal and cooperative network performance obtained from AFL games to facilitate their practical use and interpretability. Secondly, these newly derived metrics were utilised to simultaneously examine the relationship between technical, physical, spatiotemporal, and cooperative network performance and quarter outcome as determined by point differential. Lastly, using these metrics, this project investigated the differences in spatiotemporal and physical behaviour exhibited by a professional Australian Football team during specific phases of play. Subsequently, behaviour exhibited in successful and unsuccessful phases were compared to provide specific insight into factors influencing success. The examination of behaviour in this context would provide insight into the specific factors that guide decision-making and behavioural responses of the team and the individuals that make up this team. The proposed research addressed these aspects via a sequence of related studies which will be outlined in the following section.

1.4 Project Aims and Hypotheses

1.4.1 Studies one-four: Simplifying the complexities of Australian Football

Aims

The aim of studies one to four was to reduce the dimensionality of commonly reported cooperative network, technical, physical, spatiotemporal and cooperative network characteristics obtained from AFL games in order to facilitate their practical use and interpretability. All games of the 2016, 2017 and 2018 AFL seasons were examined from one professional team and subsequently used to derive key constructs. The objective of studies one to four was to reduce the number of variables via statistical procedures, whilst maintaining most of the variability in the original data sets.

Hypotheses

It was hypothesised that:

1. A principal components analysis would reduce the number of characteristics related to the network analysis by grouping network characteristics at the individual and team level. More specifically, at the individual level, metrics pertaining to the reception of possession will be placed in the same component while metrics quantifying the distribution of possession will be grouped together in the same component. At the team level, metrics quantifying the overall level and strength of network interactions between teammates will be placed in the same component while metrics pertaining to the mutuality of involvement, i.e., variability of involvement, will be grouped together.
2. A principal components analysis would reduce the number of variables obtained from team-based technical skill counts in Australian Football by grouping variables whilst maintaining most of the variance in the original data set. More specifically, contest-based metrics, e.g., first possession, hardball get and tackle, metrics will be placed on the same component while uncontested metrics, e.g., short kick and uncontested mark, will be grouped together. Further, metrics pertaining to scoring such as inside 50 and shot at goal will be grouped together.
3. A principal components analysis would reduce the number of physical variables obtained from individual based GNSS analyses in Australian Football by grouping variables whilst maintaining most of the variance in the original data set. Low threshold velocity metrics will be placed in the same component while high threshold metrics will be placed in another. Further, inertial movement analysis metrics that tally changes in direction will also be grouped in a component together.
4. A principal components analysis would reduce the number of spatiotemporal variables obtained from individual- and team-based GNSS analyses in Australian Football whilst maintaining most of the variance in the original data set. More specifically, metrics providing information on the dispersion of the team, e.g., effective area and stretch index, will be grouped together while those pertaining to

measures of variability, regularity and synchrony will be placed in a component together due to their ability to quantify temporal shifts over certain periods of time.

1.4.2 Study Five: Completing the performance puzzle: A holistic model of performance for professional Australian Football

Aim

Due to the theoretical inter-relationships between physical, technical and tactical constructs, the aim of study five was to utilise the metrics derived in studies one, two, three and four to examine the relationships between these constructs and performance, and their associations with match quarter outcome. This theoretical model of performance was then assessed through structural equation modelling as this technique has the ability to depict relationships between these constructs.[33] All games of the 2016, 2017 and 2018 AFL seasons were examined from one professional team and subsequently used to identify key factors relating to match performance. The objectives of study five were to: a) to examine and identify which variables primarily contribute to match performance and b) to investigate the relationships between physical, technical, and tactical behaviour.

Hypotheses

It was hypothesised that:

1. Technical, spatiotemporal and cooperative network variables would influence the model to a greater extent than physical variables.
2. Physical behaviour would exhibit an association with spatiotemporal behaviour and technical outputs.
3. Spatiotemporal behaviour would influence network structures and technical outputs.
4. Technical outputs would exhibit a relationship with network behaviour.

1.4.3 Study Six: An assessment of physical and spatiotemporal behaviour during different phases of match play in professional Australian Football

Aim

Spatiotemporal analysis in professional soccer has revealed common associations between emergent behaviour and successful outcomes in specific phases of play. However, this level of detailed analysis has yet to be conducted in a professional Australian Football match context. Therefore, the aim of study six was to assess the relationship between intra-team spatiotemporal measures via microtechnology and phase of play in professional Australian Football with particular reference to an ecological dynamics framework. The physical and spatiotemporal metrics developed in studies three and four, respectively, were used to assess differences in behaviour in different phases of play in a professional Australian Football club. As this form of analysis had been conducted in other football contexts and reportedly provides highly relevant tactical information, it was deemed appropriate to assess in Australian Football. The primary objective of study six was to identify common tactical patterns associated with specific phases of play including offence, defence, contested possession, set-shots, goal resets and umpire stoppages.

Hypothesis

It was hypothesised that:

1. An increase in dispersion variables would be associated with attacking success while conversely, a decrease in dispersion variables would be associated with defensive success.
2. Greater variability coupled with lower regularity and synchrony in both dispersion and positional variables would be exhibited in attacking sequences. Conversely, lower variability, greater regularity, and an increase in synchrony in dispersion and positioning variables would be exhibited in defensive sequences.
3. An increase in running demands would be associated with greater variability in dispersion values coupled with a decrease in regularity.

1.4.4 Study Seven: Physical and spatiotemporal behaviour associated with successful phases of play

Aim

In the past decade applied research in Australian Football has primarily focused on a wide array of physical variables to derive practical applications aimed at improving a team's performance. However, with recent technological advancements, including the increase in sensitivity and application of GNSS devices, in conjunction with novel statistical approaches, it is possible to objectively measure and quantify collective team movement behaviour providing insight into tactical strategies and behaviours. While microtechnology data have provided valuable information regarding the characteristics of match play, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance over the course of a game or quarter.[22, 31] While attempts to clarify discrepancies have been made by investigating physical and spatiotemporal behaviour at a more complex level, i.e. specific phases of play, studies either examined these components in isolation of one another,[34-37] analysed a limited number of phases,[34, 36] utilised a limited number of metrics,[34-37] or failed to examine behaviour with reference to a performance outcome.[37] Accordingly, the physical and spatiotemporal metrics developed in studies three and four, respectively, were used to assess differences in behaviour in different phases of play in a professional Australian Football club with reference to successful and unsuccessful outcomes. As this form of analysis has been conducted in other football contexts and reportedly provides highly relevant tactical information, it was deemed appropriate to assess this in Australian Football. The primary objective of study seven was to identify patterns of behaviour associated with successful outcomes in specific phases of play including offence, defence, contested possession, set-shots, goal resets and umpire stoppages.

Hypothesis

It was hypothesised that:

1. Successful offensive phases would reveal lower values in all physical metrics with increased dispersion and reduced regularity and synchrony.
2. Successful defensive phases would exhibit higher volume in all physical metrics along with superior scores with lower values of dispersion and increased regularity and synchrony.
3. Due to their unpredictable nature, contested phases resulting in a successful outcome would demonstrate superior physical metrics with reduced regularity, synchrony and dispersion.
4. Due to their relatively lower physical demands and predictable nature, successful outcomes in set shots, goal resets and umpire stoppages would present superior regularity and synchrony.

1.5 Project Considerations

1.5.1 Research Limitations

There were inherent limitations associated with the research studies. While we acknowledge that the limitations listed below may influence the results of the ensuing studies, and often form the basis of discussion following these results, they have been listed as limitations as they were not able to be accurately accounted for or controlled in the study design. These include:

1. Not all matches were suitable for analysis. Some matches required different microtechnology units to be worn due to use of local positioning systems (LPS) instead of GNSS and were therefore excluded from the analysis.
2. Injuries during match-play that could lead to reductions in available match samples.
3. Within-match changes in physical, technical and tactical domains due to player rotations.
4. Coaching influence on the physical, technical and tactical performance of players throughout the data collection period due to specific game plans or instructions.
5. Within-match changes in player positions that relate to coaching tactics.
6. Results and contextual factors associated with the matches analysed thus implicating the samples associated with successful and unsuccessful quarter outcomes, opposition calibre and environmental conditions.
7. Reliance on third-party statistical information provided by ChampionData®.

1.5.2 Research Delimitations

The following delimitations were evident in this research:

1. The use of 3 seasons of match-play from 2016-2018.
2. Standardised definitions of the phases of Australian Football match-play used to categorise phase context.
3. The use of SportsCode as a coding tool to assess the video footage.
4. The sample size utilised in the research. The results of this project were based on 43 professional Australian Football players from one team. Therefore, the suggested implications may only apply to this group and may not be representative of athletes from different teams or level of competition (e.g., applicable to players from sub-elite Australian Football competitions).
5. The use of associated tactical and physical performance measures derived from a GNSS system.
6. The use of ChampionData® statistics to measure the technical and cooperative network elements of match-play.
7. The use of specific technical, physical, tactical and cooperative network variables to assess performance.

1.6 Approach to the Problem

As evident from the brief introduction, the application of tactical methods of analysis in Australian Football is limited. Accordingly, the following section will utilise soccer as a medium to provide a synopsis of the current available literature on methods for analysing tactical behaviour in team-based sport. The subsequent chapters will then describe, in more detail, how the methods identified in the literature review will be applied in an Australian Football context and utilised in the ensuing studies. Each study examines specific aspects of match-analysis with a view to informing the understanding of match-play in Australian Football and ultimately assisting the design and implementation of training to enhance individual and team performance.

Chapter 2

Literature Review

The forest through the trees: Making sense of an ecological dynamics approach to tactical analysis and intervention in association football

Sheehan, W., Tribolet, R, Watsford, M.L. & Fransen, J. (Eds). (2022). The forest through the trees: Making sense of an ecological dynamics approach to measuring and developing collective behaviour in football. Society for Transparency, Openness, and Replication in Kinesiology. https://doi.org/10.51224/B2000

2.1 Overview of review

As identified in the previous chapter, relative to other contextually similar sports, there is a lack of research investigating tactical behaviour in professional Australian Football. Therefore, this chapter will review literature analysing association football (often referred to as 'soccer', or herein in this review as 'football') performance from a tactical standpoint and will be interpreted using an ecological dynamics perspective. This approach focuses on the performer-environment relationship and provides a basis for understanding the dynamic nature of performance in collective team sports and may therefore provide an appropriate framework for analysing behaviour in Australian Football.[29] The first section of this review will provide a brief overview of the game of football, also highlighting similarities to Australian Football, as well as existing performance analysis techniques utilised in sport. The subsequent section will briefly examine some traditional and commonly considered theories and training practices related to team coordination, decision-making, and performance enhancement in team sport. These will be contrasted against a framework grounded in ecological dynamics. Forming the focus of the review, this framework will then be applied to aid in the interpretation of the findings in the current literature and the significance of these findings for tactical analysis in team sports will be presented. The ensuing sections of the review will firstly identify and provide detail on current methodological approaches for measuring tactical behaviour in football. Subsequently the key findings from the literature and their associated implications for improving performance will be examined particularly in reference to team coordinative behaviour and decision-making. The concluding sections of this review will investigate how small-sided games offer potential performance and training implications for the development of enhanced tactical behaviour in football. A small-sided games approach was chosen as the as they provide representative modified environments that act as a modality to improve performance. This approach allows the simultaneous development of players' technical skills, conditioning and ability to solve and overcome tactical challenges through coordinative behaviour and effective decision-making .[38-41] They provide an environment that mimics the perception-action couplings of in-situ performance allowing superior transferability of learned behaviour in small-sided games to in-game performance.[40, 42]

2.2 Introduction

Football is a collective team sport played between two opposing teams, both containing eleven players, that compete to score by moving a ball, with their feet, into the opponent's goal.[43] Similar to Australian Football both teams must coordinate their own actions to recapture, conserve and move the ball to bring it within the scoring zone to score a goal.[44] This is commonly referred to as attacking. There are two basic ways of achieving this; either by moving a ball individually or by kicking and receiving a ball between members of the same team.[43] When a football team is attacking, the players aim to maintain possession of the ball, moving and passing through and into empty pitch regions in the direction of the goal to create scoring opportunities.[45] Players must also decide whether to dribble, pass, or shoot at goal.[46] When a team is not in possession of the ball, it is defending. In defence, the players must move and coordinate to protect their own goal and attempt to recover possession of the ball.[45]

Football shares similarities and dissimilarities with other collective team games such as field hockey, water polo, Australian Football, basketball, and rugby union. The 360-degree nature of the sport, in that the ball can move in both a forward-back and side-side direction, is similar to that of many other collective team games. However, in football, except for the goalkeeper, all players use their feet to move the ball. Furthermore, collective team games such as Rugby and Australian Football are considered as contact sports, which are characterised by frequent collisions to stop the attacking team from progressing. Regardless of these differences, the principles behind the scientific analysis of sports performance remains the same and aims to advance understanding of game behaviour and subsequently improve future outcomes.[47] In recent years, notational analysis has been utilised to help teams improve their performance and achieve the aim of scoring more points/goals than their opposing team.[48] In collective team sports, this form of analysis has specifically been used to examine passages of play where an initiative or opportunity to score is present (attack) as well as to prevent the opposing team from scoring (defence).[48]

Traditionally, in an effort to deepen the level of understanding of match performance, notational analysis has been used to subjectively audit and describe the behaviours of performers during different sub-phases of play, i.e., attack and defence, to provide additional information for practitioners.[26, 49] This has typically occurred through verbal descriptions of lived experiences or game observation.[27] While these processes may offer insight, such methods are not objective and are less systematic, relying on subjective impressions and procedural knowledge of expert performers.[28] In contrast, in an attempt to objectively quantify the underpinnings of successful performance, analysts have focused on identifying associated physical workloads such as total distance covered or distances covered at different intensities as measured by a global navigation satellite system (GNSS).[10] Furthermore, the assessment of discrete on-field actions such as the number of completed passes, time spent in possession of the ball, or the amount of tackles made, have endeavoured to provide reliable technical descriptions of game demands as predictors of success.[17] However, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance. For example, in football, some studies have revealed that successful teams maintain ball possession for longer than unsuccessful teams[50] while others demonstrated that during the 1990 and 1994 FIFA World Cup finals, over 80% of goals were scored from a total of four consecutive passes or less.[51] The excessive emphasis placed on performance outcomes in these analyses presents an underlying issue. This approach fails to provide a meaningful understanding of the factors related to successful performance and exemplifies the need for a theoretical rationale of performance behaviours.[24, 25]

Implementing tactical analysis in team sports may offer further insight as to 'why' or 'how' certain behaviours emerge.[27, 52] A more in-depth analysis of tactical performance is deemed necessary as the ability to effectively make decisions and coordinate one's actions with those of others is important for success in collective performance contexts. Research in football has been able to discriminate between different levels of opposition[53, 54] and positions[55] by analysing tactical performance where distance, speed, and physical variables have failed to do so. In collective team sports, expert performance is distinguished from novice performance by the achievement of higher levels of task outcomes, with effective and adaptive interactions between teammates.[24] It is evident that experts are able to combine their relevant individual expertise and coordinate behaviour collectively to form functional linkages, known as synergies, between players to achieve a common goal.[30] Through effective coordination and adaptability, proficient players exploit functional couplings to quickly and accurately solve tactical problems as they emerge from variable situations.[30] In an attempt to measure and quantify synergistic behaviour, it has been suggested that technological advancements, such as an increase in sensitivity of GNSS devices and improved application of their output, in conjunction with novel statistical approaches, may allow practitioners to quantitatively model, infer and predict performance outcomes in team sports, particularly during critical in-game events.[17] However, the complexity associated with the reporting of these methods, and a lack of clarity regarding which theoretical framework can appropriately contextualise and describe behaviour, makes application difficult in a sporting context. Ecological dynamics has been considered as a viable framework as it actively focuses on a malleable performer-environment relationship, and may subsequently provide a basis for understanding the dynamic nature of performance in team sport.[29] Utilisation of these novel methods within this framework may upgrade the understanding of currently used methods of analysis, thereby acknowledging the 'how' and 'why' successful behaviour occurs as opposed to just 'when' they occur.[26] This framework provides an alternative to traditional frameworks that have attempted to provide insight into individual decision-making and team behaviour in collective team sports.

2.3 Traditional frameworks for decision-making and team coordination

2.3.1 Individual decision-making

Decision-making is a dynamic process that is reliant on effective and efficient use of perceptual-cognitive mechanisms. Perceptual-cognitive skill refers to the ability to identify and acquire environmental information for integration with existing knowledge so that appropriate responses can be selected and executed.[56] A deterministic (predictable) and static rational approach to the assessment of decision-making implies that decision-based processes are derived from the ability of performers to discriminate between different situational outcomes. This framework suggests that performers must mentally calculate the ratio between potential gains and losses resulting from a decision to act before selecting and carrying out appropriate desired actions.[57] This model advocates that individuals can effectively and efficiently evaluate the costs and benefits of every specific performance solution prior to the solution being implemented.[52] In a sporting context, this has been researched by analysing the gaps between hypothesised normative options and actual selected options by problem-solving athletes.[58] However, for this to be viable, a set of specific choices must be available in advance and the process of discriminating between solutions would be a vast computational load which would need to occur in a short amount of time. Furthermore, this approach does not allow for variability in responses. Inevitably, this framework is only viable in a closed system incorporating linear processes.[52] In contrast, the sporting performance environment is proposed to be an open, non-linear complex system which is a result of subunit (i.e. player) interaction and is subject to variable changes in both the surrounding environment (including opposing performers) and an individual's actions.[59] Accordingly, it has been proposed that future research on decision-making in sport needs to consider a more dynamic perspective considering both cognition and action.[60] This may subsequently allow the characterisation of system sub-units, in the form of their individual abilities to make informed decisions and provide insight into how the decision-making process influences individual behavioural outcomes and ensuing team coordination.

2.3.2 Team coordination

Several authors have identified a potentially viable framework for explaining team coordinative behaviour that is based on shared knowledge or group cognition. Within this framework, performance is underpinned by the existence of a representation or schema that is responsible for the organisation and regulation of behaviour.[27, 52] These representations provide a basic, shared understanding of the methods required to achieve desired performance outcomes on both an individual and team level[27] and are maintained by shared knowledge of complimentary goals, strategies, expectations and relevant tactics.[52] Team coordination and cohesion may be enhanced when representation of a collective action, such as tactical guidelines, playing style or directions from a coach are linked to a mental representation of a performance context and is somehow shared by all players and implemented into practice.[27] Conversely, the absence of coordination may imply that a shared cognitive state is yet to be achieved amongst team members.[48] Similar to the static rational explanation of the multifaceted nature of decision-making, some proposed limitations have rendered this approach as potentially invalid in an open, non-linear sporting context. Through variations in game play, informational cues are likely to be used differently by each performer, consequentially making the process of indirectly perceiving 'who knows what' throughout the game an immense computational load.[27] Further, the ability to explain re-formulations of a performers schema's or shared knowledge, when changes occur in another teammate's schema, for example due to the opposition's response to tactical guidelines and playing style, has proven difficult to verify.[30, 48]

A key difficulty in research on this topic is to justify how mental representations exist beyond the mind of an individual organism and can somehow be shared in a collective representation.[27, 30, 48] Similarly, as players possess and rely on different types of knowledge (e.g. declarative, procedural and strategic), this likely results in different knowledge of the game and ultimately different representations between players.[52] As per the existing framework governing individual level of decision-making, group cognition requires an appropriate theoretical framework that can adequately explain how synergistic behaviour rapidly emerges between teammates as the environment presents new and unpredictable situations. Such a framework will be explored in subsequent sections of this review. Coaches can subsequently utilise this information to appropriately design training tasks and drills that promote coordinative and co-adaptive behaviour between players and therefore may potentially improve team performance.

2.4 Traditional approaches to improving performance

Effective decision-making and coordinative behaviour is associated with superior performance.[24, 30] Accordingly, it is justified that training and preparation are required to improve these aspects and subsequent sporting performance. One traditional approach emphasises deliberate practice and early specialisation as key for expert performance.[59, 61] Conceptualised by Simon and Chase in chess[62], but implicated by Ericsson,[63] it is suggested that learners exposed to 10 000 hours, or 10 years, of intense, repetitive practice will gain the capacity to develop repeatable behaviours and enhance automatic control of movement, both deemed necessary for superior, expert performance.[61] While time spent in a sport may, in some circumstances, distinguish expert from novice performers, only 1% of the variance in elite-level sporting performance can be accounted for by deliberate practice[64] suggesting that the adoption of a purely nurturistic view to the development of expertise is nonsensical[65] and disregards the importance of variability in movement and practice.[59] While a substantial amount of time in practice for a specific sport is deemed necessary for success, research suggests that attainment of expert performance is not always accomplished through deliberate practice[59] and that the functional role of adaptive movement variability, which is commonly associated with poor performance in a deliberate practice environment, is imperative for achieving expert levels of performance.[61] Effectively exposing performers to diverse sporting environments may promote the utilisation of movement variability. This consequentially allows athletes and teammates to diversely coordinate and adapt to unpredictable situations which dynamically emerge over time in the sporting environment.[59]

When implementing decision-making and performance tasks, similar to traditional practice methods identified above, open variability is often neglected. Traditionally, decision-making assessments have often adopted a closed-system analysis approach endeavouring to establish causal relationships. Former studies have implemented tasks without opposition and/or in a static environment with physical performance and responses measured in a non-representative way which subsequently isolates it from the task (i.e., pressing buttons, viewing video footage, etc.).[59, 66] These approaches ignore the hierarchical structure of the decision-making process whereby individual decision-making is based on the interaction with fellow teammates who themselves act according to an underlying tactical strategy dictated by the current game context.[56] As a result, former approaches have failed to provide information regarding athletic potential and adaptability in different sporting situations and have had little success in distinguishing expert from novice performers.[59] Phillips et al.[59] attributed these results to contextual flaws in the task design as team-based sports are often performed in dynamic, open environments characterised by marked temporal and spatial variability. In contrast to a closed-system design, contemporary approaches applying a representative task design, which sample relevant information from the performance environment and couple it with task-specific actions, allows the ongoing co-adaptation of an individual within the dynamically changing environment.[61] Within a representative design, expertise effects become more apparent for requisite responses as performers are required, and able, to perform sporting actions for a stimulus presented under in situ conditions.[57] In order to appropriately design decision-making and training tasks, a relevant theorectical framework needs to be identified and appropriately applied in a manner which emphasises the functional role of adaptive movement variability in an ecologically valid environment.[61]

Ecological dynamics has recently gained applicable momentum in the realm of performance analysis as well as training implementation. This may be attributed to its overarching theoretical background that focuses on the performer, the environment in which they act, and the influence of key interacting constraints (i.e., organismic, task and environmental)[67] that guide and govern behaviour (Figure 2.1). A focus on the performer-environment is fundamental for representative task designs and provides the basis for understanding performance in team sport.[29] However, despite a recent increase in popularity and the apparent applicability of this framework in the sport of rugby,[68] sailing,[69] basketball,[70] volleyball,[71] and handball,[72] the implementation of an ecological dynamical systems framework in a sporting context has presented several issues. As this framework is conceptually based in ecological psychology and dynamical systems theory, difficulty arises in the interpretation and understanding of associated ideas and terminologies. Additionally, appropriately applying relevant concepts to help explain team performance in a concise manner so it can easily be adopted by practitioners concerned with team sport performance has proven difficult. However, an ecological dynamics framework has potential if these issues can be addressed. Providing a clear and succinct outline of the key concepts and terms associated with this framework may be an appropriate starting point for enhancing understanding and applicability.

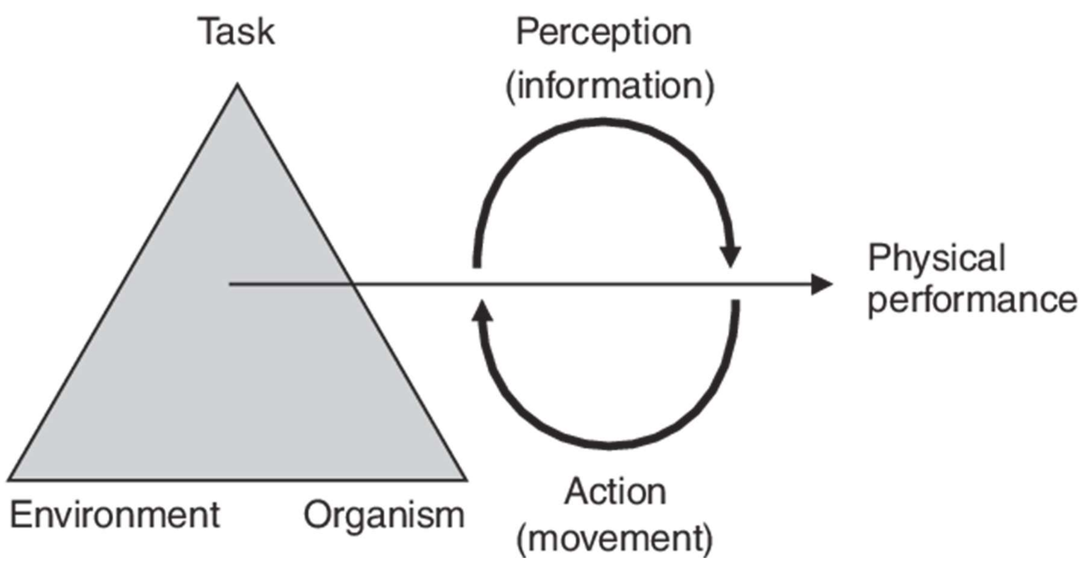

Figure 2.1: Newell's model of interacting constraints.[73]

2.5 Ecological dynamics theory

Ecological dynamics is a combination of ecological psychology, emphasising the cyclical, lawful relations between any individual and the environment in which they function,[74] and dynamical systems theory, providing an explanation for neurobiological coordination at multiple levels with roots in thermodynamics and synergetics.[61]

An ecological dynamics approach uses the concepts and tools of dynamical systems theory to understand phenomena that occur at an ecological scale.[61] The most relevant information for decision-making, regulation of action and coordination arises from the continuous performer-environment interaction.[29] Within the performer-environment, humans are surrounded by various sources of information banks of energy flows or arrays which act as specifying information variables when perceived by performers.[75] This critical information augments decision-making and collective organisation and consequently shapes behaviour during goal-directed activity.[29] The influence of environmental information and ensuing behaviour has been demonstrated in nature. For example, amidst insect fauna, a colony of millions of insects avoid random behaviours (i.e., coordinate their behaviour), and guide the decisions of others, by exploiting information in the environment. This information is presented through pheromones that the insects secrete into the earth to guide their cooperative nest-building activity.[76] Through the analysis of an organism and its environment, or similarly a performer in their environment, it becomes apparent as to how ecological dynamics can provide information as well as predictions about which conditions will produce favourable, coordinative movements. Furthermore, this framework can help identify features of a situation will facilitate or disrupt interpersonal, as well as collective, coordination in goal-directed activity.[27]

The scale of analysis is an important consideration when identifying key information variables that influence decision-making and coordination. The lowest dimension of coordination is evident on a macroscopic scale, representing the global synergy between all individuals within a performer-environment system. This system is a product of all complex non-linear subsystems and their non-linear interactions within the environment.[77] It is imperative to first understand the global dynamics at the behavioural level of analysis.[77] Subsequently, this global system can be decomposed and examined at a mesoscopic level (subsystems/functional units) and, ultimately, a microscopic level to provide specific in-depth information regarding functional linkages between specific individual components (dyadic relations). In a sporting context such as football, the inter-team relationship between two opposing teams might represent the global, macroscopic scale while the intra-team relationships between players in their respective teams would signify the mesoscopic level. Exploring even further, dyadic relations between two cohesive teammates or an attacker and a defender would represent the microscopic level. Utilising this approach, researchers can work in a hierarchical manner to examine the impact of relevant variable components on the overall dynamics of the sporting environment.[48]

2.6 Components of systems within an ecological dynamics framework

2.6.1 Perceiving affordances for action

Contrary to alternate theories, such as those based on discriminating between desired movement solutions prior to action, decision-making from an ecological dynamics perspective is centred around the perception of, and attunement to environmental properties or energy arrays.[66, 75] In his theory of direct perception, Gibson[75] proposed that humans perceive and act on substances (e.g., grass), surfaces (e.g., a football field), places (e.g., a stadium), objects (e.g., a ball) and events (e.g., a football game) in the environment. These components provide opportunities for action, known as affordances.[75] At each subsequent moment, an individual must choose from all available affordances which will allow the performer to subsequently act in a way that will facilitate the achievement of an intended goal. However, as an individual continuously moves within the environment, other affordances continuously persist, emerge and dissolve, providing a dynamically changing perceptual landscape of opportunities for action.[66] Moreover, the varying intrinsic dynamics of each individual, shaped by past experiences, beliefs, knowledge of the game, etc, will afford different responses or solutions to different situations.[78] For example, while a teammate may be situated in open space, free of a defender, 40 metres away, a ball carrier may pass only if they believe, or have previously had positive interactions with similar affordance before successfully performing a similar length/type of pass before, they are capable of performing a pass over that distance. Conversely, another individual may not pass, and choose to dribble instead, if they believe they cannot pass the required distance. Through continual perception of affordances, humans have the ability to regulate actions and adjust movements relevant to their environment.[74] It is the perception of affordances that consequently control behaviour.[79] Additionally, the ability of an individual to perceptually attune to persisting or changing affordances can often help distinguish between novice and expert performers with the latter possessing an ability to better attune their movements and actions with that of the available information in the environment around them. The theory of direct perception may be preferred over traditional theories as the decision-making process in this context limits or negates the cognitive processing required for the vast amount of sensory information a performer interacts with in the environment. In contrast, this theory emphasises that it is the implicit coupling of perception and action that leads to emergent behaviour. The theory of direct perception also provides a basis for understanding how individuals coordinate their actions with those around them.

Just as affordances guide individual actions, in collective team sports collective affordances, i.e. similar affordances or opportunities perceived by team members who are linked and part of the same coordinative unit, allow synergistic behaviours to emerge and are sustained by common goals between players who want to achieve success.[24] In a game of football, for example, both teams have the same objective to overcome the opposition and win. Synergistic team behaviour is dependent on the ability of players to be collectively attuned to shared affordances. Collectively, players need to be attuned to affordances 'for' others (affordances an individual can provide for others under given environmental conditions) and 'of' others (affordances a fellow player can provide a perceiver).[52] Successful teams are composed of players who have learned to perceive shared affordances 'for' and 'of' other players.[48, 52, 80] Furthermore, these affordances may appear and disappear instantaneously, leading to fluctuations in the state of system organisation.[24] These collective affordances are shaped by surrounding constraints within the performer-environment and guide the emergence of coordinated playing configurations.[26] For example, in football, the relative position of a defender constrains passing opportunities. The positional displacement of a defender nearest to an attacking ball carrier can be collectively perceived by both the ball carrier and his/her teammate.[81, 82] As a defender approaches the ball, attacking teammates need to position themselves in a way that offers a passing affordance 'for' the ball carrier while, simultaneously, the ball carrier needs to move and deviate in a way that opens up passing lines, allowing them to perceive the affordance provided 'of' a fellow player.[81, 82] The collective perception of the defenders positioning allows teammates to coordinate in a way that provides opportunities for action prior to the resultant action being performed.

2.6.3 Constraining affordances

Contrary to traditional information processing theories, movement is not a pre-determined entity stored in the central nervous system, rather it is a dynamically changing process resulting from the interaction between environmental constraints and the internal resources of the performer in light of the task at hand.[83] Constraints are either intrinsically or extrinsically bound and are considered as boundaries, limitations or design features which shape affordances and therefore guide action and ensuing organisation of the components within an individual or sub-system.[25] There are two key classifications of extrinsic constraint:

i) Environmental constraints relate to the structural and physical properties of the current system such as temperature, surface, altitude and external information available to the performer.[29]

ii) Task constraints are implied constraints or restrictions, such as gameplay rules, which must be met within some tolerance range in order for the movement to produce a successful action.[25]

Further to these conditions, goals can also constrain behaviour. Similar to task constraints, these guide behaviour by taking the form of a rule which determines how an individual should act to achieve a certain outcome. This rule asserts that a performer should seek specific information, presenting relevant affordances, that are specific to a desired outcome.[66] For example, in football, one of the primary objectives is to prevent conceding a goal. This shared goal affects the emergence of coordinated behaviour with players of the defending team positioning themselves between their goal and the opposition team to limit goal scoring opportunities.[84]

Individuals possess unique intrinsic dynamics which act as constraints on behaviour.[78] They are the structural and functional characteristics of performers and include aspects related to their physical, psychological, cognitive and emotional make-up.[78] Individual variations in intrinsic dynamics allow unique, functional solutions to emerge. Furthermore, as an individual develops, these dynamics will diversify and change.[59] Collectively, it is the confluence of interacting constraints, both intrinsic and extrinsic that shape perceived affordances and determine subsequent coordination and behavioural outcomes. Often small changes in one constraint can have a large influence on ensuing coordination patterns.[25] For example, adding one player to each team in small-sided football game, i.e. from 4v4 to 5v5, results in an increase in separation between the two teams, as measured through the average position of all players in both teams.[85] The interaction of constraints forces performers, both individually and cooperatively, to become attuned to the changing dynamics of the performer-environment. Effective attunement allows performers to seek stable and effective patterns of behaviour that successfully satisfy constraints and aid goal achievement.[29, 78] Expertise can be defined as the ability of an individual or team to functionally interact with imposing constraints and exploit them to successfully achieve performance outcomes on an individual and team level.[29] This concept may also highlight why experts may, or may not, be selected in the best sporting teams. While an individual may possess superior performance at an individual level, failing to interact cohesively at an intra-team level may jeopardise team performance and hence the respective player's selection into that team.

In collective team sports, functional patterns of behaviour develop through a process of self-organisation and co-adaptation. Organisation emerges from performers' interactions with each other, the environment, and associated constraints.[24] Performance analysis from an ecological dynamics perspective seeks to explain how the interaction between players (and teams) and environmental information constrains emerging patterns of stability and variability, along with the associated transitions in organisational states that occur due to the latter.[24] Synergistic behaviour in team sports requires a finely tuned balance between stability and variability at all associated levels (macro-microscopic level) simultaneously in order to achieve a common task goal.[77] Once constraints and ensuing patterns have been identified, appropriate training methods that are guided by ecological information can be implemented in the form of small-sided team games. These may allow functional patterns may emerge through the interaction of players working towards a common goal.

2.6.4 Stability and variability

Changes in informational constraints give rise to potential attractors (favourable affordances) and repellers (unfavourable affordances) which subsequently guide behaviour. An attractor or attractive state can be classified as a stable, functional linkage or movement solution. Conversely, states to be avoided are known as repellers and are associated with dysfunctional movement outcomes which hinder task-achievement.[66] As new affordances continually arise and dissipate, new, non-linear behaviour emerges as a result of the continual interaction between attractors and repellers at bifurcation points.[66] Bifurcation points are associated with changes in affordances and, consequentially, the available number of attractors and repellers precede transitions in behaviour.[66, 86] At these points, performers are required to undertake the functional and emergent process of decision-making. In training and game contexts, manipulation of relevant constraints can either increase or decrease the number of available attractor/repeller states.[87] For example, in football, providing numerical superiority in attack, such as a 5v3 format, will likely provide additional passing attractors as the uneven number of players will leave fellow attacking players in open space free to receive a pass. Conversely, providing an even format, e.g., 5v5, may present relatively more repellers that need to be considered in the decision-making process as each player will likely be marked by a defender, resulting in difficulty finding players in free space. The ability to be attuned to relevant attractors and repellers in the performer-environment landscape through direct perception underpins successful decision-making in sporting environments and allows organised, functional patterns to emerge.[26, 66]

Bifurcation points can lead to fluctuations in the organisational state of the team sporting environment. When fluctuations are powerful enough to perturb existing balance, a stability-breaking process occurs transiting the game into a new dynamic state of organisation.[26] For example, in a 1v1 drill, when an attacking player decides to reduce the relative distance to the goal against a defender, the system enters a transition phase.[84, 88] The system will then transition into one of two states: 1) The defender maintains stability and remains between the goal and the attacker, minimising scoring affordances or 2) The attacker successfully breaks stability and passes the defender towards the goal providing a scoring opportunity.[84] In team-based sports, stability is often linked with favourable co-ordination between players, i.e. players move cohesively to achieve a common goal, while instability is associated with the loss of co-ordination.[26] Analysis from an ecological dynamics perspective can help distinguish between successful and unsuccessful performances and patterns of play by examining the stability breaking processes that emerge throughout the functional interaction between players, teams and environmental affordances and constraints.[26] This form of analysis can be used to identify the distinct properties that contribute to the stability or variability in emergent behaviour in collective team sports.

2.6.5 Adapting to change

The ability to perceptually attune to affordances and favourable attractors is linked to superior levels of expertise.[66] This is particularly important when multiple affordances/attractors are perceivable by the performer, where certain affordances may be more valid than others in order to achieve an intended goal.[66] At this instant, performers enter a region of metastability where multiple stable, functional states (multi-stability) become available and an inherent decision is required.[59] Within this region, individuals have the ability to exploit co-existing co-ordination tendencies in order to maintain stability at bifurcation points.[61] For example, in football, when players are required to pass to a moving teammate at increased distances, lofted passes are preferred. In contrast, when required to pass into a stationary goal at similar distances, while players may use a lofted pass to achieve the task goal, they often opt to utilise a low trajectory pass as this is perceived as a superiorly valid option.[46] The authors highlighted that the lower trajectory was likely due to an "inside-foot pass-kick" which is preferred over shorter distances when precision is the main focus while an "instep-foot pass-kick" is preferred when passing over longer distances due to the ability to generate more speed.[(46)] This highlights that while different performance solutions are available, a specific solution may be better suited to the task at hand. Individuals can transition between multiple states (multi-stability) of organisation under different constraints, subsequently aiding the achievement of successful performance.[61] This has been demonstrated in cricket where batsmen were able to successfully hit the ball, pitched at the same length, using either front- or rear-foot batting strokes.[89] Conversely, shorter pitched deliveries afforded rear-foot attractors, resulting in strokes being played off the rear-foot while fuller deliveries, alternatively, afforded front-foot attractors.[89] With experience and practice, coordination and behaviour converge towards stable states of movement and synchrony through effective decisions made at bifurcation points between attractors and repellers. Through continuous exposure to sufficiently variable training environments, players are afforded the opportunity to exploit multiple problem-solving strategies allowing multiple movement solutions to emerge.[89]

Performers adapt in numerous ways to achieve stability and are able to assemble functional coordinative patterns from an abundance of degrees of freedom.[87] In pursuit of stability, a system or performer with many degrees of freedom can act as if it were a simpler system if sufficient constraints, or linkages, are established among its components by coupling them into a synergy.[66, 90] In human movement, the wide array of peripheral degrees of freedom, represented by the many interacting aspects related to motor behaviour (i.e. physiological, anatomical and biomechanical), allows the assembly of varying movement solutions. Similarly, in a collective team environment, emergence of coordination and stability can emerge as a result of dimensional compression, where independent degrees of freedom (e.g. players in a team) are coupled so that a synergy is created with fewer degrees of freedom.[48] Dimensional compression allows the reduction of system dimensionality into smaller, coordinative synergies or sub-units.[52] In football, players have demonstrated coordinative behaviour with their own position-specific teammates (i.e., defenders synchronise with fellow defenders), acting as a cohesive synergy.[91] This coupling is based upon a social perception-action system supported by shared affordances (e.g. the movements of opposition attackers or the opposition team's ability to counter-attack quickly) and has the capability for varied patterns of coordination due to the numerous degrees of freedom.[30]

In contrast, while freezing, or dimensionally compressing specific degrees of freedom can be utilised to develop desired movement solutions or coordination, abundant degrees of freedom may allow individuals to achieve specific performance goals and adapt to metastable regions in a variety of ways.[29, 86] An ecological dynamics approach recognises degeneracy, or functional equivalence, in human subsystems and refers to the ability of structurally different components, or degrees of freedom, to coordinate in a way that allows the achievement of the same behavioural goal.[59] As noted, cricketers have the ability to produce the same performance outcome (hitting the ball) utilising different movement patterns.[89] In team systems, reciprocal compensation allows coordination and stability to persist. Certain components, or players, have the ability to adjust their respective contributions or efforts, so that task performance goals can still be achieved despite variation in the contribution from other components.[48] Through analysis of synergistic linkages (dimensional compression), reciprocal compensation and degeneracy in collective team sports, practitioners can effectively explain how successful, stable performance outcomes emerge despite demonstrating different movement solutions or tactical patterns.[26] With reference to these concepts, it can be inferred that variability in movement solutions may not be the expression of a dysfunctional, noisy system, as commonly thought in practical applications, but an essential component of flexible and stable behaviours.[77] In learning environments and game situations alike, it may be appropriate to promote decision-making tasks that allow for degenerate solutions to emerge, enabling individuals and teams to appropriately adapt to dynamically changing environments which are implicitly linked with collective team sports.[61]

2.7 Improving decision-making and coordination through appropriate task design

Successful decision-making is defined as the capacity of a performer to select functional actions from a number of affordances at bifurcation points to achieve a specific task goal.[57] In training, the goal is to improve a performer's capacity to make appropriate decisions at these bifurcation points. As identified, traditional approaches to decision-making tasks and evaluation tests, such as those used in talent identification, incorporate a limited number of constraints, restricting possibilities for action.[61] These tasks have exposed performers to constraints and affordances that would not normally be available in an in-situ environment.[92] For example, selected designs have incorporated slide images or video presentations, as opposed to in-situ stimuli. Furthermore, these were coupled with verbal or micro-movements (pressing buttons, moving a joystick), as opposed to sports specific action responses.[17] These approaches lack representative task design and consequently remove functional perception-action couplings that would otherwise be present in competition conditions.[93] Additionally, traditional designs fail to recognise the importance of variability in the environment and performer which are both essential for improving performance, as well as distinguishing between expert and non-expert performers.[61]

An ecological dynamics approach to improving decision-making and collective team performance requires a setting that is representative of the original performance environment, possessing all the associated information.[66] Furthermore, decision-making tasks must be designed in a manner that is eminently anticipatory and cyclical, allowing the performer to perceive dynamically changing information sources resulting from their own actions within the external environment. This additional information then consequentially triggers new affordances for action. Furthermore, these settings must allow performers to utilise movement variability as they explore and create opportunities for action.[29, 66] Through this exploration, new affordances and ensuing patterns may emerge due to adaptive processes such as dimensional compression, degeneracy or reciprocal compensation. Task designs utilising in-situ environments, coupled with specific action responses, may improve performance as they provide performers with the opportunity to perceive in order to act as well as act in order to perceive, both in a way that is specific to the intended generalisations of the sport.[92]

Task designs utilising a representative design framework have been able to distinguish between novice and expert performers, as well as improve performance.[17] In-situ performance tasks, coupled with relevant constraints and environmental information, may improve individual performance through the enhanced attunement to relevant and valid affordances, consequently allowing the performer to satisfy the unique set of imposing and interacting constraints.[61] In training task designs, constraints can be manipulated to progressively direct individuals to specific or favourable affordances that support the achievement of a task goal or allow the stabilisation of an intended performance outcome.[29] Similarly, in collective team sports, appropriate designs may allow players to become perceptually attuned to affordances 'of' and 'for' others, providing individuals with the opportunity to refine and adjust behaviours in a way that allows the functional adaptation to those of teammates and opponents.[27]

Tasks that provide performers with metastable regions in which they can explore affordances and associated attractors and repellers at bifurcation points, may allow individuals and synergies to develop healthy variability in movement organisation and performance output.[61] While expert performance is characterised as stable and consistent over time, as well as resistant to perturbations, it is also flexible and adaptive (or 'degenerate').[61] Highly proficient players and teams have the ability to appropriately control variability, adapting to unexpected task-specific constraints.[77] Davids et al.[29] identified five key components for consideration when designing representative tasks to improve decision-making from an ecological dynamics perspective . Task designs should possess:

i) Noise: Promote noisy and messy tasks which encourage performers to search and assemble functional movement patterns in adverse situations.

ii) Predicated perception-action responses: Enable, and facilitate the perception of information that specifies favourable, or superiorly valid, affordances or attractors in a performance environment.

iii) Open-system qualities: Avoid discrete sequences and design tasks that are ongoing and can evolve over different timescales.

iv) Representative affordances: Provide possibilities for action that are relevant to the intended performance environment (i.e., competition).

v) Components scaled to the performer: Acknowledge individual differences (i.e., intrinsic dynamics) and variation in movement solutions.

Additionally, for appropriate task design, Araujo et al.[86] highlighted that coaches and performance analysts need to identify primary constraints to be manipulated, or considered, during practice as well as desired movement patterns and outcomes. To identify desirable patterns and behaviours, and track improvements associated with practice, order and control parameters need to be identified. These parameters can effectively describe behaviour and allow the validation of control laws which regulate action.[66] Existing literature analysing pattern formation in sports has identified order parameters, which refer to collectively stable and reproducible relationships among a system's components, and control parameters, which move the system through its many different attractor/coordinative states.[25] Temporal, non-linear changes in order parameters have been observed with systematic changes in control parameters and stability is often observed in the order parameter in low control parameter values.[25] For example, in a football attacker-defender dyadic subsystem, the interpersonal distance between the two players acts as a control parameter while the relative distance to the goal acts as an order parameter. As the control parameter changes, manipulated by the attacker trying to pass the defender, the order parameter changes as the attacker gets relatively closer to the goal. If the system is sufficiently perturbed, e.g. the attacker misaligns the opposing player, and the defender's stability is broken, the attacker may move past the defender and closer to the goal, relative to the defender.[84] It is therefore evident that a change in the control parameter can induce a change in the collectively defined order parameter. There is a need to identify relevant control and order parameters that specify functional collective behaviour, as these underpin interpersonal synergies between performers.[27, 66] This can subsequently act as a starting point for designing relevant tasks and setting functional goals as they have the capacity to identify favourable patterns of behaviour. Ensuing the successful development through appropriate training modalities, these behavioural patterns can then be coordinate and exploited tactically to achieve success.

2.8 Tactical performance in football

A viable framework that can provide a basis for understanding performance in team sports such as soccer and Australian Football, is essential to provide an upgrade to more operational methods of analysis, acknowledging 'how' and 'why' behaviour emerges. An ecological dynamics approach has been applied to provide a better understanding of tactical behaviour of teams, and players within these teams. Whilst existing literature has examined performance in this context, current research examining tactical behaviour in team sport is scattered and the adoption of a 'foreign' framework means that associated terminology and concepts are often not interpretable by researchers and practitioners. Further, while the literature examining tactical behaviour in Professional Australian Football is limited, the interpretation of findings within a viable framework such as ecological dynamics is also scarce. Therefore, using football as an example, this review will present an ecological dynamics approach to better understand tactical performance in team sport. The ensuing sections will identify current methodological approaches to tactical analysis on an inter-team (macroscopic) and intra-team (mesoscopic) level in football, which will subsequently be adopted and applied in Australian Football context, followed by a review of tactical findings and associated applications. Accordingly, to gather literature for this review, electronic databases PubMed and Google Scholar were used. Search terms included 'ecological dynamics', 'football', 'football', 'tactics' and 'tactical analysis' with combinations of search terms also applied. Additional sources were obtained via comprehensive use of article reference lists. Following screening of titles and abstracts for relevance, 106 articles were used for further review.

2.9 Methodological approaches

Table 2.1 identifies previously utilised order and control parameters which, when used appropriately, offer insight into the tactical behaviours demonstrated by individuals and teams. These variables help identify 'why' and 'how' patterns of coordination and functional behaviour emerge.[17, 26, 48] Through analysis of attacking and defending phases of play, these parameters are capable of recognising favourable patterns of behaviour which may assist teams in their attempt to score more points/goals than their opposing team.[48] From an ecological dynamics perspective, football is a performance-environment sub-system where players and teams perceive affordances which guide decision-making and coordinative behaviour. Football teams can utilise key ecologically bound strategies such as degeneracy, dimensional compression, reciprocal compensation, and interpersonal linkages to maintain system stability.[94-99] These aspects can be objectively identified and analysed using relevant statistical approaches, with the variables identified in Table 2.1.

2.9.1 Statistical procedures

Parameters identified in table 2.1 have often been used in association with specific statistical procedures. Running correlations are often applied over time-series data to examine the spatiotemporal interactions between teams (e.g. two centroids) or respective participants (attacker-defender dyad) during attacking and defending sequences.[100] Utilising this technique it is possible to identify stable/symmetric and unstable/non-symmetrical patterns.[100] Conversely, a lower coefficient of variation, demonstrating lower values in a given parameter, may be associated with regularity and stability.[101] While the coefficient of variation may offer insight, it has been suggested that a non-linear metric such as entropy should be utilised as it can provide additional information about the structure of the variability in a non-linear system that evolves over time.[102] Similar to the coefficient of variation, lower values represent more predictable or regular patterns, often associated with less chaotic sequences of data points.[103] Finally, studies have sought to identify specific patterns or values at which individuals, or systems, enter a period of criticality. For example, in a 1-on-1 football drill, when an attacking player is within 1-2.5 metres of the defending player, the system enters a transition phase whereby changes in relative velocity determine the outcome of the transition. When the relative velocity remains low, the defender maintains stability and remains between the goal and the attacker but, alternatively, when relative velocity supersedes a certain threshold in the attacker's favour, the attacker breaks the stability and moves closer to the goal providing a scoring opportunity.[84, 88] In this transition region, sub-systems may be forced to transit from one state of organisation to another (either stability or variability), potentially allowing one team or an individual to gain tactical advantage over the opposition.[66]

Table 2.1: Methodological approaches for the analysis of tactical behaviour in soccer

Variable	Variable defined	Level of analysis	Studies
Centroid	Calculates the mean lateral and longitudinal position of each player in a team and can represent, in a single variable, the relative positioning of both teams in forward-backward and side-to-side movement displacement[30, 48] Weighted centroids account for the relative positioning of the ball, i.e., if the ball is closer to an individual, their position will be more relevant[104]	Macro-level Meso-level	30 studies - [28, 42, 44, 85, 91, 98, 100, 104-126]
Stretch index	Computes the average radial distance of all players to their team centroid and provides a distinct measure of dispersion in lateral and longitudinal directions[30] Weighted stretch index computes the average distance to weighted centroid[30] Relative stretch index demonstrates how teams expand and contract relative to one another[121]	Macro-level Meso-level	28 studies - [28, 42, 44, 45, 53, 85, 91, 97, 98, 101, 105-111, 116-118, 121-124, 127-130]
Length/Width	The displacement value between the two farthest players in either the lateral (width) on longitudinal (length) direction at a given time. Length per width ratio represents the relationship between the playing length and width and describes the preferable axis direction towards which the players from both teams are distribute[119]	Macro-level Meso-level	12 studies - [41, 42, 110-112, 116, 117, 119, 124, 125, 131, 132]
Surface area/Effective play space	Team surface area can be either rectangular (team length by width)[133] or by detecting all possible triangulations formed by team players. The combined area of all triangles is then computed providing the total area covered by a team[45] Effective play space is defined by the smallest polygonal area or convex hull delimited by the peripheral players, containing all players in the game[30, 45]	Macro-level Meso-level	24 studies - [44, 45, 100, 103, 106-108, 110, 111, 113, 115, 116, 119, 122, 129, 131-139]
Voronoi diagram/Dominant region	Voronoi diagrams are spatial constructions that allows a spatial partitioning of the field area into cells, each associated with each of the players, according to their positions.[140] Interpreted as the respective dominant region of each player within the limits of the playing area[141] Superimposed Voronoi diagrams convey the maximum percentage of overlapped area of a team or two opposing cells as well as the percentage of free area[141]	Macro-level Meso-level	5 studies - [42, 43, 140-142]
Heat map	Heat maps highlight, with warmer colours, the zones where each player has encountered for longer periods throughout a match.[48] Used to identify most occupied areas for each individual[88]	Meso-level	3 studies - [88, 102, 136]
Cluster/relative--phase method	Quantifies the collective spatiotemporal phase synchronisation, of oscillatory movement components (e.g., team players movement displacement trajectories or velocities) in a single collective parameter[143] When players moving in synchrony, they are 'in-phase' (0 degrees) and conversely are asynchronous (180 degrees) when players go in opposite directions[26]	Macro-level Meso-level Micro-level	15 studies - [28, 39, 54, 81, 84, 88, 97, 118, 120, 143-148]
Interpersonal distance	Straight line distance between two corresponding teammates or, alternatively an attacker and a defender. Similarly, may also include passing and shooting distances which are calculated as if ball would travel in a straight line. Interception variables may also include the perpendicular distance of each player to the ball's trajectory, the time for the ball to arrive at the same point and the required movement velocity of the nearest defender and goalkeeper to intercept the ball[82] Team separateness is defined as the sum of distances between each team player and the closest opponent – Higher value symbolises freedom of movement[119]	Meso-level Micro level	34 studies - [38-41, 46, 81, 82, 84, 88, 97, 98, 119, 120, 122, 127, 128, 139, 140, 142, 145-147, 149-161]
Interpersonal angle	May represent the relative angle between two players with respect to the goal[26] or to another player or opponent[149] Also included passing angles which are formed by the ball carrier, his teammate, and an opponent, and shooting angle which may be formed by the ball carrier, the goal, and the opponents[149]	Meso-level Micro level	7 studies - [88, 120, 145, 147, 149, 156, 162]
Relative velocity	Velocity of one player, or centroid, relative to the other.	Micro-level	7 studies - [82, 84, 88, 120, 147, 152, 153]
Displacement	Provides lateral and longitudinal movements of players.[143] Can be measured using global positioning system devices[14]	Meso-level	5 studies - [54, 95, 139, 160, 163]
Complex network analysis	Convey the local structure of organisation among players. In these networks, nodes represent players, and links are weighted according to the number of passes or positional changes completed between players.[48] Includes measures such as network density, intensity, centrality, betweenness, in- or out-degree measures, closeness, reciprocity index and transitivity index.	Meso-level	17 studies - [55, 96, 99, 142, 164-176]
Tactical strategies	Possession types (e.g., type of ball recovery, counter-attack vs elaborate attacks) or balanced vs imbalanced defence), tactical patterns (risky vs conservative) and timescales (short vs long).	Macro-level Meso-level	4 studies - [5, 6, 177-179]

2.10 Coordinative behaviour in football

2.10.1 Inter-team

The lowest dimension of the assessment of coordination is evident on a macroscopic scale, representing the global synergy between all individuals within a performer-environment system. In a football context, macroscopic analysis occurs on an inter-team level whereby two opposing teams are inextricably linked, each reciprocally acting in response to the other team's behaviour and patterning. This system is a product of all complex non-linear subsystems and their non-linear interactions within the environment or, in this case, a football game.[77] It is essential to first understand the global dynamics at the behavioural level of analysis [77] so that ensuing functional linkages and patterns can be analysed at a mesoscopic level (subsystems/functional units). At the inter-team level of analysis, studies have methodologically utilised surface area/effective play space (Figure 2.2a), length and width (Figure 2.2b), centroids (Figure 2.2c), stretch indices (Figure 2.2d), Voronoi diagrams (Figure 2.3), phase analysis, and tactical strategies to help identify favourable patterns of behaviour that lead to successful attacking (goal scoring opportunities) and defensive (preventing goal scoring opportunities) sequences of play.

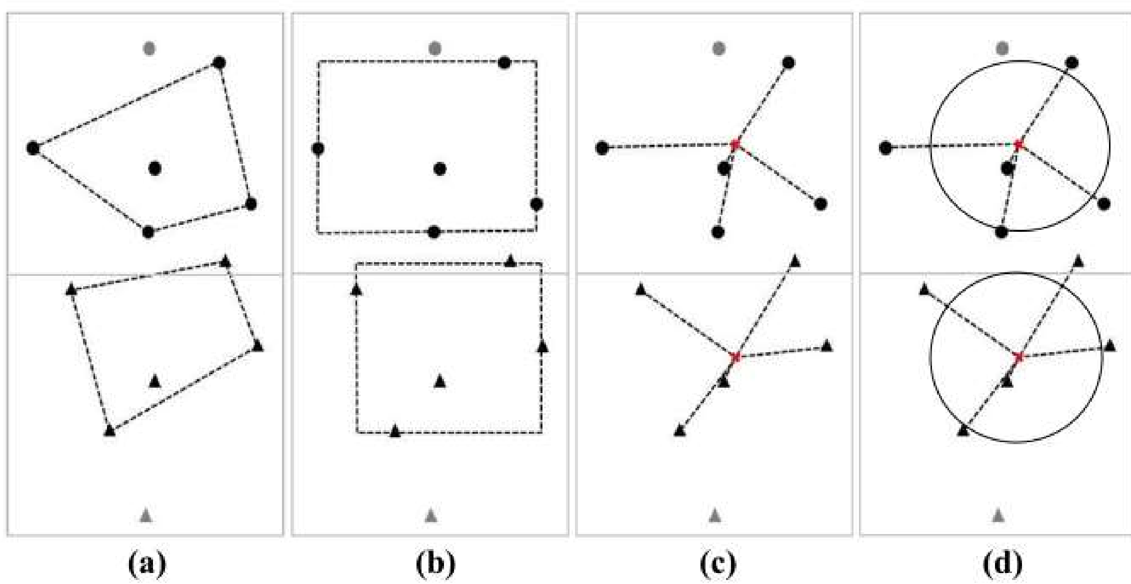

Figure 2.2: Variables for measuring tactical behaviour – (a) effective area, (b) length/width, (c) centroid and (d) stretch index.[141]

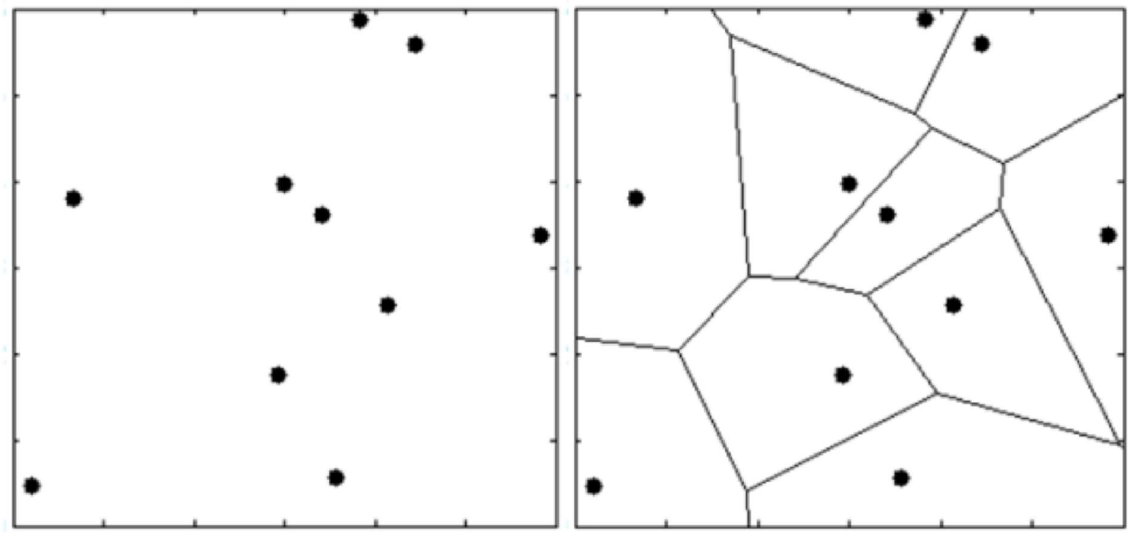

Figure 2.3: Example of a Voronoi diagram which demonstrated the dominant regions of players.[141]

In general, centroid and cluster phase measures have demonstrated synchronous behaviour between opposing teams in lateral and longitudinal directions in both 5v5 (futsal)[98, 113, 119, 120] and 11-a side (regular)[28, 104, 106, 114, 123, 144] football formats. Similarly, co-adaptive inter-team coordination patterns have been demonstrated in amateurs[98, 107, 113, 119, 120] and professionals[28, 104, 106, 114, 123, 144] alike, and in both younger (under-18)[98, 107, 113, 119] and older (over-18)[28, 104, 106, 114, 120, 123, 144] age groups. It is suggested that synergistic behaviour emerges as a result of the co-adaptation between the two opposing teams, each using the information of the other team's positioning to guide decision-making and behaviour.[144] Furthermore, information conveyed via displacement of the ball through passing and shooting in both lateral and longitudinal directions may afford different action possibilities and appears to guide behaviour in those directions.[114] In support of this concept, Frencken et al.[140] demonstrated that critical match periods identified via longitudinal and lateral inter-team centroid displacement, and their rates of change, were associated with 93% and 87%, respectively, of match events in which the ball was passed longitudinally or laterally. This may offer a possible explanation into Bartlett et al.'s[106] findings which revealed a strong relationship, using correlation measures, between the geographical positioning of team centroids in plays leading to goals or shots on goal.

It is evident that opposing teams, despite possessional status, either being in attack or defence, synonymously use the positioning of the ball as a key informational variable to guide behaviour.[144] Further, a plethora of existing research indicates a higher level of synchronicity in the longitudinal direction than in the lateral direction .[28, 104, 106, 113, 114, 119, 123, 144, 148] This may be due to off-side constraints, limiting attacker's positioning relative to the defenders, and the position of the goals,[144] with the primary attacking objective to advance up the field to create goal scoring opportunities.[114] Lower synchronisation in the lateral direction may reflect a tactical strategy of the attacking team with players deciding to keep a certain degree of asymmetry with the defence, passing the ball from side-to-side, aiming to increase affordances for scoring a goal by creating a misalignment between the opposition defenders.[123] Conversely, a lack of synchrony may reflect defensive tactical behaviour as players may decide to use a conservative approach, adopting preferential symmetry in the longitudinal direction as opposed to the lateral direction attempting to protect their goal.[123] In these instances, task constraints (off-side rules) and team strategies (score/prevent goal scoring) may align performers with specific information in the environment that provides affordances for outcome-directed action. Furthermore, greater inter-team synchrony has been demonstrated in the first[28, 114] compared to the second half of a football match.[144] This increase in variability in the second half may be due to changes in specific performance constraints such as fatigue or other strategic (team formation) or situational changes (change in score line).[28, 114, 144] Changes that are due to fatigue may have implications for pre- and in-season physical preparation strategies. Alternatively, players may need to be exposed to varying situational factors in a training environment, potentially using vignettes, providing individuals with the opportunity to adapt to contextual changes. In Australian Football, the ball, task constraints (can only handball or kick the ball), team strategies and situational variables (1st quarter vs 2nd quarter) would also likely provide important information that governs team behaviour. Therefore, examining levels of synchronicity may provide more insight into the influence of these components on critical game moments and the subsequent effect on game outcome.

For measures of team dispersion, it has been demonstrated that teams co-adaptively expand or contract together along the pitch in synchrony while lacking synchrony in the lateral direction.[106] This may once again reflect the influence of off-side task constraints along with the primary goal constraint in the game, to progress up the field in order to increase the probability of scoring. Conversely, other studies revealed that dispersion of teams' players tended to follow a dynamical counter-phase relation where when one team contracted, the other dispersed.[44, 123] This may reflect tactical strategies employed in both offense and defence. In offense, teams try to increase team dispersion to explore potential goal-scoring affordances while defensive teams contract to limit the available space and ultimately protect the goal and limit goal-scoring opportunities.[107] Interestingly, only a few studies examining dispersion via team surface area revealed no tendency for a positive (in-phase) or negative (counter-phase) synergistic relationship between teams.[113, 115] However, these studies utilised a 5v5 small-sided game format which may be methodologically limited as the examined area is only formed by four outfield players where adjustments in one player's positioning may drastically effect the overall surface area.[113] Furthermore, the presence of extra players in an 11-a side format may provide sufficient information to guide synergistic behaviour and decision-making processes. Additional players may augment relevant information and provide an opportunity for each team to optimally co-adapt to one another.[128]

Finally, freedom of longitudinal movement in the absence of the off-side rule may limit interpretation of results in relation to 11-a side football as players in this format would normally impose a penalty.[113] While dispersion measures offer useful insights, caution must be taken when analysing surface area in an 11-a side format as these measures only account for the most peripheral bound individuals, neglecting the influence of players within the given area.[107] A more appropriate method may be the use of superimposed Voronoi diagrams (Figure 2.4). These have the ability to account for every player and can effectively describe spatiotemporal relationships at both an inter-individual and inter-team level.[141] For example, when opposing players are tightly paired (such as in man-to-man defence), the percentage of free area among players and teams is small with limited free space for teams to explore affordances in offense.[141] While this is yet to be examined in relation to successful and unsuccessful patterns of play, these variables, based on teams' overlapping areas and the relative position of players, may offer further insight regarding the spatial interaction and decision-making processes used by players and teams.

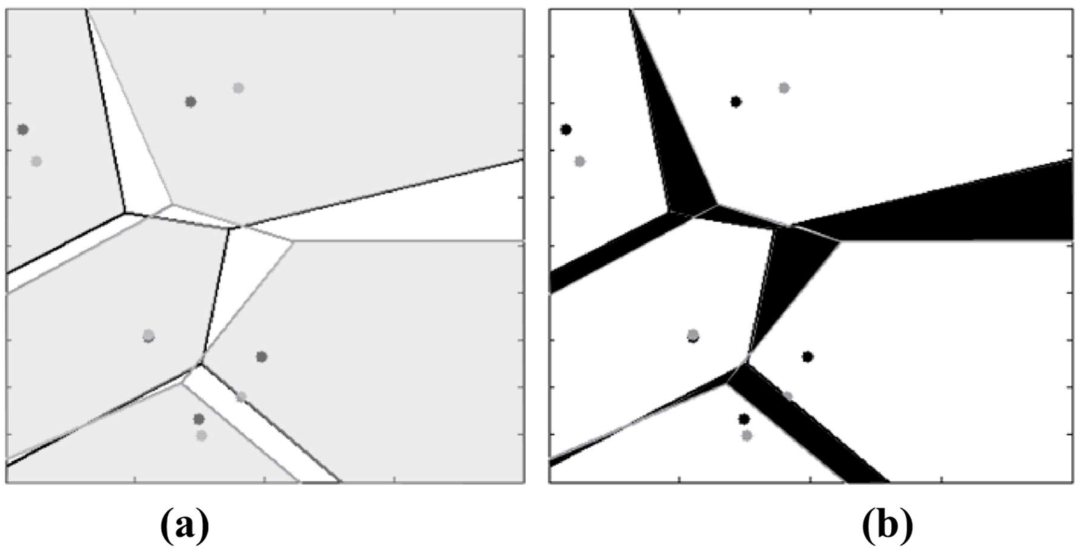

Figure 2.4: Example of a superimposed Voronoi diagram: (a) shaded grey areas are the maximum overlapped area for each player of the team represented with black dots; (b) the sum of the shaded black area is the free area.[141]

Such findings may need to be interpreted with caution as they may be limited by the global timescale of analysis. One study revealed higher values of coordination over longer sequences of play in a 5v5 format in contrast with shorter sequences of play[105] Furthermore, Frencken et al.[114] revealed that 51 of 242 critical match periods - instances commonly associated with phase transitions - detected in a professional football game were aligned with dead-ball situations**.** It may be more relevant to analyse synergistic behaviour over shorter timescales, such as a specific time period leading up to successful or unsuccessful scoring attempts (e.g., from the moment of a turnover until a subsequent shot on goal). This may offer supplementary insight into favourable patterns of play as larger time scales demonstrating higher degrees of synergy may subdue the variability otherwise observed in shorter sequences of play.[114] Further, discretion is advised when interpreting results from centroid measures. Despite different displacements of players, centroids can remain in the same relative position. For example, each player 4m apart will have the same relative effect on a centroid measure as if they were 8m apart.[104] Additionally, while providing useful information on a global scale, utilising centroid measures neglects to provide a complete understanding of the strategic distribution of players on the field.[106] For a deeper understanding of synergistic behaviour and emergent tactical patterns evident at a macroscopic level, it is necessary to examine dynamical behaviour on a higher dimensional scale that synonymously observes dispersion and synchrony between teammates. A macroscopic or intra-team level of analysis may be sufficient to provide further insight regarding desirable patterns of play.

2.10.2 Intra-team

With the lowest (macroscopic) dimension of coordination identified, subsequent analysis on a mesoscopic scale can be undertaken to identify synergistic and co-adaptive behaviours that emerge on an intra-team level. At this level, parameters are often measured in isolation of the opposition team but still offer additional insight especially when analysed with reference to successful and unsuccessful phases of play, i.e., goal scoring opportunities or turnovers. Measures of dispersion, displacement, and social connectedness, when effectively utilised, can reveal patterns of behaviour and decision-making that emerge through degenerate adaptation, dimensional compression, and reciprocal compensation, all afforded and governed by information in the performer-environment sub-system. This level of analysis may be deemed important for team performance and success as tactical coordination patterns revealed through collective positioning variables are superiorly sensitive to changes in constraints in comparison to physical variables.[53]

Aligning with the macroscopic scale of analysis, patterns of expansion and contraction in attack and defence, respectively, have been identified between players of the same team. In amateurs[108, 132] and professionals[110, 117, 129] alike, studies have demonstrated an increase in team dispersion when in possession of the ball through measures of stretch index[108, 110, 117, 129], surface area[108, 110, 129, 132], and length and width.[110, 132] Conversely, without possession, the same team revealed a decreasing tendency in dispersion measures.[108, 117, 129, 132] As identified on an inter-team level, these emergent patterns may align with the ambition of either dispersing in an attempt to explore potential goal-scoring affordances or contract in an attempt to limit the available space and subsequently protect the goal and limit goal-scoring opportunities for the opposition.[107] Furthermore, the half of a match appears to influence players' spatiotemporal relationships and, consequently, their ability to disperse in offense or contract in defence. Team dispersion measures typically reduce in the second half (i.e. in offence players are less dispersed in the second than in the first half of a game), which could attributed to the onset of fatigue in the second half of a game,[108] demonstrating the inter-relationship between the physical and tactical domains of performance in football. With diminished physical capacities, the ability of players to explore the whole width and length of field while trying to unbalance an opposing team is compromised.[108] Furthermore, the speed at which players expand and contract their team formations during defending and attacking plays has also been investigated in relation to game time. Concurrent with the decrease in absolute dispersion values, the rate of change in dispersion measures has also demonstrated a decrease in the second half once again implicating the potential effects of fatigue.[45] While running demands were not concomitantly assessed with dispersion measures, previous studies have revealed a reduction in high-intensity runs by players in the second half,[180] again reinforcing the inextricable link between physical and tactical parameters. Once again, the decrement in the above measures may be associated with increased fatigue and may limit the ability of a team to effectively respond to new emerging affordances and constraints.[45]

To evaluate the space-time coordination tendencies between each individual player and their team as a singular unit, relative phase analysis may be incorporated (Figure 2.5). Once again, aligning with emergent synergistic behaviours between opposing teams, phase analysis between teammates has demonstrated that intra-team synchronicity is superior in the longitudinal direction compared to the lateral direction.[54, 95, 144, 148] As identified earlier in the review, these patterns may emerge due to off-side constraints, positioning of the goals, and the primary objective to advance up the field and score.[144] However, contrary to the macroscopic analysis which demonstrated a decrease in synchrony between teams, individuals display greater synchrony within team in the second half in comparison to the first half.[144] This may be a result of developing shared affordances during games, allowing players to become increasingly attuned to affordances 'of' and 'for' others.[52] Alternatively, this may be a result of the decrease in total dispersion values and rates of change in these values (i.e. players are less dispersed and disperse or contract at a slower rate in the second compared to the first half), as highlighted above, due to the onset fatigue.[45, 108] Additionally, during heavily congested fixtures, players experience a decrease in synchronicity in both lateral (at moderate intensities) and longitudinal directions (at low and moderate intensities).[95] In their study, Folgado et al.[95] revealed that players covered the same amount of distance at similar intensities, highlighting no changes in physical capacity in both congested and non-congested fixtures, and proposed that the reduction in synchronisation may be associated with an increased perception of fatigue and consequent adaptation strategies. Interestingly, players were able to maintain a higher level of coordination, as measured via synchrony, at higher speeds. This may be associated with critical game phases where opportunities are created. This suggests that players may decide to switch off mentally at lower intensities to preserve the limited capacity of cognitive resources[95] as this has been shown to adversely influence synchronicity and rates of dispersion in a football context.[127]

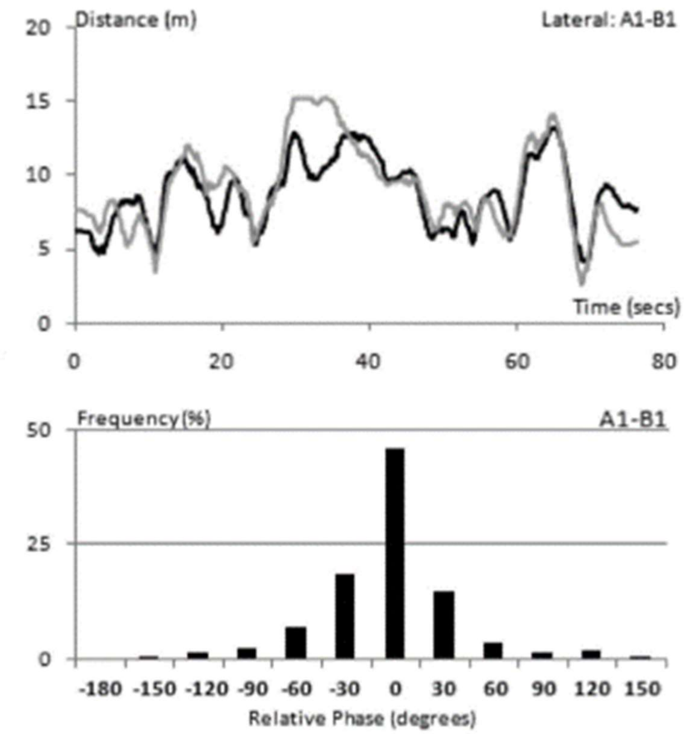

Figure 2.5: Relative phase analysis of the displacement of two players (top). Frequency histogram (bottom) reveals that both players spend a large proportion of time in synchrony. Values closer to 0 degrees signify synchrony and values closer to -180 or 180 degrees indicate asynchrony.[181]

The literature has revealed that the displacement of all players (defenders, midfielders and forwards) was nearer and more coordinated with their own positional-group centroids than with the other centroids.[91] Positional centroids appear to guide emergent, position-specific behaviour as the decision-making process and inter-player coordination becomes facilitated when inter-player roles are similar and distances between teammates are smaller.[91] Furthermore, defenders[95, 148] and midfielders[91] spend more time in synchrony with each other and their own positional centroids than with forward players, meaning that positional groups move in a synchronised manner by matching their position with that of other members of the same positional group. An absence of synergistic behaviour in attack may be a consequence of the forwards role to be less predictable, or degenerate, while aiming to destabilise opponent defensive stability with sudden changes in speed and direction.[91, 148] Dimensional compression, conveyed by stronger coupling between defenders and midfielders, is likely a result of the players' awareness of the risks of asynchronous behaviour in the defensive pitch, collectively trying to reduce open spaces and affordances for opposition scoring.[91, 107, 148] Individually, midfielders are likely constrained by a common goal, to control the pitch's centre by maintaining effective inter-player spacing.[91] Interestingly, positional centroid measures have revealed stronger in-phase relationships in the lateral direction,[91] contrasting with inter-team centroid and intra-team displacement measures of synchrony in the longitudinal direction. Gonçalves et al.[91] suggested that this may be related to the need to reduce lateral spaces in defence to minimise oppositional attacking opportunites. This may be well justified as in attack the occupation of the lateral corridors in a synchronised manner is considered to be the greatest destabilising factor of opponents' organisation since the critical, or transitional, game periods appear to be associated with changes in lateral distance between teams.[91] As Australian Football possesses similar positional groups as those identified above, examining the dispersion and synchrony within and between these groups may offer novel insight into behaviour influencing similar critical in-game moments.

While synchronicity measures can demonstrate dimensional compression, measures of predictability and variability, as determined through the analysis of entropy measures, may reflect stable or degenerate behaviour. These measures reflect the regularity in behaviours exhibited by players or teams. High predictability may indicate pattern maintenance by a team throughout a match or competition, signifying a high level of organisation.[136] Conversely, significant changes in a team's structure or behaviour could yield unpredictability or a higher capacity to co-adapt to unexpected or variable situations during a match or championship. Through the use of different tactical solutions, teams may still be able to achieve task goals, despite demonstrating considerable amounts of variability in how these task goals are achieved (degeneracy).[136] Selected studies have demonstrated higher predictability in offense, potentially signifying that a standardised pattern of behaviour may be regularly utilised in an attempt to overcome the opposition's defence.[133] Similarly, in defence, low entropy values (higher predictability) are evident, particularly near scoring zones, reflecting the need to regularly reduce the available space afforded to opponents limiting consequential scoring opportunities.[133] These low entropy values in defence and attack may represent the strategy or playing style used by a team to attempt to score goals or prevent the opposition from scoring, respectively. Entropy values have revealed a tendency to decrease during halves, signifying that teams become more regular and predictable in their organisational shape with ensuing time, potentially due to decreases in dispersion measures and concurrent increases in synchrony, perceptual attunement to teammate behaviour, fatigue, and performance-related stress.[110, 111] This co-adaptation to fatigue as a performance constraint may push teams into their preferred attractor states (i.e. reverting to well-established learned and trained tactical behaviour), reducing coordination complexity and dimensionally compressing to stabilise performance and increase regularity in patterning.[111] However, while entropy values may decrease throughout the match, critical periods characterised by larger entropy scores (decrease in predictability), that eventuate into scoring opportunities, may still be present later on the match, but may be less prevalent due to the onset of fatigue. The spatiotemporal examination of goal scoring opportunities throughout the second half of the match, along with the prevalence of these opportunities, may provide further insight into behaviour, and the decay in entropy, that emerges as the game concludes.

Position-specific entropy measures have offered insight into the value of fostering stability or unpredictability. Forwards have demonstrated more irregularity in comparison to other players potentially as a consequence of their need to be less predictable in offence in an attempt to deceive and destabilise the defence.[91, 102] Conversely, greater regularity has been displayed in midfielders, with the role of these players to control the pitch's centre and act as a communicator, and defenders, whom coordinate and stabilise patterning in an attempt to minimise affordances for the attacking team.[28, 91] Furthermore, defenders need to stabilise coordinative behaviours and maintain their trajectories within their specific regions to ensure the possibility of recovering the ball in the offensive attempts by the opponent team.[102] However, in contrast, Moura et al.[136] revealed that external midfielders and external defenders demonstrated the greatest variability in spatial distribution throughout the 2012 UEFA European Championship. This outcome may reflect these players' tactical roles, and the changes within these roles with the introduction of modern football tactics. While central players have a well defined role (either solely attack or defend) during a match, the external defenders not only act as a defender but also support the midfielders during attacking phases[136] while midfielders act as a link between the defenders and attackers.[102] Additionally, in modern football, these positional groups often cross multiple 'lines', where lateral defenders often run to the opposition goal line to deliver a centre. Lastly, goalkeepers are the most predictable players, likely due to their positional constraint, spending the majority of time in the defensive square.[102] It appears that player roles and tactical intentions act as a determining constraint on emergent behaviour and needs to be considered when analysing player specific regularity measures.

A further way to gauge intra-team synergy is through implementation of a complex network analysis which convey the local structure of organisation among players. In these networks, nodes represent players, and links are weighted according to the number of passes or positional changes completed between players.[48] By analysing passes and kicks made within a team, this form of analysis allows practitioners to map the relationships between players during a game. Through analysis of professional players in an 11-a side format, scaled connectivity measures[164] revealed that all players usually cooperate in attack. On an individual level, scaled connectivity represents the connectivity of a player in which higher values represent a higher co-operation, as demonstrated by a player being connected with more players. On a global scale, centralisation values represent the distribution level of the network whereby larger values signify a network's dependence on one player. Similar to scaled connectivity, through the use of centralisation measures, Clemente et al.[165] revealed that in professional football there are generally no focal players, i.e. each player had nearly the same connectivity. A higher level of connectedness between players, along with lower centralisation, may allow degenerate, or multiple stable patterns of play to emerge with multiple passing options available between multiple players.[164] However, values of centrality increased in the 2nd half, showing a decreasing participation of all players at the same level, with the emergence of a (number of) focal player(s). This increase in centrality was accompanied by a decrease in network density, an indicator of global connectivity amongst players with higher values suggesting that players interact with each other, and an increase in network heterogeneity, quantifying the variability in the level of connectedness between different players, revealing that as time ensued, intra-team clusters of players at different levels emerged.[165] This may implicitly occur or represent a decision to tactically decrease the number of players involved, allowing players to rest. Alternatively, deciding to change to a direct style of play, favouring certain players due to skill, or the existence of ambiguous relationships to create offence plays, may give rise to the apparent changes between halves.[165]

It is also possible to identify social centroid players who are the most highly connected in the network.[164] Due to their tactical roles, it has been revealed that defenders and midfielders are centroid players.[164-166, 171, 173] These players are often responsible for recovering possession, particularly in the defensive zone, which would increase participation in offensive plays. Additionally, if a team decides to adopt a building style of offense, as opposed to a direct style, in an attempt to attract the opponents out of their defensive zone to provide offensive affordances for attackers, midfielders and defenders will display higher centralisation.[164] It has also been revealed that topological dependency, identifying players who are heavily depended-upon, highlighted that midfielders are the players that connect most easily with any other player and are also the players that interact most with remaining teammates.[164] This was supported by Clemente et al.[55] who revealed superior degree prestige, a variable that considers the inbound links from other players in midfielders in comparison to defenders and goalkeepers. This superior dependency is likely due to the role of midfielders to connect offensive play from the defensive zone to the offensive zone.[55] Further, attackers require players to recover the ball in defence and generate offensive plays.[164] Alternatively, Gama et al.[96] highlighted that professional football teams prioritise circulation and maintenance of ball possession, by passing to the centroid player/s several times. Additionally, these players may play a pivotal role in the self-organisation processes of the team, exhibiting a higher level of quality during both execution and reception of passes, contributing to an increase in social intensity and density within the network.[96] In amateur football, Clemente et al.[55] revealed that higher performing players with lower fatigue, and who had previously performed better in dribbling tasks, demonstrated high betweenness centrality in matches. Such values signify that a player is often situated between teammates And this may indicate that players with excellent technical ability, and the ability to maintain excellent performance throughout the entirety of the game, might be considered references for improving co-operation among teammates.[55] Additionally, expert central defenders and midfielders have demonstrated superior closeness, indicative of the ease of connectivity with a player, and betweenness centrality values than other positional players emphasising the pivotal role of these positions in fostering cooperation among teammates.[171]

Further utilising complex network analyses, clustering coefficients indicate which players contribute the most to the generation of team clusters with a higher value signifying that the greatest cooperation among teammates occurs around these players.[164] In general, average clustering coefficient values revealed the emergence of clusters within the team and have been associated with success in the 2010 FIFA world cup.[170] Additionally, the players with the highest values were the wing midfielders and the forwards suggesting that these players participate in more attacking plays that involve a large number of teammates.[164] Clemente et al.[164] revealed that players with a higher clustering coefficient also tended to have lower connectivity values. These results suggest that these players participate in offensive plays with teammates that have a higher level of interaction with each other. The higher interaction between centre midfielders and defenders may indicate adaptation through reciprocal compensation for the lack of involvement from lateral and forward players. Gama et al.[167] demonstrated that emergent compensatory behaviours can emerge in football when one of the regularly key players has less interactions in a game, thus requiring other players to emerge to replace them.[167] The results revealed by Clemente et al.[164] may once again be a result of an offensive building style whereby central and defending players increase passing between themselves until the appropriate opportunity is afforded to the forward players. These positions have also revealed superior betweenness and closeness values indicative of their role in controlling and distributing possession.[171] As Australian Football is heavily reliant on the transfer of possession between teammates and different parts of the field, the analysis of player passing networks would likely be a useful method for exploring tactical behaviour and the influence on performance outcomes. To explore these relationships further, and the mechanisms behind intra-team coordination, collective parameters and co-adaptive tendencies can be observed on a dyadic level as different situations may afford varying emergent behaviour between players.

2.11 Patterns for performance

2.11.1 Inter-team

When looking at individual phases of play, recent investigations have identified common inter-team tactical behaviours in both attack and defence that emerge over time. Centroid analysis in professional football games has demonstrated that when in defence, teams tend to move closer to their defensive zone in an attempt to ensure that their centroid is nearer to its goal than the offensive team's centroid.[106] Furthermore, teams that consistently allocate more players in certain areas of the field closer to their own goal exhibit numerical dominance during defensive phases of play.[137] This numerical dominance may contribute to the observed defensive centroid positioning and reflect an attempt to protect the goal, one of the primary task constraints in football.[42, 44] This same study also revealed that winning teams demonstrate greater regularity in corresponding centre-back sub areas of play in regard to numerical dominance, implying that for successful defence, numerical dominance must be consistently present in defensive areas.[137] It has also been highlighted that winning teams maintain a greater separation between their own centroid and that of the opposing team when in defence.[104] This separation decreases the imposed pressure on the defensive team and allows more time to modify behaviours relative to that of the attacking team, allowing minimisation of the number of affordances available to the offense.[44, 104, 106, 122]

Focusing on specific defensive and offensive strategies can be harnessed to alter behaviour as it provides a modified task constraint. In defence, implementing zone strategies leads to superior distance and variability between centroids compared to man-to-man defence.[116] In zone, defensive teams function collectively as a compact block between the ball and the goal with the increased distance and variability, with respect to man-to-man defence, attributed to a shared focus on fellow teammate positions as well as ball displacement information. In contrast, with the utilisation of man-to-man defence, the emergent behaviour of players is constrained by the task of perceiving and acting in accordance with a specific opposing player.[116] In training, incorporating specified defensive strategies may force attacking teams to search for new affordances in the performer-environment landscape, potentially leading to alternative solutions enabling the scoring of goals. Alternatively, in attack, teams utilising counterattacks (direct play) have been more effective than elaborate (possession play) attacks when playing against an imbalanced defence. Tenga et al.[6] revealed that 94% of goals were scored against an imbalanced defence while only 2.5% were scored against a balance defence. The main objective of counterattacking is to exploit imbalances in the opponent's defence to achieve penetration.[6] While this study neglected quantitative tactical measures, a direct style of play may sufficiently perturb defensive lines as it does not provide the defending team with enough time to modify their synergistic behaviours relative to the ball or the attacking teams movements.[122]

Additionally, assessing the synchronicity in professional 11-a side football, utilising a cross-correlation in spread measures between teams, Moura et al.[130] demonstrated that opposing teams have a tendency to present in-phase coordination with a short time lag, suggesting that one team has the ability to lead the other and influence emergent behaviour.[130] This study revealed that in the preliminary stages of offensive sequences that ended in a shot at goal, a greater anti-phase in coordination was present than those ending in a tackle. These results suggest that the attacking team may seek to present a contrary behaviour of its opponent (or may lead the adversary behaviour) in the beginning of the attacking play, regarding to the distribution strategy, to increase the chances of a shot on goal.[130] Further, the only main difference was in the initial stages, and not the final stages of the attacking play. This highlights the importance of breaking the usual in-phase coordination between teams and may also explain why counterattacks are an important strategy for scoring goals.[130] Further, in semi-professional contexts, when instructed to employ an offensive vs defensive strategy, greater length, width and effective playing space were demonstrated in offensive condition.[132] The results confirmed that the use of coaches strategic defensive and offensive instructions constrains the technical, tactical, and physical performance of players and teams. When defensive behaviours are emphasised, players tend to compact the game space making their positioning more regular among teammates. Tactical strategies imposed by coaches should be carefully considered as they have the potential to constrain player behaviours as well as coordinative outcomes. Coaches may incorporate different strategies or playing styles in a bid to enhance attunement to specified affordances and, consequentially, promote multi-stable regions of performance that allow players and teams to achieve relevant goals.[61] This may better prepare teams for the tactical patterns used by opposing teams.

Contrary to traditional thoughts on defensive success, utilising measures of dispersion Bartlett et al.[106], revealed that smaller stretch index values (contraction) in defence relative to larger values in attack (expansion) were associated with more successful attacks, i.e. goal scoring opportunities.[106] This contradicts original ideas that defensive teams need to contract to protect the goal and limit goal-scoring opportunities for the attacking team.[107] However, the results demonstrated by Bartlett et al.[106] may not acknowledge the offensive team's ability to perturb the coordinative behaviours of defensive lines. In attack, this ability to disrupt the stability of the defensive team has shown to be an influential factor for creating goal scoring opportunities which, when capitalised upon, are necessary for success.[6] Contrary to the conflicting defensive patterns demonstrated in this study, the evident offensive patterns concur with original ideas in that teams need to increase team dispersion, relative to the defence to generate potential goal-scoring affordances.[107] This is reinforced in the literature as numerous studies have shown that effective area,[108] surface area,[111] length/width,[111] and dominant regions[140] increase when teams regain possession and transition to offense. Concurrent analysis of inter-team dispersion measures, along with intra-team variability, may further clarify the importance of relative measures of dispersion.

Evidence suggests that the ability of an offensive team to perturb opponent inter-team stability is important for success.[6, 28, 107] Utilising centroid measures, an unbalancing of phase coupling between opposing teams in the lateral direction has preceded the scoring of a goal.[107] More specifically, utilising positional centroids, a crossing of attacking- and defensive-line centroids was evident in the lead up to goals and goal scoring opportunities in professional football.[28] Additionally, increased variability between attacking- and defensive-line centroids has been identified in the lead up to goal scoring opportunities with a continual increase in this variability up until the critical moment (goal attempt).[28] These studies reinforce the notion that offensive teams need to utilise positional information to destabilise their defensive counterparts and subsequently exploit imbalances in the defence, leading to more opportunities for goal scoring actions.[6] This may be deemed necessary as successful defensive shadowing, where defensive teams effectively organise and create triangles towards the ball (effective area), can limit the spaces and opportunities with which an attacking opponent can pass or dribble (Figure 2.6).[182] This intra-team coordinative behaviour will consequently limit goal-scoring opportunities which are pivotal for game success.[48]

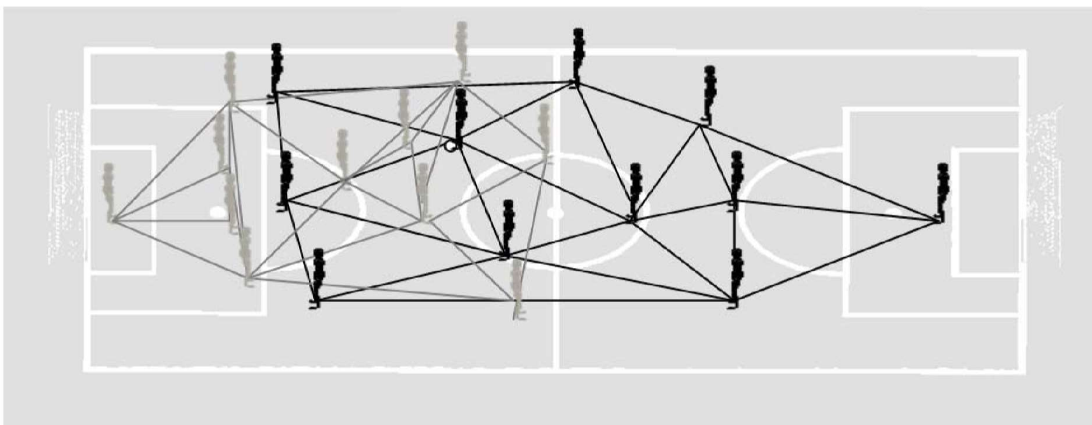

Figure 2.6: Defensive (grey) effective area that limits the space and passing opportunities for attacking opponents (black).[107]

2.11.2 Intra-team

Aligning with the macroscopic level of analysis, investigation of intra-team coordination has revealed behavioural patterns associated with in-game success. Through the analysis of dispersion,[129, 133, 143] displacement,[148] and complex network measures,[142, 168, 170, 172-174, 176] favourable patterns in both professionals[129, 133, 148, 168, 170, 172-174, 176] and amateurs[43, 142] can be identified and consequently used as a reference to guide the decision-making process or for training prescription and attempts to optimise team performance.

Despite the limitation of being examined in isolation of the opposing team, mesoscopic analyses of dispersion have revealed similar patterns of success to that of a macroscopic level. This would be expected as even though no opposition measures were recorded, players are presented with similar task and goal-directed constraints. Moura et al.[129] revealed that in defence, when a team presented a greater area and spread, they were required to defend against more shots on goal. In contrast, with smaller dispersion, they successfully performed more tackles.[129] The presence of task constraints, along with the need to protect the goal and limit goal-scoring opportunities for the opposition appear to guide defensive behaviour, leading to the emergent decision to contract dispersion.[104, 106, 107] Furthermore, aligning with inter-team patterns, superior measures of dispersion, as revealed through the use of Voronoi diagrams, have been associated with successful attacking phases of play. Taki & Hasegawa[43] revealed that attacking teams cooperatively increase their dominant regions, leading to goal scoring opportunities. It is suggested that an increase in dominant region will afford favourable passing opportunities for teammates, as passes made within a teammates dominant region will increase the chances of the pass being successful.[43] While successful patterns of play were not directly analysed, stronger teams demonstrated greater offensive length, width and surface area in an attempt to move forward into the score zones and create shot opportunities when playing against weaker teams as determined by competition rank .[133] Conversely, weaker teams displayed greater defensive length, width and surface area against stronger teams. Greater dispersion by superior teams may be related to an enhanced ability to effectively disperse to create scoring affordances. Conversely, more dispersion in defensive patterns exhibited by weaker teams may reflect an ineffective co-adaptation to the stronger offensive team, mirroring their movements in attack.[133] While superior teams may demonstrate distinguishable behavioural patterns, the absence of contextual information, as provided through reference to successful and unsuccessful patterns of play, may limit the interpretability of conveyed information.

When examining intra-team player displacement, one study revealed that winning teams demonstrate superior values of synchrony over a match compared to losing teams.[148] These larger values may highlight the importance of defensive success in influencing match outcome as this study also demonstrated superior defensive dyadic synchrony relative to attacking dyads (105). Defensive synchrony, and the association with match success, may reflect the ability of players to co-ordinate their actions and remain between the attackers and the goal to minimise goal scoring affordances.[44, 104, 106] This may be a priority over the lower synchronicity and regularity commonly demonstrated by forward attacking dyads who often attempt to destabilise the defence with sudden changes in speed and direction.[91] However, an absence of relevant contextual information, such as the amount of time spent in offensive or defensive phases of play, was not quantified. A larger amount of time spent defending may inherently lead to a greater proportion of the match spent in synchrony as this is deemed necessary for defensive success. While this research failed to account for specific phases of play, global movement synchrony may be considered as a measure of a teams' tactical performance throughout the season.[148] It is also likely that due to the similar task goals of the match, a similar metric may also be useful in Australian Football.

In addition to the measures of team dispersion and displacement, network analyses have exposed favourable social characteristics within teams. Through examination of player interactions in the English Premier League and the number of goals scored, Grund[168] revealed a clear network intensity effect demonstrating that increases in passing rate lead to increased team performance. This study revealed that lower centralisation values, where a team is not dependent on single or selected players, are associated with superior performance. This was also demonstrated in other professional teams[172, 173] and higher performing amateur teams.[142] Analysis of the 2018 FIFA World Cup revealed similar tendencies for success with large positive correlations found between shots and total connections and density in drawn matches and moderate positive correlations between shots and total connections and density in matches one.[172] It was concluded that in general, the succeeding teams had a greater distribution of interaction between team players than non-succeeding teams[172, 173, 176] suggesting that decentralised teams, where all players are equally central, or are equally likely to receive the ball, fosters interdependence, which encourages co-ordination and co-operation. This may also provide teams with more flexibility and foster degeneracy, allowing multiple effective scoring affordances and solutions to emerge.[168] Interestingly, McLean and colleagues also revealed that in general, goals were scored via networks of short duration involving few players and few pitch zones with minimal reciprocity of passes between players. Implicating a direct style of play for success.[174] Furthermore, Peña & Touchette[170] through the analysis of the 2010 World Cup revealed that Spain, the tournament winner, had the highest number of passes, high edge connectivity, and a low betweenness score. This aligns with Grund's[168] findings as edge connectivity is defined as the number of edges one needs to remove to make a network disconnected while betweenness indicates how the ball-flow between other players depends on a selected player. This suggests that a large number of passes would need to be intercepted to disrupt the team's preferred ball movement patterns and that this team does not rely on certain players.[170] Additionally, Spain demonstrated the largest clustering and clique values.[170] Clustering represents the percentage of all possible triangles containing a specific node while clique values represent a subset of players that are all pairwise-connected by direct passes.[170] The superior values demonstrated by the Spanish team signifies that most players interact with each other. This further suggests that successful performance relies on degeneracy, allowing team co-adaptation to different game situations or constraints, which consequently fosters task achievement.

As noted, caution must be taken when interpreting intra-team measures in isolation as most studies examine behaviour in one team only. While reasoning behind emergent behaviour can be inferred in relation to lower dimensional level of analysis, i.e., inter-team literature, future research should incorporate concurrent examination of similar variables in both teams, similar to that evident in inter-team analysis. This may offer further insight as to how the actions and tactical patterning of opposition teams afford unique opportunities and constraints. Further, while there is a plethora of research on intra-team coordination, many studies examined emergent behaviours without reference to successful and unsuccessful passages of play, such as goal scoring or turnover sequences.[28, 45, 55, 91, 95, 96, 102, 107, 108, 111, 112, 133, 136, 144, 164-166, 168, 170] Whilst these studies provide useful information, future research should assess tactical behaviour with contextual reference to both favourable and unfavourable outcomes as this may assist training intervention and enable the establishment of performance guidelines for intra-team coordination. Subsequently a deeper analysis can then occur between selected individuals of the same, or opposing, team.

Through the examination of behaviour at the macro- and mesoscopic level of analysis, general patterns and behavioural trends between and within teams have been well identified. Throughout the match, teams positionally mirror each other, particularly in the longitudinal direction, whilst demonstrating a counter-phase relationship in measures of dispersion. During attacking phases of play, teams tend to expand, increasing interpersonal distances, moving in an unpredicatble manner while conversely, during defensive phases, players tend to contract and move in synchrony, collectively positioning themselves between the opposition team and their goal. Of particular interest, these patterns reemerge with the concurrent examination of behaviour and performance outcomes (i.e. winning/losing or goals scored/goals prevented). The expansive, unpredictable behaviour that emerges in attack is deemed necessary to perturb defensive stability and consequentially create goal scoring opportunities. Additionally, winning teams demonstrate well connected passing networks with decentralised tendencies where there are no focal players, i.e. each player has nearly the same connectivity. In contrast, when defending, the collective positioning of the team's centroid between that of the opposition and the goal while while remaining in a synchrnous, contracted state is required for defensive success. Regardless of the phase of play, players need to move and act in a way that provides favourable affordances, or opportunites, for themselves and their teammates as it is the subsequent perception of, and effect attunement to, these affordances that allows players to co-adapt and achieve performance success. Accordingly, it is important to provide teams and individuals with an opportunity to create, perceive, attune and act on different affordances prior to competition. Within a practice environment, appropriate manipulation of small-sided games may provide this opportunity and allow coaches to promote and develop favourable patterns of coordination on all levels of behaviour. The use of small-sided games provides an environment that mimics the perception-action couplings of in-situ (match-play) performance and allows superior transferability of learned behaviour in this context to in-game performance.[40, 42]

2.12 Tactical intervention using small-sided games

Quantifiable tactical information gathered from research can be utilised to appropriately design training tasks that promote similar, and favourable, behaviours to those seen in an in-situ environment. Small-sided games are modified games played on reduced pitch dimensions, often using adapted rules and involving a smaller number of players than traditional games.[38, 39] When designed appropriately in accordance with Davids et al.'s[29] five key considerations for designing representative tasks (See Improving decision-making and coordination through appropriate task design), small-sided games are considered a valuable tool to promote adaptive decision-making and coordination at all levels of the performer-environment sub-system. Practitioners and coaches have utilised small-sided games as a modality to improve performance through the development of an individuals, or teams, ability to solve and overcome tactical challenges.[38-41] The effective use of small-sided games allows performers to develop in a spatiotemporally varying training environment that reflects the formal and functional structure of a football game, with relevant informational constraints that reflect those of an official-match,[38, 40, 41, 157] despite being represented in a more manageable format in small-sided games. It is believed that small-sided games allow players to adjust their tactical behaviours, both individually and collectively, due to perceived information and opportunities for action.[40, 42] This format of training facilitates the transfer of action and decision-making from the training process to the competitive context as it provides attractors and repellers, along with associated bifurcation points, that are representative of the traditional 11-a side format of the game.[40, 42] Small-sided games allow coaches to design and manipulate specific constraints (environmental, task and goal) which guide players' exploration and discovery of solutions in metastable regions and may also provide a useful medium for developing favourable movement behaviours in Australian Football. This occurs through the continual perception and adaptation to a dynamically changing environment.[38, 40, 42] The effect of these constraint manipulations on emergent behaviour is evident on two different scales of analysis - the macro- and mesoscopic level.

2.12.1 Macroscopic-level intervention

Small-sided games have demonstrated representative features at the inter-team level of coordination. The utilisation of numerical and spatial constraints, manipulated via the number of players (2v2, 3v3, 4v4, 5v4 & 5v5) as well as relative space per player, enable small-sided games to demonstrate similar patterns to those of the traditional 11-a side format. [44, 98, 100, 113, 120, 122, 124, 140] Similar to normal football match-play, centroid measures have demonstrated synchronous behaviour in both lateral and longitudinal directions[98, 100, 113, 120, 122, 124] as well as a converging or crossing of centroids prior to goal scoring opportunities.[44, 113] Further, utilising Voronoi diagrams, larger dominant regions for attacking teams have been demonstrated relative to the defending team,[140] aligning with conventional notions that offensive teams attempt to increase team dispersion in order to explore potential goal-scoring affordances while conversely, defensive teams contract to protect the goal and limit goal-scoring opportunities.[107] It therefore appears appropriate, on a macroscopic scale, that incorporating this form of training may present teams with similar informational variables to those demonstrated in 11-a side football. From an inter-team perspective small-sided games may promote and/or preserve inter-team coordinative behaviour and decision-making as the presence of an opposition and ball provide relevant information that guides co-adaptive behaviour.[114, 144] However, the precise constraints that are implemented in small-sided games and that act on and guide emergent behaviour require more extensive research to determine how manipulating small-sided games task constraints such as rules, line markings, etc. affect tactical behaviour on a macroscopic scale.

A common task constraint used in small-sided games is the manipulation of the number of players, or the relative (dis) proportion of attackers versus defenders. It has been demonstrated that from a 2- to 4-a side format, distance between centroids decreases followed by an increase again within a 5-a side format.[85] For coaches attempting to encourage similar offensive patterns to those of an 11-a side match, it is postulated that the utilisation of a 3- or 4-a side format, as opposed to 2- or 5-a side, may be more appropriate to emulate the patterns that emerge in the traditional format. Additionally, as demonstrated in 11-a side, a decrease in inter-team centroid positioning is associated with the primary attacking objective of the game, to advance up the field to create goal scoring opportunities.[114] Shorter distances between team centroids have been linked with higher pressure[44] and from an attacking perspective and this may lead to a disruption in defensive stability. Conversely, using a 2- or 5-a side format may promote effective defensive patterning as defenders conventionally try to preserve a greater distance between teams, minimising pressure and positioning themselves between the goal and the offensive team.[44, 104, 106] Further, Almeida et al.[177] demonstrated that the majority of regained possessions occurred when two or more defenders were between the attackers and the goal in a 4v4 format. Additionally, using a 3-a side format, Duarte et al.[100] revealed an increase in surface area of the offensive team as they approached the scoring zone coupled with a decrease in centroid inter-team distances. Again, this aligns with traditional offensive patterns as attacking teams attempt to disturb defensive stability by increasing team dispersion, relative to the defence, and applying pressure to explore potential goal-scoring affordances.[100, 107] It is apparent that a small manipulation in the number of players, may adequately alter perceivable information in the performer-environment rendering significantly different co-adaptive behaviours.

Small manipulations in numerical inferiority and superiority can constrain or afford different offensive/defensive behaviours. Centroid analysis demonstrated increases in inter-team distances with numerical superiority in defence (5v5, 4v5 and 3v5).[42] Despite a numerical advantage, defending teams may still decide to prioritise the protection of their own goal and the minimisation of pressure, maintaining positioning between their goal and the attacking team, allowing enough time to co-evolve with offensive patterning.[42, 44] Additionally, when numerically inferior in defence with one less player (5v5 vs 5v4)[122] or in the presence of 2 side-line floaters on the offensive team (7v7 + 2 floaters), [41] increases in centroid distances and team separateness have been demonstrated (see Table 2.2 at end of section). These findings may indicate an adjustment that affords the defending team more time to modify their individual and collective behaviours according to changes in ball and/or attacking movements.[122] Further, numerical inferiority has also been associated with reductions in surface area in defence, signifying a relative contraction to protect the goal.[122] It is suggested that defending players restrict space between themselves, and, consequently, the occupied area in front of goal, thereby restricting space for external kicks, such as diagonal or longitudinal passes to free players.[122]

When faced with numerical inferiority in offense, attackers may also contribute to the increased separation evident between defending and attacking teams as the additional distance may allow more time and space for the attacking team to coordinate and search for attractors in the performer-environment landscape.[42] Alternatively, numerical superiority in offense appears to afford decreases in inter-team distances along with heightened values of distance between the lateral lines of the overloaded team and the lateral lines of the underloaded team (Figure 2.9).[42] This decrease in inter-team distance may allow the attacking side to perturb the defensive line through additional pressure while greater width provides more relative dispersion, potentially affording further goal-scoring opportunities.[42] It is clear that manipulation of the number of players reveals synergistic patterns and tactical behaviours that closely align with traditional patterns seen in the 11-a side format of the game. In attack, providing teams with numerical superiority may facilitate a learning experience that allows players to become perceptually attuned to the shared affordances available as a result of overloading in specific spatial areas.[42] Conversely, when inferiorly loaded, players may have to search metastable regions for alternative ways to stretch and perturb defensive stability to create goal scoring opportunities. Similarly, in defence, despite being either over-or underloaded, the aim of defenders remains constant; to collectively position oneself between their own goal and the offensive team, often contracting to minimise goal scoring opportunities.[104, 106] Through the perception of affordances 'for' and 'of' others, defending teams can learn to coordinate and adapt to numerical differences, attuning to informational variables that may be present in an 11-a side context.

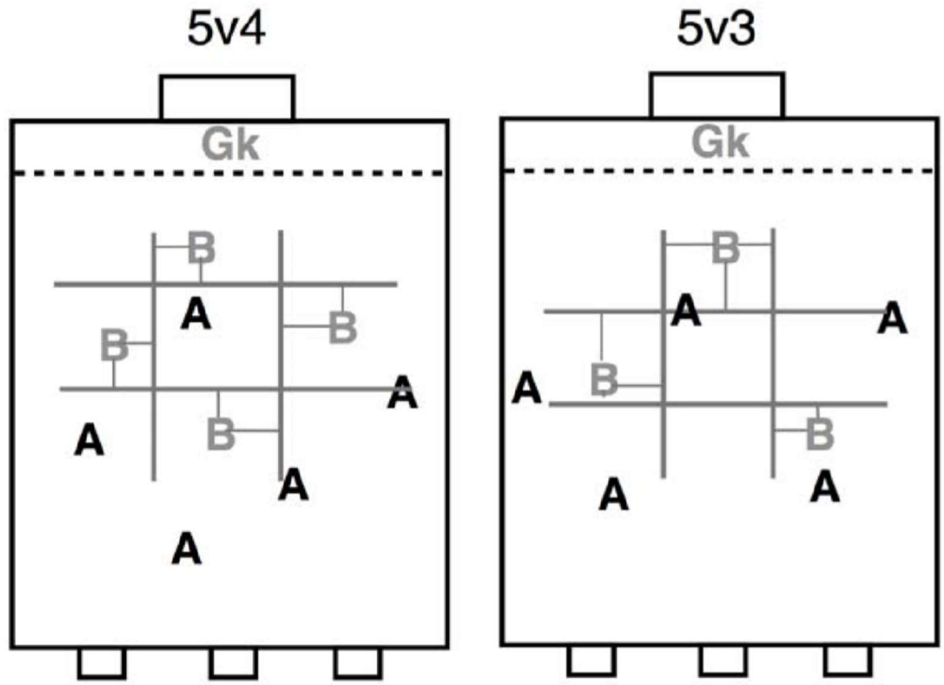

Figure 2.7: Heightened distance between lateral lines of the overloaded team (A) and underloaded team (B). [42]

While varying the number of players can influence the relative space per player,[98] manipulating pitch size can also alter this variable and consequentially the affordances available to teams. Increases in pitch size have led to an elevation in team separateness which may favour defensive coordination.[119] This separation allows the defending team additional time to modify positioning and movements relative to that of the attacking team.[122] Alternatively, relatively narrower (30x16m v 30x20m), and shorter (24x20m v 30x20m), pitches have decreased inter-team distance which may favour attacking teams, providing more opportunities to perturb defensive lines.[115, 125] This attacking advantage is further exemplified through a decrease in centroid coupling in both lateral and longitudinal direction in shorter pitches and a decrease in the lateral direction in narrower pitches, with significantly more irregularity in distances to nearest opponents in smaller fields.[115, 125] This irregularity and instability between teams' centroids is synonymous with offensive success as it affords the attacking team with the opportunity to disrupt the defensive line, potentially leading to goal scoring opportunities.[28] However, it is important to note that effective decision-making is still required by offensive teams as they select affordances and attractors that lead to goal-scoring opportunities.[27, 52]

Altering the goal scoring modality can also guide inter-team synergistic behaviour. Increasing the number of goals, from one to upwards of three at each end (Figure 2.10), has concomitantly led to an increase in distance between team centroids[121] as well as team separateness.[41] Use of multiple goals may force defenders to create distance between themselves and the offending team and, conversely, be harnessed by the attacking team in an attempt to stretch the opposition defenders and promote the creation of free spaces.[41] However, contrary to traditional central goal scoring modalities, Travassos et al.[121] found small decreases in relative stretch index, more time spent in left corridors and more time spent in defensive zones with the use of additional goals. While time spent in the defensive zone is expected, as defenders remain between the goal and attackers, the wider distribution may reflect tactical co-adaptation in defending teams. The use of multiple goals, as opposed to a single central goal, decreases the odds of regaining possession with elongated playing shapes, implicating the need for broader playing patterns.[177] Players can defend more efficiently if they are able to cover and press most of the possible passing lines available for an opponent implying that their ability to spread out and cover the width of the field is of importance in small-sided games with multiple goals.[177] The use of additional goals potentially expands players' breadth of attention and perceived stimuli and has implications for improving tactical performance as defending teams coordinate and search for new affordances to cope with modified scoring modalities while attackers try to break defensive stability and search for scoring opportunities.[121] Alternatively, the use of additional goals may be primarily used to augment relevant information for attacking players as they co-adapt and make decisions that will stretch and perturb the defensive line providing more free space for passing and shooting opportunities.

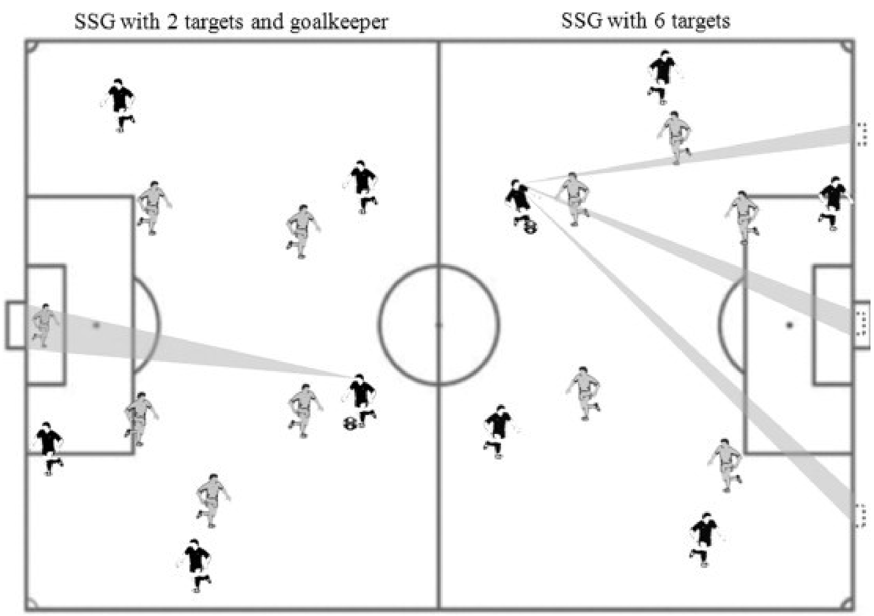

Figure 2.8: Two different 5v5 small-sided games played on a 30 x 25m pitch with different goal constraints. Drill one utilises 2 standard size (7.32 x 2.44 m) goals at either end while drill 2 utilises three smaller (1.2 x 0.8 m) goals at either end.[121]

While manipulating the number of players, pitch size, scoring modality, and tactical strategies can influence inter-team coordinative behaviour, external influences such as match status, location, quality of opposition and vignettes can also constrain emergent patterns of behaviour and should be considered when designing small-sided games. Tactical analysis in 11-a side football has revealed that, when losing, there is a tendency for teams to defend in more advanced pitch zones (Figure 2.11). This may be to apply defensive pressure by decreasing inter-team distances, attempting to force a turnover.[44] A similar pattern also emerges when teams are playing at home.[134] It was suggested that home crowd support is associated with an increased functional aggressive response, which, consequently, enhances the effectiveness of defensive actions such as interceptions and tackles.[183] Further, independent of these factors, higher ranked teams have proven to be more effective at applying defensive pressure in more advanced pitch zones and have dominated ball possession, as identified through notational analysis, demonstrating more stable patterns of play independently of the evolving score-line.[134] While traditionally it has been thought that greater inter-team distance is necessary for successful defensive performance, the findings of this study, despite no centroid or macroscopic-level measures, suggests that defensive strategies implemented by relatively superior teams utilise more intense and organised collective processes to pressure the opposing team, particularly away from their own goal.[134] Superiorly ranked teams may not require extensive amounts of time and space to modify their behaviours relative to those of the attacking team as previously thought due to an elevated ability to collectively, and efficiently, attune to relevant environmental information that affords goal-directed activity.[122] Identifying the impact of these external influences may appropriately guide training design as the emulation of these specific factors may afford teams, and players, with an opportunity to coordinate and co-adapt to specific situations in a representative environment.

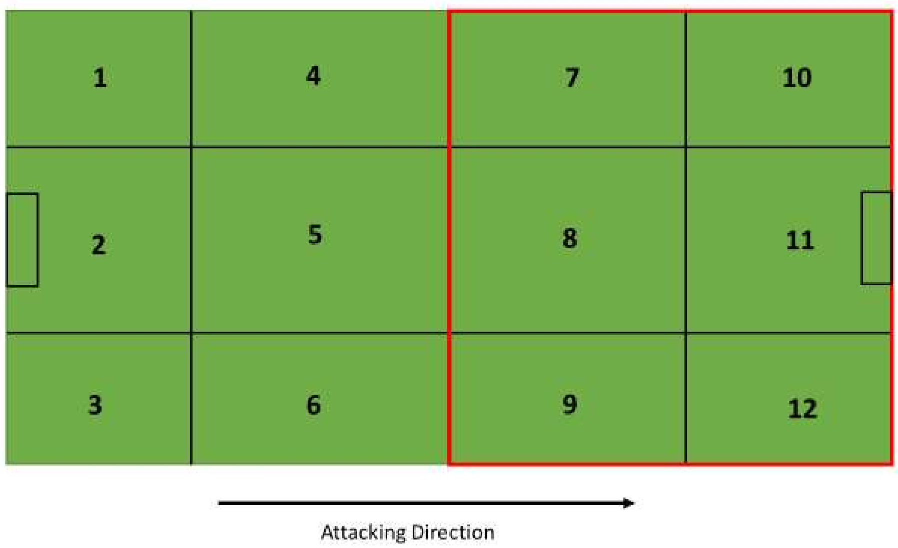

Figure 2.9: Red square signifying advanced pitch zones (zone 7-12).

Coaches and practitioners can incorporate vignettes or manipulate games with specific scenarios, such as a team initially starting behind on the score-board, to promote different adaptive behaviours.[184] In sport, performers must adapt to constraints and conditions whilst concurrently performing under different emotional states that in turn constrain player perception and action.[184] Traditional models generally view emotions as negative or detrimental in performance and have accordingly attempted to remove this aspect from practice task contexts until desired skills have been established. However, this reductionist approach may inadequately challenge performers from a cognitive perspective, subsequently rendering performers unprepared for the emotion-laden experiences that are inevitable in a sporting context.[185] Implementing vignettes or scenarios, such as being in front or behind on the score-board with a specific amount of time remaining, within a training context may allow performers to experience the emotional feelings associated with specific match-contexts in a learning environment that simulates the external task demands of a new environment.[184] This style of representative learning may promote effective development of skill and expertise in sport allowing performers to achieve functional task outcomes in a variety of different scenarios under different affective constraints. However, further research is required to elucidate the impact of affective constraints and learning on cognition, perception, and resultant team and player behaviour in a football context.[184] Further examination of the influence of these components on intra-team behaviour, in a training environment, may provide insight as to why specific behaviour emerges between two opposing teams in certain situations.

2.12.2 Mesoscopic intervention

Intra-team coordination can improve with appropriate training utilising 11-a side training. One study revealed an improvement in team ability to reciprocally compensate as demonstrated by the readjustment delays between the co-positioning of team members, consequently enabling faster regulation of coordinated team actions.[97] This highlights that intra-team coordination is a trainable phenomenon and warrants further investigation into different modalities that coaches and practitioners can implement to induce co-adaptive improvements at this level. Similar to the macroscopic scale, small-sided games appear to be an appropriate format of intervention on the mesoscopic level. Providing a format with less players than the traditional 11-a side format[85, 98, 99, 101, 103, 112, 118, 119, 138, 143, 169, 175] along with the manipulation of levels of inferiority or superiority,[40, 42, 120, 122, 128, 140, 179] pitch size,[98, 101, 103, 138] and goal type,[41] coaches and practitioners can improve coordinative behaviour in a training environment that enables performers to act and perceive in a way that is representative of an 11-a side match.

Similar to 11-a side training implementation,[97] adopting a 5-a side training format over a 13-week period in amateur players has induced improvements in intra-team coordination as indicated by increases in longitudinal synchronicity, regularity in player displacements and dispersion measures.[118] Equal manipulation in the number of players on each team appears to afford relevent mesoscopic coordinative behaviours. Increasing the number of players from 2- to 10-a side (particulary 3- to 5-a side) appears to promote an increase in dispersion measures[85, 98, 138] along with regularity [85, 138] (see Table 2.2 at end of section). Whether there is an increase in the number of players with a concomitant increase in pitch size,[85] keeping relative space per player the same, or a decrease in relative space per player with an increase in player numbers on the same sized pitch,[98, 138] dispersion and regularity increase. With a smaller number of players, participants need to move continuously, and often irregularly, in close proximity to the ball to create passing opportunities for teammates. Conversely, a format with more players requires players to harness degeneracy to enable co-adaptation to new spatiotemporal constraints in the form of less relative space per player.[98] As players need to develop their activity in a larger area, roles become more specific and are not always involved or required to be in close proximity with the ball.[85] Further, the increase in tactical dispersion is representative of that found in offense in an 11-a side format whereby players spread in search for goal scoring affordance.[107] Additionally, via manipulating of relative space per player using the number of players on field, i.e. 7v7-9v9, Silva et al.[138] revealed superior measures of dispersion and regularity than when space was manipulated by dimensions. The increase in regularity, and dispersion, with the number of players infers that training stable tactical coordination requires the use of a higher number of players. 4- or 5-a side formats appear to be adequate to promote team-related emergent and self-organised behaviour. However, the smaller formats (2- and 3-a side), associated with game unpredictability,[85] may allow players to harness irregularity in an attempt to destabilise defensive teams. This intra-team unpredictability has been associated with offensive success in an 11-a side format.[6, 28, 107]

Manipulating numbers to promote offensive or defensive superiority/inferiority can encourage favourable intra-team patterns of performance (see Table 2.2 at end of section). When numerically superior in a 5v3,[42] 5v4,[42, 122, 128, 140] 4v3, 7v4[128] format, or with floaters (4+2 floaters v 4),[40] teams in possession of the ball tend to increase dispersion while numerically inferior teams contract in defence.[40, 42, 122, 128, 140] The use of additional players may provide players with an opportunity to create numerical advantages in offense by selectively picking up shared affordances that consequently lead to passing and goal scoring attractors.[42] Alternatively, defending in numerically inferior situations may promote team defensive stability as teams decrease space between players during defensive organisation in an attempt to reduce passing and shooting affordances available for the opposition.[40] Furthermore, an increase in the number of opponents has revealed stronger in-phase relations between defending players and the ball[120, 122] indicating that when faced with a numerical disadvantage defenders prioritise the protection of the goal against ball displacements rather than against movements of the attackers. On the contrary, attacking teams have demonstrated greater phase variability between players and the ball. This may reflect an emphasis being placed on the constant probing as a result of playing against an organised defensive structure in an attempt to increase action possibilities for goal scoring.[120]

Furthermore, when looking at manipulations of superiority and inferiority in the design of small-sided games, differences are apparent between professionals and amateurs. In high inferiority scenarios, amateurs generally reduce distances to their own centroid. A lower degree of contraction in professionals may reflect an anticipation of the importance of optimising collective decision-making and may be linked to improved decisions based on opponents' positioning information.[128] Elite players may make improved decisions based on affordances perceived at an earlier stage in the decision-making process. Additionally, the superior skill levels of experts may also afford them the ability to defend relatively larger areas of 'individual space'. Furthermore, amateurs reveal a greater increase in regularity with higher teammate numbers. It is suggested that the presence of more teammates is associated with the self-organisation process and the effect of this is augmented in amateur players.[128] Professional players have also demonstrated similar area distributions and stretch indices in balanced (5v5) and numerically inferior (5v4) scenarios, indicating that dropping a player isn't enough to disturb coordination tendencies.[42] Additionally in these scenarios, professional players have demonstrated, to a greater extent, dispersed dominant regions, which compared to those of amateurs which were more superimposed (Figure 2.12).[42] The above examples highlight that professionals are able to maintain a more balanced distribution, degenerately adapting to different numerical constraints allowing the maintenance of intra-team coordination.[42] Gradually increasing inferiority, or increasing superiority, may also probe the stability of their coordinated behaviour. It is apparent that varying the number of opponents to elicit numerical inferiority may be more suitable to improve professional collective decision-making tactical performance as this induces increased team-related functional adaptations. Alternatively, manipulating the number of teammates to provide numerical superiority might emphasise the amateurs players' local perceptions, augmenting relevant environmental information and affordances.[128]

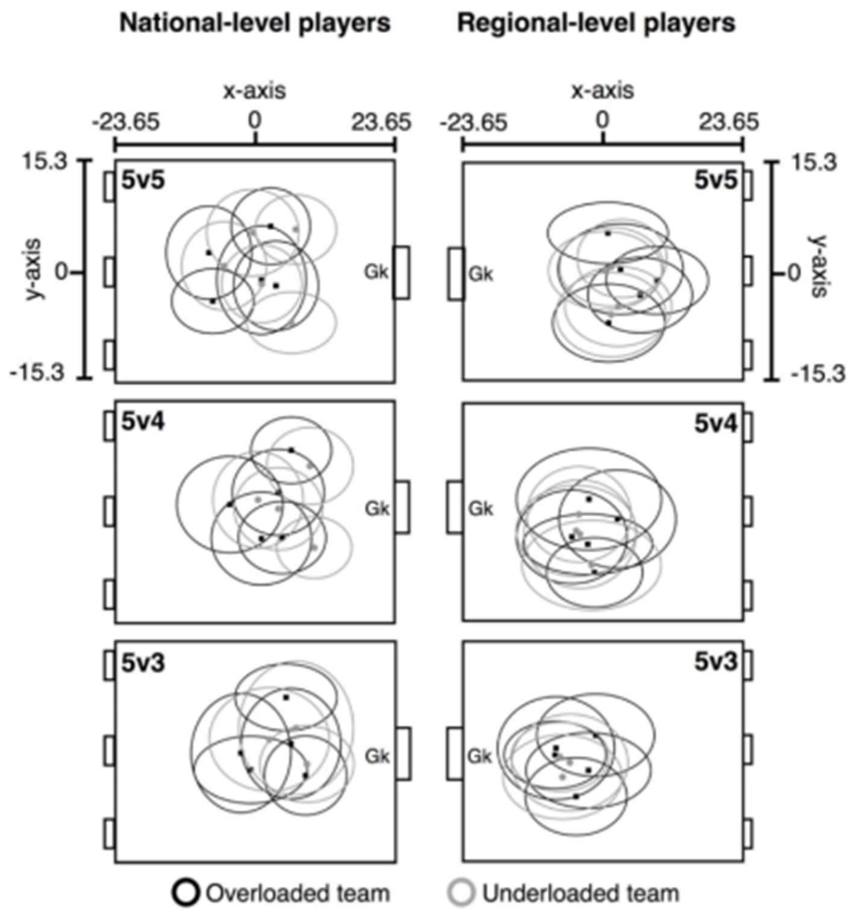

Figure 2.10: Comparison of dominant regions demonstrated by professional and amateur players under different numerical constraints.[42]

When considering pitch size, Silva et al.[101] demonstrated that U18 players in a 5v5 game increased dispersion from their preferred zone in a more regular manner with an increase in pitch size. This study also revealed that national league players demonstrate higher variability, as evidenced by the higher coefficient of variation in movement trajectories (Figure 2.13). On larger pitches, the increase in dispersion and regularity may be explained by the need for players to self-organise into specific roles and positions to ensure a balanced occupation of the full playing field.[101] Furthermore, the increase in the coefficient of variation highlights the need for players to move more and explore space on smaller fields to promote affordances.[101] Conversely, on smaller pitches, national league players revealed less regularity and variability in comparison to regional players.[101] Lower levels of regularity may reflect the higher frequency of perturbations with more tackles, shots, challenges and changes in ball possession occurring due to the reduced playing area or, alternatively, the degenerate ability of higher level players to co-adapt with less relative space per player.[101] Further, the lower variability demonstrated by skilled players may reflect their superior ability to search for and move to more variable areas of the pitch to cope with the constraints imposed by smaller spaces, while simultaneously maintaining higher consistency in the distances to their preferred zone.[101] Accordingly, coaches can manipulate field dimensions to afford learning opportunities for professionals and amateurs alike as both appear to respond similarly to changes in field size. However, this may be more appropriate for amateur players. Despite demonstrating similar tendencies to that of elite players, these behaviours may be less pronounced or prevalent (Figure 2.13). Utilising a large field (57.8 x 37.4 m) may force attacking players to search for affordances resulting in behaviour that highly variable, while conversely, a small field (36.8 x 23.8 m) may promote stable patterns of behaviour defensive patters that are less variable.[101]

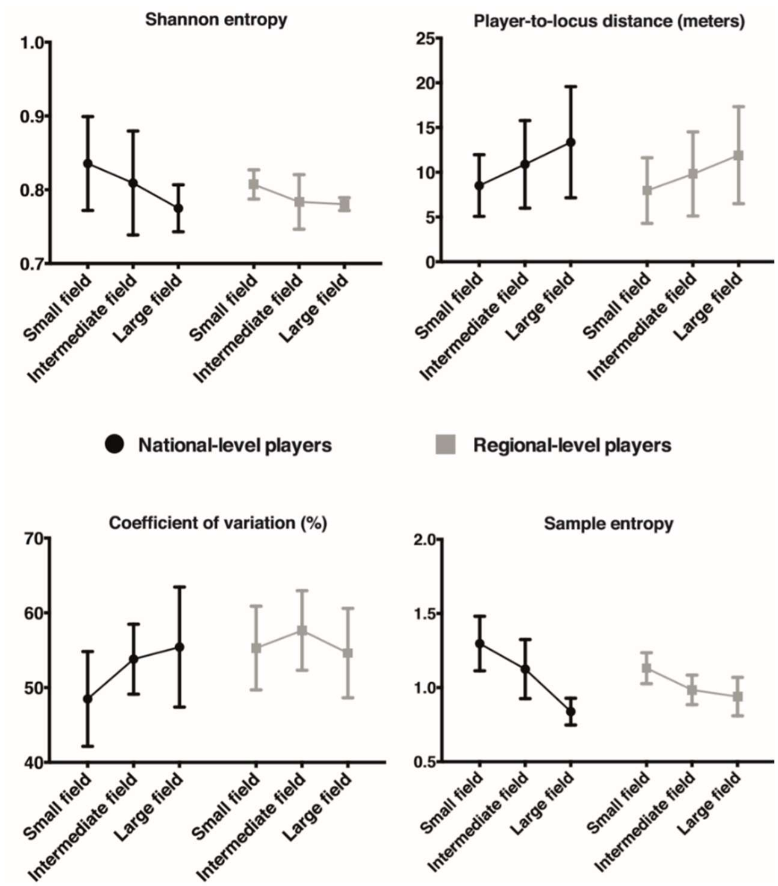

Figure 2.11: Changes in regularity (entropy), variability (coefficient of variation) and dispersion of elite and amateur players with changes in field size.[101]

As pitch size provides different affordances for coordinative behaviour and decision-making, it appears that area of occupancy during team possession influences the shape of dispersion. Rectangular surface area measures in a professional 11-a side format were analysed to guide modifications in pitch dimensions for small-sided games.[135] This study identified that the rectangular surface area width, covered by players on the field, was generally greater than the length, with the exception of when the ball carriers were in the zone closest to either goal, with length equalling the width. While the above information did not consider measures with respect to successful and unsuccessful patterns of play, it is suggested that the midfield area is where play is established with a transition from defensive to offensive patterning. Players therefore disperse laterally to deal with the concentration of players, attempting to provide passing affordances for teammates in this area.[135] Interestingly, one study revealed that playing length per width ratio increased with pitch size for national league players but remained relatively constant for regional players.[119] This may reflect an offensive strategy to approach the goals more quickly in larger areas by playing preferably outstretched in the goal-to-goal direction, affording longer passes for teammates.[119] Based on 11-a side area measures, Fradua et al. (2013) suggested that pitch sizes with individual areas between 70-110m^2 with a length to width ratio of 1:1 should be utilised for training offensive build-up and finishing phases of play while practitioners and coaches should incorporate smaller individual playing areas to train transitioning (65-95m^2) with a L:W of 1:1.3.[135]

Goal type and defensive strategy need to be considered when designing small-sided games. Castellano et al.[41] revealed that team shapes were more elongated in defence except for a small goal condition (two small goals at each end measuring 2.5m wide and 1m high at either end of the goal line) (Figure 2.14) where players were more dispersed laterally. While utilising two smaller goals at each end induces favourable patterns of dispersion in offence, allowing attacking players to spread in search for goal scoring affordances, this format may be detrimental to defensive patterning. Defensive dispersion may be contraindicative to the desired 11-a side formation as with one goal, teams in the defensive phase often accumulate players to defend one goal situated on the goal line on the central axis of the pitch.[41] As noted, increasing the number of goals may primarily benefit attacking passages of play as it augments a favourable situation whereby the defending line is perturbed and dispersed. Additionally, when utilising a zone defence over man-to-man defence, players spend more time in synchrony, particularly in the lateral direction.[143] This lateral synchrony may be beneficial as Gonçalves et al.[91] suggested that there is a need to reduce lateral spaces in defence as the occupation of the lateral corridors by attackers is considered to be the greatest destabilising factor of defensive organisation since the critical game periods appear to be associated with changes in lateral distance between teams.[91] On the contrary, man-to-man defence entails following an opposing player who is trying to create space and perturb the system.[143] Inherently, following variable attackers will likely lead to asynchronous behaviour in defence. These differences provide the opportunity for coaches to optimally prescribe training drills in order to promote desired defensive behaviour. Further, from an offensive perspective in a 5v5 format, when facing a conservative defence, such as zone defence, professional football teams have revealed increases in the number of passes between field zones, higher levels of reciprocal passing between different areas, superior closeness centralisation values and higher betweenness.[99] This signifies that incorporating a conservative defensive pattern in small-sided games may force attacking players to explore different areas of the field with greater dispersion of ball passing trajectories in the search for goal scoring opportunities.[99]

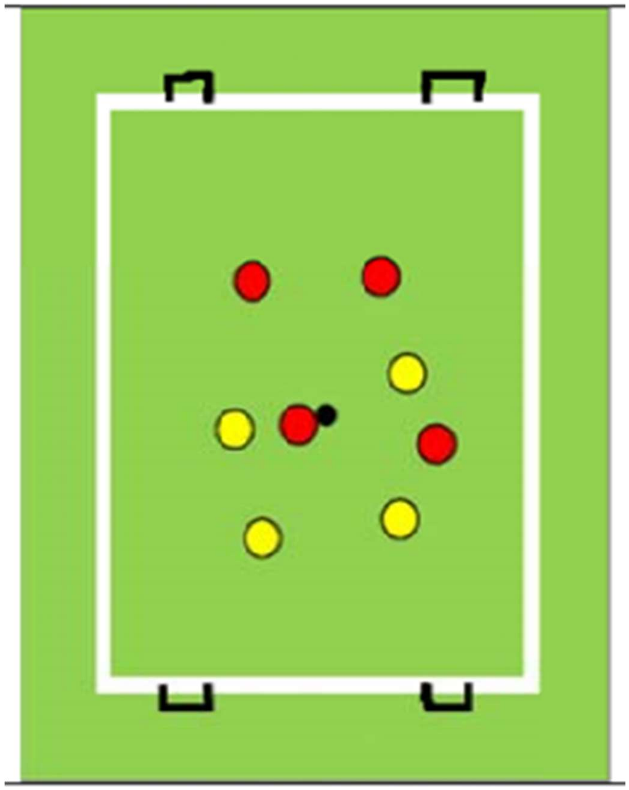

Figure 2.12: Small-sided game format utilising small (2.5 x 1m) goals at either end of a 40 x 20m pitch.[41]

Lastly, the timescale used for small-sided games is important. Over shorter periods, play is characterised by high intra-team variability while conversely, longer periods allow enough time for players to co-adapt to one another, resulting in superior levels of synchronicity.[105, 179] This may be particularly important for younger players, as older players have demonstrated less variability in dispersion measures.[112, 131] However, despite differences in dispersion measures, analysis of complex network variables from U12s through to U16s revealed no difference in centrality measures in a 5v5 format. Additionally, Costa et al. (2010) revealed no systematic advantage for early-born players when considering tactical aspects in U11 through to U17 players[5] It was observed that players born in all quarters had similar movement patterns and tactical performance indexes.[5] From this it can be inferred that players of different ages should benefit in a similar capacity independent of the timescale employed within a small-sided game.

While small-sided games and tasks are often governed by time, a player driven criterion approach, whereby players decide what the goal or outcomes of the small-sided game/drill should be, can be adopted. This approach requires players involved to agree about the basic assumptions such as what the situation is, what can be done about it, and what should be done about it.[186] Collectively, players then agree upon what the desired outcome will be and the best way to achieve this. This process fosters intra-team coordinative behaviour via collective intelligence where initially independent agents, or players, develop a unified approach to solving a shared problem. Upon the agreeance of a desired outcome, all players involved implicitly become attuned to desirable affordances for action that will allow the achievement of the agreed upon outcome. This collective action provides many functional advantages and has led to superior performance of groups over single organisms in a wide array of human social phenomena.[187] As an example, in football a criterion approach can be incorporated with in a small-sided game with vignettes whereby a team (team A) initially begin the game losing to the opposition team (team B) by 1 goal. As the overarching goal of soccer is to score more goals than the opposition team, team A as a collective group may decide that in order to achieve this, they need more possession of the ball whilst concurrently limiting team B's scoring opportunities. This subsequently leads to the common agreement that when in defence, they need to force more early turnovers. As a result, team A decide they need to force five turnovers in order to provide themselves with the opportunity to score. The drill then continues until five turnovers have been achieved, regardless of the amount of time that has passed. This process whereby players agree on an outcome solution will result in the implicit attunement to specific affordances that allow players to coordinate behaviour at an intra-team level resulting in the achievement of goal outcomes.

2.12.4 Tactical Intervention Summary

Table 2.2 below reveals ensuing patterns of coordination proceeding the implementation of varying constraints in small-sided games. When utilised with reference to favourable, or desired, performance outcomes, small-sided games appear to effectively guide players towards specific behavioural outcomes. The appropriate imposing constraints can actively challenge players to adapt to variable situations, allowing the achievement of task outcomes in a variety of ways. Table 2.2 also reveals a variety of shortcomings in the small-sided games literature. The blank spaces in the table identify areas that require clarification or further research regarding the emergent tactical behaviour in football.

Table 2.2: Review summary of tactically induced patterns using small-sided games

Scale		Macroscopic (Inter-team)										Mesoscopic (Intra-team)							
Status		Attack					Defence					Attack				Defence			
		TS	Disp	CSyn	Reg	CVar	TS	Disp	CSyn	Reg	CVar	Disp	Sync	Reg	Var	Disp	Sync	Reg	Var
	2-4	↓					↓												
↑ in players												↑		↑		↑		↑	
	5-10	↑					↑												
↑ inferiority		↑					↑	↓					↓		↑	↓	↑		↓
↑ Superiority		↓	↑				↑					↑			↑			↑	
↑ Pitch Size		↑		↑	↑	↓	↑		↑	↑	↓	↑		↑	↑	↑		↑	↑
↑ in goals		↑	↑				↑	↑				↑				↑			
↑spatial restriction																			
Winning v Losing		↑					↑												
Home v Away		↓					↓												
Playing High vs. low ranked team		↓					↓					↓				↑			
1^{st} vs 2^{nd} half				↑		↓			↑		↓	↑	↓	↓		↑		↓	↓
Zone Def v Man-on		↑		↓		↑	↑		↓		↑						↑		
Non-congested vs congested													↑				↑		
↑ Drill time													↑		↓		↑		↓

TS, Team Separation; Disp, Dispersion; CSyn, Centroid Synchrony; Reg, Regularity; CVar, Centroid Variability; Sync, Synchronicity; Var, Variability

2.13 Directions for future research

Each of the studies included in this review used a male cohort, making it difficult to transpose findings into a female context. While in recent years there has been an exponential rise in the professionalism and success of female sports, this delay in this rise has likely contributed to a lack of research incorporating female cohorts.[188] With professionalisation comes the ability to train full time while also providing access to coaching, sports science, sports medicine, and other resources that help maximise performance potential. The inability to train full time or access these resources has meant that female "sports performance" literature has primarily recruited "recreational athletes".[188] With the increase in professionalism and access to elite female athletes and resources, the expansion of this research using female cohorts is essential given the differences in match-play styles between genders.

At the professional level, males have demonstrated superior running demands and pass completion rates throughout a match along with fewer turnovers in possession, all of which are likely to influence, or be influenced by, emergent coordinative behaviour.[189] Additionally, while few studies offer superior insight through analysis of behaviour in relation to successful and unsuccessful performances, i.e. goal scoring opportunities or ball turnovers, most research failed to contextualise performance in relation to tactical intent. For example, analysis of zone and man-to-man defence both reveal conflicting effects on synchronicity and variability.[143] A man-on-man defensive style will often result in defensive asymmetry and lack of coordination, as the defending team's emergent behaviour is guided by the opposition's displacement.[143] However, through the analysis of goal scoring opportunities, the disruption in defensive stability, as marked by changes in synchronicity and variability, has been associated with attacking success.[6] Whether this defensive disruption is a result of attacking behaviour, sufficiently perturbing the defence, or if it was tactically intended by the defending team is rarely clarified in the studies reviewed here. If a defending team is utilising a man-on-man defence, this asynchrony may be deemed favourable as this signifies that players may be using the offensive team to guide behaviour. In contrast, if the intention was to use a zone defence where success is marked by synchronistic behaviour, then the disruption in stability, likely due to offensive perturbation, may deemed unfavourable. Likewise, in offense if the intent or coaches' instruction is to be unpredictable and asynchronistic, then tactical analysis revealing this will signify offensive success. Alternatively, if the attacking team are trying to move as a singular entity, moving in a coordinated way, then increases in variability or unpredictability may be contraindicative to performance outcomes. Therefore, it is important to identify or contextualise tactical intent regarding attacking or defending behaviour as this constrains and guides emergent behaviour.[39]

On a macroscopic scale of analysis, while the potential to provide further understanding has been recognised, Voronoi diagrams are yet to be implemented in an 11-a side context and associated with performance. This tool has the ability to account for every player and can effectively describe spatiotemporal relationships at both an inter-individual and inter-team level.[141] Incorporating this method of analysis may clarify existing ideas surrounding effective patterns of dispersion in attack and defence. Furthermore, a link between relative dispersion measures and the associated variability in these measures is also required. While increases in dispersion, accompanied by heightened variability, have been associated with attacking success at an intra-team level, this was observed in isolation of the opposing team's behaviour patterns. Incorporating these measures on an inter-team scale may offer further insight regarding how players should collectively move and disperse or contract to promote opportunities for success. From a tactical intervention perspective, while different defensive strategies have been analysed, i.e., zone vs man-on-man defence, future research should examine tactical analysis of a variety of offensive strategies, such as penetration/counter-attack vs possession play strategies as these will both likely lead to different observable outcomes. Further, while different contexts such as home vs away, winning vs losing or superiority vs inferiority lead to variations in emergent behaviour, research designs examining these components have typically failed to do so with reference to successful and unsuccessful performance outcomes.

At the mesoscopic level of analysis, while fatigue is suggested to be a confounding influence on second half tactical performance,[45, 108] future studies should examine relevant tactical variables in association with running demands, skill performance, team cohesion metrics, and perceptual measures. This will provide an enhanced understanding of the influence of fatigue on tactical performance. Further, linking these associated changes with opportunities for success, i.e., goal scoring or turnover affordances, may offer insight regarding the effect of fatigue on match outcome. As noted, a substantial amount of intra-team literature has also been analysed in the absence of an understanding of successful and unsuccessful patterns of play, or without context, neglecting to provide tactical intent as defined by the coaches' instructions. While examination with reference to critical match events has proven useful, contextualising outcome measures with associated intent may provide an additional marker of tactical success. Selected studies examining the effect of small-sided games manipulations on intra-team coordination did so on a general scale, failing to distinguish between attacking or defensive phases. While this may provide relevant detail when comparing two teams, i.e., one team demonstrated less synchrony in the second half, potentially signifying a greater onset of fatigue, it is necessary to distinguish between attacking and defending passages of play. This is important when examining a team in isolation as possessional status has revealed significantly different tactical tendencies on an 11-a side scale. This is likely due to different task-specific goals as well as varied environmental information available for perception.

Finally, few studies have examined the effects of training interventions on emergent team tactical behaviour over a specified training period. While the effect of different small-sided games manipulations on acute coordinative behaviours has been assessed an analysed in a football context, additional research is required to elucidate the chronic effects, particularly assessing whether these changes in behaviour persist and appropriately transpose to the 11-a side context.

2.14 Summary

Traditionally, to distinguish between successful and unsuccessful performances, i.e., winning vs losing, practitioners have focused on associated physical demands, such as distance covered at certain speeds or workloads, or discrete on-field actions, such as time in possession or number of passes preceding a goal. However, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance. Additionally, a shortcoming of these approaches is the focus on performance outcomes rather than the underlying processes, lacking explanation as to 'why' or 'how' certain performance outcomes emerge. Furthermore, for the vast majority of performance analyses in sport, the unit of analysis remains on the individual, the positional group, or the team. However, there is a need to analyse performance at the interaction rather than the individual level, making the smallest unit of analysis not one player's output, but the output of one player's interaction with another. With recent advances in technology, in conjunction with novel statistical approaches, researchers and practitioners have been able to examine tactical performance in collective team sports with reference to an ecological dynamics framework, offering a novel perspective on the mechanisms behind sporting success.

Borrowed from ecology psychology and dynamical systems theory, an ecological dynamics framework, when effectively incorporated, can provide a useful tool for describing 'how' and 'why' certain behaviours emerge over time. Additionally, this framework has the potential to distinguish between non-expert and expert performers, the latter having an enhanced capability to achieve higher levels of task outcomes, with effective and adaptive interactions between teammates. From an ecological dynamics perspective, football is a performance-environment sub-system where players and teams perceive affordances which guide decision-making and subsequent actions. Football teams can utilise key ecologically bound strategies such as degeneracy, dimensional compression, reciprocal compensation and interpersonal linkages to satisfy imposing constraints and successfully achieve task-objectives.[94-99] Implementing a hierarchical approach, researchers and practitioners can examine coordinative behaviour that emerges initially on a macroscopic level and then subsequently on a mesoscopic level. This top-down form of analysis provides an all-encompassing framework that describes 'how' and 'why' certain behaviours emerge as a result of inter-player, intra-team, and inter-team decision-making and coordination.

At both levels of analysis, i.e., macro- and mesoscopic, players rely on information afforded to them by surrounding players as well as the displacement of the ball. Furthermore, specific task-constraints, such as field dimensions and specific limitations, for example off-side and handball rules, provide additional information and boundaries that guide behaviour. On a macroscopic scale of analysis, it is apparent that teams tend to move in synchrony throughout the match, with this attractor state governed by positioning information of the other team. When in possession of the ball however, disruption of this synchrony, or attractor state, that potentially affords new goal scoring opportunities for attacking teams. Additionally, relative dispersion measures signify that attacking teams tend to spread out to provide scoring opportunities while defending teams contract, positioning themselves between the goal and the attacking team trying to minimise goal scoring affordances. It is the reciprocal exchange of information that drives synergistic, or antagonistic, cooperation between two opposing teams, both with the same objective, to overcome the opposition and win.

While inter-team analyses can adequately describe the dynamic relationship between two teams over time, a higher dimensional level of analysis can be undertaken to identify synergistic and co-adaptive behaviours that emerge on an intra-team level. Often measured in isolation of the opposing teams, in defence, there is a tendency for players to utilise afforded information provided by surrounding players to maintain synchrony and stability, consequently minimising goal scoring opportunities for the offending team. Conversely, aligning with patterns of centroid coupling at an inter-team level, attacking players trying to perturb this stability by dispersing and moving in a variable, unpredictable manner, drawing players away from their goal to provide scoring opportunities. Furthermore, position specific analysis offers further insight as defenders and midfielders spend more time in synchrony with their own position specific centroids than attackers. These emergent stable states (defenders and midfielders) and variable states (attackers) may reflect tactical roles as defenders remain dimensionally compressed to protect the goal while attackers remain unpredictable or degenerate to perturb the opposing defensive line. Additionally, complex network analyses have revealed common tendencies in successful teams, with minimal reliance on focal players being a common characteristic associated with successful performances. Further, the ability for teams to offensively co-adapt and reciprocally compensate when one or two key players are removed, or unavailable to pass to, is important for attacking success, allowing teams to achieve task-outcomes by fostering different relationships between players. When correctly utilised, a complex network analysis can reveal centroid players, i.e., those that are the most highly connected with in a team. These players appear to be midfielders and may be linked with their positional role as they are often responsible for recovering possession, particularly in the defensive zone, which would increase participation in offensive plays. Further, being centrally located, these players play a transitional role, often linking defenders and attackers.

Small-sided games appear to be an appropriate representative modality of training that allows coaches and practitioners to train and guide desirable behaviour at all levels of coordination by manipulating the task and environmental constraints that act upon small-sided games. The effective use of small-sided games allows performers to develop in a spatiotemporal varying training environment that reflects the formal and functional structure of a football game, with relevant informational constraints that reflect that of an official-match. As highlighted in Table 2.2, manipulating games by imposing specific constraints can guide players towards specified attractor states through enhance attunement to relevant perceptual information and affordances that allow favourable patterns of behaviour to emerge. This format of training facilitates the transfer of action and decision-making from the training process to the competitive context as it provides attractors and repellers, along with associated bifurcation points, that are representative of the traditional 11-a side format of the game. Further, this format of training provides an open noisy environment that can be actively scaled to fit the requirements of performers.

As highlighted, further research is still required regarding tactical analysis in football at each level of coordination. Female players are yet to be incorporated in studies utilising these forms of analysis and a wide array of existing studies lack contextual background regarding observed tactical patterning. Finally, as ecological dynamics is conceptually based in ecological psychology and dynamical systems theory, difficulty arises in the interpretation and understanding of associated ideas and terms. Consequentially, appropriately applying relevant concepts to help explain team sporting performance in a concise manner has proven difficult. A challenge for practitioners is to familiarise coaches and relevant stakeholders with the appropriate terminology and concepts allowing an enhanced understanding as to 'how' and 'why' coordinative behaviour emerges in collective team sports. Subsequently, practice tasks and drills can then be designed accordingly to promote favourable patterns of coordination.

2.15 Relevance to Australian Football

Evident in this chapter, there is a large amount of research exploring the different methods of tactical analysis as well as behavioural insights resulting from these analyses in football (soccer). These lines of analysis also provide a wide array of associated practical applications and means of analysing tactical behaviour in other contextually similar sports. More specifically, due to the apparent unexplored avenues of tactical analysis in Australian Football, these methods of analysis may be suitably applied in an Australian Football context. Accordingly, the following chapter describes, in more detail, how the methods identified in the literature review will be applied in an Australian Football context and subsequently utilised in the ensuing studies.

Chapter 3

Extended Methodology

3.1 Experimental Approach to the Problem

A retrospective, longitudinal case study design was used to investigate the sport-specific physical, technical, cooperative network and tactical demands of a professional Australian Football team and the relationship with team performance as determined by match, quarter, and scoring outcomes. Further, the influence of opposition level, phase of play and match outcome was assessed to provide insight into the extent to which contextual factors affect performance in these areas. Performance was assessed using data from the 2016, 2017 and 2018 Australian Football League (AFL) seasons.

3.2 Participants

The sample for the sequence of studies consisted of 48 male professional Australian Football players (age: 24.97 ± 3.78 years; playing experience: 5.22 ± 3.44 years) from one AFL team. Each participant played at least one game over the three-year (2016-2018) analysis window. Data was collected retrospectively and did not require direct contact with the players who were competing. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution (ETH18-3126) and the designated club provided their written informed consent prior to the commencement of the study.

3.2.1 Study one and two

ChampionData® statistics provided 73 team-based files and 1605 individual-based files (33.4 ± 25.6 per player) from the designated AFL team for technical and complex network analysis. ChampionData® statistics were also collected on each opposition team for all 73 matches used in this study, providing an additional 73 team-based files (4.3 ± 1.4 per team) and 1603 individual-based files (2.5 ± 1.5 per player).

3.2.2 Study three

Not all matches were suitable for analysis. Some matches required different units to be worn due to use of local positioning systems (LPS) instead of GNSS. Subsequently, data from 63 senior matches were used for analysis, providing 1376 individual based GNSS files (28.7 ± 21.8 per player) from the designated AFL team to be used for physical analysis.

3.2.3 Study four

Not all matches were suitable for analysis. Some matches required different units to be worn due to use of local positioning systems (LPS) instead of GNSS. Further, some matches were conducted at ground locations in which boundary coordinates were not directly measured by the researcher which is required for tactical analysis. These matches were also excluded. Subsequently, data from 50 senior matches were used for analysis providing 1376 individual based GNSS files (22.9 ± 17.6 per player) to be used for tactical analysis.

3.2.4 Study five

Not all matches were suitable for analysis. Some matches required different units to be worn due to use of local positioning systems (LPS) instead of GNSS. Further, some matches were conducted at ground locations in which boundary coordinates were not directly measured by the researcher which is required for tactical analysis. These matches were also excluded. Subsequently, data from 50 senior matches were used for analysis providing 200 team-based files for match quarters. The variables derived in studies 1-4 were used to provide the data to be used for structural equation modelling.

3.2.5 Study six and seven

Phase of play data were collected from 17 senior matches and were subsequently used for tactical analysis. This approach provided 9788 samples (n = Offence: 2057, Defence: 2016, Contested Play: 3291, Set-Shot: 384, Goal Reset: 342, Umpire Stoppage: 1256).

3.3 Measurement Equipment

Data was collected via the use of global navigation satellite system (GNSS) units sampling at 10Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia), SportsCode (Sportstec, Warriewood, New South Wales, Australia), and ChampionData® match statistics (Champion Data, Melbourne, Australia). Data was processed and analysed using a combination of MatLab code (Mathworks Inc., Natick, MA), R statistical software,[190] and customised Microsoft Excel spreadsheets (Microsoft Excel, Microsoft, Redmond, WA, USA). The GNSS units were worn by the players within a custom-built pouch sewn into the rear of their jersey. The device sits superior to the player's shoulder blades at the base of the neck and records data pertaining to the players latitudinal and longitudinal positioning. This information was subsequently processed and used for physical and tactical analysis. All players wore the same unit for each game during the season to minimise inter-unit variation. Critical match events were coded using SportsCode with subsequent analysis of all tactical variables being calculated and assessed using MatLab code. Additionally, player match performance statistics, which are collected by ChampionData® during each match, were used for cooperative network and technical analyses using a combination of a customised Microsoft Excel spreadsheets and MatLab code.

Intra-class correlation coefficients (ICCs) for Catapult GNSS devices have demonstrated high to very high reliability (r = 0.86-0.99) for distances covered and time spent at low-, high-, and very high-speed running.[16] Additionally, the same study utilising the typical error of measurement (TEM) demonstrated good reliability (TEM = 0.8-4.8%) for low- and high-speed running variables but poor reliability (TEM = 11.5-11.7%) for very high-speed running variables.[16] ICCs for coding phases of play with Sportscode have demonstrated very high reliability (r = 0.902-0.992) with TEM of total time spent in each phase of play demonstrating moderate to good reliability (TEM = 1.8-9.3%).[49] ChampionData® code all AFL matches for a myriad of skill involvements[8, 18] and while commonly used in Australian Football research, the reliability of all statistical indicators have not been empirically assessed.[8, 23, 49] Only a selection of statistical indicators have been reviewed, reporting a high level of reliability (ICC range = 0.947-1.000; RMSE range = 0.0–4.5).[19] The only other reliability information provided about ChampionData® statistics states that "quantity-based statistics are logged at better than 99% accuracy".[8]

3.4 Tactical Analysis

To objectively quantify the underpinnings of successful performance, to-date analysts have focused on identifying associated physical demands using GNSS devices.[10] Additionally, the assessment of discrete on-field actions such as frequency of kicks, handballs, possessions, marks, ruck-contests and tackles have attempted to provide information regarding successful performance in Australian football.[2, 19, 20] While the combination of GNSS and technical skill data present the most common assessment methods and causal indicators of physical and technical performance constructs in Australian football, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance. It has been suggested that this approach fails to provide a meaningful understanding of 'why' or 'how' underlying factors relate to successful performance and exemplifies the need for a theoretical rationale of performance behaviours.[24, 25] In an attempt to address this issue, it has been suggested, and previously demonstrated in soccer, that the measurement and quantification of synergistic and tactical behaviour may provide the necessary insight into the factors primarily related to successful performance. Technological advancements, such as an increase in sensitivity and application of GNSS devices, in conjunction with novel statistical approaches, may allow practitioners to quantitatively model, infer and predict performance outcomes in collective team sports, particularly during critical phases of play in-game.[17]

3.4.1 Cooperative Network Analysis

Network Set-Up

Player network analyses are able to identify effective coordinative sub-units or key players within a team. This information can then subsequently be used to guide training intervention and develop favourable match-play strategies.

ChampionData® match statistics were used to create a weighted *n* x *n,* directed adjacency matrix (figure 3.1) for each game where *n* is equal to the total number of players in the network.[164] This matrix has the ability to reveal the directed number of completed passes between certain players. A pass was counted if a handball or kick reached the intended target player. This matrix is then used to create a weighted directed graph (figure 3.2) with the graphed nodes representing individual players and weighted edges signifying the direction and number of passes between players. This weighted adjacency matrix and directed graph can be subsequently used for analysis using dedicated MatLab[191] routines, as described in the following pages.

Player	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22

1	-	2	1	0	1	0	0	2	0	0	2	0	0	0	0	2	0	1	2	3	1	1
2	0	-	2	0	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0	0	1
3	0	1	-	1	2	1	1	0	0	1	0	1	4	2	0	1	1	0	0	1	0	2
4	1	1	0	-	0	0	0	1	0	0	2	0	0	0	0	0	0	1	0	0	0	1
5	1	0	0	0	-	0	0	0	0	0	1	1	0	0	1	0	1	1	0	2	0	1
6	0	0	1	0	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	1	1	0	0	0	0	-	0	0	0	0	2	0	0	0	0	1	0	1	0	0	0
8	1	0	1	0	0	0	0	-	0	2	1	0	1	0	2	0	1	1	0	1	0	0
9	1	0	0	3	0	1	0	2	-	1	0	0	0	0	0	1	0	2	0	0	0	1
10	0	0	2	0	0	0	0	1	0	-	0	1	0	2	1	0	3	0	1	1	1	1
11	3	2	2	3	0	0	0	2	1	0	-	3	1	0	0	0	0	0	1	0	0	1
12	5	0	0	0	2	0	1	0	1	2	4	-	0	1	1	0	0	0	1	0	0	1
13	0	0	0	2	0	0	0	0	0	0	0	2	-	1	3	0	1	2	1	1	2	2
14	1	1	1	0	0	0	0	0	0	0	0	0	0	-	3	0	0	0	0	1	0	2
15	0	0	1	0	1	1	1	0	0	1	0	0	1	0	-	1	0	0	2	1	3	0
16	1	0	1	1	0	0	0	0	0	0	2	0	1	0	0	-	3	0	0	2	0	1
17	2	1	1	0	0	0	0	0	0	1	2	0	0	0	0	0	-	0	0	0	0	1
18	2	0	0	0	0	1	0	2	3	0	2	2	0	0	0	1	0	-	0	0	0	1
19	0	0	0	0	1	0	0	0	0	1	0	1	1	0	2	0	0	0	-	1	0	0
20	0	0	0	0	0	0	1	0	1	0	1	0	0	0	2	0	0	0	0	-	2	0
21	0	1	0	0	0	0	0	0	0	2	0	0	0	0	1	1	0	0	0	1	-	0
22	0	0	2	0	1	0	1	0	0	0	0	0	1	2	5	0	0	1	0	1	1	-

Figure 3.1: Example weighted adjacency matrix for interactions from one match.

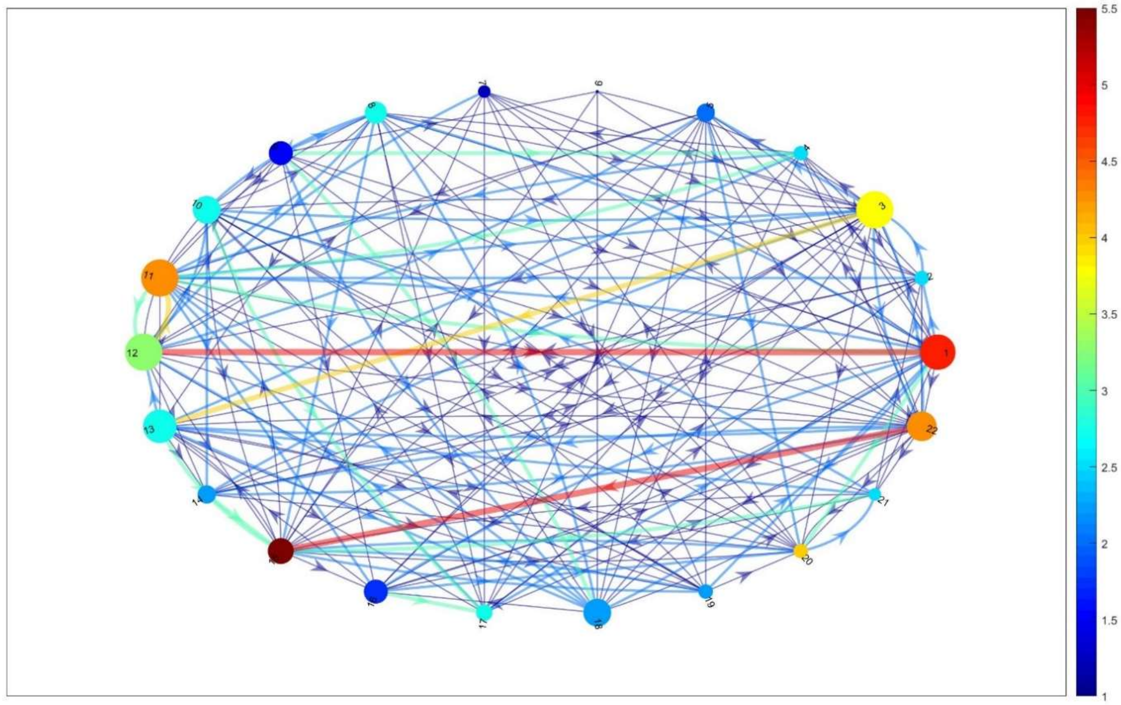

Figure 3.2: Example weighted directed graph of 22 players from a single match. Node colour and size represents the individual in- and out-degree importance, respectively, while line colour and width represent the number of passes between players.

Global Player Network Summary Statistics

Network density is one of the most widely used network features and is used to investigate, on a global level, how well players within a team interact with one another. Density is calculated as the number of existing ties, or connections, in a network divided by the number of potential ties. This measure therefore has the ability to signify mutual interdependence and level of interaction within the network with values closer to one showing a more complete network whereby most players interact with the majority of the team.[168] If the directed weighted adjacency matrix = $\in Rn^{n \times n}$ with *n* players, network density can be calculated using all non-zero elements *(nnz)* in columns and rows:

$$\boldsymbol{Density} = \frac{\sum \boldsymbol{Column}(\boldsymbol{nnz}) + \sum \boldsymbol{Row}(\boldsymbol{nnz})}{(\boldsymbol{n}^2 - \boldsymbol{n})}$$

Network intensity is indicative of the amount of ball movement in the network with superior values signifying a greater amount of ball movement. Intensity represents the total number of passes in the network and can be calculated by averaging the sum of the weighted values in both the column (in-strength) and row (out-strength) dimensions of the directed weighted adjacency matrix $\in Rn^{n \times n}$.[168]

$$\boldsymbol{Intensity} = \frac{\sum \boldsymbol{Column} + \sum \boldsymbol{Row}}{\boldsymbol{2}}$$

Individual Interaction Level Statistics

Individual Connectivity Level - Node

In- and out-degree node centrality represent the number of incoming or outgoing edges at each node or player. In other words, players with more incoming or outgoing edges are connected with more players within the network. Accordingly, these measures of centrality have the ability to identify which players are connected with more players via reception of a pass (in-degree) and which players connect more with other players via distribution of a pass (out-degree).[2] For example, in figure 3.2, a greater number of edges to or from a single node indicates the level of connectivity. If the directed weighted adjacency matrix = $\in Rn^{n \times n}$, then for a given player *i,* the in-degree and out-degree node centrality can be calculated using all non-zero elements column- and row-wise respectively:

$$\boldsymbol{In - Degree\ Node(i) = \sum Column(nnz)(i)}$$

$$\boldsymbol{Out - Degree\ Node(i) = \sum Row(nnz)(i)}$$

Expanding on the metric above and offering further insight into the connectivity of individual players, in- or out-degree node centrality proportion signifies how well connected a certain player is within the network relative to the total number of players in the network. Accordingly, is calculated using in- and out-degree node centrality scores and the number of players in the network. Values closer to one signify that the player is well connected and connects with the majority of other players in the network. Using pre-calculated node centrality scores for a given player *i* where *n* is equal to the number of players in the network, node centrality proportion can be calculated as:

$$\boldsymbol{In - Node\ Proportion\ (i) = \frac{In - degree\ Node(i)}{(n - 1)}}$$

$$\boldsymbol{Out - Node\ Proportion(i) = \frac{Out - degree\ Node(i)}{(n - 1)}}$$

Finally, a node ratio can be used to identify whether a specific player is either connected with or connects with more players in the network thereby offering additional insight as to the specific role a player may play. Values greater than one signify that the number of players an individual receives possession from is greater than the number of players they distribute to. Conversely, values less than one reveal that a specific player distributes to a greater number of players than they receive. This value is simply calculated as a ratio using player *i* node centrality scores:

$$\boldsymbol{Node\ Ratio(i) = \frac{In - Degree\ Node(i)}{Out - Degree\ Node(i)}}$$

Individual Connectivity Level - Passing

Similar to node centrality, passing centrality measures can identify key players within the network, specifically with reference to ball movement. In- and out-degree pass centrality reveal the total number of passes a player receives or distributes and has the ability to identify players that receive (in-degree) and distribute (out-degree) most of the possession.[165] For example, in figure 3.2, a thicker, darker edge between nodes indicates that those specific players pass to or from each other more so than other players. Superior values may signify that a given player is important during attacking sequences with key players receiving and distributing more possession than other players. If the weighted directed adjacency matrix = ∈ $Rn^{n \times n}$, then for player *i,* the in-degree and out degree pass centrality can be calculated using the sum of column- and row-wise values for a given player:

$$\boldsymbol{In - Degree\ Pass} = \sum \boldsymbol{Colum(i)}$$

$$\boldsymbol{Out - Degree\ Pass(i)} = \sum \boldsymbol{Row(i)}$$

Similarly expanding on the measure above, player passing centrality scores can be expressed in relative terms as an in- or out-degree pass centrality proportion, subsequently indicating the proportion of all network passes that are either received (in-degree) or distributed (out-degree) by a specific player. As per node proportions, scores closer to 1 signify that a player is well connected or important in the network. Using pre-calculated in- and out-degree pass centrality scores for player *i* and the network intensity, pass centrality proportion can be calculated as:

$$\boldsymbol{In - Pass\ Proportion(i)} = \frac{\boldsymbol{In - degree\ Pass(i)}}{\boldsymbol{Intensity}}$$

$$\boldsymbol{Out - Pass\ Proportion(i)} = \frac{\boldsymbol{Out - degree\ Pass(i)}}{\boldsymbol{Intensity}}$$

Finally, centrality pass ratio scores can identify whether a player receives or distributes more passes within the network, again providing further insight into the role a specific individual may play within the player network. Values greater than one signify that a player receives a greater number of passes than they distribute. Conversely, values less than one reveal that a player distributes more passes than they receive. This value is simply calculated as a ratio using player *i* pass centrality scores:

$$\boldsymbol{Pass\ Ratio(i)} = \frac{\boldsymbol{In - Degree\ Pass(i)}}{\boldsymbol{Out - Degree\ Pass}(i)}$$

Individual Proximity – Ease of Connectivity

While the individual measures presented above are capable of identifying connectivity levels of players within the network, closeness centrality indicates how easy it is for a player to be connected with, or connect with, surrounding teammates.[142] Closeness centrality can be defined as the inverse of the sum of its distance to all other nodes and signifies how close a player is to their peers. Higher values assume a positive meaning in the node's proximity. In figure 3.2, the further the node colouring is towards the red end of the colour spectrum the easier that player connects with the rest of the team. Two variations of closeness centrality were calculated in the current research: a) In-closeness, which counts inbound links, i.e., how easily reachable is a player; and b) Out-closeness, which counts outbound links, i.e., how easily does a given player reach other players in the network. With *A(i)* as the number of reachable players from player *i* (not counting *i*), *n* as the number of players in the network, and *C(i)* is the sum of distances from player *i* to all reachable players, closeness can be calculated as:

$$\boldsymbol{Closeness(i)} = \left(\frac{\boldsymbol{A(i)}}{\boldsymbol{n-1}}\right)^{2} \frac{\boldsymbol{1}}{\boldsymbol{C(i)}}$$

If no players are reachable from player *i,* then closeness of that player is zero signifying low closeness. For in-closeness and out-closeness for a given player, the distance measure is from all other nodes to that player (in-closeness) or conversely, from that player to all other nodes (out-closeness).[191]

Betweenness centrality can provide further insight into a player's specific role, revealing the influence of that player on network flow and connectivity. Betweenness centrality is indicative of how often each graph node appears on a shortest path between two nodes in the graph.[170, 191] A player with a higher value is crucial to maintain team passing connections by acting as a connecting bridge[142] and is important for passing flow in the network.[2] In figure 3.2, node size is indicative of betweenness centrality with larger nodes being of greater importance for bridging players within the network. Since there can be several shortest paths between two players, player *s* and player *t,* the betweenness centrality of player *i* is:

$$\boldsymbol{Betweenness(i)} = \sum_{s,t \neq i} \frac{\boldsymbol{n_{st}(i)}}{\boldsymbol{N_{st}}}$$

where $n_{st}(i)$ is the number of shortest paths from player *s* to player *t* that pass-through player *i,* and N_{st} is the total number of shortest paths from s to t.[191]

Individual Importance

Pagerank centrality has the ability to identify important players within the network. This measure holds that a node, or player, is popular or of importance if they receive passes from other important players.[170, 192] Player scores are therefore not only dependent on the number of incoming passes, but also the number of incoming links to teammates. Mathematically, Pagerank centrality can be calculated as:

$$\boldsymbol{Pagerank(i)} = \boldsymbol{p} \sum_{j \neq i} \frac{\boldsymbol{A_{ji}}}{\boldsymbol{L_j^{out}}} \boldsymbol{x_j} + \boldsymbol{q}$$

where $L_j^{out} = \sum_k A_{jk}$ is the total number of passes made by player *j, p* is a heuristic parameter representing the probability that a player will decide to give the ball away, and *q* is a parameter awarding a 'free' popularity to each player.[170] Pagerank assigns to each player the probability that they will have the ball after a reasonable number of passes being made in the network.[170]

Additionally, all variables can be relatively scaled to provide relative connectivity on a match-to-match basis. In this instance, superior values (closer to one) signify that the selected player *i* participates with most other players in the group.[164] For player *i*, when k_i and k_{max} are the player's score and the maximum score demonstrated by another player in the network respectively, scaled connectivity *s(i)* can be calculated as:

$$\boldsymbol{S(i) = \frac{k_i}{k_{max}}}$$

Team equality statistics

Team in- and out-degree node centrality variability reveals global centralisation characteristics of the team where lower values signify that all players interact with the same number of players and, conversely, superior values suggest that certain players connect more with other players. Node variability was adapted from previous literature[168, 193] and can be calculated as:

$$\boldsymbol{Node\ Variability = \frac{\sum_n i_{max} - i_n}{(n-1) \times Density}}$$

Additionally, team in- and out-degree pass centrality variability can be used to assess centralisation tendencies with lower values signifying that all players receive and/or distribute the same amount of possession through passing and, conversely, superior values suggest that certain players receive or distribute more possession than other players. Node variability was adapted from previous literature[168, 193] and can be calculated as:

$$\boldsymbol{Pass\ Variability = \frac{\sum_n i_{max} - i_n}{(n-1) \times Intensity}}$$

Finally, table 3.1 presents additional team social network outcomes. Individual player values were used in the calculation of team social network values, both offering varying, but insightful information regarding social network equality, or centralisation, within the team. Calculation 1 is simply the mean of all player values, with superior values signifying that players are equally important.[2] Additionally, calculation 2 uses the variance between the maximum value (i_{max}) and every other player's value with lower values signifying equality, or decentralisation in the network.[168, 193] With *n* representing the number of players in the network, mean and variability can be calculated as follows:

Table 3.1: Global social network measures.

$$(1)\ \boldsymbol{Global\ Mean} = \frac{\sum_n \boldsymbol{i_n}}{\boldsymbol{n}} \qquad (2)\ \boldsymbol{Global\ Variability} = \frac{\sum_n \boldsymbol{i_{max}} - \boldsymbol{i_n}}{\boldsymbol{n-1}}$$

Global In-Closeness	In-Closeness Variability
Global Out-Closeness	Out-Closeness Variability
Global Betweenness	Betweenness Variability
Global Pagerank	Pagerank Variability

3.4.2 Match Event and Contextual Information Analysis

Coding Events

Each match from the three-year data period was viewed and coded using Sportscode software. Sportscode allows the efficient and accurate coding of match-play phases providing timestamps for events of interest. The following table (Table 3.2) identifies all phases of play and events that were coded for with a brief description of each variable and the associated contextual information. These timestamps provide necessary data that can be used to calculate the event-specific tactical variables below. Additionally, match-day and outcome contextual information was recorded for subsequent analysis (Table 3.3).

Table 3.2: Phases of match-play description adapted from Rennie et al.[49]

Match Phase	**Description**	**Contextual Information**
Offence/Defence	The reference team/opposition has clear control of the ball via a hard ball get, a mark, handball or an intercept during open play or there are two uninterrupted touches from players of the same team. A turnover from a penalty, infringement or behind also constitutes a change in possession.	Quarter*: 1, 2, 3 or 4* Match status: *Point differential (margin)* Location 1: *Forward-50, midfield, or defensive-50* Location 2: *Left, middle or right corridor* Possession from: *Contested play, turnover, free kick, kick-in* Duration: *Time until next phase of play* Number of touches between teammates: *Number* Inside-50: *Y or N* Rebound-50: *Y or N* Result: *Goal, behind or set-shot* Kick-in decision: *Run, kick or error*

Contested Play	Neither team has clear control or possession of the ball due to tackling or opposition pressure. The ball is not secured via a mark or clean receive from a fellow player of the same team.	Quarter*: 1, 2, 3 or 4* Match status: *Point differential (margin)* Location 1: *Forward-50, midfield, or defensive-50* Location 2: *Left, middle or right corridor* Contested type: *Centre bounce, ball-up, boundary throw-in or general play* Duration: *Time until next phase of play* Ruckmen first touch: *Y or N*
Umpire Stoppage	The umpire signals a stoppage in play to indicate a ball up, boundary throw-in or goal review. Blood rules or stoppages due to injury were also included in the analysis.	Quarter*: 1, 2, 3 or 4* Match status: *Winning or losing* Location 1: *Forward-50, midfield, or defensive-50* Location 2: *Left, middle or right corridor* Duration: *Time until next phase of play*
Set-Shot	Commences the moment a player marks the ball in a scoring position, executes the shot and the umpire indicates either a goal or behind. If an umpire requests a score review, the phase is defined as an umpire stoppage.	Quarter*: 1, 2, 3 or 4* Status: *For or Against* Match status: *Point differential (margin)* Location 1: *Forward-50, midfield, or defensive-50* Location 2: *Left, middle or right corridor* Duration: *Time until next phase of play* Result: *Goal, behind or no result*
Goal Reset	Includes the duration between the umpire signalling a goal has been scored to the proceeding centre bounce.	Quarter*: 1, 2, 3 or 4* Match status: *Winning or losing* Duration: *Time until next phase of play*

Table 3.3: Match contextual information.

Contextual Information	**Description**
Match location: *Ground Name*	The name of the ground at which the team is playing.
Opposition rank: *Position on the table relative to team*	Whether the opposition team is ranked above or below on the competition table at the commencement of the game and by how many places. For round 1 using previous year standings.
Temperature: *C^o^*	Average temperature over course of match.
Match conditions: *Wet or Dry*	Whether the conditions are dry or wet. Dry is classified as there being no rain fall on the day of, or during, the match.
Match time: *Time of day*	Was the match played during the day, twilight or in the night. Game classified as a twilight game if the game begins when it is light and finishes when it is dark.
Match turnaround: *Number of days*	Number of full days between the previous match and the current match.
Round: *Round number*	What round number is it in the season. All finals games were classified as round '*F*'.
Outcome: *Win or Lose*	Did the team win or lose the game.
Margin: *Point differential*	Number of points the team won or lost by.

3.4.3 Spatiotemporal Analysis at the Intra-Team Level

Data Filtering

Tactical variables were calculated from raw individual player latitudinal (x_i) and longitudinal (y_i) positional data. This information was collected via GNSS devices worn by players during the game sampling at a rate of 10Hz. Data was subsequently analysed through the use of dedicated MatLab coding using MatLab software.[191] MatLab's *inpolygon* function was utilised as it returns indexing values indicating whether player coordinates (x_n, y_n) are inside or on the edge of the polygonal region specified by the boundary coordinates of the field (x_f, y_f) (Figure 3.3). Using these values, all player data points that fall outside the field region were removed so they are not included in the following calculations.[191] This was conducted to remove players that were on the bench. Field boundary coordinates were collected by walking around the outside of the oval, approximately 0.5 m outside the boundary line, while carrying a GNSS device. This was undertaken at every oval where a match was contested.

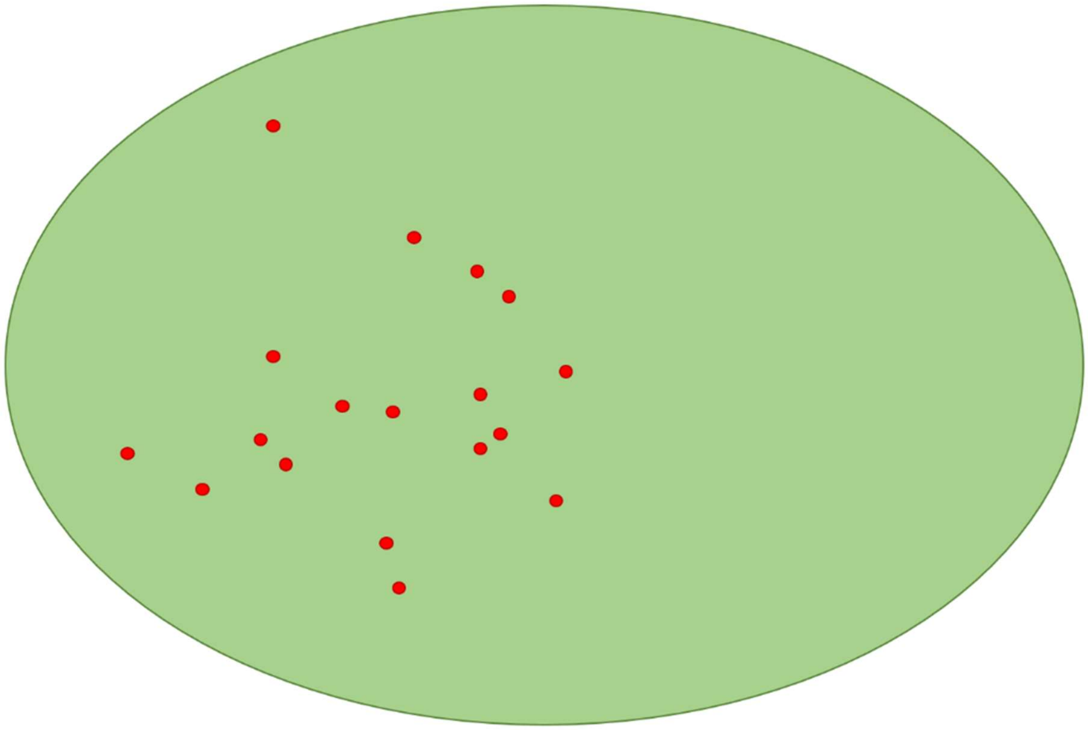

Figure 3.3: Example representation of individual players inside the polygonal region of the field.

Measures of Displacement and Dispersion

A centroid is the geometrical centre of a team and provides information on the global positioning of the team over time. It is calculated as the mean position ($\bar{x}$,$\bar{y}$) of all players on the field (x_n,y_n) over time in the x- and y-component of motion, i.e. latitude and longitude (Figure 3.4).[100, 107] Following the calculations, the field's centre coordinates were subtracted from centroid values to provide a standardised value. Additionally, this simplified the interpretation of which half, both latitudinally and longitudinally, the centroid was located in.

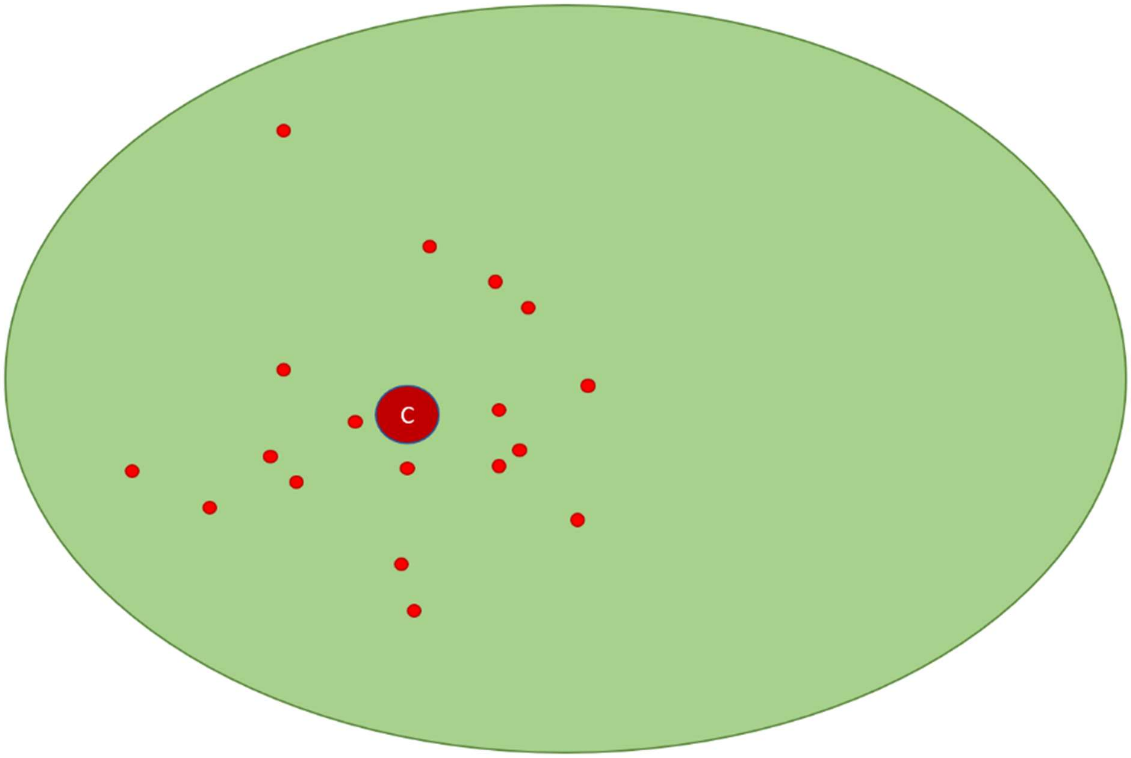

Figure 3.4: Larger filled red circle demonstrating the team's centroid.

The team's stretch index metric can provide information regarding the dispersion and contraction patterns of the team in relation to the team centroid (Figure 3.5).[194] It is calculated using the mean of the distances between each player (x_n,y_n) and the centroid of the team ($\bar{x}$,$\bar{y}$) at a given time:

$$Stretch\ Index = \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}$$

Due to the input of units being in degrees, post-calculation results were converted using MatLab's *distdim* function which takes angular units (degrees or radians) and converts to linear distance (metres).[191] This conversion is made along a great circle arc on a sphere with a radius of 6371 km, the mean radius of the Earth.[191]

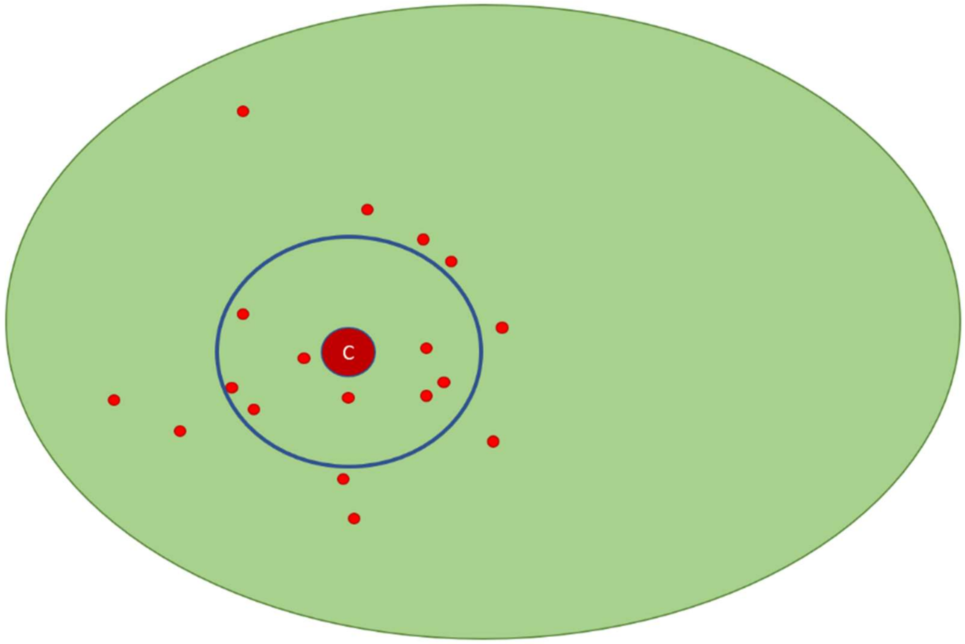

Figure 3.5: Larger un-filled blue circle demonstrating the team's stretch index.

Dispersion can also be assessed using surface area, defined as the total space covered by a team and calculated as the area within the convex hull.[113] The convex hull is determined by the outermost players on the field (Figure 3.6) and were calculated using MatLab's *convhull* function which returns an index array of the outermost players at a given time.[191] The polygonal area can then be calculated using MatLab's *areaint* function which calculates the spherical surface area of the polygon specified by the convex hull input vectors (*x,y*).

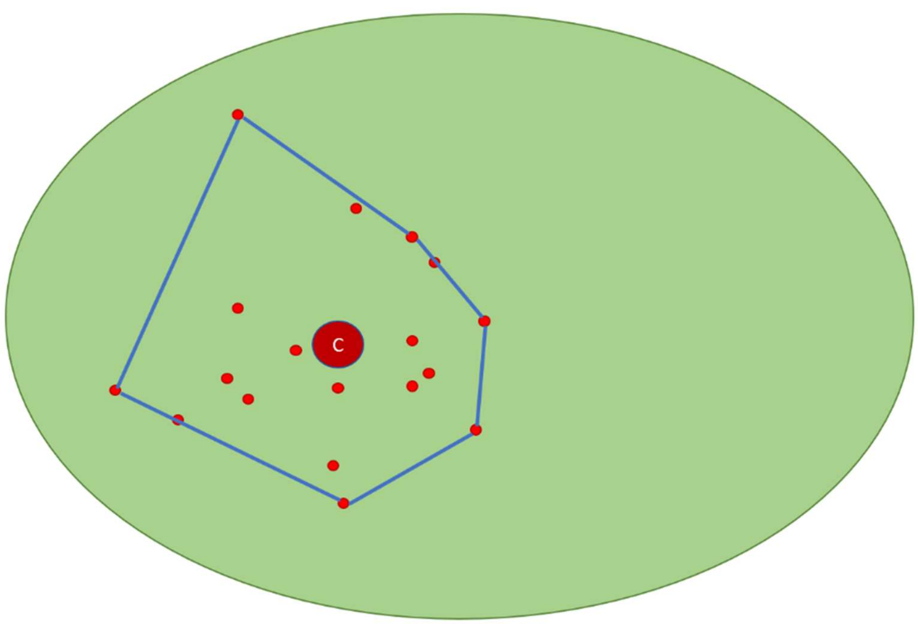

Figure 3.6: Surface area of the team determined by convex hull of outermost players.

Additional information can be derived using the raw values generated from the above calculations. Such values provide insight into the general positioning and shape of the team over a certain period while concurrently providing information into the variability and/or regularity of exhibited behaviour. For all critical events, the mean and coefficient of variation were calculated using the specified time-period duration commencing from the beginning of the phase of play until the beginning of the next phase of play, as specified by the variable duration. The coefficient of variation is a form of linear analysis that uses the standard deviation *(s_k)* and mean *($\bar{k}$)* to quantify the overall variability of the team's spatiotemporal characteristics during specific passages of play, with lower values representing lower variability.[101] These measures can be calculated taking all measures from the specified time-period where *k* is the variable under examination and *n* is the number of sample points:

$$\mathbf{1)}\ \boldsymbol{Mean} = \frac{\sum_n \boldsymbol{k_n}}{\boldsymbol{n}} \quad \mathbf{2)}\ \boldsymbol{Coefficient\ of\ Variation} = \frac{\boldsymbol{s_k}}{\bar{\boldsymbol{k}}}$$

To assess the predictability of team movements and patterning, the above measures were complimented with sample entropy analysis. This measure provides a non-linear measure of variability that is important in describing the magnitude of variability.[101] Sample Entropy is defined as the negative natural logarithm for conditional properties that a series of data points a certain distance apart, m, would repeat itself at $m + 1$.[195, 196] Given the time series $t(n) = t(1), t(2), \dots, t(n)$, with *n* number of data points, a sequence of *m*-length vectors is formed. Comparisons are then made against each *m*-length vector within the time series. Vectors are considered alike if the tail or head of the vector fall within a certain tolerance level as determined by $r \times SD$.[101] The sum of the total number of like vectors is then divided by $n - m + 1$ and is equal to *B*. Additionally, *A* is equal to the subset of *B* that also matched for $m + 1$. Sample entropy is then calculated:

$$\boldsymbol{SampEn} = -\boldsymbol{ln}\frac{\boldsymbol{A}}{\boldsymbol{B}}$$

A time series with similar distances between data points would result in a lower sample entropy value and large differences would result in greater sample entropy values, with no upper limit possible. Thus, a perfectly repeatable time series would elicit a value ~0 and a perfectly random time series would elicit a value converging toward infinity.[195, 196] Sample entropy can determine the predictability and regularity of a time series, with values closer to zero signifying greater regularity/predictability. Based on previous literature, the parameters to be used in this study are *m* = 2 and *r* = 0.2.[133, 195, 197]

3.4.4 Tactical Analysis at an Inter-Player Level

Measures of Displacement and Dispersion

GNSS positional data (x_n,y_n) was used for tactical analysis at in inter-player level. Raw latitudinal (x_n) and longitudinal (y_n) values were used to determine each player's exact position on the field. Similar to team centroid measures, following the calculations, the field's centre coordinates are subtracted from displacement values to provide a standardised value.

Individual dispersion will also be calculated as the perpendicular distance of a given player (x_i,y_i) to the team's centroid ($\bar{x}$,$\bar{y}$) (Figure 3.7) as per the equation:

$$Interpersonal\ Distance = \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}$$

As per intra-team measures, mean, coefficient of variation and sample entropy calculations were applied to the sample period of the critical events for the aforementioned variables.

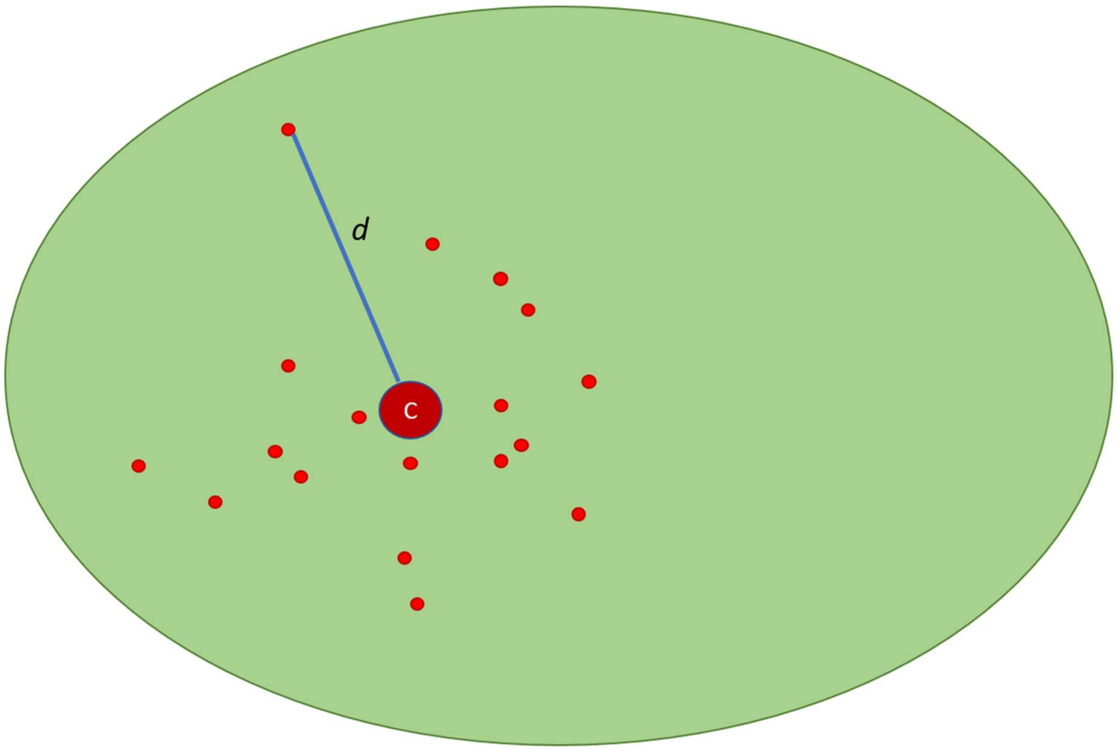

Figure 3.7: Interpersonal distance (d) at a given point in time.

Synchrony

Using individual measures of displacement and dispersion, individual synchronicity was assessed at two different levels: a) at an inter-player level, assessing the degree to which two different players move in synchrony, and b) at a player-team level, evaluating the degree to which a player moves with respect to the rest of the team. Pairwise correlations were used to assess synchronicity with values closer to one signifying that players demonstrate similar movements for the event period. At an inter-player level, pairwise correlations were conducted using displacement (x_i,y_i) and stretch index measures of player *i* and every other player on the field. At the player-team level, pairwise correlations were conducted between the same measures for player *i* and the team's centroid ($\bar{x}$,$\bar{y}$) (Figure 3.8) and stretch index (Figure 3.9).

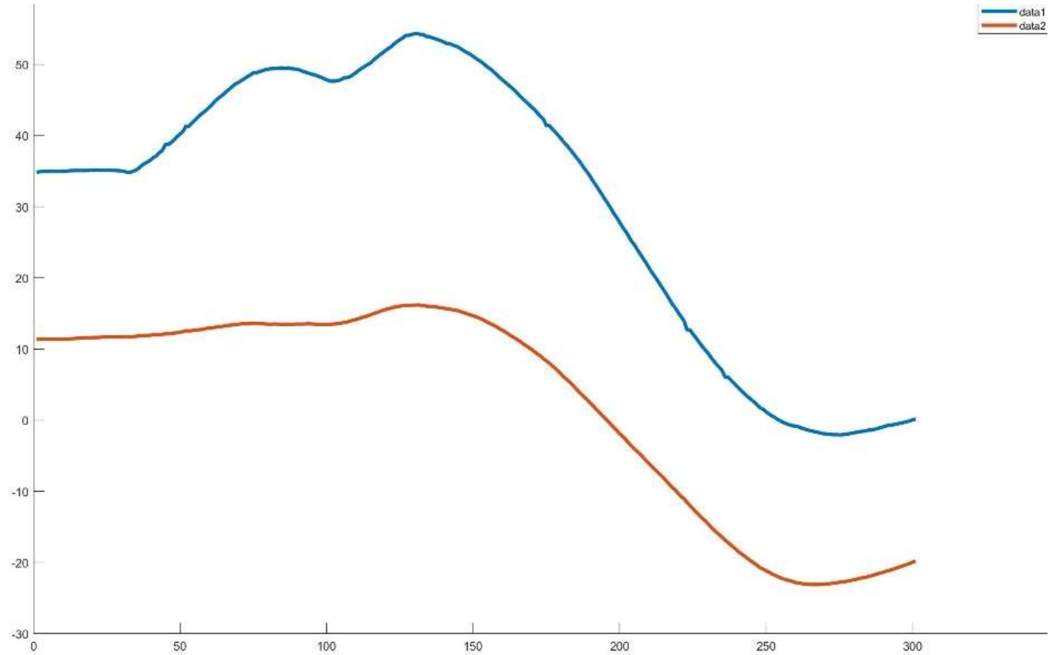

Figure 3.8: Examples of an extremely large relationship (r > 0.9) between a player (xi,yi) (data 1) and the team's centroid (x̄,ȳ) (data 2) during an offensive match-phase.

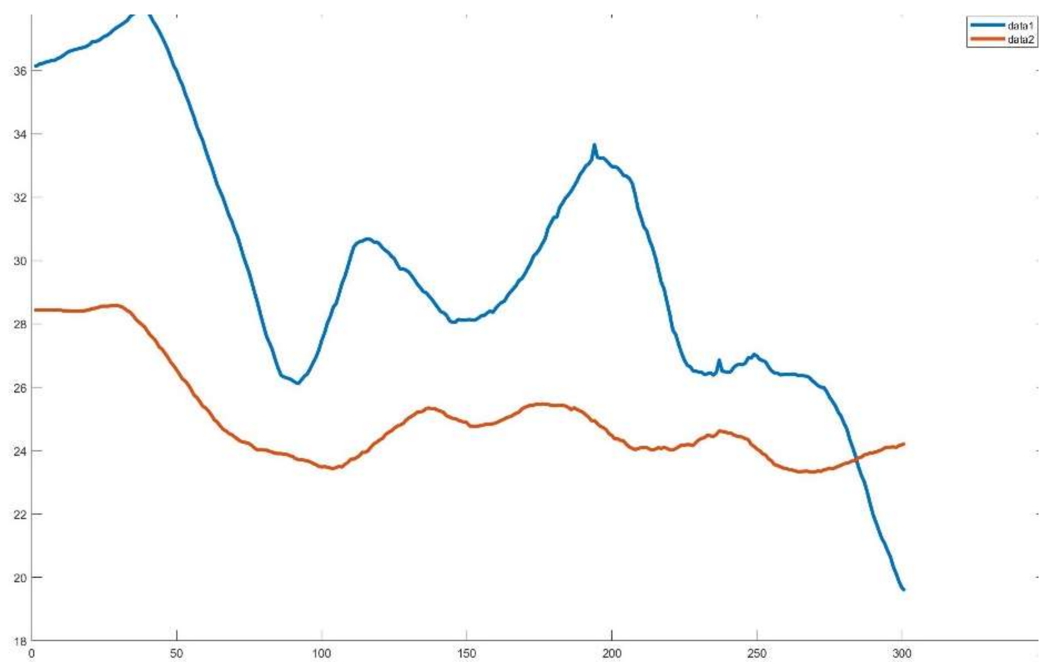

Figure 3.9: Examples of an extremely large relationship (r > 0.9) between a player's interpersonal distance (data 1) and the team's stretch index (data 2) during an offensive match phase.

Furthermore, inter-player correlation scores for player *i* were averaged to provide an indication of the level of synchronicity with that player and the rest of the team for both displacement and dispersion. Correlation techniques have been used previously to assess synchronous behaviour in complex systems.[115, 130, 198] Pairwise correlations were used to calculate the coefficient on a pairwise basis which provided a matrix of correlation coefficients for each pairwise variable combination (Figure 3.10):[191]

$$\boldsymbol{R} = \begin{pmatrix} \boldsymbol{\rho(A,A)} & \boldsymbol{\rho(A,B)} \\ \boldsymbol{\rho(B,A)} & \boldsymbol{\rho(B,B)} \end{pmatrix}$$

Since A and B are always directly correlated to themselves, the diagonal entries are always 1, therefore:

$$\boldsymbol{R} = \begin{pmatrix} \boldsymbol{1} & \boldsymbol{\rho(A,B)} \\ \boldsymbol{\rho(B,A)} & \boldsymbol{1} \end{pmatrix}$$

Player	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	Cen
1	1.00	0.83	0.93	NaN	0.73	-0.57	NaN	0.76	0.89	0.58	0.81	0.99	0.74	0.99	NaN	0.87	0.93	0.99	NaN	0.92	0.88	-0.23	0.96
2	0.83	1.00	0.84	NaN	0.73	-0.39	NaN	0.74	0.78	0.28	0.75	0.81	0.34	0.82	NaN	0.65	0.81	0.80	NaN	0.84	0.88	-0.22	0.84
3	0.93	0.84	1.00	NaN	0.92	-0.26	NaN	0.94	0.99	0.24	0.97	0.96	0.48	0.96	NaN	0.67	0.99	0.93	NaN	1.00	0.73	-0.37	0.99
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5	0.73	0.73	0.92	NaN	1.00	0.13	NaN	0.99	0.95	-0.12	0.98	0.80	0.17	0.79	NaN	0.40	0.93	0.76	NaN	0.94	0.47	-0.47	0.88
6	-0.57	-0.39	-0.26	NaN	0.13	1.00	NaN	0.07	-0.15	-0.93	-0.02	-0.46	-0.77	-0.47	NaN	-0.74	-0.23	-0.51	NaN	-0.21	-0.74	-0.20	-0.34
7	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
8	0.76	0.74	0.94	NaN	0.99	0.07	NaN	1.00	0.96	-0.08	0.98	0.82	0.23	0.81	NaN	0.45	0.94	0.79	NaN	0.95	0.49	-0.52	0.90
9	0.89	0.78	0.99	NaN	0.95	-0.15	NaN	0.96	1.00	0.17	0.99	0.93	0.43	0.93	NaN	0.61	0.99	0.90	NaN	0.99	0.64	-0.35	0.97
10	0.58	0.28	0.24	NaN	-0.12	-0.93	NaN	-0.08	0.17	1.00	0.01	0.49	0.88	0.50	NaN	0.76	0.25	0.54	NaN	0.21	0.68	0.27	0.35
11	0.81	0.75	0.97	NaN	0.98	-0.02	NaN	0.98	0.99	0.01	1.00	0.87	0.30	0.86	NaN	0.49	0.97	0.83	NaN	0.97	0.54	-0.43	0.93
12	0.99	0.81	0.96	NaN	0.80	-0.46	NaN	0.82	0.93	0.49	0.87	1.00	0.68	1.00	NaN	0.83	0.96	0.99	NaN	0.95	0.81	-0.25	0.98
13	0.74	0.34	0.48	NaN	0.17	-0.77	NaN	0.23	0.43	0.88	0.30	0.68	1.00	0.69	NaN	0.86	0.51	0.72	NaN	0.46	0.66	-0.01	0.58
14	0.99	0.82	0.96	NaN	0.79	-0.47	NaN	0.81	0.93	0.50	0.86	1.00	0.69	1.00	NaN	0.83	0.96	0.99	NaN	0.95	0.84	-0.24	0.98
15	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
16	0.87	0.65	0.67	NaN	0.40	-0.74	NaN	0.45	0.61	0.76	0.49	0.83	0.86	0.83	NaN	1.00	0.66	0.86	NaN	0.65	0.82	-0.05	0.75
17	0.93	0.81	0.99	NaN	0.93	-0.23	NaN	0.94	0.99	0.25	0.97	0.96	0.51	0.96	NaN	0.66	1.00	0.94	NaN	0.99	0.70	-0.37	0.99
18	0.99	0.80	0.93	NaN	0.76	-0.51	NaN	0.79	0.90	0.54	0.83	0.99	0.72	0.99	NaN	0.86	0.94	1.00	NaN	0.92	0.84	-0.26	0.97
19	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
20	0.92	0.84	1.00	NaN	0.94	-0.21	NaN	0.95	0.99	0.21	0.97	0.95	0.46	0.95	NaN	0.65	0.99	0.92	NaN	1.00	0.71	-0.37	0.99
21	0.88	0.88	0.73	NaN	0.47	-0.74	NaN	0.49	0.64	0.68	0.54	0.81	0.66	0.84	NaN	0.82	0.70	0.84	NaN	0.71	1.00	-0.01	0.78
22	-0.23	-0.22	-0.37	NaN	-0.47	-0.20	NaN	-0.52	-0.35	0.27	-0.43	-0.25	-0.01	-0.24	NaN	-0.05	-0.37	-0.26	NaN	-0.37	-0.01	1.00	-0.32
Centroid	0.96	0.84	0.99	NaN	0.88	-0.34	NaN	0.90	0.97	0.35	0.93	0.98	0.58	0.98	NaN	0.75	0.99	0.97	NaN	0.99	0.78	-0.32	1.00

Figure 3.10: An example of a pairwise-correlation matrix for a specified phase of match-play. 'NaN' signifies the players that were off the field during the period.

Finally, as used in previous football research,[143] the cluster-phase method was utilised to quantify the collective spatiotemporal phase synchrony. Based on the Kuramoto order parameter,[199] this method is capable of analysing group synchrony within systems that contain a small number of oscillating movement components (e.g. player movement trajectories) in a single collective parameter ranging from 0 to 1 for a given time period (Figure 3.11*).*[200] Synchronisation was assessed at two levels: 1) the team level, providing an average degree of synchrony, and a singular value, for the whole group and, 2) the individual level which is indicative of the degree to which each individual is synchronizing with the group. The larger the resultant value (i.e., the closer to 1), the larger the degree of group, or individual with the group, synchronisation.[201]

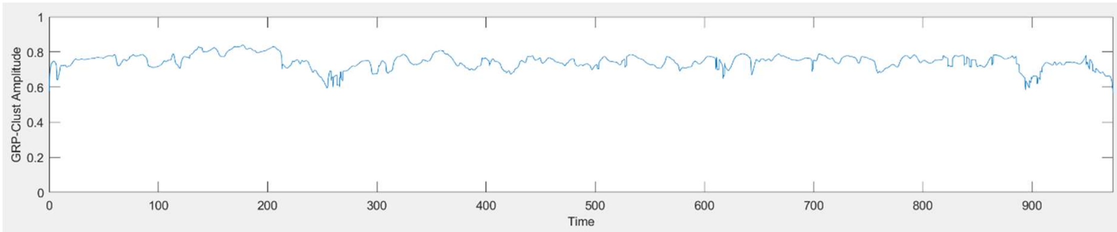

Figure 3.11: Group cluster phase demonstrating synchrony levels in stretch index values over a given time-period.

3.4.5 Physical Variables

Physical Demands

Currently in the AFL, all elite teams evaluate the physical external loads of game play using this technology which are capable of providing a plethora of associated variables.[7, 9] Australian Football match-play involves higher running volumes compared to any other team sport with players performing frequent intermittent bouts of high-speed running, accelerations, decelerations, changes of direction and frequent collisions with opposing players.[1, 13] Data pertaining to player movement was collected due to the likely influence of physical demands on technical proficiency and tactical behaviour.[45, 95, 108] This data was collected as per tactical behaviour with portable GNSS units sampling at 10Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia). The validity and reliability of GNSS technology and a variety of subsequently derived individual measures of physical performance have been assessed and have been valuable in guiding current physical performance research.[14-16] Specific distance and acceleration variables were collected to provide an indication of the effect of these physical demands on performance.[202, 203] The velocity bands were selected as they have been embedded in the host organisation and were chosen to better delineate between physical performances. Following an internal examination, and comparison with other professional sport literature, a larger portion of the game is spent at higher velocities with higher banded thresholds required to provide more sensitivity when comparing individuals. The data that was collected is described in table 3.4:

Table 3.4: Physical characteristics captured by GNSS technology.

Physical Variable	Description	Bands
Total Duration	The total amount of time spent on-field. Does not include time on the bench.	-
Total Distance	Total distance covered during time spent on field. Does not include distance covered while on the bench.	-
Banded Velocity Distance	The total amount of distance covered in a designated velocity band.	B1: 0-6 $km{\cdot}hr^{-1}$; B2: 6-14.4 $km{\cdot}hr^{-1}$; B3: 14.4-18 $km{\cdot}hr^{-1}$; B4: 18-22 $km{\cdot}hr^{-1}$; B5: 22-25 $km{\cdot}hr^{-1}$; B6: >25 $km{\cdot}hr^{-1}$
Banded Velocity Efforts	Counts the number of times an athlete reaches the designated velocity band for a specific amount of time. Effort must be sustained within the band for at least 1s.	B1: 0-6 $km{\cdot}hr^{-1}$; B2: 6-14.4 $km{\cdot}hr^{-1}$; B3: 14.4-18 $km{\cdot}hr^{-1}$; B4: 18-22 $km{\cdot}hr^{-1}$; B5: 22-25 $km{\cdot}hr^{-1}$; B6: >25 $km{\cdot}hr^{-1}$
Banded Acceleration & Deceleration Distance	The total amount of distance covered accelerating or decelerating in the designated band.	Acceleration: B1: 1.36-2.15 $m{\cdot}s^{-2}$; 2.151-2.75 $m{\cdot}s^{-2}$; > 2.751 $m{\cdot}s^{-2}$ Deceleration: B1: -1.36- -2.15 $m{\cdot}s^{-2}$; -2.151- -2.75 $m{\cdot}s^{-2}$; < -2.751 $m{\cdot}s^{-2}$
Banded Acceleration & Deceleration Duration	The total amount of time spent accelerating or decelerating in a certain range.	Acceleration: B1: 1.36-2.15 $m{\cdot}s^{-2}$; 2.151-2.75 $m{\cdot}s^{-2}$; > 2.751 $m{\cdot}s^{-2}$ Deceleration: B1: −1.36-−2.15 $m{\cdot}s^{-2}$; -2.151-−2.75 $m{\cdot}s^{-2}$; < −2.751 $m{\cdot}s^{-2}$
Banded Acceleration & Deceleration Efforts	Counts the number of times an athlete reaches the designated acceleration or deceleration band for a specific amount of time. Effort must be sustained within the band for at least 0.4s	Acceleration: B1: 1.36-2.15 $m{\cdot}s^{-2}$; 2.151-2.75 $m{\cdot}s^{-2}$; > 2.751 $m{\cdot}s^{-2}$ Deceleration: B1: −1.36-−2.15 $m{\cdot}s^{-2}$; -2.151-−2.75 $m{\cdot}s^{-2}$; < −2.751 $m{\cdot}s^{-2}$
Banded Inertial Movement Analysis (IMA)	Using raw accelerometer and gyroscope data to create a non-gravitational acceleration vector, reveals the magnitude and the direction of an agility action. It can classify events within intensity, and distinguish between forward (acceleration), backward (deceleration), vertical (jump) and left and right lateral events.	Low: 1.5-2.5 $m{\cdot}s^{-1}$; Medium: 2.5-3.5 $m{\cdot}s^{-1}$; High: >3.5 $m{\cdot}s^{-1}$

3.4.6 Technical Variables

Technical Demands

In soccer, the assessment of discrete technical on-field actions such as the number of completed passes, time spent in possession of the ball, or the amount of tackles made, has endeavoured to provide reliable descriptions of game the game's demands and subsequently aid in the prediction of success.[17] Technical skill counts are often provided by methods of manual notation analysis. In Australian Football, ChampionData® code all AFL matches for a myriad of technical skills.[8, 18] The most common technical skills reported in Australian Football research include the frequency of kicks, handballs, possessions, marks, ruck-contests and tackles.[9] Additionally, variables incorporating these skills such as disposal efficiency, shot efficiency, passing rate, inside 50's, marks inside 50, and contested possessions have been able to reveal particular playing styles and contribute to models predicting performance outcome.[2, 19, 20] In Australian Football, a combination of GNSS and technical skill data present the most common methods and causal indicators of physical and technical performance constructs. The assessment of these components allows coaching and conditioning staff to develop training programs that simultaneously develop these parameters and consequentially aim to improve team performance. Accordingly, technical indicators were collected for further analysis. Table 3.5 identifies specific technical attributes that were counted in each match and assessed:

Table 3.5: Technical skill descriptions produced by ChampionData®.[204]

Technical Indicator	Description
Baulk	Using deception as the ball carrier to beat an opponent, by sidestepping or feigning disposal.
Behind	A minor score, as judged by the goal umpire. Behinds are worth one point to a team's total score.
Behind Assist	Creating a behind by getting the ball to a teammate either via a disposal, knock-on, ground kick or hit-out, or by winning a free kick before the advantage is paid.
Block	Effectively shepherding an opponent out of a contest to the benefit of a teammate.
Broken Tackle	Evading a tackle attempt by an opponent and legally disposing of the ball in space.
Clangers	Number of handballs or kicks that give possession directly to the opposition.
Clanger Handball	Handballs that give possession directly to the opposition.
Clanger Kick	Kicks that give possession directly to the opposition.
Clearance	Credited to the player who has the first effective disposal in a chain that clears the stoppage area, or an ineffective kick or clanger kick that clears the stoppage area.
Contested Knock On	Using the hand to knock the ball to a teammate's advantage rather than attempting to take possession from a contested situation.
Contested Mark	When a player takes a mark under physical pressure of an opponent or in a pack.
Contested Mark from Opposition	When a player takes a mark under physical pressure of an opponent or in a pack from an opposition kick.
Contested Mark from Team	When a player takes a mark under physical pressure of an opponent or in a pack from a teammates kick.
Contested Possession	A possession which has been won when the ball is in dispute. Includes looseball-gets, hardball-gets, contested marks, gathers from a hit-out and frees for.
Crumb	A type of groundball-get that is won by a player at ground level after a marking contest. The player must not be involved in the original contest. Crumbing Possessions can be either hardball or looseball-gets.
Disposal	Legally getting rid of the ball, via a handball or kick.
Effective Disposal	Legally getting rid of the ball, via a handball or kick, and reaching an intended target.
Effective Handball	A handball to a teammate that hits the intended target.

Effective Kick	A kick of more than 40 metres to a 50/50 contest or better for the team or a kick of less than 40 metres that results in the intended target retaining possession.
First Possession	The initial possession that follows a stoppage, including a looseball-get, hardball-get, intended ball-get (gather), free kick or ground kick.
Free Against	When an infringement occurs resulting in the opposition receiving a free kick from the umpires.
Free For	When a player is interfered with and is awarded a free kick by the umpires.
Gather	Possessions that were a result of a teammate deliberately directing the ball in the player's direction, via a hit-out, disposal or knock-on, excluding marks and handball receives. Gathers from a hit-out are contested possessions the rest are uncontested.
Gather from Hit-Out	A possession gained from a teammate's hit-out to advantage. Counted as a contested possession.
Goal	A major score, as judged by the goal umpire. Worth six points to a team's total score.
Goal Assist	Creating a goal by getting the ball to a teammate either via a disposal, knock-on, ground kick or hit-out, or by winning a free kick before the advantage is paid to the goal scorer.
Ground Ball Get	Contested possessions won at ground level, excluding free kicks. Groundball gets can either be hardball gets or looseball gets.
Ground Kick	A deliberate kick without taking possession that gains either significant distance from the point of contact or an uncontested possession for a teammate.
Handball	Disposing of the ball by hand.
Hardball Get	A disputed ball at ground level under direct physical pressure or out of a ruck contest, resulting in an opportunity to affect a legal disposal.
Hit-Out	Knocking the ball out of a ruck contest following a stoppage with clear control, regardless of which side wins the following contest at ground level.
Hit-Out Shark	Winning clear possession of the ball from the opposition ruck's hit-out.
Hit-Out Sharked	A hit-out that directly results in an opponent's possession.
Hit-Out to Advantage	A hit-out that reaches an intended teammate.
Hold	Holding the ball in when the umpire calls for a ball up.
Ineffective Disposals	Kicks or handballs that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Ineffective Ground Kick	Ground kicks that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Ineffective Handball	Handballs that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Ineffective Kick	Kicks that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Inside 50	Moving the ball from the midfield into the forward zone. Excludes multiple entries within the same chain of possession.
Inside 50 Result	Successful reception of an inside-50
Kick	Total number of times a player disposes the ball by foot

Kick-In	When a player kicks the ball back into play after an opposition behind. Kick-ins are regarded as a function of the team and do not count as kicks, although they are similarly graded for quality.
Kick Inside 50	When a player records an inside 50 for his team by kicking the ball from the midfield zone into the forward line.
Kick Long Advantage	A long kick that results in an uncontested possession by a teammate. If an error is made by the player 'receiving' the kick, a 'kick long to advantage' is still recorded for the player kicking the ball.
Knock On	When a player uses his hand to knock the ball to a teammate's advantage rather than attempting to take possession within his team's chain of play.
Long Kick	A kick of more than 40 metres to a 50/50 contest or better for the team.
Looseball Get	A disputed ball at ground level not under direct physical pressure that results in an opportunity to record a legal disposal.
Mark	When a player cleanly catches (is deemed to have controlled the ball for sufficient time) a kicked ball that has travelled more than 15 metres without anyone else touching it or the ball hitting the ground.
Mark from Opposition Kick	As per above but from an opposition kick.
Mark Fumbled	Unsuccessful reception of a kick.
Mark on Lead	An uncontested mark taken after outsprinting an opponent.
Mark Play On	Playing on immediately without retreating behind the mark.
Missed Tackles	Attempted tackles that are missed, allowing the ball carrier to break into space.
One on One Contest Defender	Being isolated in a one-on-one contest as the defender.
One on One Contest Target	Being isolated in a one-on-one contest as the target of the kick.
Out on the Full	A kick that travels over the boundary line on the full.
Rebound 50	Moving the ball from the defensive zone into the midfield.
Receive Handball	An uncontested possession that is the result of a teammate's handball.
Ruck Hardball Get	Taking possession of the ball directly out of the ruck.
Running Bounce	Touching the ball to the ground, either directly or via a bounce, to allow a player to avoid being penalised for running too far.
Score Assist	Creating a score by getting the ball to a teammate either via a disposal, knock-on, ground kick or hit-out, or by winning a free kick before the advantage is paid to the goal scorer.
Short Kick	A kick of less than 40 metres that results in the intended target retaining possession. Does not include kicks that are spoiled by the opposition.
Shot at Goal	A kick directed at goal
Smother	Suppressing an opposition disposal by either changing the trajectory of the ball immediately after the disposal or by blocking the disposal altogether.
Spoil	Knocking the ball away from a marking contest preventing an opponent from taking a mark.
Spoil Gaining Possession	Spoils directed straight to a teammate.

Spoil Ineffective	Spoils directed straight to an opposition player.
Tackle	Using physical contact to prevent an opponent in possession of the ball from getting an effective disposal.
Uncontested Gather	Winning possession of the ball uncontested at ground level.
Uncontested Mark	Marks taken under no physical pressure from an opponent. Includes marks taken on a lead and from opposition kicks.
Uncontested Mark from Opposition	Marks taken from an opposition kick under no physical pressure from an opponent.
Uncontested Mark from Team	Marks taken from a teammate's kick under no physical pressure from an opponent.
Uncontested Possession	Possessions gained whilst under no physical pressure, either from a teammate's disposal or an opposition's clanger kick. Includes handball receives, uncontested marks (including lead marks) and intended ball gets from a disposal.

3.5 Statistical Analysis

3.5.1 Studies one-four

To dimensionally reduce the number factors involved at the individual and team level of analysis for complex networks, tactical behaviour, and physical demands, a principal components analysis was conducted through a Principal Component Analysis (PCA). A PCA is data reduction technique that reduces the dimensionality of a data set containing numerous variables into a smaller set of variables, called principle components, whilst maintaining most of the variability in the original data set.[205, 206] Following the analysis, no correlation exists between the principle components, but each contain their own highly correlated variables that measure some underlying construct. This method ensures only distinct information remains within the data set.[207] A PCA involves the removal of the mean, calculation of the covariance of the data, determination of the eigenvalues and eigenvectors of the covariance matrix, and a varimax rotation of the original data onto a coordinate system spanned by the eigenvectors of the covariance matrix.[206] Separate, exploratory PCA's were executed using SPSS for Windows (Version 25)[208] to determine whether common underlying constructs are present firstly in the individual-derived variables, and secondly, in the team-derived variables. Linear relationships will initially be assessed using a correlation matrix while the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data is suitable for data reduction.[208] In all data sets, all variables were initially included, upon which variables with communalities (relative importance for inclusion in the factor) lower than 0.40 were excluded.[209] Each PCA was subsequently rerun using only variables of significant importance and consequentially used to derive factor loadings associated with each of the variables in the PCA. These factor loadings could then be used to calculate summed variables for both individual- and team-based complex network measures.

3.5.2 Study five

Structural equation modelling (SEM) was used to quantitatively test a theoretical model of performance incorporating physical, technical, and tactical components. SEM techniques allow complex phenomena to be statistically modelled and tested at more than one level and is the preferred method for confirming, or disconfirming, theoretical models.[33] Once the observed variables were collected, the SEM process involved the following five steps:[33]

1. Model specification: Develop the theoretical model and pick appropriate variables using variance-covariance data.
2. Model identification: Specify model parameters.
3. Model estimation: Obtain estimates for each of the parameters in the model.
4. Model testing: Assess how well the data fits the model.
5. Model modification: Modify the model if the theoretical model is not as strong as expected.

Maximum likelihood estimation in SEM investigates the association between components/constructs and an outcome in the model. The components are tested by analysing associations between independent variables and a dependent variable. To determine the appropriateness of the SEM model, the normed chi-square index (χ^2/df) was selected over the traditional chi-square statistic as this nearly always rejects the model when large samples are used[210] with indices below three representing a parsimonious fit.[211] The Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and standardised root mean square residual (SRMR) indices are also assessed with indices >0.90, <0.10, and <0.08, respectively, signifying an acceptable model fit.[212] Finally, due to the anticipated complexity of the model, the Parsimonious Normed Fit Index (PNFI) was also calculated with indices >0.50 representing a parsimonious fit.[211] Laavan[213] and PiecewiseSEM[214] statistical packages were used in RStudio to conduct the analysis. Direct effects were classified as either *small* = 0.10, *medium* = 0.30, or *Large* >0.50.[215]

3.5.3 Study six

A multinomial logistic regression was executed to determine which physical and spatiotemporal measures (from study three and four) are associated with each phase of play. A main effects model was produced with phase of play as the dependent variable and duration, physical and spatiotemporal variables as covariates. Contested plays were selected as the reference group as this was the most common phase of play. Statistical significance was identified where $p < 0.05$ for all tests. Further, the Akaike Information Criterion (AIC), Nagelkerke R^2, F and p values of the specified model were used to determine whether multinomial regression yielded a superior data fit than a null model or a model with no independent variables. Further, odds ratios and their confidence intervals along with the percentage of correct classification were also utilised to provide insight into the results.

3.5.3 Study seven

A binomial Generalised Mixed Effects Regression model was used to individually estimate the effects of duration, physical and spatiotemporal variables (derived in study three and four) on the probability of a successful outcome in different phases of play. Round number was included as a random factor while physical and spatiotemporal sum scores along with duration were added as fixed effects. Outputs (odds ratios and their confidence intervals, conditional and marginal explained variance), Akaike Information Criterion and misclassification error percentages were derived from each model and compared for model evaluation. All statistical analyses were conducted using the lme4[216] package in R statistical software[190] with significance values set at $p<0.05$.

Chapter 4

Study One: Using cooperative networks to analyse behaviour in professional Australian Football

As per the manuscript published in *Journal of Science and Medicine in Sport:*

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Note: The referencing system used in this manuscript conforms to the style used in the remainder of the thesis. The citation numbers relate to the thesis reference list and are different to the published manuscript. Otherwise, this manuscript appears as published.

4.1 Abstract

Objectives: Reducing the dimensionality of commonly reported complex network characteristics obtained from Australian Football League (AFL) games to facilitate their practical use and interpretability. Design: Retrospective longitudinal design where individual players' interactions, determined through the distribution and receipt of kicks and handballs, during official AFL games were collected over three seasons. Methods: A principal component analysis was used to reduce the number of characteristics related to the cooperative network analysis. Results: The principal component analysis derived two individual-based principal components pertaining to in- and out-degree importance and three team-based principal components related to connectedness and in- and out-degree centralisation. Conclusions: This study is the first to provide a simplified, novel method for analysing complex network structures in an Australian Football context with both the team- and individual- derived metrics revealing useful information for coaches and practitioners. This may consequently guide opposition analysis, training implementation, player performance ratings and player selection.

Key Words: Performance analysis; Tactics; Social network; Player interaction; Principal component analysis

4.2 Practical Applications

- The simplified complex network measures developed in this study provide supporting data for performance analysts currently using video and skill involvement counts to analyse games.
- The derived metrics allow coaches to identify strengths and weaknesses in the opposition team that can be exploited through the implementation of game tactics.
- This information enables coaching staff to develop training interventions that are representative of the skill demands of competition needed for successful team performance.

4.3 Introduction

Australian Football is a contact-based, team invasion sport played on an oval-shaped field by two teams of 22 players, with 18 players on the field, over four 20-minute (in-play time) quarters, where the aim is to score as many points as possible by kicking between goal posts on each end of the oval. It involves phases of ball possession, contested play and stoppages of varying durations. In the Australian Football League (AFL), the pinnacle of Australian Football, the physical element of the game is characterised by intermittent high-speed running coupled with frequent collisions and changes of direction and speed.[1, 217] Playing in the AFL requires high skill proficiency with players utilising hand and foot skills for passing, scoring and gaining ball possession.[4] Players also have certain position specific roles that lead to differences in performance outcomes. For example, nomadic players, such as midfielders, small forwards and small defenders, tend to have more skill involvements (touches of the football) and cover greater distance throughout the game than fixed position players, such as tall forwards and tall backs.[217] Teams also utilise a variety of tactical strategies depending on their own personnel, coaching philosophies, opposing team and environmental conditions during the match.[4]

Collectively, players adapt their physical abilities, skills, and tactical strategies to cope with the ever-changing demands of the game. However, most team sport performance research has adopted a reductionist approach investigating these factors in isolation. Previously, performance analysts have largely related discrete technical on-field actions such as the frequency of kicks, handballs, possessions and marks,[9] in association with variables incorporating these skills such as disposal efficiency, shot efficiency, and passing rate to performance outcomes.[2, 19] However, the excessive emphasis placed on performance outcome rather than process measures presents an underlying issue that primarily focuses on 'who did what, when' failing to provide a meaningful understanding of the underlying factors of successful performance in complex team invasion games. This stresses the need for a theoretical rationale that can provide insight into performance behaviours.[24] By utilising appropriate tactical analysis techniques, in association with a viable framework to explain behaviour in team sports, further insight as to 'why' or 'how' certain behaviours emerge can be elucidated and provide an understanding into the process characteristics underpinning successful performance.[52]

The ecological dynamics framework focuses on the performer-environment relationship and may provide a viable basis for understanding performance in team sport.[29] From an ecological dynamics perspective, Australian Football is a complex performance-environment sub-system where players and teams perceive opportunities for action which guide decision-making and subsequent actions. The perception of relevant environmental information sources allows players to self-organise into stable states of coordination that allows the achievement of task goals.[29] In this complex system, task-constraints such as field dimensions and passing rules, along with physical and informational constraints such as player size and opposition player movements, provide information and boundaries that govern behaviour. The resultant behaviour in a complex system is the interaction between its constituents. Therefore, it is important to examine the role played by player interactions when analysing performance from an ecological dynamics perspective. While passing interactions between players have been extensively researched in other football codes such as soccer,[142, 168] minimal research exists in Australian Football.[2]

The implementation of complex network analysis can provide additional information that captures the dynamic nature of team sport performance.[48] The analysis of passing sequences within a team allows practitioners to map and quantify the interactions between different players during a game. Complex network analyses can reveal the local structure of organisation among players. In professional soccer, network analyses have revealed common tendencies in successful teams, with minimal reliance on key players (i.e. decentralisation) being a common characteristic associated with successful team performance.[168] It is suggested that decentralised teams foster interdependence whereby players do not solely rely on one or two key players. This encourages coordination and cooperation which is beneficial to a team's performance, as determined by match outcome.[168] When correctly implemented, a complex network analysis can identify key players, i.e. those that display high connectivity within a team such as midfielders in soccer, who link defenders and attackers through transfer of possession.[164] Such analysis may also be relevant in Australian Football as certain positions, similar to soccer, may have role-specific technical, tactical and physical demands that may influence inter-player interaction.[22]

Only one study has examined complex network structures in the context of Australian Football.[2] This study investigated how the complex network structures of different teams in the AFL competition self-organised into purposeful behaviour and how the characteristics of these complex networks were related to successful performance outcomes. The current manuscript revealed similar relationships to those in soccer, suggesting that successful offensive strategies were varied but frequently decentralised with the majority of players being well connected in successful teams. However, the array of complex network variables presented in this study, similar to soccer research, makes it difficult to delineate and interpret the effect of specific network structures on performance outcomes for its goal audience (i.e., coaches, recruiters, and performance analysts). Therefore, in order for complex networks to be adopted for practical performance analysis in sport, their analysis and interpretation should be simplified. This will also facilitate how researchers further investigate the relationship between complex network structures and performance outcome measures such as winning or losing games and contextual factors such as opposition team strength and playing at home or away. Therefore, the aim of this study was to reduce the dimensionality of commonly reported complex network characteristics obtained from AFL games in order to facilitate their practical use and interpretability. It was hypothesised that a factor analysis would successfully reduce the number of variables obtained from individual and team-based complex network analyses in Australian Football.

4.4 Methods

The study sample consisted of 48 male professional Australian Football players (age: 24.97 ± 3.78 years; playing experience: 5.22 ± 3.44 years) from one AFL team. Each participant played at least one game over the three-year (2016-2018) analysis window. Data from seventy-three senior matches were used for analysis. This sample provided 73 team-based files with 1605 individual files (33.4 ± 25.6 per player) from the designated AFL team. Furthermore, data was collected on each opposition team for all 73 matches used in this study, providing an additional 73 team-based files (4.3 ± 1.4 per team) and 1603 individual files (2.5 ± 1.5 per player). The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

The study followed a retrospective longitudinal design where individual players' interactions, as determined through the distribution and receipt of kicks and handballs, during official AFL games were collected over a period of three seasons. A Principal Component Analysis (PCA) was used to reduce the number of characteristics related to the complex network analysis.

Data was obtained from ChampionData®, the official data provider to the AFL.[2] ChampionData® code all AFL matches for a myriad of skill involvements[8] and are commonly used in Australian Football research.[8, 23, 49] A selection of statistical indicators have been empirically reviewed, including an array of disposal and possession-related statistics used in the current study, reporting a high level of reliability (ICC range = 0.980-0.998 RMSE range = 0.0–4.5).[19] The only other reliability information provided about ChampionData® statistics states that "quantity-based statistics are logged at better than 99% accuracy"[8] ChampionData® match statistics were used to create a weighted and directed, 22 x 22 adjacency matrix for each game, which reveals the number of interactions between certain players.[164] An interaction was counted if a handball or kick reached the intended target player. This matrix was then used to create a weighted directed graph with the graphed nodes representing individual players and weighted edges signifying the direction and number of passes between players. The adjacency matrices and graphs were subsequently used for analysis using MatLab routines.[191]

Table 4.1 identifies the variables that were included for analysis, the method of calculation, and their relevance and interpretation of outcome. The complex network variables describe the interaction between players such as the number of passes (kicks and handballs) that a player produces or receives along with the metrics that can be derived from that data such as a player's relative importance within the entire network. Additionally, all measures were derived from the matrix at the individual as well as the team-based level.

Table 4.1: Complex network variables.

Variable (Source)	Calculation	Relevance and interpretation of outcome
Global Player Network Summary Statistics[168]		
Network density	$Density = \frac{\sum Column(nnz) + \sum Row(nnz)}{(n^2 - n)}$	With *n* equalling the number of players, and *nnz* equalling non-zero elements in the matrix, density signifies the global level of interaction within the network with values closer to 1 showing a more complete network whereby most players interact with the majority of the team.
Network intensity	$Intensity = \frac{\sum Column + \sum Row}{2}$	Indicative of the amount of ball movement in the network with higher values demonstrating a greater amount of ball movement.
Individual Interaction Level (Source)[2, 165]		
In- and *out-degree node centrality*	$In - Degree\ Node(i) = \sum Column(nnz)(i)$ $Out - Degree\ Node(i) = \sum Row(nnz)(i)$	Represents the number of incoming or outgoing connections at each node or player *(i)* with higher values signifying that players interact with more players via reception of a pass (in-degree) or interact more with other players via distribution of a pass (out-degree).
In- and *out-degree node centrality proportion*	$In - Node\ Proportion\ (i) = \frac{In - degree\ Node(i)}{(n - 1)}$ $Out - Node\ Proportion(i) = \frac{Out - degree\ Node(i)}{(n - 1)}$	Signifies how well connected a certain player *(i)* is within the network relative to the total number of players in the network. Values closer to 1 signify that the player is well connected and interacts with the majority of other players in the network.
Node ratio	$Node\ Ratio(i) = \frac{In - Degree\ Node(i)}{Out - Degree\ Node(i)}$	Identifies whether a specific player *(i)* is either connected with or connects with more players in the network. Values greater than 1 signify that the number of players an individual receives possession from is greater than the number of players they distribute to.
In- and *out-degree pass centrality*	$In - Degree\ Pass(i) = \sum Colum(i)$ $Out - Deegree\ Pass(i) = \sum Row(i)$	Reveals the total number of passes a player *(i)* receives or distributes
In- and *out-degree pass centrality proportions*	$In - Pass\ Proportion(i) = \frac{In - degree\ Pass(i)}{Intensity}$ $Out - Pass\ Proportion(i) = \frac{Out - degree\ Pass(i)}{Intensity}$	Indicates the proportion of all network passes that are either received (in-degree) or distributed (out-degree) by a specific player *(i)*. As per node proportions, scores closer to 1 signify that a player is well connected or important in the network.

Centrality pass ratio	$Pass\ Ratio(i) = \frac{In - Degree\ Pass(i)}{Out - Degree\ Pass(i)}$	Identifies whether a player *(i)* receives or distributes more passes within the network. Values greater than 1 signify that a player receives a greater number of passes than they distribute.
Individual Proximity[142, 170, 191]		
In- and *out- closeness*	$Closeness(i) = \left(\frac{A(i)}{n-1}\right)^2 \frac{1}{C(i)}$	With *A(i)* as the number of reachable players from player *i* (not counting *i*), *n* as the number of players in the network, and *C(i)* is the sum of distances from player *i* to all reachable players, closeness signifies how easy is it for a given player to reach (out-closeness) or be reached (in-closeness) by other players in the network. Higher values assume a positive meaning in the node's proximity and indicate that a player requires a shorter number of passes to connect with other players.
Betweenness centrality	$Betweenness(i) = \sum_{s,t \neq i} \frac{n_{st}(i)}{N_{st}}$	Indicative of how often a player appears on a shortest path between two players in the network. A player with a higher value is crucial to maintain team passing connections by acting as a connecting bridge and is important for passing flow in the network. $n_{st}(i)$ is the number of shortest paths from player *s* to player *t* that pass-through player *i*, and *Nst* is the total number of shortest paths from *s* to *t*.
Individual Importance[170, 192]		
Pagerank centrality	$Pagerank(i) = p \sum_{j \neq i} \frac{A_{ji}}{L_j^{out}} x_j + q$	Ability to identify important players within the network. This measure holds that a player is of importance if they receive passes from other important players. Assigns to each player the probability that they will have the ball after a reasonable number of passes being made in the network. $L_j^{out} = \sum_k A_{jk}$ is the total number of passes made by player *j*, *p* is a heuristic parameter representing the probability that a player will decide to give the ball away, and *q* is a parameter awarding a 'free' popularity to each player.
Team Equality Statistics[168, 193]		
In- and *out-degree node centrality variability*	$Node\ Variability = \frac{\sum_n i_{max} - i_n}{(n-1) \times Density}$	With i_{max} being the maximum value in the network and i_n representing every value in the network, this parameter reveals global centralisation characteristics of the team with lower values signifying that all players interact with the same number of players and, conversely, larger values suggesting that certain players connect more with other players.
In- and *out-degree pass centrality variability*	$Pass\ Variability = \frac{\sum_n i_{max} - i_n}{(n-1) \times Intensity}$	Assess centralisation tendencies with lower variability signifying that all players receive and/or distribute the same amount of possession through passing. Conversely, higher variability suggests that certain players receive or distribute more possession than other players.
Global In-Closeness *Global Out-Closeness* *Global Betweenness* *Global Pagerank*	$Global\ Mean = \frac{\sum_n i_n}{n}$	Individual player values were used in the calculation of team complex network values, both providing information regarding network equality, or centralisation, within the team. Indicates the average value in the given measure.
In-Closeness Variability *Out-Closeness Variability* *Betweenness Variability* *Pagerank Variability*	$Global\ Variability = \frac{\sum_n i_{max} - i_n}{n-1}$	Lower values signifying equality, or decentralisation in the network. Indicates the variability within the team in the given measure.

All network values were converted to z-scores and normalised to the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)). This subsequently facilitated dimensional reduction using a factor analysis.[218]

A data reduction technique was used to reduce the number of characteristics related to the network analysis by grouping network characteristics at the individual and team level. More specifically, an exploratory factor analysis was conducted through a PCA to reduce the dimensionality of the data into a smaller set of variables whilst maintaining most of the variance in the original data set.[205, 206] As a result of PCA, no correlation exists between the principal components, but each contain their own highly correlated variables that measure an underlying, yet independent construct. This method ensures only distinct information remains within the data set.[207] A PCA involves the removal of the mean, calculation of the covariance of the data, determination of the eigenvalues and eigenvectors of the covariance matrix, and a varimax rotation of the original data onto a coordinate system spanned by the eigenvectors of the covariance matrix.[206] Two separate exploratory PCAs were executed using SPSS for Windows (Version 25)[208] where the aim was to determine whether common underlying constructs were present in the fourteen individual-derived variables, and in the fourteen team-derived variables. Linear relationships were initially assessed using a correlation matrix while the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction.[208] In both data sets, all network variables were initially included, upon which variables with communalities (relative importance for inclusion in the factor) lower than 0.40 were excluded.[209] Each PCA was subsequently rerun using only variables of significant importance and consequentially used to derive factor loadings associated with each of the variables in the PCA. These factor loadings were then used to calculate summed variables for each component.

4.5 Results

Only one variable, *global pagerank*, was excluded from the PCA due to a communality below 0.40. Upon inspection of the subsequent correlation matrix, linear relationships existed between all variables at the individual and team-based level. An examination of the KMO measure of sampling adequacy suggested that the sample was factorable for both the team (KMO = 0.805) and individual (KMO = 0.756) data set. Additionally, Bartlett's test of sphericity was significant for both data sets ($p < 0.001$).[208] Table 4.2 reveals the total explained variance from the individual and team PCA, respectively.

Table 4.2: Total variance explained from individual- and team-derived variables.

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	Explained Variance	Cumulative %	Total	Explained Variance	Cumulative %	Total	Explained Variance	Cumulative %
Individual									
1	8.770	62.642	62.642	8.770	62.642	62.642	7.057	50.407	50.407
2	3.451	24.648	87.290	3.451	24.648	87.290	5.164	36.883	87.290
Team									
1	6.401	49.242	49.242	6.401	49.242	49.242	4.960	38.152	38.152
2	2.400	18.463	67.705	2.400	18.463	67.705	3.008	23.135	61.287
3	1.728	13.290	80.994	1.728	13.290	80.994	2.562	19.707	80.994

The rotated component matrix produced factor weightings for each variable in their respective principal component. The five equations were derived from the analysis and are displayed in Table 4.3.

Table 4.3: Resultant equations from principal components analysis.

Equation Number	Variable	Calculation
1	In-Degree Importance	0.960 × In Degree Node + 0.960 × In Degree Node Proportion + 0.923 × In Closeness Centrality + 0.915 × In Degree Pass + 0.915 × Pagerank Centrality + 0.909 × In Degree Pass Proportion + 0.681 × Betweenness Centrality
2	Out-Degree Importance	0.849 × Out Degree Node + 0.848 × Out Degree Node Proportion + 0.848 × Out Closeness Centrality - 0.846 × Centrality Ratio Node - 0.820 × Centrality Ratio Pass + 0.792 × Out Degree Pass Proportion + 0.792 × Out Degree Pass
3	Connectedness	0.964 × Network Density - 0.949 × Team Betweenness Centrality + 0.939 × Team Out Closeness Centrality + 0.935 × Team In Closeness Centrality + 0.931 × Network Intensity
4	In-Degree Variability	0.925 × Team In Degree Node Variability + 0.925 × Team In Closeness Centrality Variability + 0.714 × Pagerank Centrality Variability + 0.613 × In Degree Pass variability
5	Out-Degree Variability	0.945 × Team Out Closeness Centrality Variability + 0.895 × Team Out Degree Node Variability + 0.626 × Out Degree Pass variability + 0.523 × Team Betweenness Centrality Variability

4.6 Discussion

Australian Football match performance is a complex network, consisting of many independent and interacting degrees of freedom that show the potential for self-organisation into states of coordination. While many studies have attempted to describe the features of complex networks in sports, the present study was the first to describe and dimensionally reduce an array of network features in an Australian Football context to facilitate their practical application, interpretation, and reporting to performance staff. Fourteen individual and fourteen team-based variables were reduced to two individual and three team-based components, respectively. These principal components adequately represent different constructs whilst maintaining a large amount of the variability from the original data (Table 4.2).[208] These new components facilitate the interpretation of complex network features and subsequently allow practitioners and coaches to design and implement training that emulates specific network features and consequentially promotes favourable outcomes.

Equation 1 provides an indication of a player's level of interaction regarding incoming network relationships such as receiving a kick or handball (in-degree). Resultant sum scores from this equation provide insight regarding the level of possessions received (*in-degree pass* and *in-degree pass proportion*), ease of reachability (*in-closeness centrality*), the incoming level of connectivity within the network (*in-degree node*, *in-degree node proportion* and *pagerank*) and a player's importance for linking specific players within the network (*betweenness centrality*). Higher values may signify that a player is located centrally and is used by more players within a team. Furthermore, this sum score highlights a player's ability to link other players together or obtain possession of the ball and score. Accordingly, this may reflect a player's positional role with the specific task of receiving and distributing possession, such as a midfielder.[2, 219] Alternatively, specific players such as key attackers may be relied upon to score goals in key attacking positions and therefore would display a high level of in-degree importance.[219]

In contrast, equation 2 provides an indication of a player's level of interaction regarding outgoing network relationships such as performing a kick or handball (out-degree). Higher sum scores are reflective of an individual's ability to distribute possession. This is influenced by the ability of a player to connect with other players (*out-degree node* and *out-degree node proportion*), distribute a large amount of possession (*out-degree pass* & *out-degree pass proportion*), and easily reach other players within the network (*out-closeness centrality*). Additionally, if a player receives more possession than they distribute, this will negatively impact upon the resultant sum score, as would be the case in players in terminal positions such as goal scoring attackers or in players who frequently lose ball possession. Superior scores may also reflect positional roles. For example, defenders have the primary role of disrupting opponent offensive movements, ideally in the form of an intercept. This may lead to greater out-degree values as these players intercept opposition possession and then distribute to players around them.[2] Alternatively, midfield or ruck players who obtain possession without receiving the ball directly from teammates or interception, by winning the ball in contested play, may also display higher values due to their positional role. Collectively, the relationship between in-degree and out-degree importance is also relevant, as it highlights where the linking players are within a unit/team. While theoretical insight can be drawn from other similar sporting contexts, such as soccer, association between these metrics and position specific roles requires validation.

From a team perspective, equations 3, 4 and 5 reveal global characteristics of the network. Equation 3 provides insight into the level of connectedness within the team with higher values signifying that most players connect bi-directionally (*network density*) and are easily reachable for others (team *in-* and *out-closeness centrality*). Additionally, the negative contribution of team *betweenness centrality* indicates that lower scores benefit overall connectedness. A lower team *betweenness centrality* score signifies that most players within the network can connect with one another without relying on a linking individual. As measures of possession are a determinant of success in Australian Football[2, 19] and soccer,[50] superior displays of connectedness will likely be associated with positive outcomes. However, future studies are required to validate the use of the above metric in relation to match outcomes in Australian Football.

In conjunction with equation 3, equations 4 and 5 provide information regarding the mutuality of involvement from all players within the network. Lower values imply that the network is decentralised with all players interacting and contributing equally to the network. Conversely, greater values suggest that specific players are relied upon for receiving (equation 4) or distributing (equation 5) possession, resulting in the network being more centralised. While variability is yet to be examined in an Australian Football context, successful teams have demonstrated decentralised characteristics in soccer whereby adept teams often do not rely on a single player. From equations 3, 4 and 5, it is expected that in a decentralised network, sum scores would reveal a high connectivity score (equation 3), with low variability scores in both the in- and out-degree direction (equation 4 & 5). While the three outputs from these equations are capable of revealing the structure of complex team networks, future studies are required to validate their use in an Australian Football context and their association with successful performance.

Complex networks in Australian Football are multi-layered with the varying individual dynamics influencing the overall structures that emerge at the team level and, consequentially, inter-team match behaviour. The metrics derived in this study may provide means for coaches and practitioners to further understand the influence of these varied structures and the influence of varying contextual factors. While the present study is the first to provide a simplified, novel method for analysing complex network structures in an Australian Football context, these metrics are yet to be validated in relation to individual and team performance. The results of this study provide supporting data for performance analysts currently using video and skill involvement counts to analyse games and could allow coaches to identify strengths and weaknesses in the opposition team that can be exploited through the implementation of game tactics. This new information also allows coaching staff to develop training interventions that are representative of competition demands as they can now quantify and emulate complex network structures evident in game scenarios. At an individual level, the examination of the individually derived metrics may highlight favourable task-specific characteristics associated with different positions in the network and provide an additional objective means of assessing player match-performance. This information could therefore facilitate the recruitment of new players that can be a valuable addition to the existing network. These metrics may also allow coaches to longitudinally assess the development of an individual players role within the network over time. Lastly, findings from this study may also prove useful in other sports other than Australian Football, following its validation in these other sports.

4.7 Conclusion

This study is the first to provide a simplified, novel method for analysing complex network structures in an Australian Football context with both the individual and team-based metrics revealing useful information for coaches and practitioners. While theoretical insight can be drawn from similar sporting contexts, future studies are required to validate the use of these new metrics in association with individual and team performance outcomes. This may consequently guide opposition analysis, training implementation, player performance ratings and player development, selection, and recruitment. Further, if proven valid, the findings from the current study may provide a viable framework of analysis in other contextually similar sports.

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Chapter 5

Study Two: Improving the interpretation of skill indicators in professional Australian Football

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Note: The referencing system used in this manuscript conforms to the style used in the remainder of the thesis. The citation numbers relate to the thesis reference list and are different to the published manuscript. Otherwise, this manuscript appears as published.

5.1 Abstract

Objectives: This study aimed to provide a simplified, novel method for analysing technical skill involvements in an Australian Football context by reducing the dimensionality of commonly reported skill counts obtained from Australian Football League (AFL) games. This may facilitate their practical use and interpretability. Design: Retrospective longitudinal design where individual players' technical skill counts were collected over three seasons of official AFL games. Method: Seventy-three skill count values provided publicly by ChampionData® were collected for each match over a three-year analysis period. A principal component analysis was used to reduce the dimensionality of a large number of correlated technical skill indicators into a smaller set of uncorrelated components whilst maintaining most of the variance from the original data set. Results: The principal component analysis derived four principal components pertaining to *high-pressure success*, *low-pressure success*, *attacking ball movement ability* and *scoring ability*. Conclusions: This study is the first to provide a simplified, novel method for analysing technical skill counts in Australian Football. The derived metrics reveal useful information for coaches and practitioners. This may consequently ease the interpretation of skill count data available to coaches from games, guide opposition analysis, help in the design of representative practice and inform player performance ratings.

Key Words: Performance analysis; ChampionData; Technical; Principal component analysis

5.2 Practical Applications

- The simplified measures of technical skill involvement developed in this study provide supporting data for performance analysts currently using video and technical skill counts to analyse games.
- The derived metrics can limit the potential misinterpretation that arises from dealing with a vast array of technical count data that is obtained from every game. Accordingly, they can allow coaches to identify individual strengths, weaknesses, and roles within a team. This can subsequently guide player development and list-management decisions.
- These derived principal components also allow performance analysts and coaches to quantify the strengths and weaknesses of opposition players which may be exploited through the implementation of game tactics.
- This method of data reduction can be used in other team sports, where technical skill counts are commonly recorded.

5.3 Introduction

Professional Australian Football is a complex team invasion sport consisting of two teams of 22 players with 18 taking the field and four interchange. Match play consists of four 20-minute quarters of in-play time, with time stopping when the ball leaves the field of play or is deemed unplayable by the umpire. The game is played on an oval-shaped field that varies in length (149 – 175 m) and width (122 – 136 m), with two central 'goal' posts and two outer 'behind' posts at each end.[1] If the ball is kicked between the two goal posts by the attacking team, a goal worth six points is awarded. If the ball passes between the goal posts in any other way, hits a goalpost or passes between a goal post and a behind post, one point is awarded.[2] In the Australian Football League (AFL), the pinnacle of Australian Football, players must utilise an array of technical skills in order to score more points than the opponent.[1] Teams also utilise a variety of tactical strategies depending on their own players' strengths and weaknesses, coaching philosophies, opposing team tactics and environmental conditions during the match.[4]

In the last decade, performance analysts have successfully quantified a plethora of physical and technical skill demands to derive practical applications for improving team performance. Specifically, physical demands have been extensively researched using global navigation satellite system (GNSS)[10] while the assessment of discrete, technical, on-field actions such as frequency of *kicks*, *handballs*, *possessions* and *marks*[9] have been able to contribute to models predicting performance outcomes.[7, 19, 22, 31] Further, though scarcely examined in Australian Football, recent lines of inquiry have sought to objectively quantify tactical behaviour using cooperative network analyses that examine passing interactions between teammates,[2, 220] as well as spatiotemporal analyses assessing dispersion, synchrony and regularity.[34] Whilst the examination of these components, often in isolation, have provided valuable insight into the physical, technical and, to a lesser degree, the tactical requirements of the game, discrepancies exist when associating these components with successful and unsuccessful performance outcomes.[7, 18, 21-23] These discrepancies may occur as players need to collectively adapt their physical abilities, technical skills and tactical strategies to perform successfully as the demands of the game evolve. Integrating and collectively analysing all these components may provide insight into existing discrepancies and provide a greater indication into factors affecting performance.[27, 52]

Players require high levels of technical skill proficiency to perform successfully in the AFL and cope with the evolving game demands.[7] Accordingly, the technical skill demands of professional Australian Football have been quantified using methods of manual notational analysis.[4, 8] ChampionData® code all AFL matches for a variety of technical skill indicators and the validity of these data have been investigated previously.[8, 18, 19] Such data reveals particular playing styles and contributes to models predicting performance outcome.[2, 19, 20] Technical skill count data presents the most common indicator of technical performance with the information provided allowing coaches and practitioners to understand which technical skills to develop during training and consequently improve performance.

While the large volume of information provided by ChampionData® regarding the technical skill demands are useful, inconsistencies and discrepancies exist in the literature between indicators of successful and unsuccessful performance. For example, one study highlighted that the number of handballs and turnovers had no significant effect on match outcome.[31] Conversely, other researchers reported the same indicators to be significant contributors to performance.[19] These discrepancies may partially be a result of researchers only incorporating a select number of indicators, accounting for a small portion of variance, to quantify performance outcomes. The extensive array of technical skill variables available to analysts and practitioners potentially makes it difficult to delineate and interpret the effect of specific technical skill variables on performance outcomes. For practical performance analysis in sport, the interpretation of these variables needs to be objectively simplified. Previous research methods have attempted to address this by focussing on a select number of variables and statistics primarily associated with possession,[7, 9, 31] ChampionData® ranking[9, 18, 22] or a coaches subjective rating of performance.[18, 21] While this reductionist approach has facilitated the interpretation of technical skill count data, it fails to incorporate all available technical skill components that relate to performance success in Australian Football. Therefore, an approach that incorporates all relevant variables, holistically capturing technical skill performance, is required. The objective simplification of a wider variety of technical variables previously provided by ChampionData® may facilitate subsequent integration with physical and tactical components making it easier to interpret the effect of these components on performance outcome. This may further guide coaching staff in developing training programs where these performance elements are trained simultaneously.

In order for technical skill indicators to be adopted for practical performance analysis in sport, and integrated with other performance components, their analysis and interpretation needs to be objectively simplified through feature reduction techniques such as a principal component analysis.[205, 206] This further facilitates investigation into the relationship between these technical components and performance outcome measures such as winning or losing games and contextual factors such as opposition team strength or playing at home or away. Accordingly, the aim of this study was to reduce the dimensionality of commonly reported technical skill indicators obtained from AFL games to facilitate their practical use and interpretability. It was hypothesised that a principal component analysis would reduce the number of variables obtained from individual-based skill counts in Australian Football. Since technical performance is an integral contributor to success in Australian Football, the derived principal components will have a theoretical underpinning which will aid and simplify the interpretation of technical skill involvements associated with AFL match play. Given the modifiable nature of these components, subsequent implementation of training programs may enable the optimisation of physical performance.

5.4 Methods

The study sample consisted of 48 male professional Australian Football players (age: 24.97 ± 3.78 years; playing experience: 5.22 ± 3.44 years) from one AFL team. Each participant played at least one game over the three-year (2016-2018) analysis window. Seventy-three senior matches were used for analysis providing a sample of 1605 individual files (33.4 ± 25.6 per player) from the designated AFL team. Furthermore, data was collected on each opposition team for all 73 matches used in this study, providing an additional 1603 individual files (2.5 ± 1.5 per player). The procedures used in this study were conducted with approval from the Human Research Ethics Committee of the local institution.

The study followed a retrospective longitudinal design where all players' technical skill counts during AFL games were collected over three seasons. Data were obtained from ChampionData®, the official data provider to the AFL.[2] ChampionData® code all AFL matches for a variety of skill involvements[8] and are commonly used in Australian Football research.[8, 23, 49] A selection of statistical indicators have been empirically reviewed, reporting a high level of reliability (ICC range = 0.947-1.000; RMSE range = 0.0–4.5).[19] Other reliability information provided about ChampionData® statistics states that "quantity-based statistics are logged at better than 99% accuracy".[8]

Seventy-three skill count values provided publicly by ChampionData® were collected for each individual for each match (Table 3.5). Specific variables were removed if they had a mean and standard deviation < 1. This was deemed appropriate as skill involvements that occur less than once per game by players were unlikely to influence match outcome.[221] Further, collective variables that were made up of other smaller variables in the data set were removed to mitigate duplication while retaining granularity in the analysis. For example, an individual's *effective disposal* count was a direct result of summating a player's *effective kick* and *effective handball* count. As the latter two technical skill count variables had a mean and standard deviation > 1 and were not initially removed, the *effective disposal* variable was removed from the dataset. Figure 5.1 identifies the variables that were removed prior to analysis and Table 5.1 contains definitions of the included variables.

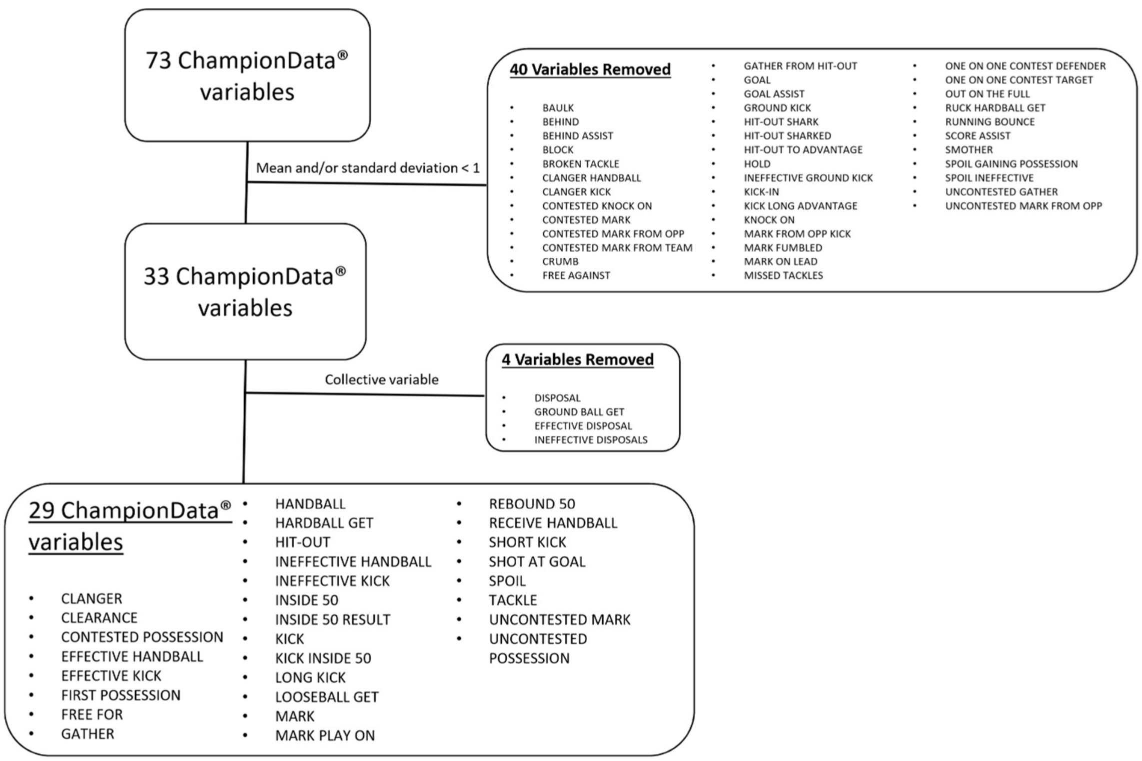

Figure 5.1: Skill indicator selection criteria.

Table 5.1: Technical involvement indicators included in the principal component analysis.

Technical Indicator	Description
Clanger	A handball or kick that give possession directly to the opposition.
Clearance	Credited to the player who has the first effective disposal in a chain that clears the stoppage area, or an ineffective kick or clanger kick that clears the stoppage area.
Contested Possession	A possession which has been won when the ball is in dispute. Includes looseball-gets, hardball-gets, contested marks, gathers from a hit-out and frees for.
Effective Handball	A handball to a teammate that hits the intended target.
Effective Kick	A kick of more than 40 metres to a 50/50 contest or better for the team or a kick of less than 40 metres that results in the intended target retaining possession.
First Possession	The initial possession that follows a stoppage, including a looseball-get, hardball-get, intended ball-get (gather), free kick or ground kick.
Free For	When a player is interfered with and is awarded a free kick by the umpires.
Gather	Possessions that were a result of a teammate deliberately directing the ball in the player's direction, via a hit-out, disposal or knock-on, excluding marks and handball receives. Gathers from a hit-out are contested possessions the rest are uncontested.
Handball	Disposing of the ball by hand.
Hardball Get	A disputed ball at ground level under direct physical pressure or out of a ruck contest, resulting in an opportunity to affect a legal disposal.
Hit-Out	Knocking the ball out of a ruck contest following a stoppage with clear control, regardless of which side wins the following contest at ground level.
Ineffective Handball	Handballs that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Ineffective Kick	Kicks that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Inside 50	Moving the ball from the midfield into the forward zone. Excludes multiple entries within the same chain of possession.
Inside 50 Result	Successful reception of an inside-50
Kick	Total number of times a player disposes the ball by foot
Kick Inside 50	When a player records an inside 50 for his team by kicking the ball from the midfield zone into the forward line.
Long Kick	A kick of more than 40 metres to a 50/50 contest or better for the team.
Looseball Get	A disputed ball at ground level not under direct physical pressure that results in an opportunity to record a legal disposal.
Mark	When a player cleanly catches (is deemed to have controlled the ball for sufficient time) a kicked ball that has travelled more than 15 metres without anyone else touching it or the ball hitting the ground.
Mark Play On	Playing on immediately without retreating behind the mark.

Rebound 50	Moving the ball from the defensive zone into the midfield.
Receive Handball	An uncontested possession that is the result of a teammate's handball.
Short Kick	A kick of less than 40 metres that results in the intended target retaining possession. Does not include kicks that are spoiled by the opposition.
Shot at Goal	A kick directed at goal
Spoil	Knocking the ball away from a marking contest preventing an opponent from taking a mark.
Tackle	Using physical contact to prevent an opponent in possession of the ball from getting an effective disposal.
Uncontested Mark	Marks taken under no physical pressure from an opponent. Includes marks taken on a lead and from opposition kicks.
Uncontested Possession	Possessions gained whilst under no physical pressure, either from a teammate's disposal or an opposition's clanger kick. Includes handball receives, uncontested marks (including lead marks) and intended ball gets from a disposal.

Remaining skill counts were converted to z-scores and normalised to the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)). This subsequently facilitated dimensional reduction.[218] A data reduction technique was used to reduce the dimensionality of technical skill indicators. More specifically, a principal component analysis (PCA) was conducted to reduce the dimensionality of the correlated technical skill indicators into a smaller set of uncorrelated components whilst maintaining most of the variance from the original dataset.[205, 206] Indeed, as a result of PCA, while the principal components that are derived are uncorrelated, each contain their own highly correlated variables that measure an underlying, independent construct. This method ensures only distinct information remains within the dataset.[206, 207] The PCA was undertaken using SPSS for Windows (Version 25)[208] where the aim was to determine the presence of underlying constructs in the remaining 29 technical skill variables. Linear relationships were initially assessed using a correlation matrix while the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction.[208] All 29 variables were initially included, upon which variables with communalities (relative importance for inclusion in the component) lower than 0.40 were excluded.[209] The PCA was subsequently re-processed using a varimax rotation method with only the variables of significant importance. The number of principal components to be retained was determined using a scree plot displaying the derived component eigenvalues.[222] The scree plot was assessed for a break resembling an 'elbow' shape between components, with relatively large eigenvalues and those with similar eigenvalues with the components that occur before the break assumed to be meaningful and are retained.[223] These components were subsequently used to derive component loadings associated with each variable in the PCA. These component loadings were then used to calculate summed variables for each component by treating them as coefficients in a linear regression model.

5.5 Results

No variables were excluded from the PCA as all communalities were greater than 0.40. Upon inspection of the subsequent correlation matrix, linear relationships existed between all variables. An examination of the KMO measure of sampling adequacy suggested that the sample was factorable (KMO = 0.578). Additionally, Bartlett's test of sphericity was significant ($p < 0.001$).[208] Upon inspection of the scree plot, four components occurred before the break in eigenvalues and were subsequently retained and accounted for 55% of the variance. Table 5.2 reveals the cumulative explained variance for each component from the PCA. The rotated component matrix produced component weightings for each variable in their respective principal component. The four equations derived from the analysis are displayed in Table 5.3.

Table 5.2: Total variance explained for each derived component from the principal component analysis.

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	Explained Variance	Cumulative %	Total	Explained Variance	Cumulative %	Total	Explained Variance	Cumulative %
1	7.928	27.337	27.337	7.928	27.337	27.337	6.082	20.972	20.972
2	4.882	16.834	44.171	4.882	16.834	44.171	4.469	15.410	36.382
3	2.704	9.324	53.495	2.704	9.324	53.495	3.253	11.216	47.599
4	1.580	5.449	58.944	1.580	5.449	58.944	2.231	7.693	55.291

Table 5.3: Resultant equations from principal component analysis.

Equation	Variable	Calculation
1	High-Pressure Success	0.867 × Handball + 0.865 × Contested Possession + 0.844 × First Possession + 0.805 × Clearance + 0.781 × Hardball Get + 0.771 × Effective Handball + 0.629 × Ineffective Handball + 0.586 × Gather + 0.515 × Looseball Get + 0.455 × Tackle
2	Low-Pressure Success	0.922 × Uncontested Mark + 0.909 × Mark + 0.749 × Mark Play On + 0.727 × Short Kick + 0.677 × Effective Kick + 0.655 × Uncontested Possession + 0.563 × Kick
3	Attacking Ball Movement Ability	0.902 × Kick Inside 50 + 0.882 × Inside 50 + 0.620 × Long Kick + 0.416 × Ineffective Kick
4	Scoring Ability	0.853 × Shot at Goal + 0.837 × Inside 50 Result

5.6 Discussion

Australian Football is a complex sport where an array of physical, tactical, and technical skills are needed to achieve success. While many studies have attempted to delineate the influence of technical skill demands on performance outcomes, often in isolation of other components, the present study was the first to describe and dimensionally reduce an array of technical skill indicators in an Australian Football context to facilitate their practical application, interpretation, and reporting to performance staff. The 29 individual-derived skill count variables were reduced to four components which adequately represent different constructs whilst maintaining 55% of the variance in the original data set (Table 5.2).[208] Whilst some of the explained variance in the original dataset was lost, not all indicators provided by ChampionData® are reportedly relevant when assessing performance outcome.[19, 31] By reducing a large number of variables into four new variables, each with a different theoretical underpinning, these new components facilitate the interpretation of technical skill indicators. This may subsequently allow practitioners and coaches to assess and monitor individual player performance and development in addition to guiding list-management decisions that may subsequently lead to favourable performance outcomes.

Equation 1, *high-pressure success*, provides an indication of a player's ability to succeed in congested passages or high-pressure phases of play in which ball possession is in dispute (contested play). Resultant sum scores from this equation provide insights into an individual's ability to attain possession (*contested possession, first possession, hardball get, looseball get* and *gather*) and subsequently move the ball through (*handball* and *effective handball*) and away from (*clearance*) these congested passages of play. Larger scores may also reflect an individual's ability to shut down opposition players during congested phases of play with *tackles* positively contributing to this sum score. Higher values for this variable signify that a player is important for winning a ball that is in dispute and subsequently securing possession for the team to attack. This could be indicative of a player's positional role within the team, such as a midfielder, who has the specific task of winning disputed possession and then subsequently moving it forward to provide attacking opportunities.[2, 219]

In contrast, equation 2, *low-pressure success*, provides an indication of a player's ability to succeed in uncongested, attacking passages of play. Higher sum scores are reflective of an individual's ability to successfully receive possession in the absence of pressure (*mark, uncontested mark,* and *uncontested possession*) and continue to move the ball (*mark play on, kick, short kick,* and *effective kick*) in an attempt to maintain possession. This may also reflect a position-specific role such as key or roaming defenders who are responsible for moving possession out of the defensive half without risking a turnover in possession.[219]

Equation 3, *attacking ball movement ability*, reflects an individual's ability to move the ball in the attacking direction. A *kick inside 50* and an *inside 50* both reflect movement of the ball, for the attacking team, inside the opposition's 50m arc, a requirement for creating scoring opportunities. Further, conducting a *long kick* will also increase resultant sum scores and may result from an attempt to cover large distances to move the ball away from an individual's defensive half or alternatively shift the movement of play to areas of the ground that are not occupied by the defensive team, in turn providing opportunities to advance the ball. Additionally, while it may be considered as a negative attribute, the contribution of an *ineffective kick* to resultant sum scores is appropriate as kicks entering an attacking team's forward half, or that are deemed as threatening, are often heavily defended in an attempt to turn possession over. Midfielders or small forwards who demonstrate superior *ineffective kick* values may be responsible for attacking movements and setting up attacking passages of play.[2, 219]

Finally, equation 4, *scoring ability*, reveals a player's ability to receive possession inside the attacking 50m arc (*inside 50 result*) and attempt to score points (*shot at goal*). As with equations 1-3, higher sum scores may reflect positional roles with key forwards, who are positioned in the forward half, receiving a larger amount of possession in the forward 50 and ideally performing more shots at goal.[219] Conversely, attacking players who possess low sum scores for this metric may reflect an inability to successfully receive possession inside the attacking portion of the field consequently resulting in less shots on goal. Alternatively, lower scores may be indicative of a defensive player and having little direct involvement with ball movement and scoring opportunities.

The metrics derived in this study provide a method for coaches and practitioners to further understand the influence of technical aspects and the influence of varying contextual factors on technical skill counts, along with the relationship with physical and tactical components. These metrics provide specific insight into the technical skill demands of the game, specifically pertaining to the use of possession. While this study is the first to provide a simplified, novel method for analysing technical skill indicators in an Australian Football context, these metrics are yet to be validated in relation to team performance outcomes.

The results of this study provide supporting data for performance analysts currently using video and technical skill counts to analyse games and could allow coaches to identify strengths and weaknesses in the opposition team that can be exploited through the implementation of game tactics. This new information also allows coaching staff to develop training interventions that are representative of competition demands as they can now quantify and emulate technical skill demands evident in game scenarios. Further, the derived component scores can facilitate and simplify the information and feedback coaches provide to players. At the individual level, examination of the derived metrics may highlight favourable role-specific characteristics associated with different positions in the team and provide an additional objective means of assessing player match-performance. This information could therefore facilitate weekly team selection or, alternatively, the recruitment of new players that might be of particular value to the team. These metrics may also allow coaches to longitudinally assess the development of an individual player's role within the team over time. Lastly, the findings and methodological approach utilised in this study may also prove useful in sports other than Australian Football following the calculation of components and respective weightings. Additionally, as the results from this study are not generalisable to other sporting contexts, it is recommended that those who are adopting this form of methodology continue to update component loadings as new data is acquired each season. This will ensure that factor loadings remain accurate and stable throughout the season. The methodology provided in this study can be followed by practitioners working with technical skill indicators in any sport, to help them understand the technical characteristics of match play.

5.7 Conclusion

This study is the first to provide a simplified, novel method for analysing technical skill indicators in an Australian Football context, providing useful information with reduced dimensionality for coaches and practitioners. The derived components provide specific insight into individual player performance and the technical skill demands of match play, particularly the movement of possession. This may consequently guide opposition analysis, training implementation, player performance ratings and player development, selection, and recruitment. Further, if proven valid, the findings from the current study may provide a viable framework of analysis in other contextually similar sports.

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Chapter 6

Study Three: Simplifying the complexity of assessing physical performance in professional Australian Football

As per the manuscript published in *Science and Medicine in Football:*

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6.1 Abstract

Purpose: To provide a simplified, novel method for analysing the physical demands in an Australian Football context by reducing the dimensionality of commonly reported physical external load metrics obtained from match play. This may facilitate their practical use and interpretability. Methods: A retrospective longitudinal design was utilised with individual players' physical outputs, measured via global navigation satellite system devices, collected during official Australian Football League matches over three seasons. A principal component analysis was used to reduce a large number of correlated physical external load metrics related to the analysis of physical match demands into a smaller set of uncorrelated components. Results: Forty-six variables were reduced to five principal components whilst maintaining 56% of the variance in the original dataset. The principal component analysis derived five individual-based principal components pertaining to *low-moderate movement volume*, *high speed running volume*, *accelerations*, *change of direction* and *impacts*. Conclusions: Utilising factor loadings (eigenvectors) derived from a principal component analysis, this study is the first to provide a simplified, novel method for analysing the physical demands in an Australian Football context with the derived metrics revealing useful information for coaches and practitioners. This may consequently guide training implementation, player performance ratings and player selection. Further, these new values may facilitate the monitoring of physical player loads.

Key Words: Performance analysis; Physical demands; GPS; GNSS; Principal component analysis

6.2 Introduction

Professional Australian Football is the most popular form of football in Australia and is classified as a contact, team sport.[1] The game takes place on an oval-shaped field that varies in length (149 – 175 m) and width (122 – 136 m), with two larger central 'goal' posts and two outer 'behind' posts.[1] If the ball is kicked between the two goal posts by the attacking team, a goal worth 6 points is awarded. If the ball passes between the goal posts in any other way, hits a goalpost, or passes between a goal post and a behind post, a behind worth 1 point is awarded.[2] The primary aim is to score more points than the opposing team. Match play is carried out by two teams of 22 players, with 18 on the field at a time who contest play over four 20-minute quarters of 'in-play', with the clock stopping every time a goal is scored, the ball goes out of play, or play is ceased by the officiating umpires. Match play involves phases of ball possessions, contested play (where both teams compete for possession) and stoppages of varying durations.[1] The physical element of the game is characterised by intermittent high-speed running coupled with frequent collisions and changes of direction.[1] Additionally, competing at this level requires a high level of skill proficiency with players utilising a myriad of hand and foot skills for passing, scoring and gaining possession of the ball.[4] Teams also utilise a variety of tactical strategies depending on player availability, coaching philosophies, the opposing team and environmental conditions during the match.[5]

Collectively, players require superior physical abilities, technical skills and tactical strategies to cope with the ever-changing demands of the game.[7] Team success in Australian Football is a culmination of the aforementioned variables with superior performance allowing teams to fulfil the main objective of the game, to score the most points through goal kicking. Accordingly, in the past decade applied research in this context has investigated these factors, each with a wide array of variables, to derive practical applications aimed at improving a team's performance. Through the analysis of games played in the Australian Football League (AFL), the technical and physical activity profiles of professional Australian Football have been adequately quantified using notational analysis techniques[4] and microtechnology such as global navigation satellite system (GNSS) and accelerometers.[7] Further, whilst scarcely examined in Australian Football, recent lines of inquiry have sought to objectively quantify tactical behaviour using cooperative network analyses,[2, 220] passing interactions between teammates, as well as spatiotemporal analyses assessing measures of space and shape.[34] Despite providing valuable insight into the physical, technical and, to a lesser degree, the tactical requirements of the game, discrepancies exist when associating these components with successful and unsuccessful performance outcomes.[7, 18, 21-23] These discrepancies may occur as players need to collectively adapt their physical abilities, skills and tactical strategies to cope with the ever-changing demands of a game. Attempts to ease the integration of all these components for collective analysis may provide insight into existing discrepancies as well as provide a greater indication into factors affecting performance.[52]

In an attempt to objectively quantify the underpinnings of successful performance, sports scientists have focused on identifying associated external physical loads using GNSS devices with a plethora of ensuing research quantifying the physical activity profiles of the game.[7, 18, 21-23] Currently in the AFL, all professional teams evaluate the external physical loads of game play using this technology which are capable of providing a wide array of associated variables.[7] Specifically, speed-based running indices and accelerometry data have led to many publications that have quantified the physical components of Australian Football using a combination of these variables.[7, 18, 21-23] These studies revealed that Australian Football match-play involves higher running volumes compared to any other team sport, with players performing frequent intermittent bouts of high-speed running, accelerations, decelerations, changes of direction and frequent collisions with opposing players.[1]

While microtechnology data have provided valuable information regarding the external physical loads associated with the game, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance.[7, 18, 21-23] One study of a cohort of elite players revealed that higher rated players, as determined by Coaches' subjective ratings, covered a greater percentage of distance at high speed and greater sprint distance than lower rated players.[18] On the contrary, another study revealed that more proficient players spent a greater percentage of time at low speed and covered less distance than less proficient players.[21] While this research examined performance using a select number of variables to measure technical and physical activity profiles, there are inherent limitations present when using Coaches' ratings of performance, as these are subjective in nature, making it difficult to translate or compare findings in different contexts.[18, 21] Further, manually selecting a small number of the available physical metrics may have failed to holistically capture an athlete's physical activity profile.

Literary inconsistencies are further exemplified when assessing the relationship between objectively quantified technical and external physical load indicators. Previous literature demonstrated a negative relationship between ChampionData® Player Rank (a holistic measure of technical performance), and physical output measures.[7, 18] On the contrary, another study revealed a positive relationship between the number of high speed efforts conducted per minute, and the number of disposals (a positive indicator of technical performance).[23] While this line of work attempts to delineate the simultaneous influence of physical and technical indicators on team performance success, limitations when implementing only a select number of technical and physical GNSS output variables in the study design are evident.

Furthermore, when examining the relationship between GNSS derived data, quarters won and lost, and contextual variables such as weather, ground location and game turnaround time, inconsistencies in research findings are also evident. One study associated lower physical output with quarters won,[31] while conversely another failed to identify any relationship between physical derived metrics, quarter success, or contextual variables.[22] These studies may have failed to fully account for the physical, technical and tactical components, selecting only a few GNSS derived variables, or, with the latter, neglecting to include a sufficient number of variables to adequately quantify external physical loads. Accordingly, including and simplifying a wider array of physical variables, through use of dedicated statistical techniques, such as principal component analysis,[224-226] may facilitate the use and integration of these data with technical and tactical information. This may subsequently allow performance analysts and coaches to collectively evaluate these components and the relationship with contextual factors and performance outcomes. Additionally, despite the widespread use of GNSS technology in sport, confusion still remains around the most appropriate metrics to use, and how information generated can be most effectively reported back to key stakeholders.[227] Therefore, the aim of this study was to reduce the dimensionality of commonly reported physical load indicators obtained from AFL games in order to facilitate their practical use and interpretability. It was hypothesised that a principal component analysis would reduce the number of external physical load metrics associated with Australian Football match play whilst maintaining most of the variance in the original dataset. Since an athlete's physical activity profile is an integral contributor to success in Australian Football, the derived principal components will have a theoretical underpinning which will aid and simplify the interpretation of the external physical load metrics associated with AFL match play. Given the modifiable nature of these components, subsequent implementation of training programs may enable the optimisation of a player's physical activity profile.

6.3 Methods

Participants

The study sample consisted of 48 male professional Australian Football players (age: 25.0 ± 3.8 years; playing experience: 5.2 ± 3.4 years) from one AFL team. Each participant played at least one game over the three-year (2016-2018) analysis window. Sixty-three senior matches were used for analysis providing a sample of 1376 individual files (28.7 ± 21.8 per player) from the designated AFL team. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

Study Design

The study followed a retrospective longitudinal design where individual players' physical match loads, as measured via GNSS technology, during official AFL games were collected over a period of three seasons. A principal component analysis was used to reduce the number of characteristics related to the analysis of physical match characteristics whilst maintaining most of the variance in the original dataset.

Data Collection

Data was collected via the use of GNSS units sampling at 10Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia). Currently in the AFL, all elite teams evaluate the external physical loads of game play using this technology.[7] The GNSS units were worn by the players within a custom-built pouch sewn into the rear of the player's jersey. The device sits superior to the player's shoulder blades at the base of the neck and records data pertaining to physical match characteristics. While GNSS provider vests may provide enhanced validity and reliability, player jerseys were fit tightly and were used as an alternative.[228] Intra-class correlation coefficients (ICCs) for Catapult GNSS devices have demonstrated high to very high reliability (r = 0.86-0.99) for distances covered at low-, high-, and very high-speed running intensities.[16] Additionally, the same study utilising the typical error of measurement (TEM) demonstrated good reliability (TEM = 0.8-4.8%) for low- and high-speed running variables but poor reliability (TEM = 11.5-11.7%) for very high-speed running variables.[16] Utilising a coefficient of variation (CV), other studies demonstrated good reliability (CV < 5%) for variables pertaining to banded inertial movement analyses (IMA) and moderate reliability (CV 5-10%) for direction specific IMA counts[229] and good to moderate reliability for acceleration measures (CV 1.8-9.1%).[230]

Physical Variables

Table 6.1 identifies the variables that were included for analysis, their description, and associated bands used for analysis. These variables have previously been used in Australian Football to quantify the physical match characteristics at the individual level of analysis.[1, 4, 7, 18, 21-23, 31, 202, 231]

Table 6.1: GNSS derived physical variables.

Physical Variable	Description	Bands
Total Duration	The total amount of time spent on-field. Does not include time on the bench.	-
Total Distance	Total distance covered during time spent on field. Does not include distance covered while on the bench.	-
Banded Velocity Distance	The total amount of distance covered in a designated velocity band.	B1: 0-6 $km{\cdot}hr^{-1}$; B2: 6-14.4 $km{\cdot}hr^{-1}$; B3: 14.4-18 $km{\cdot}hr^{-1}$; B4: 18-22 $km{\cdot}hr^{-1}$; B5: 22-25 $km{\cdot}hr^{-1}$; B6: >25 $km{\cdot}hr^{-1}$
Banded Velocity Efforts	Counts the number of times an athlete reaches the designated velocity band for a specific amount of time. Effort must be sustained within the band for at least 1s.	B1: 0-6 $km{\cdot}hr^{-1}$; B2: 6-14.4 $km{\cdot}hr^{-1}$; B3: 14.4-18 $km{\cdot}hr^{-1}$; B4: 18-22 $km{\cdot}hr^{-1}$; B5: 22-25 $km{\cdot}hr^{-1}$; B6: >25 $km{\cdot}hr^{-1}$
Banded Acceleration & Deceleration Distance	The total amount of distance covered accelerating or decelerating in the designated band.	Acceleration: B1: 1.36-2.15 $m{\cdot}s^{-2}$; 2.151-2.75 $m{\cdot}s^{-2}$; > 2.751 $m{\cdot}s^{-2}$ Deceleration: B1: -1.36- -2.15 $m{\cdot}s^{-2}$; -2.151- -2.75 $m{\cdot}s^{-2}$; < -2.751 $m{\cdot}s^{-2}$
Banded Acceleration & Deceleration Duration	The total amount of time spent accelerating or decelerating in a certain range.	Acceleration: B1: 1.36-2.15 $m{\cdot}s^{-2}$; 2.151-2.75 $m{\cdot}s^{-2}$; > 2.751 $m{\cdot}s^{-2}$ Deceleration: B1: −1.36-−2.15 $m{\cdot}s^{-2}$; -2.151-−2.75 $m{\cdot}s^{-2}$; < −2.751 $m{\cdot}s^{-2}$
Banded Acceleration & Deceleration Efforts	Counts the number of times an athlete reaches the designated acceleration or deceleration band for a specific amount of time. Effort must be sustained within the band for at least 0.4s	Acceleration: B1: 1.36-2.15 $m{\cdot}s^{-2}$; 2.151-2.75 $m{\cdot}s^{-2}$; > 2.751 $m{\cdot}s^{-2}$ Deceleration: B1: −1.36-−2.15 $m{\cdot}s^{-2}$; -2.151-−2.75 $m{\cdot}s^{-2}$; < −2.751 $m{\cdot}s^{-2}$
Banded Inertial Movement Analysis (IMA)	Using raw accelerometer and gyroscope data to create a non-gravitational acceleration vector, reveals the magnitude and the direction of an agility action. It can classify events within intensity, and distinguish between forward (acceleration), backward (deceleration), vertical (jump) and left and right lateral events.	Low: 1.5-2.5 $m{\cdot}s^{-1}$; Medium: 2.5-3.5 $m{\cdot}s^{-1}$; High: >3.5 $m{\cdot}s^{-1}$

Statistical Analysis

A data reduction technique was used to reduce the dimensionality of physical load characteristics at the individual level. More specifically, a factor analysis was conducted through a principal component analysis to reduce the dimensionality of the physical load variables into a smaller set of uncorrelated components whilst maintaining most of the variance from the original data set.[205, 206] As a result of the selected analysis technique, no correlation exists between the principal components, but each contain their own highly correlated variables that measure an underlying, yet independent construct. This method ensures only distinct information remains within the data set.[207] A principal component analysis involves the removal of the mean, calculation of the covariance of the data, determination of the eigenvalues and eigenvectors of the covariance matrix, and a varimax rotation of the original data onto a coordinate system spanned by the eigenvectors of the covariance matrix.[206] The analysis was executed using SPSS for Windows (Version 25)[208] where the aim was to determine whether common underlying constructs were present in the 46 physical load variables. Linear relationships were initially assessed using a correlation matrix while the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction.[208] All 46 variables were initially included, upon which variables with communalities (relative importance for inclusion in the factor) lower than 0.40 were excluded.[209, 232] The principal components analysis was subsequently re-run using only variables of significant importance. The number of principal components to be retained was determined using the scree plot which is a line plot of the derived factor eigenvalues.[222] The scree plot was assessed for a break or separation, resembling an 'elbow' shape, between factors with relatively large eigenvalues and those with similar eigenvalues. The components that occur before the break are assumed to be meaningful and are retained.[223] These components were subsequently used to derive factor loadings (eigenvectors) associated with each of the variables in the analysis. These factor loadings (eigenvectors) were then used to calculate summed variables (sum scores) for each component by treating them as coefficients in a linear regression model. For interpretation, sum scores are calculated by multiplying the factor loadings (eigenvectors) with the associated standardised physical GNSS variables (Table 6.3).[233] Sum scores can then be converted to z-scores and normalised to the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)) to facilitate interpretation.[218]

6.4 Results

Four variables, *band 1 deceleration duration* and *band 1, 2* and *3 acceleration duration,* were excluded from the PCA due to communalities below 0.40. Upon inspection of the subsequent correlation matrix, linear relationships existed between all variables. An examination of the KMO measure of sampling adequacy suggested that a considerable proportion of the variance in the dataset is a result of underlying factors (KMO = 0.77). Additionally, Bartlett's test of sphericity was significant ($p < 0.001$)[208] Figure 6.1 reveals the total explained variance from the PCA.

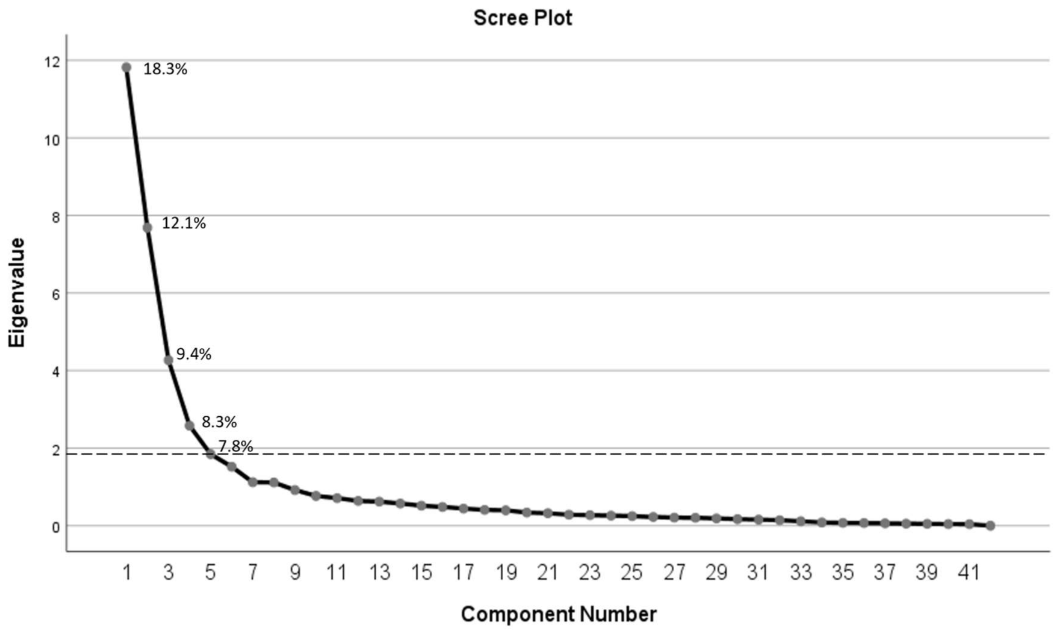

Figure 6.1: Scree plot for principal component analysis demonstrating the components, and the explained variance, that occur before the break and therefore assumed to be meaningful and are retained.

The rotated component matrix produced factor weightings for each variable in their respective principal component (Table 6.2). All variables, except one, were assigned to the component in which they had the strongest weighting. Despite having a slightly higher weighting factor (0.524) in the fourth component, *IMA change of direction left low* was placed in component two due to the theoretical and logical association with the existing variables in the component. The following equations that were subsequently derived are presented in Table 6.3.

Table 6.2: Data-reduction procedure: Rotated component matrix of GNSS variables with factor loadings (eigenvectors) >0.4.

	Component				
	1	2	3	4	5
Velocity Band 3 Distance	**.869**				
Total Distance	**.835**				
Deceleration Band 1 Efforts	**.807**				
Acceleration Band 1 Efforts	**.805**				
Velocity Band 3 Efforts	**.772**				
Velocity Band 4 Efforts	**.727**				
Velocity Band 2 Total Distance	**.713**				
Velocity Band 4 Total Distance	**.652**		.473		
Acceleration Band 1 Distance	**.649**				.408
Deceleration Band 2 Efforts	**.621**				
Deceleration Band 1 Distance	**.605**				
Acceleration Band 2 Efforts	**.560**				.446
IMA Acceleration High		**.899**			
IMA CoD Right High		**.885**			
IMA CoD Left High		**.862**			
Ima Acceleration Medium		**.738**			
Ima Cod Right Medium		**.712**			
Ima Cod Left Medium		**.706**		.492	
IMA Acceleration Low		**.526**		.468	
IMA CoD Right Low	.414	**.455**		.417	
Velocity Band 6 Total Distance			**.833**		
Velocity Band 6 Efforts			**.830**		
Velocity Band 5 Total Distance			**.823**		
Velocity Band 5 Efforts			**.701**		
Ima Deceleration Medium				**.740**	
IMA Deceleration Low				**.654**	
Ima Jump Count Low Band				**.617**	
IMA Deceleration High				**.607**	
IMA CoD Left Low	.407	**.415**		.524	
Acceleration Band 3 Efforts					**.878**
Acceleration Band 3 Distance					**.858**
Acceleration Band 2 Distance					**.823**

Note: Factor loadings assigned to component appear in **bold**.

Table 6.3: Resultant equations from principal components analysis.

Variable	Calculation
Low-Moderate Volume	0.869 × Velocity Band 3 Distance + 0.835 × Total Distance + 0.807 × Deceleration Band 1 Efforts + 0.805 × Acceleration Band 1 Efforts + 0.772 × Velocity Band 3 Efforts + 0.727 × Velocity Band 4 Efforts + 0.713 × Velocity Band 2 Distance + 0.652 × Velocity Band 4 Distance + 0.649 × Acceleration Band 1 Distance + 0.621 × Deceleration Band 2 Efforts + 0.605 × Deceleration Band 1 Distance + 0.560 × Acceleration Band 2 Efforts
High Speed Running	0.833 × Velocity Band 6 Distance + 0.830 × Velocity Band 6 Efforts + 0.823 × Velocity Band 5 Distance + 0.701 × Velocity Band 5 Efforts
Explosiveness	0.878 × Acceleration Band 3 Efforts + 0.858 × Acceleration Band 3 Distance + 0.823 × Acceleration Band 2 Distance
Change of Direction	0.899 × IMA Acceleration High + 0.885 × IMA Change of Direction Right High + 0.862 × IMA Change of Direction Left High + 0.738 × IMA Acceleration Medium + 0.712 × IMA Change of Direction Right Medium + 0.706 × IMA Change of Direction Left Medium + 0.526 × IMA Acceleration Low + 0.455 × IMA Change of Direction Right Low + 0.415 × IMA Change of Direction Left Low
Collisions/Impacts	0.740 × IMA Deceleration Medium + 0.654 × IMA Deceleration Low + 0.617 × IMA Jump Low + 0.607 × IMA Deceleration High

6.5 Discussion

Australian Football is a highly demanding sport in terms of the physical requirements. While many studies have attempted to quantify the external physical loads of the game and the associated underpinnings of successful performance, this study was the first to describe and dimensionally reduce an array of physical load variables in a professional-level context to facilitate their practical application and interpretation. Forty-six variables were reduced to five components in the principal component analysis. These new components help to reduce the complexity of analysing and interpreting the external physical loads associated with Australian Football. These principal components adequately represent different constructs whilst maintaining 56% of the variance from the original data (Figure 6.1).[208] Whilst some of the explained variance in the original dataset was lost, not all physical indicators are reportedly relevant when assessing performance outcomes.[18] These new components may firstly ease interpretation of GNSS derived variables and subsequently enable coaches and practitioners to assess and monitor individual player performance with greater certainty. Further, the new metrics derived in this study may allow coaches to develop training drills that emulate the external physical loads of the game in a more representative manner.

Equation 1 is indicative of the general match characteristics with the total running volume an individual accumulates throughout the match (*total distance*) as well as the volume completed at low and moderate intensities included in this sum score. This is appropriate as the majority of the time spent running during matches is at lower intensities.[217] Sum scores are a combination of the distance and number of efforts accumulated at low *(velocity band 2* and *velocity band 3*) and moderate (*velocity band 4*) velocities. Further, the intermittent nature of the sport, at low-moderate intensities, is captured by the number of acceleration and deceleration efforts (*band 1* and *band 2*) and accumulated acceleration and deceleration distances (*band 1*). The resultant sum scores from equation 1 may reflect position specific roles or individual physical capacities. Compared to key attackers and defenders, midfielders cover the greatest distances and have the highest work rates.[217] This is likely due to position specific roles with midfielders covering a larger area of the field relative to the fixed positional characteristics of key position players.[217] Alternatively, lower scores may be indicative of an individual's physical capacity. Recent studies have demonstrated that lower scores in the Yo-Yo Intermittent Recovery Test (level 2), an assessment of running capacity, corresponded with lower physical match outputs.[231] Therefore, lower scores may reflect an inability to complete work throughout the match.

Similarly, equation 2 provides an indication of a player's ability to accumulate distance running and complete repeated efforts at higher velocities (*velocity band 5* and *6*). Greater sum scores are indicative of an individual's physical capacity[231] and may also partly reflect positional demands. Similar to equation 1, midfielders may demonstrate larger scores as the ability to rapidly reach possession that is in dispute in different parts of the field will increase chances of retrieving possession.[217] Alternatively, superior scores may reflect offensive or defensive movements with individuals utilising high velocities to intercept opposition chains of possession or to position themselves in favourable spaces of the field where they can receive possession from a teammate. Lower scores may be an indicator of efficiency with higher calibre players being able to positively impact the game without excessively exerting themselves. This would align with previous literature that revealed that players who were perceived to have performed superiorly demonstrated lower physical outputs.[7, 18]

Aligning with equation 1 and 2, equation 3 reflects the acceleration of a player with this score comprising of moderate-high intensity acceleration variables (*Acceleration Band 2* and *3 Distance* and *Acceleration Band 2 Efforts*). Sum scores reflect the ability of a player to rapidly change velocity and may be a result of position-specific tasks. For example, rapid acceleration may allow key forwards to misalign themselves with a marking defender and move into free space to receive a pass. The importance of an attacker-defender misalignment has been associated with positive attacking outcomes in other footballing contexts.[147, 156] Alternatively, higher scores may reflect an ability of a midfielder or defender to gain possession in dispute and rapidly accelerate into free space to then pass to other unopposed players.[202, 217] As with other derived variables, there are a multitude of ways to achieve high sum scores which practitioners must be aware of for correct interpretation of the outcomes.

While equations 1, 2 and 3 pertain to the linear movement of the individual at different intensities, equations 4 and 5 are indicative of a player's ability to change direction. Solely derived from IMA measures, these sum scores may reflect positional roles with certain players needing to navigate through congested phases of play or move erratically to evade or move past an opponent whilst attacking.[202, 217] Alternatively, larger scores may be indicative of a defender's ability to block attacking movements and to increase pressure on the attacker with the aim of causing a turnover.[234] Equation 5 may also provide an indication of the number of collisions or impacts an individual is subjected to as this score is characterised by rapid decelerative movements, commonly associated with sudden stoppages. Accordingly, it may be expected that midfielders demonstrate greater scores due to a greater involvement in contested passes of play. With all available sum scores, it is important to examine outputs for each component in the context of playing position and/or specific role assigned to certain players as this may strongly influence result scores.

In Australian Football, there are a wide array of GNSS derived variables available to physical performance coaches regarding the external physical loads associated with match-play. While existing literature has provided valuable insight utilising these external physical load metrics,[7, 18, 21-23] the large number of variables makes it difficult to interpret the effect of external physical load indicators on match outcome and accordingly, which variables should be prioritised in training. The metrics derived in this study may provide a method for coaches and practitioners to further understand the influence of physical outputs and the specific physical requirements associated with varying contextual factors such as weather, ground location and game turnaround time. The results provide supporting data for performance analysts currently using GNSS technology and provide a way of objectively reviewing individual physical activity profiles. This may subsequently facilitate the development of training interventions specifically tailored towards improving individual weaknesses or further developing existing strengths. Further, these metrics may allow coaches to longitudinally assess the development of an individual player's physical output over time. While the principal components were derived from one team and may not be generalisable to other teams and styles of play, these aggregate metrics may highlight favourable role-specific characteristics associated with different positions in the team and provide an additional objective means of assessing player match-performance. Resultant scores, potentially accompanied by appropriate visualisations,[233] may highlight any positional differences (Figure 6.2) and can subsequently facilitate and simplify the information and feedback coaches provide to players post-match. Lastly, while theoretical insight can be drawn from previous research examining a wide array of physical variables, future studies are required to validate the use of these new metrics in association with individual and team performance outcomes. Findings from this study may also prove useful in sports other than Australian Football utilising GNSS technology, following the calculation of components and weightings (eigenvectors) in these other sports. Additionally, as the results from this study are not generalisable to other teams or sporting contexts, it is recommended that those who are adopting this form of methodology continue to update factor loadings (eigenvectors) as new data is acquired. This will ensure that factor loadings remain accurate. The methodology provided in this study can be followed by practitioners working with GNSS systems in any sport, to help them understand the plethora of physical variables available from their GNSS provider.

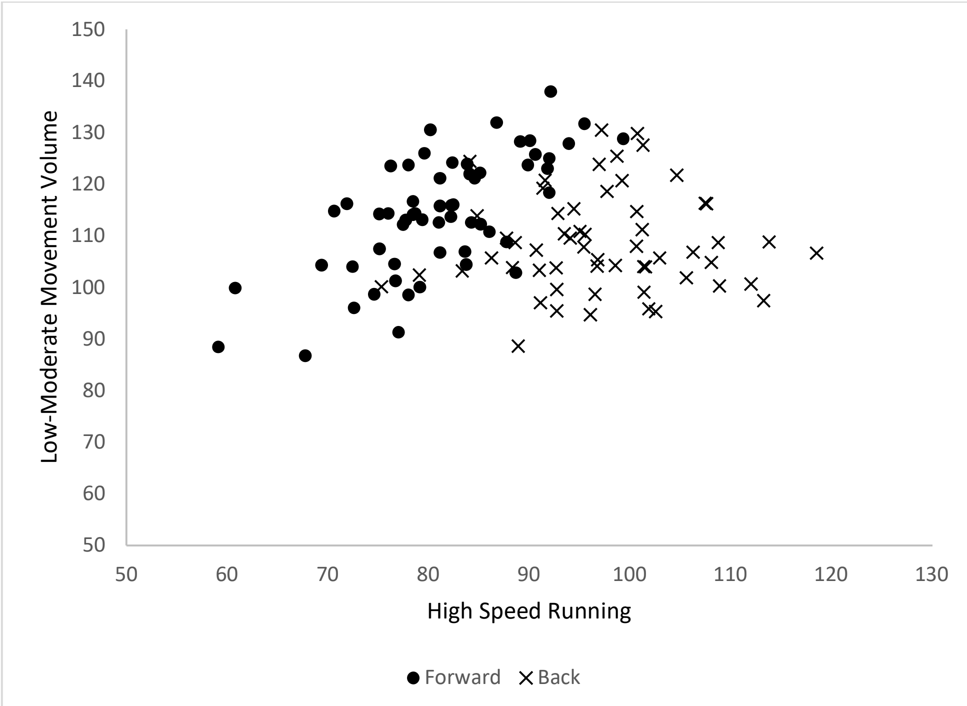

Figure 6.2: Visualisation highlighting differences in physical match characteristics between two different positions.

6.6 Practical implications

- The simplified physical load measures developed in this study provide supporting data for performance analysts and practitioners currently using GNSS technology to monitor player workloads and physical output.
- These new metrics facilitate the practical use and interpretability of GNSS derived variables and allow coaches to identify individual strengths and weaknesses which can subsequently guide player development.
- The newly derived variables may ease integration of physical load data with technical and tactical related data by reducing the complexity of the available information. This may help to determine the influence of this component on performance outcomes.

6.7 Conclusion

Utilising factor loadings (eigenvectors) derived from a principal component analysis, this study is the first to provide a simplified, novel method for analysing physical match characteristics in an Australian Football context providing useful information for coaches and practitioners. This may consequently guide training implementation, player performance ratings and player development, selection, and recruitment. Further, if proven valid, the findings from the current study may provide a viable framework of analysis in other contextually similar sports.

Chapter 7

Study Four: Tactical analysis of individual and team behaviour in professional Australian Football

As per the manuscript published in *Science and Medicine in Football:*

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Note: The referencing system used in this manuscript conforms to the style used in the remainder of the thesis. The citation numbers relate to the thesis reference list and are different to the published manuscript. Otherwise, this manuscript appears as published.

7.1 Abstract

This study sought to reduce the dimensionality of commonly reported spatiotemporal characteristics obtained from Australian Football games to facilitate their practical use and interpretability. A retrospective longitudinal design was utilised with team and individual spatiotemporal variables, measured via global navigation satellite system devices, collected during official Australian Football League matched over three seasons. Two separate principal component analyses were conducted at the team and individual level to reduce correlated spatiotemporal characteristics into a smaller set of uncorrelated components. At the team level, eighteen variables were reduced to five components pertaining to *dispersive coordination*, *lateral predictability and spacing*, *multidirectional synchrony*, *longitudinal predictability* and *longitudinal behaviour* whilst maintaining 69% of variance in the original dataset. At the individual level, fifteen variables were reduced to four components pertaining to *multidirectional and spacing synchrony, unpredictability, player movement* and *player positioning* whilst maintaining 64% of variance. This study is the first to provide a simplified, novel method for analysing spatiotemporal behaviour in an Australian Football context with both the team- and individual- derived metrics revealing useful information for coaches and practitioners. Components may provide insight into behaviours that emerge and persist throughout a game and allow coaches to distinguish between different playing/behavioural styles.

Key Words: Performance analysis; Tactics; Spatiotemporal; Principal component analysis; Ecological dynamics

7.2 Introduction

Australian Football is a contact team sport involving 18 players per side on an oval-shaped field.[1] The professional Australian Football League (AFL) is characterised by its physical demands, involving intermittent high-speed running, collisions and changes in direction;[1, 217] high levels of hand and foot skill proficiency for passing, scoring and gaining ball possession;[4] and specific tactical strategies that vary depending on team personnel, coaching philosophies, opposing team and environmental conditions.[4] While existing information regarding the technical and physical demands of Australian Football provides valuable insight into factors that contribute to team performance, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance.[7, 18, 21-23] The excessive emphasis placed on performance outcome measures focussing on 'who did what, when' fails to fully elucidate the underlying factors of successful performance in such a complex game and emphasises the need for a theoretical rationale that can provide insight into performance behaviours.[24] To enhance understandings of match performance, notational analysis and/or coaches' subjective ratings of performance have been used to assess and describe tactical behaviours of performers during match-play.[26] This has typically occurred through verbal descriptions of lived experiences or game observation.[27] While this may offer valuable insight, the reliance on subjective impressions and procedural knowledge of expert performers are clear limitations.[28] Subjective analysis presents particular issues when comparing performance between teams or players acutely or longitudinally across a season. In order to assess performance in differing contexts the use of objective assessments of tactical performance embedded within a viable theoretical framework are essential.

With recent technological advancements, such as an increase in sensitivity of GNSS devices and application of novel statistical approaches, it is possible to objectively quantify collective team behaviour. Practitioners can quantitatively model and predict performance outcomes in team sports, particularly during critical in-game events.[17] Further, embedding appropriate spatiotemporal analysis techniques within a viable framework to help explain behaviour may also provide further insight as to 'why' or 'how' certain behaviours emerge in conjunction with common analyses. This approach deepens the understanding of the process characteristics underpinning successful performance.[52] An ecological dynamics framework that focuses on the performer-environment relationship is a viable framework that provides a basis for understanding such performance in team sport.[29] From an ecological dynamics perspective, Australian Football is a complex performance-environment sub-system where players and teams perceive opportunities for action which guide decision-making and subsequent actions. The perception of relevant environmental information sources allows players to self-organise into stable states of coordination enabling the achievement of task goals.[29] In this complex system, task-constraints such as field dimensions and passing rules, along with physical and informational constraints like player size and opposition player movements provide boundaries that govern behaviour. Resultant behaviour in a complex system is an outcome of the interaction between its constituents, therefore, it is important to examine spatiotemporal behaviours between players and teams when analysing performance.

Spatiotemporal analyses can provide additional information that captures the dynamic nature of team sport.[48] While scarcely examined in Australian Football,[34] this approach has provided insight into the behaviour that characterises successful attacking and defensive phases of play in soccer.[6, 107] Only one study has utilised these metrics in Australian Football demonstrating greater team dispersion during offensive phases compared to defensive and contested phases.[34] These higher values may indicate players attempting to spread the opposition defensive players to create a greater effective playing space allowing easier passage towards the goals. In contrast, lower values of dispersion may indicate a defensive mechanism to contract rapidly if the opposition gained possession of the ball.[34] While these measures provide new insight into tactical mechanisms influencing team success, the utilisation of two 20-minute halves in a 15v15-match simulation drill does not fully represent the collective behaviour exhibited by teams during competitive match-play. Further research investigating these metrics in AFL matches may deepen the understanding of the influence of tactical behaviour on performance.

While a variety of objective measures quantifying dispersion,[44, 45] synchrony,[100] variability[101] and predictability[102] have sought to provide insight into behaviour associated with successful performance, the vast array of spatiotemporal variables presented in the literature convolutes their relationship with performance outcomes. For spatiotemporal analysis to be adopted for practical performance analysis in sport, the analysis and interpretation should be simplified. Accordingly, this study aimed to reduce the dimensionality of commonly reported spatiotemporal variables obtained from AFL games to facilitate their practical use and interpretability. In accordance with previous literature that has dimensionally reduced network,[220] technical[235] and physical[236] variables, it was hypothesised that a principal component analysis (PCA) would successfully reduce the number of variables obtained from individual- and team-based spatiotemporal analyses in Australian Football, while maintaining a large proportion of its variance.

7.3 Methods

Participants

48 male professional footballers (age: 25.0 ± 3.8 years; playing experience: 5.2 ± 3.4 years) from one AFL team were analysed over a three-year (2016-2018) analysis window. Fifty senior matches were used for analysis providing a sample of 50 team files and 1099 individual files (22.9 ± 17.6 per player) from the designated AFL team. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

Study Design

Retrospective longitudinal design where individual players' and the teams' spatiotemporal behaviours were collected during official AFL games over three seasons. A PCA reduced the number of variables related to the analysis of both individual and team spatiotemporal behaviour whilst maintaining most of the variance in the original dataset.

Data Collection

Data were collected via the use of GNSS units sampling at 10Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia). Intra-class correlation coefficients (ICCs) for Catapult GNSS devices have demonstrated high to very high reliability (r = 0.86-0.99) for distances covered at low-, high-, and very high-speed running intensities.[16] Additionally, the same study utilising the typical error of measurement (TEM) demonstrated good reliability (TEM = 0.8-4.8%) for low- and high-speed running variables but poor reliability (TEM = 11.5-11.7%) for very high-speed running variables.[16]

Spatiotemporal Variables

Spatiotemporal variables were calculated from raw individual player latitudinal and longitudinal positional data via MATLAB software.[191] Prior to analysis, all geospatial coordinates were rotated into a standardized 2D space so that longitudinal movements (y_i; towards each of the goals) and lateral movements (x_i; perpendicular to the line connecting the two goals) could be analysed together.[237] Further, as teams change their direction of play at the beginning of each quarter, coordinates from alternating quarters were rotated 180 degrees to ensure attacking direction was consistent. For each field, the boundary coordinates (x_f, y_f) were collected by walking around the outside of the oval, half a metre from the boundary line, with a GNSS device. Subsequently, MATLAB's *inpolygon* function was utilised to return `indices` identifying whether player coordinates (x_n, y_n)

were inside or outside the region specified by the boundary coordinates of the field. Using these values, all player data points that fell outside the field region (i.e. benched players) were omitted from the following calculations.[191] Further, due to the input of units being in degrees, post-calculation results were converted using MATLAB's *distdim* function which takes angular units (`degrees` or `radians`) and converts to linear distance (metres).[191] This conversion is made along a great circle arc on a sphere with a radius of 6371 km, the mean radius of the Earth.[191] Table 7.1 identifies the team and individual variables included for analysis, their description and method of calculation. These variables have been used in soccer and, to a lesser degree, Australian Football to quantify team and individual spatiotemporal movement behaviours.[100, 101, 107, 115, 130, 143, 194, 198]

Table 7.1: GNSS-derived spatiotemporal tactical variables.

Individual	
Variable	Description
Lateral: - Lateral Displacement - Lateral CV - Lateral Correlation - Lateral SaEn - Lateral Rho	Position of a player in the side-to-side direction of the playing field. Positive values are movements to the left of the field's centre respective to the attacking direction. *Lateral coefficient of variation* is the variability in player displacement in the side-to-side direction; *Lateral correlation* is a relationship between the lateral movements of the individual player and lateral movements of the team centroid; *Lateral sample entropy* is a measure of the individual's lateral movement predictability; *Lateral rho* is a measure of individual lateral phase synchronisation with respect to the rest of the team.
Longitudinal: - Longitudinal Displacement - Longitudinal CV - Longitudinal Correlation - Longitudinal SaEn - Longitudinal Rho	Position of a player in the end-to-end direction of the playing field. Positive values are movements away from the field's centre towards the defensive end and negative values are towards the attacking end. *Longitudinal coefficient of variation* is the variability in player displacement in the end-to-end direction; *Longitudinal correlation* is a relationship between the longitudinal movements of the individual player and longitudinal movements of the team centroid; *Longitudinal sample entropy* is a measure of the individual's longitudinal movement predictability; *Longitudinal rho* is a measure of individual Longitudinal phase synchronisation with respect to the rest of the team.
Stretch Index: - Stretch Index - Stretch Index CV - Stretch Index Correlation - Stretch Index SaEn - Stretch Index Rho	The distance of a player to the team centroid at a given time. It is calculated as the distances of a given player each (x_i,y_i) and the centroid of the team ($\bar{x}$,$\bar{y}$) at a given time. $Stretch\ Index\ (Distance\ Formula) = \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}$ *Stretch index coefficient of variation* is the variability in the distance of a player to the team centroid; *Stretch index correlation* is a relationship between the stretch index of the individual player and the team stretch index value; *Stretch index sample entropy* is a measure of the predictability of an individual's distance to the team's centroid; *Stretch index rho* is a measure of individual's stretch index phase synchronisation with respect to the rest of the team.
Team	
Variable	Description
Centroid: - Lateral Centroid - Longitudinal Centroid	The geometrical centre of a team.[100, 107] Calculated as the mean position ($\bar{x}$,$\bar{y}$) of all players on the field (x_n,y_n) and provides information on the global positioning of the team over time. Centroid measures provide lateral and longitudinal coordinates. Positive lateral values represent movements to the left of the field's centre and positive longitudinal values represent movements away from the field's centre towards the defensive end respective to the attacking direction.

- Surface Area	The total space covered by a team and calculated as the area within the convex hull.[113] It is calculated using MATLAB's *convhull* function which returns an index array of the outermost players at a given time.[191] The polygonal area can then be calculated using MATLAB's *areaint* function which calculates the spherical surface area of the polygon specified by the convex hull input vectors (*x,y*) Larger values indicate greater total field coverage but ignores player distribution.
- Stretch Index	The dispersion and contraction of the team in relation to the team centroid.[194] It is calculated using the mean of the distances between each player (x_n,y_n) and the centroid of the team ($\bar{x}$,$\bar{y}$) at a given time. Larger values signify that players, on average, are further away from the team centroid.
Coefficient of Variation (CV): - Surface Area CV - Stretch Index CV - Lateral CV - Longitudinal CV	A form of linear analysis that uses the standard deviation (s_k) and mean ($\bar{k}$) to quantify the overall variability of the team's spatiotemporal characteristics during specific time periods. Lower values represent lower overall variability in the selected measure.[101] $$Coefficient\ of\ Variation = \frac{s_k}{\bar{k}}$$
Pairwise Correlations: - Stretch Index Correlation - Lateral Correlation - Longitudinal Correlation	Assesses the synchronicity of players. Can be calculated using MATLAB's *corrcoef* function (pairwise option) to correlate the time-series of displacement (x_i,y_i) and stretch index measures of player *i* with the time-series of the team's centroid ($\bar{x}$,$\bar{y}$) and stretch index, respectively. For the team-derived value, scores of each player were averaged to provide an indication of the level of synchronicity for the team for both displacement and dispersion. Values closer to one signify that players within the team, on average, demonstrate similar movements for the event period.[115, 130, 198]
Sample Entropy (SaEn): - Surface Area SaEn - Stretch Index SaEn, - Lateral SaEn - Longitudinal SaEn	A non-linear measure of variability that provides an indication as to the regularity/predictability of behaviour. Calculated using *Sample Entropy* from MATLAB's File Exchange[238] and is defined as the negative natural logarithm for conditional properties that a series of data points a certain distance apart, *m*, would repeat itself at $m + 1$.[195, 196] Given a time series $t(n) = t(1), t(2), \ldots, t(n)$ with *n* number of data points, a sequence of *m*-length vectors is formed. Comparisons are then made against each *m*-length vector within the time series. Vectors are considered alike if the tail or head of the vector fall within a certain tolerance level as determined by $r \times s$.[101] The sum of the total number of like vectors is then divided by $n - m + 1$ and is equal to *B*. Additionally, *A* is equal to the subset of *B* that also matched for $m + 1$. Sample entropy is then calculated: $$SampEn = -ln\frac{A}{B}$$ A time series with similar distances between data points would result in a lower sample entropy value and large differences would result in greater sample entropy values. Thus, sample entropy can determine the predictability and regularity of a time series, with values closer to zero signifying greater regularity/predictability.[195, 196] Based on previous literature, the parameters to be used in this study are *m* = 2 and *r* = 0.2.[133, 195, 197]
Cluster Phase (Rho): - Stretch Index Rho - Lateral Rho - Longitudinal Rho	Quantifies the collective spatiotemporal phase synchronisation, of oscillatory movement components (e.g. players' movement displacement trajectories) in a single collective parameter.[201] Calculated in MATLAB using Richardson's (2020) *ClusterPhase* toolbox.[239] Prior to calculation, differential values (for each data point *i* in the time-series, the *i-1th* data point was subtracted) were created to determine whether players were synchronising their movements in the same direction, regardless of whether they were in line with each other. Values closer to 1 signify perfect synchrony.[143]

Statistical Analysis

A PCA was implemented to reduce the dimensionality of spatiotemporal characteristics at the team and individual levels. Two separate analyses (team and individual values) were utilised to reduce the dimensionality of the included variables into a smaller set of uncorrelated components whilst maintaining most of the variance from the original dataset.[205, 206] As a result of the analysis technique, no correlation exists between the principal components while each contain their own highly correlated variables that measure underlying, independent constructs. This method ensures only distinct information remains within the dataset.[207] While this method does not identify which measures are most related to performance, it dimensionally reduces available metrics into components that describe the underlying structure of those metrics. A PCA involves the removal of the mean, calculation of the covariance of the data, determination of the eigenvalues and eigenvectors of the covariance matrix, and a varimax rotation of the original data onto a coordinate system spanned by the eigenvectors of the covariance matrix.[206]

The analysis was executed using SPSS for Windows (Version 25)[208] to determine whether common underlying constructs were present in the 18 team- and 15 individual-derived spatiotemporal variables. Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction.[208] All variables were initially included, upon which variables with communalities (relative importance for inclusion in the factor) lower than 0.40 were excluded.[209, 232] The PCA was subsequently re-run using only variables of significant importance. The number of principal components to be retained was determined using the scree plot which is a line plot of the derived factor eigenvalues.[222] The scree plot was assessed for an inflection point between factors with relatively large eigenvalues and those with similar eigenvalues. The components that occur before the break are deemed meaningful and are retained.[223] These components were subsequently used to derive factor loadings associated with each of the variables in the analysis. These factor loadings were then used to calculate summed variables (sum scores) for each component by treating them as coefficients in a linear regression model. For interpretation, sum scores are calculated by multiplying the factor loadings (eigenvectors) with the associated standardised spatiotemporal variables (Table 7.2).[233] Sum scores were then converted to z-scores and normalised to the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)) to facilitate interpretation.[218]

7.4 Results

No variables were excluded from the team analysis while two variables, *individual longitudinal coefficient of variation* and *individual longitudinal correlation* were removed due to communalities below 0.40. An examination of the KMO measure of sampling adequacy suggested that a considerable proportion of the variance in the dataset was associated with the underlying factors (Team KMO = 0.58; Individual KMO = 0.62). Bartlett's test of sphericity was significant in both analyses (p<0.001).[208]

The scree plots revealed that the team analysis provided five components and the individual analysis provided four components prior to the break in eigenvalues. The nomenclature adopted for these was based on detailed discussions among the author team relating to the constituents of each component and the facet of match-play they represented. These components accounted for 69% and 64% of the variance in the team and individual dataset, respectively. Figure 7.1 reveals the cumulative explained variance for each component from the analyses. The rotated component matrix produced component weightings for each variable in their respective principal component. All variables were assigned to the component in which they had the strongest weighting. The five team (1-5) and four individual (6-9) equations derived from the analysis are displayed in Table 7.2.

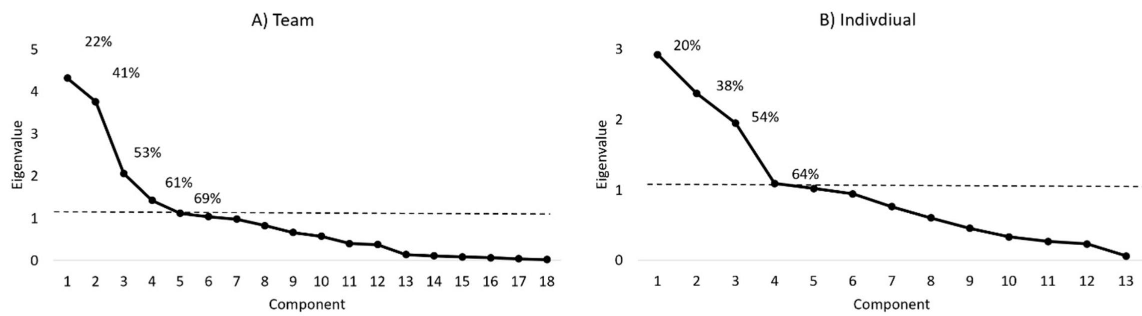

Figure 7.1: Scree plot for the A) Team and B) Individual principal component analysis demonstrating the components and the explained variance that occur before the inflection point.

Table 7.2: Resultant equations from two principal component analyses for Team and Individual measures.

Equation Number	Component	Calculation
		Team
1	Dispersive Coordination	− 0.923 × Stretch Index SaEn – 0.823 × Surface Area SaEn + 0.891 × Stretch Index CV + 0.684 × Surface Area CV + 0.850 × Team Stretch Index Correlation
2	Lateral Unpredictability and Spacing	− 0.933 × Centroid Lateral Correlation + 0.694 × Centroid Lateral SaEn + 0.923 × Surface Area + 0.832 × Stretch Index + 0.536 × Team Stretch Index Rho
3	Multidirectional Synchrony	0.955 × Centroid Longitudinal Rho + 0.936 × Centroid Lateral Rho
4	Longitudinal Unpredictability	− 0.815 × Centroid Longitudinal Correlation + 0.694 × Centroid Longitudinal SaEn
5	Longitudinal Behaviour	0.694 × Centroid Longitudinal CV − 0.686 × Centroid Longitudinal Displacement
		Individual
6	Multidirectional and Spacing Synchrony	0.900 × Individual Stretch Index Rho + 0.900 × Individual Lateral Rho + 0.891 × Individual Longitudinal Rho
7	Unpredictability	0.845 × Individual Stretch Index SaEn + 0.839 × Individual Lateral SaEn + 0.747 × Individual Longitudinal SaEn +
8	Player Movement	− 0.926 × Individual Stretch Index + 0.771 × Individual Stretch Index CV + 0.741 × Individual Lateral Correlation
9	Player Positioning	0.806 × Individual Stretch Index Correlation + 0.656 × Individual Longitudinal Displacement

CV, Coefficient of Variation; SaEn, Sample Entropy; Rho, Cluster Phase.

7.5 Discussion

Until recently, tactical behaviour has been assessed using methods of notational analysis and/or coaches' subjective ratings of performance making it difficult to objectively assess performance acutely or longitudinally or to compare between different contexts.[26, 28] Alternatively, spatiotemporal behavioural analyses have recently provided objective measures for assessing tactical behaviour.[2, 6, 28, 107, 240] While many studies have attempted to describe tactical behaviour using spatiotemporal variables in team sports, this was the first to describe and dimensionally reduce an array of spatiotemporal variables in Australian Football to facilitate their practical application and interpretation. The derived principal components adequately represent different constructs whilst maintaining a large amount of the variability from the original data (Figure 7.1).[208] Embedded in an ecological dynamics framework, these components facilitate the interpretation of spatiotemporal behaviour patterns and subsequently allow practitioners and coaches to design and implement training that promotes specific spatiotemporal tactical behaviour.

At the macroscopic level of analysis, the constructs in equations 1-5 provide useful information regarding spatiotemporal behaviour that emerges collectively at the team level. Sum scores generated from the equations derived in this study describe patterns of behaviour which could be analysed with respect to performance outcomes. As equations were derived from values that captured behaviour across the entire match, resultant sum scores provide insights into behaviours that persist or are the most prevalent throughout the game. Higher *dispersive coordination* (equation 1) and *multidirectional synchrony* (equation 3) coupled with lower *lateral unpredictability and spacing* (equation 2) scores emerge when a team spends a significant proportion of the game defending. Based on contextually similar sports,[122, 129] defensive structures are often characterised by a compact shape coupled with synchronised and predictable collective behaviour. In defence, this resultant behaviour is deemed necessary to protect the team's goals from attacking perturbations. From a defensive standpoint, larger scores generated from higher CV values in dispersion may also indicate that the team defensively shadows offensive teams as they attempt to spread and use large areas of the field.

Conversely, lower *dispersive coordination* (equation 1) and *multidirectional synchrony* (equation 3) coupled with larger *lateral unpredictability and spacing* (equation 2) scores may indicate that a team have spent a large amount of time in attack. Similarly, insights adopted from similar sporting contexts[6, 28, 107] suggest that moving asynchronously and in an unpredictable manner, with a dispersed shape, may be necessary to effectively perturb defensive lines and create scoring opportunities by misaligning defending players. Additionally, larger *longitudinal behaviour* (equation 5) scores may further indicate the prevalence of attacking behaviour as higher scores may be a result of the team's frequent positioning in the attacking half coupled with greater end-to-end position variability as a result of spatial exploration looking for opportunities to score. This higher sum score may also reflect the ability of a team to secure repeat entries into the forward 50 metre arc (the attacking zone) and prevent the opposition team leaving their defensive half.

Furthermore, the team-derived sum scores may also reflect matches characterised by a large amount of disputed possession or that consisted of regular changes in possession, i.e., frequent changes from attack to defence and vice versa. For example, frequent changes from defence, or contested play, to attack may result in larger *lateral unpredictability and spacing* (equation 2) sum scores due to an absence of unidirectional movement synchrony in the side-to-side direction concurrently with a synchronised increase in dispersion. This collective increase in dispersion when transitioning from defence into attack has also been demonstrated in contextually similar sports[6, 28, 107] and provides favourable affordances over the initial movement of the ball or alignment with teammates. Similarly, match-play characterised by frequent transitions would likely reveal larger *longitudinal unpredictability* (equation 4) sum scores as lower unidirectional synchrony and predictability in the end-to-end direction is expected as teams move from attack to defence, or vice versa, attempting to re-organise with the change in possession. While sum score may indicate the prevalence of attacking, defending, or transitioning behaviour, caution should be taken when interpreting sum scores from the entirety of a match as they emerge due to unfavourable patterns of behaviour. For example, a team may spend a large portion of the match attacking yet may not disperse effectively or move erratically enough to perturb defensive lines. As a result, the sum scores would likely reflect that of a match spent defending. Deriving sum scores from specific phases of play, i.e., attack, defence or contested phases, would provide more detailed insight into the effectiveness of emergent defensive or attacking behaviour and may indeed enhance the validity of this type of analysis.

At the individual level, the assessment of sum scores may be useful when assessing longitudinal changes in performance or when comparing players in similar positions. Across a match, specific positions may demonstrate favourable or unfavourable characteristics that align with tactical guidelines. Based on contextually similar research,[122, 129] defenders would likely spend a large proportion of the match moving synchronously with surrounding teammates and in a predictable manner, positioning themselves furthest away from the team's centroid in the defensive half between the attacking team and the goals. As a result, key defenders may display superior *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) scores coupled with lower *unpredictability* (equation 7) and *player movement* (equation 8) scores. Unified movement is theorised to be important for resisting attacking perturbations and may also result from affordances provided by the movement of the ball and fellow teammates. Alternatively, defenders who disregard the movement of teammates and tactically choose to mimic opposing tackers who tend to move erratically, may present with lower *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) sum scores. Certain scores may also reveal differences in position specific tasks. For example, small defenders who attempt to win and transfer contested possession may demonstrate higher *player movement* (equation 8) scores as they attempt to evade opposition players when in possession or when providing a target for teammates.

Alternatively, also demonstrated in contextually similar sports,[6, 28, 107] attacking players may move asynchronously and unpredictably in an attempt to perturb defensive lines and create goal scoring opportunities. Attacking players would therefore likely reveal lower *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) scores coupled with larger *unpredictability* (equation 7) and *player movement* (equation 8) scores as they place themselves primarily in the forward half, probing for scoring opportunities. As with defenders, intra-position differences may be evident. For example, smaller forwards, positioned closer to the team's centroid, may favour the movement of teammates and the ball to guide movements resulting in larger *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) sum scores.

Finally, individual sum scores may be able to distinguish between player roles within specific positional groups. For example, wing midfield players may use information provided by ball movement and teammates to guide behaviour throughout a match, resulting in superior *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) sum scores. This behaviour is justified as occupying the lateral field corridors in a synchronised manner is the greatest destabilising factor of opponents' organisation during attacking phases, which is likely evident as critical transitional game periods are associated with changes in lateral distance between teams.[91] Conversely, inside midfielders may demonstrate lower scores across a match as they move erratically to win contested possession or move into free space to create passing opportunities to teammates.

Inside midfielders may also reveal higher *player movement* (equation 8) scores as they spend more time closer to the team's centre trying to win and subsequently transfer contested possession. In other contextually similar sports, the midfield is where transition play moves from defensive to offensive patterning and players disperse laterally to deal with the congestion of players, attempting to provide passing affordances for teammates in this area.[135]

The derived spatiotemporal metrics provide a method for coaches and practitioners to further understand tactical match-play behaviour exhibited by teams and individuals. While this is the first study to provide a simplified, novel method for analysing spatiotemporal behaviour in Australian Football, these metrics are yet to be investigated with respect to individual and team performance. Further, while principal components were derived from professional-level match-play over three-years, data was derived from one team only meaning the results may not be generalisable. Regardless, the results provide supporting data for performance analysts using GNSS technology to analyse games and could allow coaches to identify strengths and weaknesses in movement patterns and exploit these through the implementation of game tactics. Collectively, at the team level, the derived sum scores provide insights into behaviours that persist over the course of a game, particularly with reference to attack, defence, and disputed/contested possession. Individually, scores may provide insight into positional tasks/roles or reveal how players use surrounding information to guide behaviour. Whether at the individual or team level of analysis, the five team and four individual equations provide a detailed analysis of movement behaviour in a simplified manner.

7.6 Practical implications

- The simplified spatiotemporal metrics provide supporting data for performance analysts and practitioners currently using GNSS technology.
- Team-derived components provide insight into spatiotemporal behaviours that emerge and persist throughout the game. Resultant values can be analysed with respect to performance outcomes.
- Individual-derived metrics provide an objective appraisal of different player styles or roles. Additionally, position-specific sum scores may demonstrate favourable or unfavourable characteristics that align with tactical guidelines.
- This information may improve the integration of spatiotemporal data with physical, technical, and tactical metrics by reducing the complexity of the available information and allow coaching staff to develop training interventions representative of competition movement demands.

7.7 Conclusion

This study is the first to provide a simplified, novel method for assessing spatiotemporal behaviour in the context of Australian Football match-play. Both the team and individual metrics provided specific movement insights for coaches and practitioners. This information can consequentially guide training implementation, player development and enable comparisons between playing styles. Further, the current findings may provide a viable framework for analysis in other contextually similar sports.

7.8 Acknowledgements

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Chapter 8

Study Five: A holistic analysis of collective behaviour and team performance in Australian Football via structural equation modelling

As per the manuscript published in *Science and Medicine in Football:*

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Note: The referencing system used in this manuscript conforms to the style used in the remainder of the thesis. The citation numbers relate to the thesis reference list and are different to the published manuscript. Otherwise, this manuscript appears as published.

8.1 Abstract

Despite awareness of the importance of quantifying technical, tactical, and physical characteristics of match play, few studies have examined the structural relationship of these aspects in professional sport. Accordingly, this study concurrently examined these components in relation to quarter outcome (n = 272) in Australian Football. The study followed a retrospective longitudinal case study design where one teams' cooperative passing network, skill counts, physical loads, and spatiotemporal behaviours during official Australian Football League games were collected from a period spanning four seasons (2016-2019). A principal components analysis (PCA) and structural equation modelling were used to explore the structural relationships between components and examine the influence on quarter outcome as determined by the point differential (*quarter margin*). *Scoring opportunity* and *ball movement* had direct associations with *quarter margin,* while *unpredictability*, *uncontested behaviour* and *physical behaviour* did not. Negative associations between *uncontested behaviour* and *scoring opportunity* suggest that elevated high-pressure success and a lack of synchrony may positively influence *scoring opportunity*, a determinant of *quarter margin.* Further, negative associations between *physical behaviour* and *ball movement* suggest that with less physical work, a team's collective ability to transfer possession between teammates is facilitated, offering an interesting dichotomy between skill and physical demands of Australian Football. While hundreds of different metrics are available, the present study was the first to concurrently examine the influence of a variety of match play components on performance outcomes in Australian Football. These results may provide direction for coaches and practitioners when contemplating practice design, tactical strategies, or the development of behaviour through specific training exercises. Game plans and training drills that focus on optimising attacking and low-pressure ball movement coupled with high levels of mutual interaction between teammates may be beneficial for performance.

Key Words: Performance analysis; Network; Technical; Physical; Spatiotemporal; Structural equation model

8.2 Introduction

Australian Football (AF), like other invasion games such as field hockey, water polo, soccer, and basketball, is characterised by its 360-degree nature with the ability for players to distribute the ball in all directions. Players require superior physical abilities, technical skills and tactical strategies to cope with the ever-changing demands of the game.[7] Team success in AF is more than the sum of its parts with a culmination of the aforementioned variables with superior performance allowing teams to fulfil the main objective of the game, to score the most points through goal kicking. In these contexts, the scientific analysis of performance aims to integrate objective, reliable and relevant data to create knowledge, and translate this by designing learning opportunities so that key stakeholders can utilise this information to advance understanding of game behaviour, guide decisions, and subsequently improve future outcomes.[47, 241] Accordingly, applied research in this context has often adopted a reductionist approach, investigating these factors (each with a wide array of variables) in isolation to derive practical applications aimed at improving a team's performance.

In an effort to deepen the level of understanding of match performance, performance analysis has been utilised to subjectively audit and describe the behaviours of performers during different sub-phases of play, i.e., attack and defence, to provide additional information for practitioners.[26, 49] This has typically occurred through verbal descriptions of lived experiences or game observation.[27] While these processes may offer insight, such methods are often not sufficiently objective and are less systematic, relying on subjective impressions and procedural knowledge of expert performers, subsequently making it difficult to translate or compare findings in different contexts[28] as well as increase the likelihood of confirmation bias.[241] As these methods likely do not provide sufficient objectivity, new objective, systematic and open-minded approaches for gathering and interrogating data need to be explored in order to make it possible to assess performance in differing contexts.

In an attempt to objectively quantify the underpinnings of successful performance, analysts have often focused on identifying associated physiological demands such as workload, total distance covered or distances covered at different intensities as measured by a global navigation satellite system (GNSS).[10] For example, in AF, the physical element of the game is characterised by large volumes of running, partly due to the large oval shaped playing field, with players covering ~12-17km of distance and completing bouts of intermittent high-speed running coupled with frequent collisions and changes of direction.[1] Furthermore, through the assessment of discrete on-field actions such as the number of completed passes, time spent in possession of the ball, or the amount of tackles made, researchers have endeavoured to provide reliable technical descriptions of game demands as predictors of success.[17] In AF, skill count analyses have emphasised the importance of skill proficiency with players utilising a myriad of hand and foot skills for passing, scoring and gaining possession of the ball.[4] While the extensive information regarding the physical and technical actions is useful, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance.[7, 18, 21-23] This has also been demonstrated in other team invasion games.[242] The excessive emphasis placed on performance outcome measures in research contexts presents an underlying issue that primarily focuses on 'who did what, when' which fails to provide a meaningful understanding of the underlying factors of successful performance in complex team sports. An absence of detailed understanding exemplifies the need for a theoretical rationale that can provide insight into performance behaviours that may emerge over time.[24, 25] Additionally, the vast dimensions of analysis somewhat complicates their interpretation, which limits the practical relevance of the research.

With technological advancements, such as an increase in sensitivity and application of GNSS devices, in conjunction with analytical approaches such as spatiotemporal analysis and cooperative passing network analysis, practitioners are able to more precisely measure team behaviour and quantitatively model, infer and predict performance outcomes in team sports such as AF.[17] For example, by analysing passing sequences within a team, practitioners can map the relationship between different players during a game and reveal the local structure of organisation among players. This form of cooperative network analysis can provide additional information that captures the dynamic nature of team sport performance[48] and provide additional insight into factors influencing success.[2] Further, while scarcely examined in AF,[243] spatiotemporal analysis of collective variables such as team or positional-group displacement and dispersion and inter-player levels of synchronicity and predictability can provide additional information that helps capture the dynamic nature of team sport.[48] This approach has provided insight into the behaviour that characterises successful attacking and defensive phases of play in soccer[6, 107] as well as AF.[240, 244, 245] For example, one study utilising these metrics in AF demonstrated greater team dispersion during offensive phases compared to defensive and contested phases.[240] These higher values likely reveal players spreading the opposition's defensive players to create a greater effective playing space allowing easier passage towards the goals. In contrast, lower values of dispersion may indicate a defensive mechanism to contract rapidly if the opposition gained possession of the ball.[240] While these metrics provide objective insight into theoretical mechanisms influencing success, the concurrent examination of the structural relationships between these indicators and other behavioural components, i.e. network, skill, and physical behaviour, and performance is yet to be explored. Further, the utilisation of two 20-minute halves in a 15v15-match simulation drill, adopted in previous studies,[34] does not fully represent the collective behaviour exhibited by teams during competitive match-play due to the increase in relative space per player. Further research investigating these metrics in AF League (AFL) matches alongside other components of match-play may deepen the understanding of the influence of tactical behaviour on performance.

There is plethora of information available for sports scientists and practitioners regarding network, technical, physical, and spatiotemporal behaviour. Nonetheless, the complexity associated with the reporting of these methods, and the absence of a sound conceptual framework that can appropriately contextualise and describe behaviour, makes the application of this information difficult. Ecological dynamics has been considered as a viable framework for analysing and understanding individual team behaviour as it actively focuses on the performer-environment relationship, and may provide a basis for understanding performance in team sports such as AF.[29] In AF, task-constraints, such as field dimensions and passing rules, along with physical and informational constraints, such as player size and opposition player movements, provide perceptual information and boundaries that guide and govern behaviour and allows players to self-organise into stable states of coordination that enables the achievement of task goals.[29] Accordingly, as resultant behaviour is the result of the interaction between its constituent components, it is important to examine the influence of interactions and behaviour exhibited by, and between, players when analysing performance in team sports from an ecological dynamics perspective. Appropriate application of statistical techniques rationalised using an ecological dynamics approach makes it possible to assess and monitor coordinative behaviour that emerges within and between teams. Further, utilising dimensional reduction techniques may help simplify and elucidate the most appropriate metrics and allow the information generated to be more effectively reported back to key stakeholders.[220, 227, 235, 236, 243]

Investigating the interrelationship between cooperative networks and team spatiotemporal measures, alongside physical and technical data within an ecological dynamics framework, may provide insight into 'how' and 'why' successful behaviours in AF occur as opposed to just 'when' they occur.[26] While several studies in AF have revealed that technical and tactical constructs are more closely related to successful quarter outcomes when compared to physical performance measures,[31, 246] the adoption of an integrated approach to the reporting of physical and technical construct data has been suggested.[247, 248] Additionally, with the objective analysis of tactical performance, the inclusion of this information using an integrated approach may provide valuable insight as all these constructs are closely linked and do not occur in isolation (Figure 1). For example, in contextually similar sports such as soccer the physical demands appear to be associated with positional information, technical and tactical performance.[45, 108] While running demands have not been concomitantly assessed with tactical measures, team dispersion measures typically reduce in the second half (i.e., in offence players are less dispersed in the second than in the first half of a game), which could be attributed to the onset of fatigue in the second half of a game,[108] demonstrating the inter-relationship between the physical and tactical domains of performance in football. With diminished physical capacities, the ability of players to explore the whole width and length of field while trying to unbalance an opposing team is compromised.[108]The concurrent examination of a myriad of physical, technical, and tactical variables may help elucidate the role of certain variables in relation to performance and team success.

Team dispersion measures typically reduce in the second half (i.e. in offence players are less dispersed in the second than in the first half of a game), which could attributed to the onset of fatigue in the second half of a game,[108] demonstrating the inter-relationship between the physical and tactical domains of performance in football. With diminished physical capacities, the ability of players to explore the whole width and length of field while trying to unbalance an opposing team is compromised.[108]

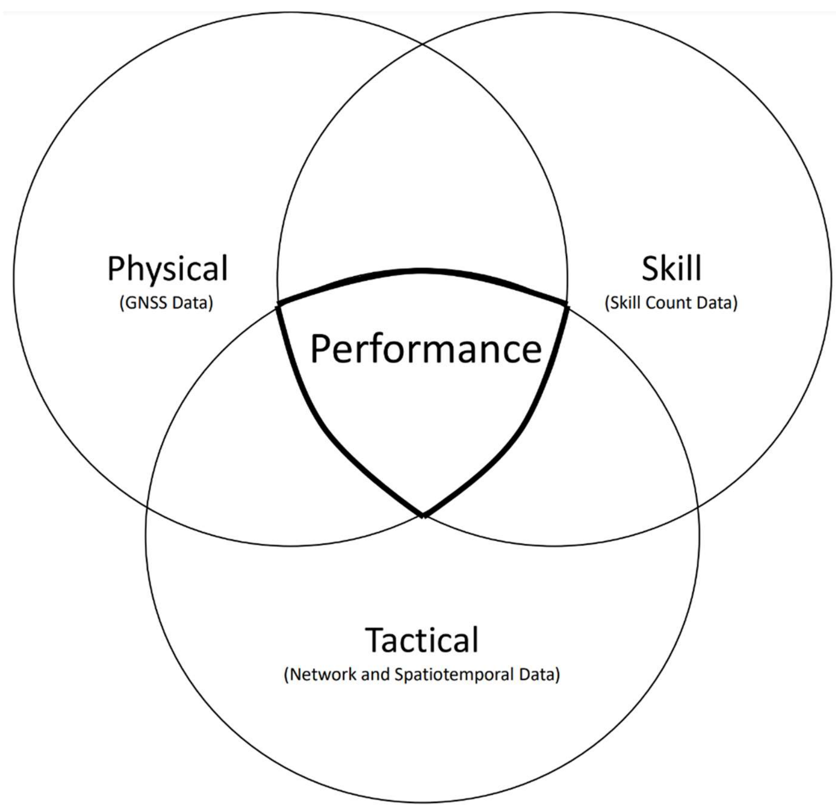

Figure 8.1: Integrated theoretical model of performance.

Due to the inter-relationships between physical, technical, and tactical characteristics the aim of the present study was to utilise aggregate metrics derived by Sheehan and colleagues[220, 235, 236, 243] to examine the relationships between these characteristics and performance as determined by match *quarter margin* (point differential) in AF. This theoretical model of performance was assessed through the use of a combined PCA and structural equation model as these techniques can reduce dimensionality and concurrently model relationships between each component and an outcome variable.[33] Based on existing literature, it was hypothesised that an interplay of physical, technical, spatiotemporal and network features would provide a detailed model of performance for AF with the latter three aspects contributing to a greater degree than the physical characteristics. Due to their inextricable link, it was also hypothesised that physical behaviour would exhibit an association with spatiotemporal behaviours while network characteristics would be associated with skill indicators.

8.3 Methods

Participants

56 male professional Australian Footballers (age: 24.8 ± 4.5 years; professional playing experience: 5.8 ± 4.3 years) from one AFL team were analysed over a four-year (2016-2019) period. Sixty-eight senior matches were used for analysis providing a sample of 272 quarters from the designated AFL team. This provided a sufficient sample size for the analysis as a ratio of 5-10 samples per expected free parameter in the model (27) is recommended.[249, 250] The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the Authors' academic institution.

Study Design

The study followed a retrospective longitudinal case study design where one team's passing interactions (cooperative network), skill counts, physical loads, and spatiotemporal behaviours during official AFL games were collected from a period spanning four seasons. Network,[220] skill,[235] physical,[236] and spatiotemporal[243] sum scores were subsequently derived according to the methods outlined by Sheehan and colleagues which have been used to provide insight into factors influencing behavioural outcomes in AFL matchplay.[244] A preliminary analysis was conducted using a PCA to explore relationships between these scores and reduce the number of individual and correlated variables for modelling with respect to an outcome variable. Structural equation modelling (SEM) was subsequently used to explore relationships between these newly derived component scores and to examine the influence of these components on quarter outcome as determined by point differential.

Data Collection

Network and Skill Analysis

Network indicators, derived from player interactions as determined through the distribution and receipt of kicks and handballs,[220] and skill counts were obtained from ChampionData® (supplementary Table 1), the official data provider to the AFL.[2] ChampionData® code all AFL matches for a variety of skill involvements[8] and are commonly used in AF research.[8, 23, 49] A selection of statistical indicators have been empirically reviewed, reporting a high level of reliability (ICC range = 0.947-1.000; RMSE range = 0.0–4.5).[251] Other reliability information provided about ChampionData® statistics states that “quantity-based statistics are logged at better than 99% accuracy”.[8] As stated, network[220] and skill[235] sum scores were generated using weightings derived by Sheehan and colleagues (Table 1).

Table 8.1: Network and skill sum score equations.

Network Variable[220]	Calculation
In-Degree Variability	0.925 × Team In Degree Node Variability + 0.925 × Team In Closeness Centrality Variability + 0.714 × Pagerank Centrality Variability + 0.613 × In Degree Pass variability
Out-Degree Variability	0.945 × Team Out Closeness Centrality Variability + 0.895 × Team Out Degree Node Variability + 0.626 × Out Degree Pass variability + 0.523 × Team Betweenness Centrality Variability
Connectedness	0.964 × Network Density - 0.949 × Team Betweenness Centrality + 0.939 × Team Out Closeness Centrality + 0.935 × Team In Closeness Centrality + 0.931 × Network Intensity
Skill Variables[235]	Calculation
High-Pressure Success	0.867 × Handball + 0.865 × Contested Possession + 0.844 × First Possession + 0.805 × Clearance + 0.781 × Hardball Get + 0.771 × Effective Handball + 0.629 × Ineffective Handball + 0.586 × Gather + 0.515 × Looseball Get + 0.455 × Tackle
Low-Pressure Success	0.922 × Uncontested Mark + 0.909 × Mark + 0.749 × Mark Play On + 0.727 × Short Kick + 0.677 × Effective Kick + 0.655 × Uncontested Possession + 0.563 × Kick
Attacking Ball Movement Ability	0.902 × Kick Inside 50 + 0.882 × Inside 50 + 0.620 × Long Kick + 0.416 × Ineffective Kick
Scoring Ability	0.853 × Shot at Goal + 0.837 × Inside 50 Result

Physical and Spatiotemporal Analysis

Data was collected via the use of GNSS units sampling at 10Hz (‘Optimeye S5’, Catapult Sports, Melbourne, Australia) which have shown to be suitably reliable at low-, high-, and very high-speed running intensities.[16] Further, variables pertaining to banded inertial movement analyses (IMA) and accelerations have also demonstrated suitable reliability.[229, 230] As stated, physical[236] and spatiotemporal[243] sum scores were generated using weightings derived by Sheehan and colleagues (Table 2).

Table 8.2: Physical and spatiotemporal sum score equations.

Physical[236]	Calculation
Low-Moderate Volume	0.869 × Velocity Band 3 Distance + 0.835 × Total Distance + 0.807 × Deceleration Band 1 Efforts + 0.805 × Acceleration Band 1 Efforts + 0.772 × Velocity Band 3 Efforts + 0.727 × Velocity Band 4 Efforts + 0.713 × Velocity Band 2 Distance + 0.652 × Velocity Band 4 Distance + 0.649 × Acceleration Band 1 Distance + 0.621 × Deceleration Band 2 Efforts + 0.605 × Deceleration Band 1 Distance + 0.560 × Acceleration Band 2 Efforts
High Speed Running	0.833 × Velocity Band 6 Distance + 0.830 × Velocity Band 6 Efforts + 0.823 × Velocity Band 5 Distance + 0.701 × Velocity Band 5 Efforts
Explosiveness	0.878 × Acceleration Band 3 Efforts + 0.858 × Acceleration Band 3 Distance + 0.823 × Acceleration Band 2 Distance
Change of Direction	0.899 × IMA Acceleration High + 0.885 × IMA Change of Direction Right High + 0.862 × IMA Change of Direction Left High + 0.738 × IMA Acceleration Medium + 0.712 × IMA Change of Direction Right Medium + 0.706 × IMA Change of Direction Left Medium + 0.526 × IMA Acceleration Low + 0.455 × IMA Change of Direction Right Low + 0.415 × IMA Change of Direction Left Low
Collisions/Impacts	0.740 × IMA Deceleration Medium + 0.654 × IMA Deceleration Low + 0.617 × IMA Jump Low + 0.607 × IMA Deceleration High
Spatiotemporal[252]	Calculation
Dispersive Coordination	− 0.923 × Stretch Index SaEn – 0.823 × Surface Area SaEn + 0.891 × Stretch Index CV + 0.684 × Surface Area CV + 0.850 × Team Stretch Index Correlation
Lateral Unpredictability and Spacing	− 0.933 × Centroid Lateral Correlation + 0.694 × Centroid Lateral SaEn + 0.923 × Surface Area + 0.832 × Stretch Index + 0.536 × Team Stretch Index Rho
Multidirectional Synchrony	0.955 × Centroid Longitudinal Rho + 0.936 × Centroid Lateral Rho
Longitudinal Unpredictability	− 0.815 × Centroid Longitudinal Correlation + 0.694 × Centroid Longitudinal SaEn
Longitudinal Behaviour	0.694 × Centroid Longitudinal CV − 0.686 × Centroid Longitudinal Displacement

Performance

Quarter margin, also known as point differential, was used as a performance outcome / dependent variable. This was calculated as the reference team's final quarter score, minus the oppositions final quarter score. This metric has previously been used in AF as a measure of performance.[31]

Statistical Analysis

Part I: Preliminary Analysis

PCA was used to reduce the number of characteristics related to network, skill, physical and spatiotemporal analyses by grouping characteristics together and providing fewer aggregate components for regression. A PCA has the ability to reduce the dimensionality of the data into a smaller set of variables whilst maintaining most of the variance in the original data set.[205, 206] As a result of PCA, no correlation exists between the principal components, but each contain their own highly correlated variables. This method ensures each component is uncorrelated and can be regressed together.[207] An exploratory PCA was executed using SPSS for Windows (Version 25)[253] where the aim was to determine a suitable number of components present in the 17 variables pertaining to cooperative network interactions, skill counts, physical, and spatiotemporal characteristics. Linear relationships were initially assessed using a correlation matrix while the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction.[253] All variables were initially included, upon which variables with communalities (relative importance for inclusion in the components) lower than 0.40 were excluded.[209] The PCA was subsequently re-run using only variables of significant importance. The number of principal components to be retained was determined using the scree plot which is a line plot of the derived factor eigenvalues.[222] The scree plot was assessed for a separation between factors with relatively large eigenvalues and those with similar eigenvalues. The components, consisting of their individually assigned variables and associated weightings, that occur before the break are assumed to be meaningful and are retained.[223] Outliers were also investigated for each variable via an outlier labelling rule which accounts for the sample size of the study. Accordingly, values that fell outside of the interquartile range multiplied by 2.2 were excluded.[254]

Part II: Structural Equation Modelling

Maximum likelihood estimation in SEM was used to investigate associations between a performance outcome (*quarter margin*), network, technical, physical, and spatiotemporal characteristics (Figure 2). SEM was used to model paths from *quarter margin* through the components. The components were tested by analysing associations between independent variables (principal components) and a dependent variable (*quarter margin*). To determine the appropriateness of the SEM model, the normed chi-square index (χ^2/df) was selected over the traditional chi-square statistic as this nearly always rejects the model when large samples are used[210] with indices below three representing a parsimonious fit.[211] The Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and standardised root mean square residual (SRMR) indices were also assessed with indices >0.90, <0.10, and <0.08, respectively, signifying an acceptable model fit.[212] Finally, due to the complexity of the model, the Parsimonious Normed Fit Index (PNFI) was also calculated with indices >0.50 representing a parsimonious fit.[211] Laavan[213] and PiecewiseSEM[214] statistical packages were used in RStudio to conduct the analysis. Direct effects were classified as either *small* = 0.10, *medium* = 0.30, or *Large* >0.50.[215]

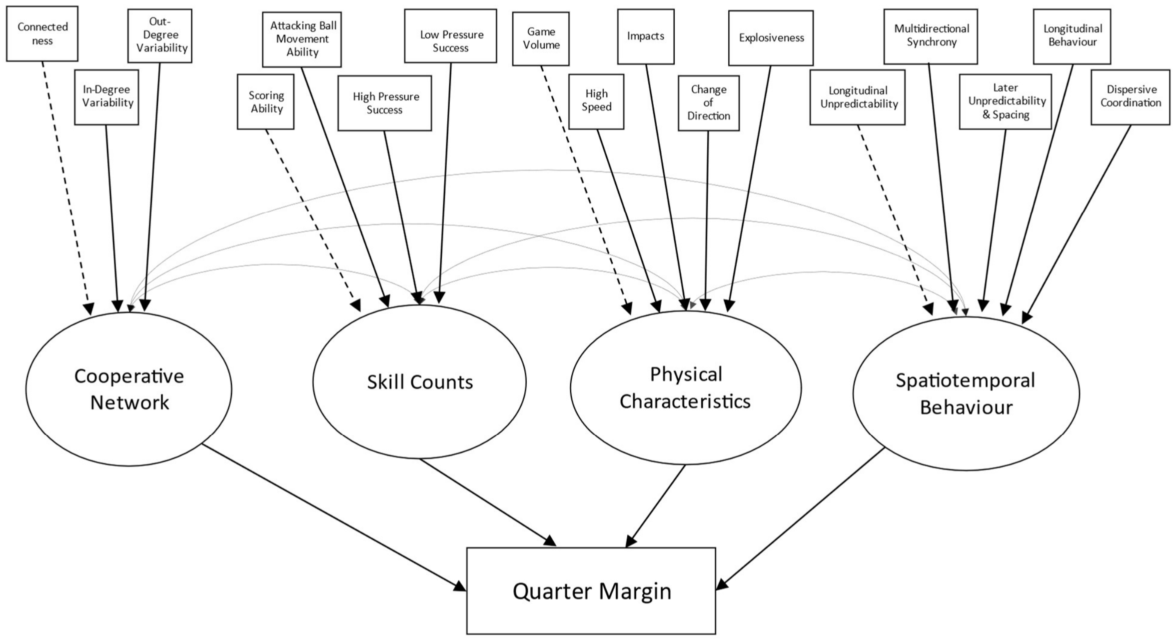

Figure 8.2: Example of an SEM model examining associations between a performance outcome (quarter margin) and performance components.

8.4 Results

Part I: Preliminary Analysis

Only one variable, out-degree variability, was excluded from the PCA due to communalities below 0.40. Outliers were detected with 19 quarters subsequently being removed. This subsequently left data from 253 quarters for inclusion. An examination of the KMO measure of sampling adequacy suggested that a considerable proportion of the variance that can be considered 'common variance' (KMO = 0.74). Additionally, Bartlett's test of sphericity was significant ($p < 0.001$).[253] Figure 3 reveals the total explained variance from the PCA. All variables were assigned to the component in which they had the strongest weighting. Resulting components (Table 3) were then entered into the SEM model (Part II).

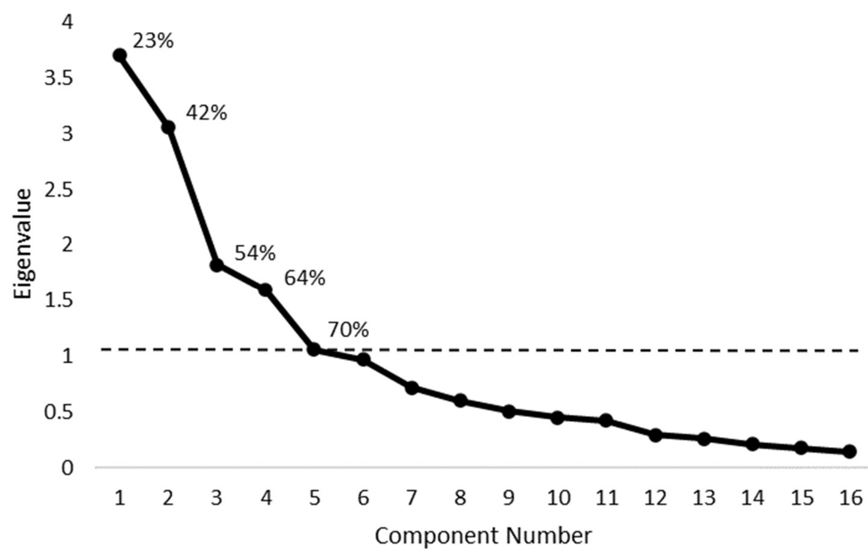

Figure 8.3: Scree plot for principal component analysis demonstrating the components, and the explained variance, that occur before the break and therefore deemed to be meaningful and are retained.

Table 8.3: Resultant constructs from principal components analysis.

Component/Construct	Variables
Physical Behaviour	Game Volume (.878) + Change of Direction (.846) + Impacts (.839) + Explosiveness (.700) + High Speed (.600)
Scoring opportunity	Attacking Ball Movement Ability (.913) + Scoring Ability (.908) + Longitudinal Behaviour (.858)
Ball Movement	Connectedness (.835) + Low Pressure Success (.807) - In Degree Variability (.679)
Unpredictability	Longitudinal Unpredictability (.831) + Lateral Unpredictability and Spacing (.726) - Dispersive Coordination (.697)
Uncontested Behaviour	Multidirectional Synchrony (.823) - High Pressure Success (.550)

Part II: Structural Equation Modelling

In the initial model, *Physical behaviour* (r = -.01), *scoring opportunity* (r = .59), *ball movement* (r = .20), *unpredictability* (r = -.08), and *uncontested behaviour* (r = -.05) were combined and loaded onto *quarter margin.* An initial model of performance failed to satisfy all model fit criterion suggesting an adequate model fit to the data: $\chi^2(105) = 377.734$; $p = 0.001$; $\chi^2/df = 3.597$; CFI = 0.858; RMSEA = 0.101; SRMR = 0.084; PNFI = 0.631. Accordingly, modification indices were utilised to refine the model, with largest indices added first, until an adequate model was fitted as per the model fit criteria: $\chi^2(101) = 283.282$; $p = 0.001$; $\chi^2/df = 2.698$; CFI = 0.905;

RMSEA = 0.084; SRMR = 0.080; PNFI = 0.641. Figure 4 demonstrates the final model of performance with *scoring opportunity* (r = .60), *ball movement* (r = .20), *unpredictability* (r = -.08), *uncontested behaviour* (r = -.03), and *physical behaviour* (r = -.00) combining and loading onto *quarter margin*.

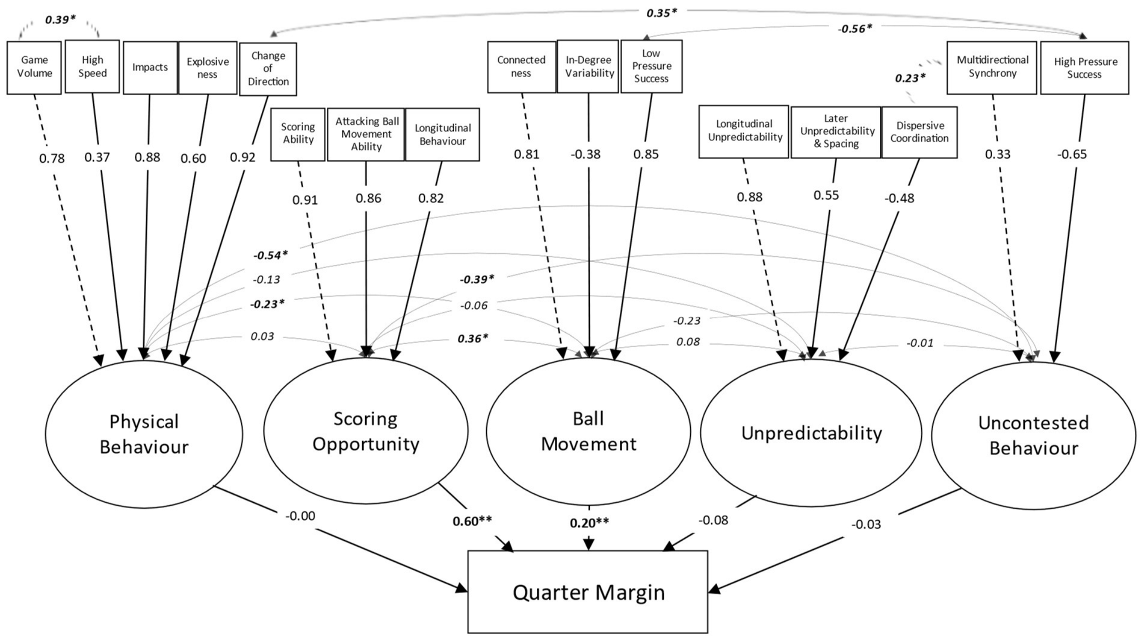

*Figure 8.4: Complete SEM model of performance visualising parameter estimates and fixed parameters (dashed line). *p < .05 for covariances; ** p < .05 for regression coefficients.*

8.5 Discussion

Hundreds of different metrics are available for performance analysts for reporting to key stakeholders, facilitating feedback to athletes and service the review and evaluation processed in AF.[241] However, only recently have these been objectively simplified with sum scores from analyses such as PCA representing different constructs of match play which simplify the interpretation of the available information.[236, 243] This is particularly important as the volume of data available to coaches, athletes and performance directors, who are often time-poor, continues to grow exponentially.[241] Despite recent studies delineating between different phases of play[244] and offering insight into factors influencing success using physical and spatiotemporal metrics,[245] the concurrent influence of all match play components, i.e. network, skill, physical and spatiotemporal, has scarcely been examined in team sport contexts and is yet to be investigated in an AF. Accordingly, the present study addressed this shortcoming providing insight into the influence of these components on performance outcomes (*quarter margin*) in professional AF. These results may subsequently provide direction for coaches and practitioners when contemplating training design focus or tactical strategies to be used during competitive games or the development of tactical behaviour through specific training exercises.

Scoring opportunity (r = .60) and *ball movement* (r = .20) were the only two components to have associations with *quarter margin* (figure 4). This was anticipated as the constituents of each of these components (table 1 and table 3) have previously been associated with successful performance in AF.[2, 19] Scoring ability (consisting of shots on goal and inside 50 results), attacking ball movement ability (calculated from inside 50s, long kicks, ineffective kicks) and longitudinal behaviour (being positioned inside the attacking half and showing greater variability in end-to-end displacement, therefore potentially exploring movement space for attacking opportunities), all positively weighted on *scoring opportunity.* Several of these aspects have previously been associated with successful performance outcomes likely due to their ability to contribute to scoring opportunities.[19, 34] Further, the association between ball movement and *quarter margin,* characterised by higher levels of low-pressure success (uncontested marks, marks, playing on from a mark, effective kicks, short kicks and kicks) and a superior passing network (delineated by a large amount of possession as measured by connectedness that is mutually shared by the majority of players (in-degree variability)) has also previously been associated with success.[2, 19, 255] This suggests that offensive strategies that are varied but frequently decentralised, with minimal reliance on key players and the majority of players being well-connected may be important for quarter success. Decentralised teams, where players do not solely rely on one or two key players, foster interdependence and encourage coordination and cooperation which are beneficial to a team's performance, as determined by match outcome.[168] Further, both of these constructs demonstrated a positive association with each other, emphasising the need to focus on these components in tandem when considering tactical strategies or training methodologies that will optimise performance.

Interestingly, *uncontested behaviour* (comprised of multidirectional synchrony and negatively weighted high-pressure success) did not reveal any influence on *quarter margin*. However, *uncontested behaviour* demonstrated a negative association with *scoring opportunity* which may indicate that elevated high-pressure success (negatively weighted on *uncontested behaviour*) and a lack of synchrony may positively influence *scoring opportunity*, a determinant of *quarter margin*. This negative association may have implications for increasing *scoring opportunity* as it has been suggested that moving asynchronously may help perturb opposition defensive formations which can help provide scoring opportunities.[6, 28, 107] Using this rationale and results from previous literature[34] it would be expected that *unpredictability* would also influence *scoring opportunity* or *quarter margin* in some capacity, however, this was not evident in the present study. It is therefore likely that this prior association is a result of contextual influences. For example, when higher *scoring opportunities* arise, opposition defensive efforts to prevent this may subsequently lead to chaotic movement or higher levels of contested behaviour (i.e., lower *uncontested behaviour*) in attempts to spoil/compete for possession. This rationale may also be more likely as previous lines of enquiry examining the influence of contested play skill indicators similar to the constituents that make up high-pressure success (e.g., handballs, contested possessions and tackles) failed to significantly contribute to models of success.[19]

As hypothesised, *physical behaviour* had a negligible influence on *quarter margin*. This may explain the discrepancies demonstrated in previous lines of enquiry looking to associate physical metrics with performance outcomes.[18, 21] However, their importance may not be completely discounted with negative associations emerging between this construct, *ball movement* and *uncontested behaviour* (Figure 4). Reducing movement, and subsequently *physical behaviour,* may be a result of attempts to synchronise and coordinate actions so that the team can function as a cohesive unit. This may make it easier to mutually interact with teammates and subsequently improve *ball movement.*[243] Alternatively, as per the theoretical relationship between *uncontested behaviour* and *scoring opportunity*, reductions in *physical behaviour* may be a by-product of contextual match factors rather than intentional action per se. For example, implementing low-pressure ball movement tactics and controlling possession (uncontested marks, uncontested possessions, short kicks) in a manner that the opposition team does not deem as threatening, may subsequently result in a reduction in *physical behaviour*. With minimal pressure being applied or pressure to compete, as required during contested phases of play or during a lead up to a scoring opportunity,[245] *physical behaviour* may remain reduced. Positive associations between change of direction scores and high-pressure success in the present study may also illuminate the physical demands of high-pressure or contested phases of play. This may also indicate that change of direction scores may have greater implications for performance in these phases than other physical metrics. Until recently, linear distances accumulated at different velocities have been a primary focus of research looking at performance outcomes, however, the current findings provide insight into an alternate component that may assert a stronger indirect influence on performance outcomes and suggest a focus for physical preparation.[49, 244, 245]

While the present study provides a comprehensive analysis encompassing multiple components of performance in an AF context, examination of these components at a more granular level, i.e., during successful and unsuccessful phases of play, may further clarify the influence of network, technical, physical, and spatiotemporal components on performance outcomes. Further, as team behaviour in a complex system is an outcome of the interaction between its constituents, it may be important to examine behaviours of, or between, individual players and positional groups when analysing performance. While the data was collected in the highly ecologically valid environment of professional football over a four-year period providing 253 quarters for analysis, only the reference team's behaviour were recorded, neglecting opposition behaviour. Accordingly, the results may not be generalisable to other teams or fully encapsulate the influence of these components. Further, final models will likely change as PCA results, those derived in part I of the analysis, may differ when conducted with different team data as this technique is capable of differentiating n team characteristics and playing styles in contextually similar sports such as soccer.[256] Future lines of enquiry should explore the possibility for collaborative projects subsequently providing a more complete picture of performance with behaviour from both teams assessed. Finally, the use of a PCA also presents some limitations. While PCAs are used for the sole purpose of dimension reduction in this paper, there may be discrepancies between the theoretical rationale for using a PCA and its practical application. While this method derives principal components that explain most of the variance in the original data, original granular variables may provide valuable insight. Further, the naming of these variables is subject to interpretation and demonstrates that a PCA may not be the sole means of dimensional reduction with other methods such as expert guided dimension reduction presenting as an option. Future studies may need to examine whether dimension reduction, or less-dimensional approaches (i.e., reducing performance down to a few separate metrics using expert guidance) offer the best approach to modelling most of the variance in complex behaviour. It is also worth noting that within this study, original principal components were not classified together. Regardless, the present study provides novel insights into the interplay of factors influencing quarter success. This provides coaches and practitioners with information that may help guide the decision-making process, provide actionable insights, develop tactical behaviours, or manipulate training environments to afford specific behavioural outcomes that optimise opportunities for performance success.[241]

8.6 Practical implications

- Skills associated with *scoring opportunity* and longitudinal team movement appear most relevant for directly assessing performance outcomes in professional AF. Training that focuses on positioning the team in the attacking half, varying movement in the end-to-end direction and optimising ball movement and possession inside the attacking 50m arc may be important for exploring the movement space and subsequently provide attacking opportunities.
- Coaches should consider game plans and training that foster low-pressure ball movement (uncontested marks, marks, playing on from a mark, effective kicks, short kicks, and kicks), positive outnumbers in offence (e.g., 12v10), and high levels of mutual interaction between players (e.g., limiting the number of times certain players can receive possession). This may promote decentralisation encouraging interdependence, coordination and cooperation and ultimately improving performance.
- Change of direction may be of greater relevance than other physical components in relation to successful match outcome. Furthermore, change of direction ability may be particularly important during contested passages of play and optimising high-pressure success and therefore should be considered when planning/reviewing training and drill designs.
- The theoretical approach and methodology utilised in this study provides a framework for sports scientists and coaches looking to explore the relationship between skilfulness, tactical, and physical behaviour in other contextually similar sports.

8.7 Conclusion

This was the first study to concurrently examine differences in network, technical, physical, and spatiotemporal characteristics with respect to quarter outcome in professional AF. *Scoring opportunity*, characterised by scoring ability, attacking ball movement behaviour and longitudinal behaviour, and *ball movement ability*, characterised by connectedness, negatively weighted in-degree, and low-pressure success, directly influenced *quarter margin.* These two components also revealed a positive association with each other implicating these components for performance success. While no direct relationship was established between *physical behaviour* or *uncontested behaviour* with *quarter margin*, these two components may elicit an indirect effect on performance. Furthermore, the association between change of direction and high-pressure success may have novel implications for athlete conditioning. It appears that the ability to promote superior levels of mutual interaction in an attacking manner, subsequently increasing *ball movement,* is beneficial for success. The findings from the present study provide novel insights for coaches and practitioners as well as subsequent implications for training and game plan design. Future research should examine the influence of individual and positional group behaviours, as well as opposition behaviours, on performance outcomes in different phases of play.

8.8 Acknowledgements

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8.9 Disclosure of interest

The authors report no conflict of interest.

Chapter 9

Study Six: An assessment of physical and spatiotemporal behaviour during different phases of match play in professional Australian Football

As per the manuscript published in the *Journal of Sports Sciences:*

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Note: The referencing system used in this manuscript conforms to the style used in the remainder of the thesis. The citation numbers relate to the thesis reference list and are different to the published manuscript. Otherwise, this manuscript appears as published.

9.1 Abstract

Despite advancements in the scale of data available for quantifying the physical and spatiotemporal characteristics of match play, there is an absence of research combining these aspects in professional sport. This study sought to differentiate between phases of play in professional Australian Football using novel physical and spatiotemporal metrics. Data was obtained from Australian Football League games to provide new insight into the specific characteristics of each phase of play. A retrospective cross-sectional design was utilised with team physical and spatiotemporal variables, measured via global navigation satellite system devices. A multinomial logistic regression was conducted to determine which physical and spatiotemporal measures were associated with each phase of play (contested play, defence, offence, set shot, goal reset, umpire stoppage). Addition of the predictors to a model that contained only the intercept significantly improved the fit between model and data with the logistic model correctly predicting phase of play for 63.7% of cases. This was the first study to concurrently examine differences in physical and spatiotemporal characteristics with respect to phase of play in an Australian Football context. Differences in duration, physical, and spatiotemporal properties were observed providing new insight for coaches and subsequently providing direction for conditioning and practice design.

Key Words: Performance analysis; Tactical analysis; Phase of Play; GPS; GNSS

9.2 Introduction

Australian Football is an intense, intermittent team sport where players require physical prowess to deal with the repeated high-speed running and collisions,[1] high levels of skill proficiency to utilise a myriad of hand and foot skills for passing, scoring and gaining possession of the ball.[4] Teams must also utilise a variety of tactical strategies that depend on the availability of team personnel, coaching philosophies, opposing team characteristics and environmental conditions during the match.[5, 6]Australian Football is a complex performance-environment sub-system where players and teams perceive opportunities for action which guide decision making and subsequent action. Perception of relevant information allows players to self-organise into functional states of coordination that subsequently allows the team to fulfil the main objective of the game, to score the most points through goal kicking.[29]

In this complex system, task-constraints such as field dimensions and passing rules, individual constraints such as players' action capabilities, and informational constraints such as opposition player movements, provide information and boundaries that govern individual and collective behaviour. Individually, players require superior technical skills, physical abilities and tactical strategies to be able to co-adapt to the dynamic nature of match play as well as cope with the ever-changing demands of the game from season to season.[7] In the past decade, applied research in this context has investigated these factors, each with a wide array of variables, to derive practical applications aimed at improving team performance. Through the analysis of games played in the Australian Football League (AFL), the assessment of discrete, technical, on-field actions such as frequency of kicks, handballs, possessions and marks[9] have contributed to models predicting performance outcomes.[7, 19, 22,

[31] Further, the physical characteristics of the game have been extensively quantified using microtechnology such as global navigation satellite system (GNSS) devices and accelerometers.[7] Currently in the AFL, all professional teams make use of this technology and its array of associated variables.[7, 9] Specifically, speed-based running indices, accelerometry data and estimates of metabolic power have led to several publications quantifying the physical components of Australian Football using a combination of these variables.[3, 11, 12]

In addition to physical metrics, researchers have utilised GNSS devices to derive novel spatiotemporal metrics and to understand the complexity of time-series data via measures such as entropy. Spatiotemporal analyses using these metrics can reveal synergistic and co-adaptive behaviours that emerge at an intra-team level, i.e. between players of the same team.[48] This includes measurement of the team's geospatial centre (centroid), average distance to this centroid (stretch index), dispersion of the outermost players (effective area), and the variability (coefficient of variation) and regularity (entropy) in these measures. However, examining each of these spatiotemporal metrics in isolation does not capture the dynamic nature of performance as elements that make up complex systems can be viewed as both independent and interacting.[257] It is therefore important to assess these components concurrently. Further, while technical, physical, and spatiotemporal components can provide a large amount of information to assess tactical strategies and describe the characteristics of match play, the sheer volume of information provided by a multitude of variables, along with the complexity of the outputs likely hinders its uptake by practitioners and researchers. However, recently several studies have attempted to increase the practicality of these methods by dimensionally reducing a multitude of characteristics into principal components.[220, 235, 236]

Across the entirety of a game, Australian Football match-play involves higher running volumes than any other team sport with players performing frequent intermittent bouts of high-speed running, accelerations, decelerations, changes of direction and frequent collisions with opposing players.[1, 13] While these lines of enquiry provided valuable insight into the physical characteristics of the game, and subsequently provided direction for conditioning and practice design, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance. Examining behaviour by summarising outputs over an entire game may fail to capture the variability in these metrics, as behaviour likely changes depending on varying contextual information such as the phase of play. This subsequently explains why it has been difficult to draw conclusions about the influence of certain physical characteristics on game success.[7, 18, 21-23] To address this, Gronow et al. compared time spent in four different speed zones when the reference team was in possession (offence) or without possession (defence).[36] This study demonstrated that in quarters won, there was less time spent >14km/hr and more time <14km/hr in offence and, in contrast, more time spent >14km/hr and less time <14km/hr in defence. The authors suggested that the ability to control the pace of the game by controlling possession, and subsequently creating more disposal options, may have attributed to the lower physical demands when in possession of the ball. However, this study was limited to the use of four physical variables, pertaining to linear velocities, which may fail to encapsulate all the physical requirements associated with Australian Football.[1, 13] Additionally, contested plays and stoppages were both neglected from physical analysis despite being considered important components of Australian Football match play.[37]

Attempts to overcome these limitations were addressed by Rennie et al. with the inclusion of an additional four physical variables (total distance, relative distance, accelerations and decelerations) and the examination of contested plays and stoppages.[37] Offensive and defensive phases were relatively similar across all measured physical characteristics with both demonstrating greater high-speed running demands over all other phases of play. The physical characteristics of stoppages were lower in all areas but this insight provided implications for the inclusion of match specific recovery cycles in training designs.[37] Lastly, with the inclusion of accelerometry data and the analysis of contested plays, these phases accumulated the most total distance, number of accelerations and number of decelerations, again providing phase-specific insight for practitioners by highlighting the change of direction demands and general unpredictability.[37] However, as the spatiotemporal movement behaviour of players was not objectively quantified, nor could it be inferred validly from linearly derived metrics that disregard player displacement over time, mechanisms underpinning greater observed accelerometry metrics can only be theorised. Further, despite acknowledging that all phases, including stoppages, involve important tactical elements, this component was not assessed using objective spatiotemporal measures to examine tactical behaviour. While the description of physical characteristics associated with each phase of play provided novel insight and highlighted the need for specificity when designing conditioning and training drills, the study was delimited to eight physical variables potentially neglecting other important physical characteristics associated with Australian Football match play.[1, 13]

Spatiotemporal analysis is yet to be extensively applied in Australian Football with only two studies utilising these measures during specific phases of play.[34, 35] These studies demonstrated greater values in length, width, and surface area during offensive phases comparative to defensive and contested phases.[34] It was suggested that greater values of dispersion may be indicative of players trying to spread the opposition defending players to create a greater effective playing space, which allows for an easier passage of the ball towards the goals. In contrast, lower values of dispersion may indicate a defensive mechanism to close down space quickly if the opposition gained possession of the ball.[34] While these measures provide some insights into potential tactical mechanisms that influence team success, its findings are limited by two 20-minute halves in a 15v15-match simulation drill, which may not fully represent actual competitive game play. Therefore, their relevance to understanding collective behaviour needs confirmation. Further, only a limited number of spatiotemporal metrics were used, and stoppage phases were not available in the analysis. More detailed information about strategies used by teams during stoppages is essential as players often need to quickly organise offensive and defensive structures or jostle for superior position to win the ball.[37] Further, while the aforementioned studies investigated collective team behaviour during a competitive match, research into collective behaviour throughout a season remains absent. Also, investigations that aim to use spatiotemporal metrics to classify phase of play are yet to be reported (in any invasion sport). Further research investigating these metrics in AFL matches with a broader array of metrics, across a wider range of phases of competitive match play, may improve the understanding of the influence of spatiotemporal behaviour on performance outcomes and provide greater detail for practitioners responsible for training design.

Previous research designs have primarily relied on a select number of physical or spatiotemporal variables, in isolation of one another, to analyse emergent behaviour in specific phases of play. This approach makes it difficult to delineate and interpret the relationship of these parameters with each phase of play and risks neglecting valuable information that may provide insight into emergent behaviour in this sporting context. Recent lines of enquiry have successfully reduced a large number of physical variables[236] and spatiotemporal variables whilst maintaining a large proportion of variance from the original dataset, facilitating their practical use and interpretability. Accordingly, to address current shortcomings in the literature, the present study incorporated these newly derived metrics to examine the influence of phase of play on physical and spatiotemporal movement behaviour. It was hypothesised that offensive and defensive phases would be characterised by higher physical sum scores, particularly low-moderate game volume and high speed. Due to their unpredictability, contested phases of play would be characterised by high explosiveness and change of direction, which would also contribute to higher lateral and longitudinal unpredictability. Finally, it was hypothesised that set shots, goal resets and umpire stoppages would yield the lowest physical scores and consequentially greater dispersive coordination and multidirectional synchrony.[6, 28, 107]

9.3 Methods

Participants

The study sample consisted of 35 male professional Australian Football players (age: 25.2 ± 3.9 years; playing experience: 5.7 ± 3.7 years) from one AFL team. Each participant played at least one game over one season. 17 senior matches from a regular season were used for analysis providing a sample of 9788 phases of play from the designated AFL team. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

Study Design

The study followed a retrospective cross-sectional design where one team's physical and spatiotemporal behaviour, as measured via GNSS technology during official AFL games, was collected from a period spanning one season. Subsequently, physical, and spatiotemporal measures were associated with each phase of play.

Data Collection

Data were collected via the use of GNSS units sampling at 10Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia) and recording data pertaining to the players latitudinal and longitudinal positioning. Following each match, video footage was manually coded for phases of offence, defence, contested play, umpire stoppage, set shot, and goal reset using SportsCode (SportsTec Limited, version 9.4.1, Warriewood, Australia). The operational definitions for these phases of play are described in table 9.1 in accordance with previous research.[37, 49]

Table 9.1: Operational definition for each phase of play coded during analysis.[37, 49]

Phase	Definition
Offence	The reference team has clear control of the ball via a hard ball get, a mark, handball, or an intercept during open play.
Defence	The opposition team has clear control of the ball via a hard ball get, a mark, handball, or an intercept during open play.
Contested Play	Neither team has clear control or possession of the ball due to tackling or opposition pressure. The ball is not secured via a mark or clean receive from a teammate.
Set Shot	Commences the moment a player marks the ball in a scoring position, executes the shot and the umpire indicates either a goal or behind. If an umpire requests a score review, the phase is defined as an umpire stoppage.
Goal Reset	Commences when the umpire signals a goal has been scored to the proceeding centre bounce.
Umpire Stoppage	Commences when the umpire signals a stoppage in play to indicate a ball up or boundary throw-in. Blood rules or stoppages due to injury were excluded from the analysis.

Spatiotemporal and Physical Variables

Data was collected from fifty senior matches were used for analysis providing a sample of 50 team files. Spatiotemporal variables were calculated from raw individual player latitudinal and longitudinal positional data via MATLAB software.[191] Table 9.2 identifies the team variables included for analysis, their description and method of calculation. These variables have been used in soccer and, to a lesser degree, Australian Football to quantify team and individual spatiotemporal movement behaviours.[100, 101, 107, 115, 130, 143, 194, 198] A principal components analysis was then conducted using SPSS for Windows (Version 25)[208] to determine whether common underlying constructs were present in the 18 team-derived spatiotemporal variables. This approach has been used previously and aims to reduce the dimensionality of spatiotemporal characteristics.[220, 235, 236] All variables were included in the analysis as all possessed communalities (relative importance for inclusion in the factor) greater than 0.4.[209, 232] Further, an examination of the KMO measure of sampling adequacy suggested that a considerable proportion of the variance in the dataset was associated with the underlying factors (KMO = 0.58). Bartlett's test of sphericity was also significant ($p<0.001$).[208] Scree plots were assessed for an inflection point between factors with relatively large eigenvalues and those with similar eigenvalues. The components that occur before the break are deemed meaningful and are retained.[223] Five components, accounting for 69% of the variance in the original dataset were subsequently used to derive factor loadings associated with each of the variables in the analysis. The factor loadings derived from physical variables by Sheehan et al. were used to represent the physical characteristics.[236] Physical and spatiotemporal sum scores were then generated from the raw data for each phase of play using factor loadings derived via principal component analyses (table 9.3).[236] Sum scores were then converted to z-scores and normalised to the same unit and magnitude, with a mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)) to facilitate interpretation of variables measured on different scales.[218]

Table 9.2: GNSS-derived spatiotemporal variables.

Variable	Description
Centroid: - Lateral Centroid - Longitudinal Centroid	The geometrical centre of a team.[100, 107] Calculated as the mean position ($\bar{x}$,$\bar{y}$) of all players on the field (x_n,y_n) and provides information on the global positioning of the team over time. Centroid measures provide lateral and longitudinal coordinates. Positive lateral values represent movements to the left of the field's centre and positive longitudinal values represent movements away from the field's centre towards the defensive end respective to the attacking direction.
- Surface Area	The total space covered by a team and calculated as the area within the convex hull.[113] It is calculated using MATLAB's *convhull* function which returns an index array of the outermost players at a given time.[191] The polygonal area can then be calculated using MATLAB's *areaint* function which calculates the spherical surface area of the polygon specified by the convex hull input vectors (*x,y*) Larger values indicate greater total field coverage but ignores player distribution.
- Stretch Index	The dispersion and contraction of the team in relation to the team centroid.[194] It is calculated using the mean of the distances between each player (x_n,y_n) and the centroid of the team ($\bar{x}$,$\bar{y}$) at a given time. Larger values signify that players, on average, are further away from the team centroid.
Coefficient of Variation (CV): - Surface Area CV - Stretch Index CV - Lateral CV - Longitudinal CV	A form of linear analysis that uses the standard deviation and mean to quantify the overall variability of the team's spatiotemporal characteristics during specific time periods. Lower values represent lower overall variability in the selected measure.[101]
Pairwise Correlations: - Stretch Index Correlation - Lateral Correlation - Longitudinal Correlation	Assesses the synchronicity of players. Can be calculated using MATLAB's *corrcoef* function (pairwise option) to correlate the time-series of displacement (x_i,y_i) and stretch index measures of player *i* with the time-series of the team's centroid ($\bar{x}$,$\bar{y}$) and stretch index, respectively. For the team-derived value, scores of each player were averaged to provide an indication of the level of synchronicity for the team for both displacement and dispersion. Values closer to one signify that players within the team, on average, demonstrate similar movements for the event period.[115, 130, 198]
Sample Entropy (SaEn): - Surface Area SaEn	A non-linear measure of variability that provides an indication as to the regularity/predictability of behaviour. Calculated using *Sample Entropy* from MATLAB's File Exchange[238] and is defined as the negative natural logarithm for conditional properties that a series of data points a certain distance apart, *m*, would repeat

- Stretch Index SaEn, - Lateral SaEn - Longitudinal SaEn	itself at $m+1$.[195, 196] Given a time series $t(n) = t(1), t(2), \ldots, t(n)$ with *n* number of data points, a sequence of *m*-length vectors is formed. Comparisons are then made against each *m*-length vector within the time series. Vectors are considered alike if the tail or head of the vector fall within a certain tolerance level as determined by $r \times s$.[101] The sum of the total number of like vectors is then divided by $n - m + 1$ and is equal to *B*. Additionally, *A* is equal to the subset of *B* that also matched for $m+1$. Sample entropy is then calculated: $$SampEn = -ln\frac{A}{B}$$ A time series with similar distances between data points would result in a lower sample entropy value and large differences would result in greater sample entropy values. Thus, sample entropy can determine the predictability and regularity of a time series, with values closer to zero signifying greater regularity/predictability.[195, 196] Based on previous literature, the parameters to be used in this study are *m* = 2 and *r* = 0.2.[133, 195, 197]
Cluster Phase (Rho): - Stretch Index Rho - Lateral Rho - Longitudinal Rho	Quantifies the collective spatiotemporal phase synchronisation, of oscillatory movement components (e.g. players' movement displacement trajectories) in a single collective parameter.[201] Calculated in MATLAB using Richardson's (2020) *ClusterPhase* toolbox.[239] Prior to calculation, differential values (for each data point *i* in the time-series, the *i-1th* data point was subtracted) were created to determine whether players were synchronising their movements in the same direction, regardless of whether they were in line with each other. Values closer to 1 signify perfect synchrony.[143]

Table 9.3: Resultant equations derived by Sheehan and colleagues.[236]

Component	Calculation	Interpretation
Physical		
Low-Moderate Volume	0.869 × Velocity Band 3 Distance + 0.835 × Total Distance + 0.807 × Deceleration Band 1 Efforts + 0.805 × Acceleration Band 1 Efforts + 0.772 × Velocity Band 3 Efforts + 0.727 × Velocity Band 4 Efforts + 0.713 × Velocity Band 2 Distance + 0.652 × Velocity Band 4 Distance + 0.649 × Acceleration Band 1 Distance + 0.621 × Deceleration Band 2 Efforts + 0.605 × Deceleration Band 1 Distance + 0.560 × Acceleration Band 2 Efforts	Superior scores indicate the accumulation of physical match load at low-moderate intensities.
High Speed Running	0.833 × Velocity Band 6 Distance + 0.830 × Velocity Band 6 Efforts + 0.823 × Velocity Band 5 Distance + 0.701 × Velocity Band 5 Efforts	Superior scores indicate that greater volume of high speed metrics have been accumulated.
Explosiveness	0.878 × Acceleration Band 3 Efforts + 0.858 × Acceleration Band 3 Distance + 0.823 × Acceleration Band 2 Distance	Superior scores reflect acceleration capability and an ability to rapidly change velocity.
Change of Direction	0.899 × IMA Acceleration High + 0.885 × IMA Change of Direction Right High + 0.862 × IMA Change of Direction Left High + 0.738 × IMA Acceleration Medium + 0.712 × IMA Change of Direction Right Medium + 0.706 × IMA Change of Direction Left Medium + 0.526 × IMA Acceleration Low + 0.455 × IMA Change of Direction Right Low + 0.415 × IMA Change of Direction Left Low	Superior scores reflect high intensity and frequent changes in direction.
Collisions/Impacts	0.740 × IMA Deceleration Medium + 0.654 × IMA Deceleration Low + 0.617 × IMA Jump Low + 0.607 × IMA Deceleration High	Superior scores indicate a higher number of collisions or impacts accumulated.
Spatiotemporal		

Dispersive Coordination	− 0.923 × Stretch Index SaEn – 0.823 × Surface Area SaEn + 0.891 × Stretch Index CV + 0.684 × Surface Area CV + 0.850 × Team Stretch Index Correlation	Superior scores indicate that players are dispersing in a varied but unison manner.
Lateral Unpredictability and Spacing	− 0.933 × Centroid Lateral Correlation + 0.694 × Centroid Lateral SaEn + 0.923 × Surface Area + 0.832 × Stretch Index + 0.536 × Team Stretch Index Rho	Superior scores indicate that the team is moving in an unpredictable manner in the side-to-side direction with a shape that is largely dispersed.
Multidirectional Synchrony	0.955 × Centroid Longitudinal Rho + 0.936 × Centroid Lateral Rho	Superior scores indicate that the change in player displacement in the end-to-end and side-to-side direction relative to the team is in-phase.
Longitudinal Unpredictability	− 0.815 × Centroid Longitudinal Correlation + 0.694 × Centroid Longitudinal SaEn	Superior scores be indicative of unpredictable behaviour and a lack of coordination in the end-to-end direction.
Longitudinal Behaviour	0.694 × Centroid Longitudinal CV − 0.686 × Centroid Longitudinal Displacement	Superior scores indicate greater range of displacement in the end-to-end direction with positioning in the reference teams' forward attacking half.

IMA, Inertial movement analysis; CV, Coefficient of Variation; SaEn, Sample Entropy; Rho, Cluster Phase.

Statistical Analysis

A multinomial logistic regression was executed using SPSS for Windows (Version 25)[208] to determine which physical and spatiotemporal measures (Table 9.3) were associated with each phase of play. A main effects model was produced with phase of play as the dependent variable and duration, physical and spatiotemporal variables as covariates. Contested plays were selected as the reference group as this was the most common phase of play. Statistical significance threshold was set at $p < 0.05$. Further, the AIC, Nagelkerke R^2, F and p values of the specified model were used to determine whether multinomial regression yielded a superior data fit than a null model or a model with no independent variables. Further, odds ratios (OR) and their confidence intervals (CI), and the percentage of correct classification were also utilised to provide insight into the results. Only phases with a duration of two seconds or more were included in the analysis as this is believed to be the minimum timescale required for interpersonal coordination to emerge in the context of team sports.[179] Outliers were also investigated for each variable via an outlier labelling rule of the interquartile range multiplied by 2.2.[254] Outliers identified via this rule were then investigated manually to determine potential causes and assess whether they were realistic values or produced by measurement or other error.

9.4 Results

Outliers were detected, however, investigation revealed that these were realistic values and not errors. A select number of phases containing extreme values were visually assessed to see if values were realistic. Further, there were a large number of them (n; 31% of total observations) which can likely be attributed to the inclusion of threshold variables such as high-speed running which have a relatively small median and IQR. Addition of the independent variables to a model that contained only the intercept significantly improved the fit between model and data (AIC for the null model and specified model was 29031.9 and 16448.7, respectively, χ^2 (55, N = 9339) = 12693, Nagelkerke R^2 = .78, $p < .001$). Using the logistic model to predict phase of play based on physical and spatiotemporal characteristics resulted in 63.7% correct classification (table 9.5). As shown in Table 9.4 and Figure 9.1, significant unique contributions were made by duration, game volume, high speed, explosiveness, change of direction, collisions/impacts, dispersive coordination, and multidirectional synchrony. With contested plays as the reference group, each predictor has five parameters, one associated with membership in each of the respective phases of play rather than the contested phase of play. Further, the OR and associated 95% Cis are shown in Figure 9.1.

Table 9.4: Predictors' Unique Contributions in the Multinomial Logistic Regression.

Predictor	χ^2	Degrees of freedom	p
Duration	3954.83	5	< .001
Game Volume	908.99	5	< .001
High Speed	60.99	5	< .001
Explosiveness	266.99	5	< .001
Change of Direction	682.74	5	< .001
Collisions/Impacts	330.50	5	< .001
Dispersive Coordination	37.77	5	< .001
Lateral Unpredictability and Spacing	3.64	5	.602
Multidirectional Synchrony	16.11	5	.007
Longitudinal Unpredictability	4.67	5	.458
Longitudinal Behaviour	4.36	5	.499

χ^2 = amount by which -2 log likelihood increases when predictor is removed from the full model

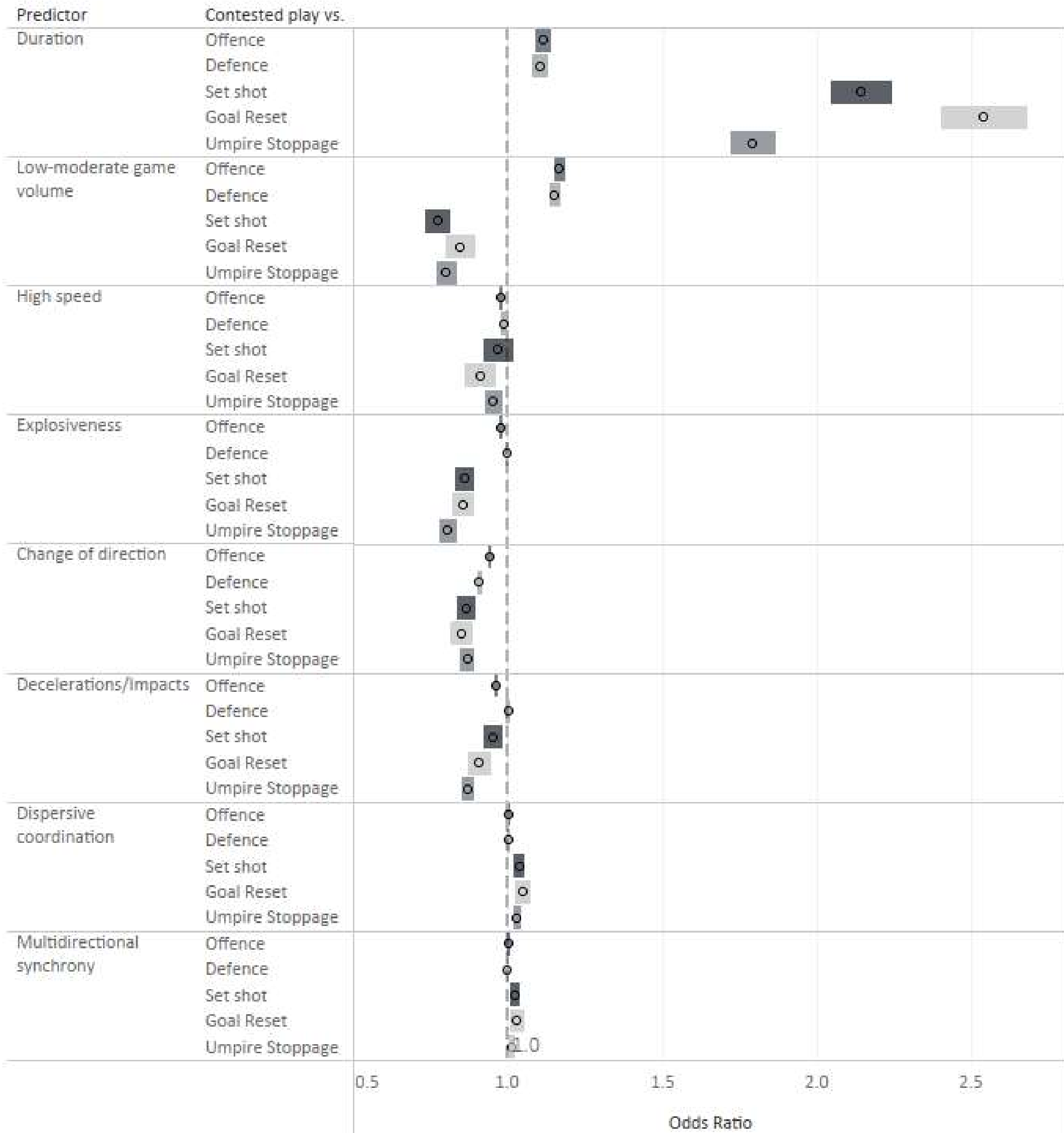

Figure 9.1: Visual representation of the odds ratios and 95% confidence intervals demonstrating the likelihood of classification and contrasting Contested Plays with each of the other phases.

Table 9.5: Classification table.

	Predicted						
Observed	Contested Play	Defence	Offence	Set Shot	Goal Reset	Umpire Stoppage	**Percent Correct**
Contested Play	2909	182	168	0	0	26	88.6%
Defence	872	593	483	13	4	50	29.4%
Offence	862	384	746	13	2	49	36.3%
Set Shot	4	5	7	258	34	76	67.2%
Goal Reset	0	1	2	28	310	1	90.6%
Umpire Stoppage	44	18	34	13	17	1130	90.0%
Overall Percentage	50.2%	12.2%	15.4%	3.5%	3.9%	14.3%	63.7%

9.5 Discussion

Dedicated statistical providers (e.g., ChampionData), advances in microtechnology and novel statistical approaches have provided a large volume of information for advancing performance analysis in sport over the past decade. While a plethora of data is available for quantifying the technical, physical, and spatiotemporal characteristics of match play, only recently have these been objectively simplified for practical implementation in AFL games with surrogate sum scores representing different constructs of the game (Table 9.2) and easing the interpretation of available information. In the present study, it was evident that the different phases of play in professional Australian Football yielded different physical and spatiotemporal characteristics, providing unique insight into match-play. Further, the ability of simplified novel metrics to adequately delineate and predict different phases of play may assist in describing and interpreting the differences in collective team behaviour in AFL. Understanding the cooperative behaviours in specific phases of play can enable coaches to assess the appropriateness of their training tasks with respect to these.

The results from the present study align with previous findings with set shots, goal resets and umpire stoppages being characterised by lower physical output.[49] The present study demonstrated markedly lower physical output for these phases of play over offensive, defensive, and contested phases for low-moderate game volume, explosiveness and change of direction. However, while these phases may not be characterised by their physicality, novel spatiotemporal metrics indicate they can be characterised by superior dispersive coordination and multidirectional synchrony over offensive, defensive and contested phases of play (reference group). This may be due to their markedly lower physical demands as well as longer durations with longer timescales potentially affording greater opportunities to for players to coordinate and synchronise behaviours with one another.[179] Despite limited discernible differences from a spatiotemporal perspective (Figure 9.1), subtle difference may still exist between set shots, umpire stoppages and goal resets. For example, physical characteristics specific to each phase of play may still provide valuable insight with set shots revealing stronger associations with explosiveness and decelerations/impacts over umpire stoppages. Fellow teammates moving to afford the ball carrier a better goal scoring position during this phase may explain the heightened physical output. Rapid changes in velocity and movement, captured in explosiveness sum scores, may be a result of teammates trying to break away from their defensive counterpart or move into free space.

With contested phases of play as the reference group, the smaller ORs demonstrated by all other phases, particularly offence, set shots, goal resets and umpire stoppages, demonstrates that change of direction, explosiveness and decelerations/impacts characterise contested phases of play (Figure 9.1). This may be a result of unpredictable movements throughout this phase, trying to evade defenders in congested passages of play, attempts to follow unpredictable movements of the ball, or bump off opposing players to gain an advantage over opponents competing for the ball. Additionally, stronger links with high speed may be a result of players using higher velocities to get to the ball first or place themselves in a position to receive possession from a fellow player. While previous findings also demonstrated that contested play involves a greater number of accelerations and decelerations than other phases due to the erratic, unpredictable movement of players,[37] these metrics relied on linear changes in velocity neglecting side to side movements. Further, no spatiotemporal metrics were incorporated in these studies to further elaborate on this finding. In the present study, lower values of dispersive coordination and, to a lesser degree, multidirectional synchrony, in each phase increased the likelihood being classified as a contested phase. This potentially validates previous theories. Additionally, the shorter duration of this phase may also contribute to lower values of dispersive coordination and multidirectional synchrony insufficient time may be available for players to co-adapt to one another and coordinate movement behaviours.[179]

As observed in previous investigations,[37] offensive and defensive phases shared similar physical and spatiotemporal characteristics. This similarity may be a result of defensive strategy with players mirroring the movements/patterns of the opposition team in offence. Higher low-moderate game volume increases the likelihood of a phase being classified as defence or offence which is likely due to the offensive aim of the game, to advance the ball up the field to score, and the defensive aim to prevent this. While phases were not examined with reference to matches won or lost, the increased odds of being classified as a defensive phase over an offensive phase with reference to high speed values aligns with previous findings.[36] As previously suggested, the ability to control the pace of the game by controlling possession, and subsequently creating more disposals may have contributed to lower high speed scores in offence while alternatively, high speed in defence may be a result of trying to shut down offensive passages of play.[36] Further, the increased likelihood of being classified as a defensive phase with increased decelerations/impacts may be a result of the need to tackle or bump opposition players in an attempt to gain possession while conversely in offence the aim is to avoid defenders whilst trying to move the ball up the field. Furthermore, in offence, superior change of direction may help advance the ball up the field and be of greater importance than high speed in offence with sudden changes in direction helping players evade defenders or misalign counterpart defenders to provide passing opportunities for teammates. Interestingly, while the current model produced a 63.7% correct prediction rate, the classification rates for each phase were varied, with erroneous classifications being most prevalent for offensive and defensive phases, each commonly being classified as one another or as contested phases of play. Incorporating team-based measures may have reduced the sensitivity of classifying each phase of play as while some phases of play may incorporate every player, other phases may require only 'a few key players'. Future investigations that include separate machine learning models, account for additional features, or analyse behaviour at the individual level with only involved ‘key players’ may provide additional insight. However, it is also possible that offensive and defensive phases would appear similar due to the adaptation the defending to and attacking team’s collective behaviour. Additionally, the inclusion of set shots, goal resets and umpire stoppages may have also reduced the sensitivity of the model with such stark differences, specifically from a physical perspective, present between these phases and offensive, defensive, and contested phases of play.

While all physical components aided in the delineation of some phases of play, dispersive coordination and multidirectional synchrony were the only spatiotemporal characteristics to contribute to the model. While spatiotemporal differences, specifically pertaining to values of dispersion, have been demonstrated in other lines of enquiry,[34] lateral unpredictability and spacing (partly derived using measures of dispersion) did not significantly contribute to the model. However, previous studies demonstrating differences in dispersion utilised a non-representative design incorporating a 15v15 format on a full-sized field which may have failed to account for the relative space per player.[34] Lower player numbers competing on larger fields affords more relative space per player and may have exacerbated the differences demonstrated between offensive and defensive phases of play. The increase in relative space may have made it easier for the offensive team to disperse and explore passing/scoring opportunities while concurrently forcing the defending team to contract towards their defensive half in an attempt to minimise scoring opportunities.[119] Other contextually similar sports have revealed similar patterns by manipulating player numbers and field size to alter the relative space per player.[101, 119] Also of interest, longitudinal behaviour, which incorporates the teams displacement, did not contribute significantly to the model or help differentiate between offensive and defensive phases of play. Since offensive and defensive phases of play in Australian Football are often short (~12 seconds on average in our sample), this may not provide enough time for players to flood certain parts of the field when a turnover occurs (i.e., flood the defensive half when a turnover in offence occurs). Further, this may not be the most efficient method due to the size of the field or may also reflect tactical strategies of players to remain on their opposition counterpart or hold their position/zone in case another turnover occurs. As the present study only analysed aggregated measures of phases, this may have limited the ability of these spatiotemporal measures to classify different team behaviours in AFL. For example, the current approach may have neglected behaviour that emerges over longer timescales or the capacity for a team to transition from one phase of play rapidly and successfully to another, i.e., lower physical scores coupled with higher synchrony during umpire stoppages to higher physical scores and lower synchrony during offensive phases which may be of importance for team success. Future research should examine these transitions in greater depth along with their association with performance outcomes.

Despite these methodological considerations, the present study showcases an ecologically valid approach to the analysis of physical and spatiotemporal variables in a cohort of professional athletes. As hypothesised, offensive and defensive phases presented with greater low-moderate volume, defensive phases revealed stronger affiliations with decelerations/impacts and contested plays demonstrated superior explosiveness and change of direction likely leading to lower values of synchrony and coordination. Interestingly, contested phases of play were strongly associated with high-speed metrics which may be due to players trying to be first to the ball or place themselves in a position to receive possession. As expected, likely due to their lower physical characteristics, set shots, goal resets and umpire stoppages demonstrated greater dispersive coordination and multidirectional synchrony than other phases. While this paper focused on detailing cooperative team behaviour in different phases of play, additional research that implements different machine learning models and features could determine whether individual phases of play can be more accurately classified. Regardless, while data was only collected from one team and therefore may not be generalisable to the rest of the competition, the current findings have implications for technical, tactical, and conditioning drill design in a range of team sports including, but not limited to Australian Football.

9.6 Practical implications

- Certain phases of match-play in professional Australian Football were associated with physical and spatiotemporal sum scores and may be useful to interpret differences in team behaviours in these phases of play.

- The timescale of each phase of play is an important consideration for training design as the manipulation of practice drills to afford more/less time in each phase of play may challenge players with respect to their physical requirements, synchrony, and coordination. For example, extending the duration or time allowed to achieve a task outcome, such as kicking a goal during a small-sided game may allow more time for players to self-organise into a stable pattern of behaviour that allows the achievement of that task outcome. Alternatively, reducing task time may challenge players to form these patterns of behaviour at a faster rate.

- This study was the first to examine the change of direction characteristics of each phase of play. This variable may be of greater importance than high speed in offensive phases of play providing novel insight for conditioning drill design and influence values of coordination and synchrony.

- Contrary to previous findings, phases of play involving set shots appear to have an important physical component revealing heightened associations with explosiveness and decelerations/impacts. Drills that require a teammate to rapidly breakaway from a defensive counterpart in a set shot simulation may help replicate this component.

9.7 Conclusion

This was the first study to concurrently examine differences in physical and spatiotemporal characteristics with respect to phase of play in the context of professional Australian Football. Low-moderate game volume, high speed, explosiveness, change of direction, decelerations/impacts, dispersive coordination, and multidirectional synchrony were able to delineate between the different phases of play, providing novel insight for coaches and practitioners and subsequently providing direction for conditioning and training design. Future research should further delineate the importance of each of these components by examining phase of play with reference to matches won and lost as well as incorporating skill indicators.

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Chapter 10

Study Seven: Collective Behaviours Influencing Phase of Play Success in Australian Football

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10.1 Abstract

Despite advancements in the scale of data available for quantifying the physical and spatiotemporal characteristics of match play, few studies combine these aspects in professional sport. This study related physical and spatiotemporal metrics of match play to behaviours associated with successful outcomes across various phases of play. A retrospective cross-sectional design was utilised with team physical and spatiotemporal variables obtained from competitive Australian Football League games via global navigation satellite system devices. A binomial generalised mixed effects regression model was used to estimate the effects of phase duration, physical and spatiotemporal variables on the probability of a successful outcome in different phases of play (contested play, defence, offence, set shot, goal reset, umpire stoppage). The addition of fixed effects, namely *duration*, *low-moderate volume*, *high speed running*, *explosiveness*, *change of direction*, *impacts*, *dispersive coordination*, *lateral unpredictability and spacing*, *multidirectional synchrony*, *longitudinal unpredictability*, and *longitudinal behaviour*, to a model that contained only the random intercept were significantly improved between model and data for offensive, defensive, and contested phases of play only. This was the first study to concurrently examine differences in physical and spatiotemporal characteristics with respect to successful outcomes in different phases of play. The results provide novel insight for coaches and may provide direction for conditioning, practice, and game plan design.

Key Words: Performance analysis; Tactical analysis; Team Sport; GPS; GNSS

10.2 Introduction

Australian Football is an 18 versus 18 (with 4 substitutions on each team) contact sport played on an oval shaped field. From an ecological dynamics perspective, Australian Football is a complex performer-environment subsystem where players and teams use information embedded within their performance environment to guide their actions and decision making. Information-rich environments consisting of teammates, opposition players, line markings, umpires, etc., afford opportunities for players to self-organise and coordinate behaviour in a way that allows the team to achieve the main objective of the game, to score the most points through goal-kicking.[29] To adequately achieve task goals while satisfying constraints, players require skilled behaviour, physical abilities and tactical strategies to co-adapt to the dynamic nature of match play as well as cope with the ever-changing demands of the game from season to season.[7] As a result, a thorough understanding of the complex interactions between the individual within their performance environment and the task at hand is required to capture the complexity of Australian Football performance.

Performance analysis in professional Australian Football has progressively evolved over the last 40 years and has proven to be integral for understanding the different constituents of match play allowing practitioners to adequately capture the complexity of Australian Football by quantifying these components.[1] Analysis of these constituents has included the assessment of discrete, technical, on-field actions such as frequency of kicks, handballs, possessions and marks,[9] which have been able to contribute to models predicting performance outcomes.[7, 19, 22, 31] Additionally the physical activity profiles associated the game have been extensively quantified using microtechnology such as global navigation satellite system (GNSS) devices and accelerometers.[7] Further, with recent technological advancements, including the increase in sensitivity and application of GNSS devices and the accessibility of novel statistical approaches, it is possible to objectively measure and quantify collective team movement (spatiotemporal characteristics) providing insight into tactical strategies and behaviours. Spatiotemporal analysis using these metrics can be undertaken to identify synergistic and co-adaptive behaviours that emerge on an intra-team level, i.e. between players of the same team.[48]

The technical, physical, and tactical areas of analysis have provided guidance and direction for coaches and practitioners when it comes to the analysis of match performance and development of representative training tasks. In the past decade, applied research in Australian Football has investigated these factors, each with a wide array of variables, to derive practical applications aimed at improving a team's performance. Currently in the Australian Football League (AFL), the pinnacle of Australian Football, all professional teams evaluate the external physical loads of game play using GNSS technology which are capable of providing a wide array of associated variables e.g. total distance, average speed, high-speed running, and acceleration characteristics.[7] As a result, the external physical loads of the game have been documented extensively.[7, 18, 21-23] Across the course of a match, players accumulate higher running volumes than any other team invasion sport whilst completing frequent intermittent bouts of high-speed running, accelerations, decelerations, changes of direction and frequent collisions with opposing players.[1, 13] While microtechnology data have provided valuable information regarding the external physical loads associated with match play, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance.[22, 31] For example, when examining differences in quarters won and lost, one study associated lower physical output for quarters that were won,[31] while conversely another failed to identify any relationship between physically derived metrics and quarter outcome.[22] Discrepancies may arise as these studies may have failed to fully account for the physical requirements of match play through the selection of only a few GNSS derived variables. Further, examining behaviour across the entirety of a match, or a quarter, instead of smaller periods across the match such as a specific phase of play, may fail to fully account for the complexity of the sport or be specific enough to delineate the influence of physical components on match success.[36]

In an attempt to capture the complexity of Australian Football, Gronow and colleagues compared the amount of time spent in four different speed zones when the reference team was in offence or defence over the length of a quarter.[36] The results may explain previous discrepancies with contrasting behaviour demonstrated in offence and defence. For example, in quarters won, more time was spent below 14km/hr in offence and less time at speeds greater than 14km/hr while in defence more time was spent at speeds greater than 14km/hr and less time below 14km/hr. The authors suggested that the ability to control the pace of the game through the control of possession, and subsequent creation of more disposal options, may have attributed to the lower physical activity profiles associated with offensive plays.[36] Results from this line of enquiry highlight the importance of examining specific phases of play as this may provide greater insight than analysing behaviour over the course of a quarter or match. Theoretically, across the course of a game an equivalent amount of time spent attacking and defending may reveal minimal differences in physical output when comparing wins and losses as both these phases appear to elicit conflicting physical demands. While this study provided further insight for practitioners into the physical activity profiles associated with offensive and defensive phases of play and the association with quarter success, this study was limited to the use of four physical variables, pertaining to linear velocities, which may fail to encapsulate all the external physical components associated with Australian Football.[1, 13] Additionally, contested plays and stoppages were both neglected from physical analysis despite being considered important components of Australian Football match play. Inclusion of these phases may further clarify the influence of physical output during specific match periods on quarter or game outcomes.[37]

The aforementioned limitations were addressed to some extent by Rennie and colleagues who assessed four additional physical variables (total distance, relative distance, accelerations and decelerations) during all phases including stoppages and contested phases of play [37]. As expected, there were differences across all phases of play with stoppages demonstrating markedly lower physical output in all areas providing implications for the inclusion of match specific recovery cycles in training designs.[37] While offensive and defensive phases were relatively similar across all variables, players accumulated more high speed running volume over all other phases. The inclusion of accelerometry data also offered novel insight into the physical activity profiles associated with contested phases with this passage of play accumulating more total distance, number of accelerations and number of decelerations than all other phases potentially reflecting the change of direction demands and unpredictable nature of game play during contested phases of play.[37] However, as player geospatial positioning was not objectively assessed in the analysis, reasons for the greater observed accelerometry metrics can only be theorised. Only recently have the validity of these claims been supported with contested phases demonstrating lower values of synchrony and coordination. Additionally, while the description of physical activity profiles associated with each phase of play provided novel insight, the study was delimited to eight physical variables using a reductionist approach, potentially neglecting other important physical load metrics associated with Australian Football match play.[1, 13] Further, these characteristics were not concurrently assessed with respect to performance success such as quarter or match success.

To-date, only one paper has examined the spatiotemporal differences between phases of match play with respect to wins and losses in Australian Football. Incorporating spatiotemporal metrics, greater values in length, width, and surface area were observed during offensive phases comparative to defensive and contested phases.[240] This increase in dispersion may be indicative of players trying to spread the opposition defending players to create a greater effective playing space, which allows for an easier passage of the ball towards the goals to provide scoring opportunities. Alternatively, the lower values of dispersion may be indicative of a collective team movement to close down space and prevent the opposition team from maintaining or transferring possession.[240] While these measures provide some insights into potential tactical mechanisms that influence team success, only a limited number of spatiotemporal metrics were utilised limiting the analysis of tactical behaviour. Incorporating variables that can measure the dynamic properties of spatiotemporal metrics, such as how they change and persist over time are crucial in describing the dynamic nature of match play. Therefore, the inclusion of variables such as such variability,[101] synchrony[201] or predictability,[102] obtained from time series of spatiotemporal measures, may offer new insights into the tactical behaviour of Australian Football teams during competitive match play. Further, despite the important tactical elements associated with stoppage phases, these phases were neglected from the analysis. Information pertaining to this phase may still be of interest as often players need to quickly organise offensive and defensive structures and jostle for superior position to win the ball.[37] Finally, the study sample incorporated two 20-minute halves in a 15 versus 15 match simulation drill, and therefore the representativeness of the collective behaviour exhibited by teams during competitive match play is questionable. While this provides a foundational understanding, further research investigating these metrics in AFL matches with a broader array of spatiotemporal measures, including variables capturing the dynamics of tactical behaviour may enhance the understanding of the influence of spatiotemporal tactical behaviour on performance outcomes. This may subsequently provide useful applications for representative training design that incorporates physical and tactical behaviours reflective of match-play.

While technological advancements in GNSS technology and the accessibility of statistical techniques that can more readily capture the complexities of performance have drastically increased the amount of available information to quantify match characteristics, this has concurrently convoluted existing findings and made variable selection for performance analysis an arduous task. With many physical and spatiotemporal metrics available for practitioners, as demonstrated, study designs have only incorporated a select number of variables which may fail to encapsulate the full complexity of the game and lead to existing discrepancies in the literature. A viable option for overcoming this issue is to dimensionally reduce the large number of available variables using statistical procedures such as a principal component analysis in conjunction with domain expertise. These dimension reduction methods have no real pedigree in performance analysis science, but principal component analysis and exploratory or confirmatory factor analysis have been used extensively in other research areas such as the development and analysis of psychological questionnaires.[258] Recent lines of enquiry have successfully reduced a large number of physical variables[236] and spatiotemporal variables[243] whilst maintaining a large proportion of variance from the original dataset, facilitating their practical use and interpretability. This approach allows analysts to practically examine the different constituents of match play whilst minimising the risk of omitting important information. However, these metrics are yet to be examined in Australian Football with respect to performance outcomes.

Accordingly, this study used the physical (*low-moderate volume*, *high speed*, *explosiveness*, *change of direction* and *collisions/impacts*)[236] and spatiotemporal (*dispersive coordination, lateral unpredictability and spacing, multidirectional synchrony*, *longitudinal unpredictability* and *longitudinal behaviour*)[243] metrics derived by Sheehan and colleagues to examine behaviours associated with successful phase outcomes across the various phases of play (Table 10.1). It was hypothesised that successful offensive phases would reveal lower values than unsuccessful phases in all physical metrics as well as decreased *multidirectional synchrony* and increased *lateral unpredictability and spacing*, *longitudinal unpredictability* and *longitudinal behaviour.* Comparatively, successful defensive phases would exhibit higher physical demands than unsuccessful phases along with superior scores of *multidirectional synchrony* coupled with lower scores in all other spatiotemporal variables. Further, in contested phases, due to their unpredictable nature, it was expected that higher *low-moderate game volume*, *change of direction* and *collisions/impact* scores along with greater *lateral unpredictability and spacing*, *longitudinal unpredictability* and lower *multidirectional synchrony* would align with successful outcomes. Due to their relatively lower physical demands and predictable nature, set shots, goal resets and umpire stoppages were hypothesised to present lower *lateral unpredictability and spacing*, *longitudinal unpredictability* and superior *multidirectional synchrony* in phases with a successful outcome due to an enhanced ability to coordinate movements and self-organise.

Table 10.1: Operational definition for each phase of play coded during analysis with definitions of successful outcomes for each phase of play as determined by coaching staff.

Phase	Definition
Offence	The reference team has clear control of the ball via a hard ball get, a mark, handball, or an intercept during open play. A turnover from penalty, infringement or behind also constitutes a change in possession. <u>Successful phases</u> lead to an entry inside the attacking 50 arc (inside 50) or a scoring opportunity (set shot or a goal or behind scored in general play).
Defence	The opposition team has clear control of the ball via a hard ball get, a mark, handball, or an intercept during open play. A turnover from penalty, infringement or behind also constitutes a change in possession. <u>Successful</u> phases lead to a direct turnover (interception) or a contested play/umpire stoppage further away from its origin in the attacking direction, i.e., further away from the defending goal.
Contested Play	Neither team has clear control or possession of the ball due to tackling or opposition pressure. The ball is not secured via a mark or clean receive from a teammate. <u>Successful phases</u> lead to possession of the ball, i.e., precedes an offensive phase.
Goal Reset	Includes the duration between the umpire signalling a goal has been scored to the proceeding centre bounce. <u>Successful phases</u> precede a contested play with a successful outcome.
Umpire Stoppage	The umpire signals a stoppage in play to indicate a ball up, boundary throw-in. Blood rules or stoppages due to injury were excluded from the analysis. <u>Successful phases</u> precede a contested play with a successful outcome.
Set Shot	Commences the moment a player marks the ball in a scoring position, executes the shot and the umpire indicates either a goal or behind. If an umpire requests a score review, the phase is defined as an umpire stoppage. <u>Successful phases</u> that occur in a quarter that is won.

10.3 Materials and Methods

Participants

The study sample consisted of 35 male professional Australian Football players (age: 25.2 ± 3.9 years; playing experience: 5.7 ± 3.7 years) from one AFL team. 17 senior matches from one season (2018) provided 9788 observations (phases of play) from one designated AFL team. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

Study Design

The study followed a retrospective cross-sectional design where one team's physical and spatiotemporal behaviours, as measured via GNSS technology during official AFL games was collected from a period spanning one season.

Data Collection

Data pertaining to the players' latitudinal and longitudinal positioning were collected via the use of GNSS units sampling at 10Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia). Following each match, video footage was manually coded for phases of offence, defence, contested play, umpire stoppage, set shot, and goal reset using SportsCode (SportsTec Limited, Warriewood, Australia). The operational definitions for these phases of play are described in Table 10.1 in accordance with previous research.[37, 49] Successful phase outcomes were also manually coded and are also defined in Table 10.1. These definitions were derived, and agreed upon, from discussions with the coaching group at the football club. Spatiotemporal variables were calculated from raw individual player latitudinal and longitudinal positional data via MATLAB software using methods previously outlined by Sheehan et al..[191, 243] Physical and spatiotemporal sum scores were then generated from the raw data for each phase of play using factor loadings previously derived via principal component analyses (Table 10.2).[236, 243] Sum scores were then converted to z-scores and normalised to the same unit and magnitude, with a mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)) to facilitate interpretation of variables measured on different scales.[259]

Table 10.2: Physical and spatiotemporal equations derived by Sheehan and colleagues.[236, 243]

Component	Calculation	Description
Physical		
Low-Moderate Volume	0.869 × Velocity Band 3 Distance + 0.835 × Total Distance + 0.807 × Deceleration Band 1 Efforts + 0.805 × Acceleration Band 1 Efforts + 0.772 × Velocity Band 3 Efforts + 0.727 × Velocity Band 4 Efforts + 0.713 × Velocity Band 2 Distance + 0.652 × Velocity Band 4 Distance + 0.649 × Acceleration Band 1 Distance + 0.621 × Deceleration Band 2 Efforts + 0.605 × Deceleration Band 1 Distance + 0.560 × Acceleration Band 2 Efforts	Superior scores indicate the accumulation of physical match load at low-moderate intensities.
High Speed Running	0.833 × Velocity Band 6 Distance + 0.830 × Velocity Band 6 Efforts + 0.823 × Velocity Band 5 Distance + 0.701 × Velocity Band 5 Efforts	Superior scores indicate that greater volume of high-speed metrics have been accumulated.
Explosiveness	0.878 × Acceleration Band 3 Efforts + 0.858 × Acceleration Band 3 Distance + 0.823 × Acceleration Band 2 Distance	Superior scores reflect acceleration capability and an ability to rapidly change velocity.
Change of Direction	0.899 × IMA Acceleration High + 0.885 × IMA Change of Direction Right High + 0.862 × IMA Change of Direction Left High + 0.738 × IMA Acceleration Medium + 0.712 × IMA Change of Direction Right Medium + 0.706 × IMA Change of Direction Left Medium + 0.526 × IMA Acceleration Low + 0.455 × IMA Change of Direction Right Low + 0.415 × IMA Change of Direction Left Low	Superior scores reflect high intensity and frequent changes in direction.
Collisions/Impacts	0.740 × IMA Deceleration Medium + 0.654 × IMA Deceleration Low + 0.617 × IMA Jump Low + 0.607 × IMA Deceleration High	Superior scores may indicate a higher number of collisions or impacts accumulated.
Spatiotemporal		
Dispersive Coordination	– 0.923 × Stretch Index SaEn – 0.823 × Surface Area SaEn + 0.891 × Stretch Index CV + 0.684 × Surface Area CV + 0.850 × Team Stretch Index Correlation	Superior scores may indicate that players are dispersing in a varied but unison manner.
Lateral Unpredictability and Spacing	– 0.933 × Centroid Lateral Correlation + 0.694 × Centroid Lateral SaEn + 0.923 × Surface Area + 0.832 × Stretch Index + 0.536 × Team Stretch Index Rho	Superior scores may indicate that the team is moving in an unpredictable manner in the side-to-side direction with a shape that is largely dispersed.
Multidirectional Synchrony	0.955 × Centroid Longitudinal Rho + 0.936 × Centroid Lateral Rho	Superior scores may indicate that the change in player displacement in the end-

		to-end and side-to-side direction relative to the team is in-phase.
Longitudinal Unpredictability	− 0.815 × Centroid Longitudinal Correlation + 0.694 × Centroid Longitudinal SaEn	Superior scores may be indicative of unpredictable behaviour and a lack of coordination in the end-to-end direction.
Longitudinal Behaviour	0.694 × Centroid Longitudinal CV − 0.686 × Centroid Longitudinal Displacement	Superior scores may indicate greater range of displacement in the end-to-end direction with positioning in the reference teams' forward attacking half.

IMA, Inertial movement analysis; CV, Coefficient of Variation; SaEn, Sample Entropy; Rho, Cluster Phase.

Statistical Analysis

For offensive and defensive periods, only phases with a duration of 12 seconds or more were included in the analysis as this is believed to be the minimum timescale required for stable patterns of interpersonal coordination to emerge in the context of team sports.[179] Due to their unpredictable nature, a lower threshold was adopted for contested plays with phases spanning three seconds or more being included.[179] All set shot, umpire stoppage and goal reset phases were included, regardless of their duration. Outliers were also investigated for each variable via an outlier labelling rule of the interquartile range multiplied by 2.2.[254] Outliers identified via this rule were then investigated manually to determine potential causes and assess whether they were realistic values or produced by measurement or other error. Due to the inherent variability in behaviour that exists between matches, a binomial Generalised Mixed Effects Regression model was used to estimate the associations between phase duration, physical and spatiotemporal variables (table 10.2) and the probability of a successful outcome in different phases of play. The competition round was included as a random effect while physical and spatiotemporal sum scores along with duration were added as fixed effects. Duration was not included as a fixed effect in umpire stoppages, goal resets or set shots as time spent in these phases of play are not necessarily in the players' control. Model outputs (odds ratios and their confidence intervals), Aikaike Information Criterion (AIC) and pseudo 'variance explained' (R^2) values were calculated to assess model goodness-of-fit. Goodness-of-fit was interpreted using Cohen's recommendations (r^2: 0.02 = *weak*, 0.13 = *moderate*, 0.26 = *substantial*).[260] All statistical analyses were conducted using the lme4 [216] package in R statistical software [190] with significance values set at $p<0.05$.

Results

Outliers were detected, however, investigation revealed that these were realistic values rather than measurement errors. A select number of phases containing extreme values were visually assessed to determine whether values were realistic. Further, there were a large number of labelled outliers (n; 31% of total observations) which can likely be attributed to the inclusion of threshold variables such as *high-speed* running which have a relatively small median and IQR. The addition of fixed effects to a model that contained only the random intercept significantly improved the model fit for offensive, defensive, and contested phases of play but not for the other phases of play. Table 10.3 demonstrates the AIC for the null model and the specified model for each phase of play along with associated chi-square and p-values. Marginal r^2 values (indicating explained variance from fixed effects only) and conditional r^2 (indicating explained variance from both fixed and random effects) are also included in Table 10.3. Further, the odds ratios (OR) and associated 95% confidence intervals are demonstrated in Figure 10.1.

Table 10.3: Model properties for each individual phase.

Model	AIC random effect only	AIC fixed and random effects	(χ^2)	df	p-value	Marginal r^2	Conditional r^2
Offence	1218.4	1038.8	201.6	11	< .001	.28	.28
Defence	1122.3	1069.3	75.0	11	< .001	.13	.13
Contested Play	3771.6	3749.2	44.4	11	< .001	.02	.02
Set Shot For	247.0	252.2	14.7	10	.142	.10	.30
Set Shot Against	234.0	243.2	10.7	10	.378	.07	.36
Umpire Stoppage	1622.5	1627.9	14.5	10	.150	.02	.02
Goal Reset	478.10	486.4	11.8	10	.300	.12	.12

χ^2 = chi-squared value; df = Model degrees of freedom

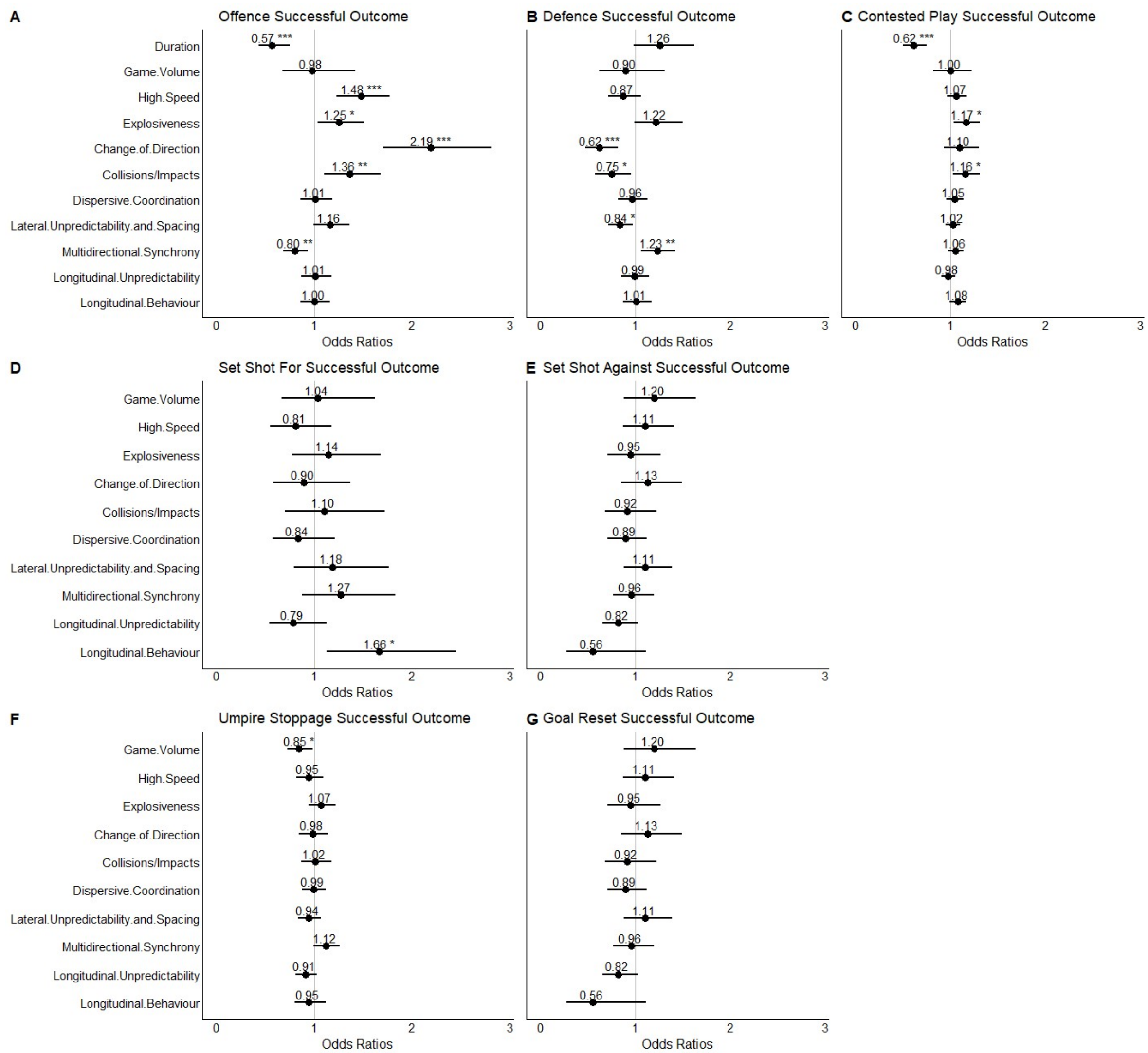

*Figure 10.1: Odds ratios and 95% confidence intervals demonstrating the likelihood of a successful outcome in each respective phase of play. Note: *< 0.05, **< 0.01, *** < 0.001.*

10.4 Discussion

While a plethora of physical and spatiotemporal data is available for performance analysis in Australian Football, only recently have these been objectively simplified with sum scores representing different constructs of Australian Football match play subsequently easing the interpretation of the available information.[236, 243] Despite these surrogate measures successfully delineating different phases of play and providing unique insights into match-play,[244] the influence of these metrics on performance outcomes was yet to be explored. Accordingly, the present study addressed this shortcoming providing insight into behavioural movement characteristics associated with successful outcomes in each phase of play. These results may subsequently provide direction for coaches and practitioners when contemplating tactical strategies to be used during competitive games or developing tactical behaviour through specific training exercises.

Reduced *duration* accompanied by superior physical output, as defined by *high speed, change of direction* and *collisions/impacts*, and reduced *multidirectional synchrony* and, to a lesser degree, *lateral unpredictability and spacing*, contributed substantially to a model predicting successful offensive phase outcomes. As demonstrated in contextually similar sports such as soccer, the ability of attacking players to move quickly and unpredictably may assist in providing scoring opportunities.[28] This behaviour may help create misalignments with opposing defenders subsequently perturbing defensive formations or providing opportunities to get into free space to receive possession from teammates inside the forward 50 arc.[28] Alternatively, these movement behaviours may emerge as a result of a direct style of play with attackers quickly playing on from marked possessions in an attempt to sufficiently perturb defensive lines as it does not provide the defending team with enough time to modify their synergistic behaviours relative to the ball or the attacking team's movements.[122] The use of a refined definition of offensive success in the present study may explain why the current study's findings contradict those of Gronow et al. who revealed that lower physical output at higher speeds was associated with quarter success, implicating the use of slower playing style and controlled possession.[36] However, only examining phases of play with reference to quarter success may be limiting as favourable behaviours leading to specific positive outcomes such as a scoring opportunity may be negated or diluted across the timespan of a quarter. In contrast, the findings from the present study indicate a direct style of play or intense, asynchronous movement patterns that can effectively perturb defensive formations. Coaches and practitioners may be able to facilitate or afford these behaviours in a training setting using small sided games with more relative space per player (larger field sizes or lower player numbers) as this has shown to promote this style of behaviour in other contextually similar sports.[85] For example, utilising a 16 V 16 format, instead of the regular 18 V 18, in a match simulation drill on an Australian Football field would provide approximately 60m2 extra of relative space per player (~460m2 vs ~520m2). Alternatively, teams that achieve performance outcomes comfortably utilising this style of play in a training setting can be challenged by decreasing the relative space per player or by using an outnumber scenario (e.g. 7 V 6 in defence and attack, respectively) as this may afford the offensive team with an environment whereby they must exhibit more unpredictable behaviour to effectively exploit less space and receive possession.[85]

As revealed in other contextually similar sports, favourable defensive outcomes tend to contrast that of successful offensive behaviour. In an Australian Football context, reduced physical output, as marked by lower *change of direction* and *collisions/impacts* values, and a tendency for increased *duration* contributed moderately to a model predicting favourable defensive outcomes. Subdued physical output, particularly alongside lower *change of direction* values, may also contribute to displays of superior *multidirectional synchrony* and inferior *lateral unpredictability and spacing* with players easing movement in an attempt to coordinate and synchronise movements to avoid being perturbed.[104] Further, the formation of a condensed defensive shape (*lateral unpredictability and spacing*) may help protect defensive zones and may also facilitate synchrony with smaller interpersonal distances between defenders providing favourable affordances to do so.[104] This condensed shape in defence was also implicated by Alexander et al. who revealed a positive association between reduced measures of dispersion and match outcome in a in 15 V 15 match simulation drill.[240] Alternatively, these behavioural outcomes may also reflect an ability of the defending team to minimise the threat of direct offensive styles of play, holding players up on the mark and slowing down offensive passages of play. Contrary to drill designs that promote favourable attacking behaviours, i.e. direct and unpredictable styles of play, coaches can incorporate small sided games with less relative space per player to facilitate these favourable behaviours or alternatively, increase relative space per player to challenge the defensive unit.[85]

While physical and spatiotemporal characteristics were able to model successful outcomes in offensive and defensive phases of play (i.e., moderate-substantial), despite reaching a $p<0.05$ threshold of significance, these characteristics were not as useful for explaining the variances evident in successful and unsuccessful outcomes in contested phases of play (R^2 = *weak)*. Regardless, as per offensive phases of play, success in this phase of play may be a result of heightened physical intensity as marked by reduced *duration* and increased *explosiveness* and *collisions/impacts.* This behaviour may be a result of players changing velocity rapidly, physically shoving other players in the process, to be first to a loose ball or successfully follow the unpredictable movement of the ball. However, given the unpredictable nature of the phase only 2% of the variance in successful outcomes could be attributed to the included physical and spatiotemporal characteristics. The seemingly random nature may make it difficult to provide distinct guidelines for achieving success in this phase or, alternatively, technical and skill components (not assessed in the current line of enquiry) may be of greater importance for success during these passages of play. Similarly, during set-shots, goal-resets and umpire stoppages, physical metrics were not associated with success which may be attributed to the lack of a technical skill assessment. Future lines of enquiry should look at concurrently incorporating physical, spatiotemporal, and technical characteristics of team performance, including how their interaction may influence performance, to provide a more holistic perspective on Australian Football Performance.

While the present study can be considered comprehensive (i.e. incorporating novel metrics derived from over 70 physical and spatiotemporal variables), inclusion of technical indicators such as the number of passes or specific player interactions through cooperative network analyses may provide additional insight into behaviour leading to successful and unsuccessful phase outcomes.[236] Further, while definitions of successful phases were derived from discussions with coaching staff (Average AFL coaching experience = 6.8 years; Average professional playing experience = 11.5 years) there may be additional ways to delineate success and therefore model the data. This study also falls short in its ability explore how movement behaviour evolves over different timescales with time providing unique affordances and likely influencing phase outcomes, which offers valuable avenues of research for future studies.[179] Lastly, while the random effect (competition round) failed to meaningfully account for any additional variance in the models, this may be indicative of tactical 'strengths' or 'habits' that are likely coached and remain stable across the season. Future investigations should consider pre-conceived tactical/coaching strategies and the influence this may have on behaviour on different phases of play. Regardless, the present study provides novel insights into factors influencing successful outcomes, particularly in offensive and defensive phases of play. Coaches and practitioners may use this information to develop tactical behaviour to optimise performance success and to manipulate training environments to afford specific behavioural outcomes.

10.5 Practical implications

- Reduced duration accompanied by superior physical output and lower measures of synchrony and predictability appear to be important for success in offensive phases of play due to the ability of attacking players to move quickly and unpredictability to perturb defensive formations and provide scoring opportunities. Alternatively, lower physical output and increased measures of synchrony and predictability may be important for defensive success and reflect an ability to slow opposition offensive sequences of play and coordinate movement to avoid disruptions in defensive formations. Accordingly, the association of specific physical and spatiotemporal sum scores with successful outcomes in certain phases of match-play indicate that these metrics may be useful for reviewing performance in these phases of play.
- Duration may be an important consideration for game plan design as this variable appears to influence offensive and, to a lesser degree, defensive outcomes. Time constraints applied in training drills may be manipulated to afford more/less time in specific phases of play which may challenge players with respect to their physical requirements, synchrony, and coordination. For example, implementing a 30-second shot clock whereby the attacking team only has 30 seconds to score when in possession of the ball may provide a suitable constraint to promote this direct behaviour.
- While there is little research examining change of direction characteristics in Australian Football, this variable may be of greater importance than traditional linear velocity-based variables. Change of direction appears to be a stronger factor influencing offensive and defensive success and thus has novel implications for conditioning and drill design. Incorporating reactive agility drills that help develop this component or manipulating match simulation drills to provide less relative space per player may encourage players to exploit change of direction ability, e.g., 11 V 11 instead of a 9 V 9 performed on half an Australian Football field and may be warranted given the association with success in the present study.

10.6 Conclusion

This was the first study to concurrently examine differences in physical and spatiotemporal characteristics with respect to successful outcomes in different phases of play in professional Australian Football. Reduced *duration* accompanied by superior physical output, as defined by *high speed, change of direction* and *collisions/impacts*, and reduced *multidirectional synchrony* were deemed meaningful for explaining some successful offensive phase outcomes. This may be a result of a direct style of play with players moving erratically and unpredictability to misalign defenders or providing passing opportunities for teammates. In contrast, defensive success was characterised by reduced physical output, as demonstrated by *change of direction* and *collisions/impacts*, lower *lateral unpredictability and spacing* and increased *multidirectional synchrony*. This may be a result of players slowing movement to coordinate and synchronise movements to avoid being perturbed. Findings from the present study provide novel insight for coaches and practitioners and potentially implicating training and game plan designs. Future research should consider including skill indicators into these models as well as the influence of specific player interactions (passing network characteristics).

10.7 Acknowledgements

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Chapter 11

General Discussion

11.1 Main findings

From an ecological dynamics perspective, the game of Australian Football is a performance-environment in which teams of players can be described as complex systems which collectively perceive opportunities for action which guide decision-making and subsequent actions. The collective perception of relevant environmental information by teams (sub-systems), and their members, facilitates the self-organisation of the players into stable states of coordination that enable the achievement of task goals.[29] These are often referred to as functional movement solutions. In this complex system, task-constraints, such as field dimensions and passing rules, along with physical and informational constraints, such as player size and opposition player movements, provide information and boundaries that guide and govern behaviour. The resultant behaviour in a complex system is the result of the interaction between its constituent components. Therefore, it is important to examine the influence of interactions and behaviour exhibited by, and between, players when analysing performance in team sports from an ecological dynamics perspective. Modelling cooperative networks and team spatiotemporal measures which help capture these elements, alongside physical and technical (skill) involvement data within an ecological dynamics framework, may improve operational methods of analysis, providing insight into 'how' and 'why' successful behaviours occur as opposed to just 'when' they occur.[26] The following section explores these insights from the perspective of each individual component and, where appropriate, the influence on performance outcomes and other facets of match play. While studies 1-4 do not convey causality, the following section speculates on some of the potential causal associations observed in these studies in the context of analysing individual and collective behaviour in Australian Football.

11.1.1 Cooperative network features

While many studies describe the individual actions and performance characteristics of Australian Footballers, capturing the cooperative and interacting nature of Australian Football team performance is far less common. While many studies have provided insights into the cooperative passing networks that underpin team performance in a variety of team sports, study one of this thesis was the first study to provide a simplified method for doing so in an Australian Football context. In this study, a small set of sum score metrics for both the individual and the team were developed using a plethora of social network parameters applied to cooperative passing networks of Australian Football teams engaging in competitive game play. These sum scores provide useful information, which can be used by coaches and practitioners to guide opposition analysis, training implementation, player performance ratings and player development, selection, and recruitment. Further, with the validation of these metrics with reference to performance as demonstrated in study five, the findings from this line of work may provide a viable framework of analysis for data obtained in practice or in other contextually similar sports that record technical involvements.

At the individual level, the two sum scores pertaining to *in-* and *out-degree importance* provide an indication of a player's level of interaction regarding incoming and outgoing network relationships, respectively, with resultant values offering potential insight into positional roles. In short, these scores provide an indication of how relevant a player is for the distribution and reception of passing interactions within the team. For example, attackers receiving more possession than they distribute will result in a greater *in-degree importance* score while defenders distributing more possession than they receive will generate a larger *out-degree importance* score. Alternatively, midfielders may score relatively equally in both sum scores, given that one of their positional roles is to connect other players within the team by both receiving and distributing possession, i.e., by acting as a link in the passing distribution and reception network. Additionally, scores may provide an indication of a player's importance or level of involvement within a network providing implications for opposition analysis. Superior scores for an individual within a team's network may indicate a key player and provide implications for tactical strategies. For example, a player who attains a significantly greater *in-degree importance* score, such as a key attacker, may need to be heavily defended by a player capable of limiting this attacker's possessions (e.g., a defender with a high *out-degree importance*) as it is likely that this player is a regular and influential target for surrounding teammates during offensive passages of play. Conversely, a player who achieves a greater *out-degree importance* score, such as a key defender, may be avoided when undertaking attacking sequences as it is likely that they are more capable of intercepting or turning over possession which can be subsequently distributed to surrounding teammates. Similarly, players who attain both large *in-* as well as *out-degree importance* scores, such as a key midfielder, may be pivotal for network and attacking success as they help move possession from the defensive half to the attacking half. This is a crucial role within Australian Football, given that many passing sequences are required for the ball to be moved across the field. As a result, a tactical coach may instruct his/her players to heavily mark or tag such linking players in order to deter fellow teammates from chaining possession through these key linking players.

At the team level of analysis, three sum scores provide insight into the global characteristics of the network. Superior values of *connectedness* could be interpreted as a mutually involved, possession-rich network whereby most players connect bi-directionally and are easily reachable by other players without relying on relatively few key linking players. Further, the other two team-derived sum scores, *in-degree variability* and *out-degree variability*, could be interpreted as the mutuality of involvement from all players within the network with lower values implying the network is decentralised whereby all players interact and contribute equally to the network. Conversely, larger values suggest that relatively few key players are relied upon for receiving (*in-degree variability*) or distributing (*out-degree variability)* possession, resulting in the network being more centralised. As measures of possession are a determinant of scoring points and ultimately success in Australian Football[2, 19] and in other contextually similar sports such as soccer,[50] measures pertaining to cooperative networks and distribution of possession will likely be associated match outcomes. When provided as exogenous variables in a holistic model of performance (study five), *connectedness* exerted a positive influence on *ball movement* while *in-degree variability*, where higher values signify reliance on few players for receiving for possession, exerted a negative influence on *ball movement* which was one of only two components positively associated with *quarter margin*. This suggests that offensive strategies that are varied but frequently decentralised (i.e., minimal reliance on key players) with most players being well connected may be important for quarter success. It has previously been suggested that decentralised teams, whereby players do not solely rely on one or two key players, foster interdependence and encourage coordination and cooperation which is beneficial to a team's performance, as determined by match outcome.[168] Further, *ball movement* demonstrated a positive association with *scoring opportunity*, the strongest determinant of *quarter margin*, which may emphasise the need to focus on this component when considering tactical strategies or training methodologies that will optimise performance. For example, in a small-sided game training design, a coach may limit the number of touches specific key players can have, thereby forcing surrounding teammates to explore other passing opportunities and movement solutions. This will likely lead to a more decentralised, well-connected network which appears to be important for success.

11.1.2 Skill indicators

While many studies have attempted to delineate the influence of technical indicators on performance outcomes, study two was the first to describe and dimensionally reduce, and apply appropriate weightings of importance to, an array of technical indicators in an Australian Football context to facilitate their practical application, interpretation, and reporting to performance staff. The derived components provide specific insight into individual player and team performance and the technical indicators of match play, particularly the movement of possession. This may consequently guide opposition analysis, training implementation, player performance ratings and player development, selection, and recruitment. The dimensional reduction of technical indicators also facilitated the integration of this component with physical and tactical components. As per cooperative network indicators, with the validation of these metrics within a holistic model of performance demonstrated in study five, the findings from the current study may provide a viable framework of analysis in Australian Football and other contextually similar sports.

The first derived sum score (which we have interpreted and labelled as *high-pressure success*) provides an indication of a player's ability to succeed in congested, or high pressure, phases of play in which ball possession is in dispute (contested play). Superior *high-pressure success* scores are characterised by an ability to attain possession that is heavily contested, or in dispute, and subsequently move the ball through and away from these contested passages of play. Scores may be indicative of a player's positional role, such as a midfielder who has the specific task of winning disputed possession and then moving it forward to provide attacking opportunities. Further, players with larger scores may be of greater importance during these contested passages and may be targeted or tagged by opposition teams to nullify this players action and subsequently increase the chance of securing possession themselves. The importance of *high-pressure success* at the team level (likely a result of superior measures for multiple players within a team) to overall performance success may be evident in study five with this variable negatively weighting on *uncontested behaviour* which in turn was negatively associated with *scoring opportunity.* Therefore, the ability to secure contested possession and initiate attacking passages of play may indirectly be important for performance outcomes by assisting to increase *scoring opportunity*. However, caution should be taken when drawing this conclusion as it is also likely that when *scoring opportunity* is elevated (i.e., there is an increase in the number of inside 50s and a greater amount of time in the attacking half), an increase in opposition defensive efforts to prevent this may subsequently lead to chaotic movement or higher levels of contested behaviour in attempts to spoil/compete for possession. This explanation appears more probable as previous lines of enquiry examining the influence of contested play technical indicators, similar to the constituents that make up *high-pressure success* (e.g., handballs, contested possessions and tackles), have not contributed substantially to models of success.[19]

The remaining sum scores derived in study two may be of greater importance for performance outcomes. *Low-pressure success* is reflective of an individual's ability to successfully receive possession in the absence of pressure and continue to move the ball to other team-mates to maintain possession. Once again, scores may be indicative of position-specific roles, such as a roaming or key defender who are responsible for moving possession out of the defensive half without risking a turnover in possession. Further, this ability to transfer possession with minimal pressure may be an important component contributing to successful outcomes as *low-pressure success*, along with *connectedness*, contributed positively to *ball movement* in study five which in turn demonstrated a positive association with *quarter margin*. The ability to transmit possession in attacking sequences with less relative pressure within a decentralised and well-connected network may be important for increasing *scoring opportunity* while simultaneously avoiding turnovers in possession. As with players demonstrating superior values of *high-pressure success,* players with superior *low-pressure success* scores may be targeted by opposition teams as these players may be important for initiating or continuing effective attacking sequences of play. Efforts to nullify the actions of these players may subsequently reduce *scoring opportunity* and subsequently reduce the *quarter margin* as interpreted from the holistic model reported in study five.

The last two technical-related sum scores reflect the ability of an individual player to move the ball in the attacking direction (*attacking ball movement ability*), i.e., move possession inside the attacking 50m zone, and receive the ball inside the attacking 50m zone and provide scoring attempts (*scoring ability*). As with *high-* and *low-pressure success*, these two sum scores may highlight position-specific players such as key midfielders or small forwards who have an ability to successfully transmit possession inside the attacking 50m zone (*attacking ball movement ability*) or key attackers who successfully receive possession inside this attacking 50m zone and subsequently attempt to score (*scoring ability*). As per the other technical indicators, players with superior scores may be heavily targeted, tagged or defended as it is likely that these players are important for either initiating (*attacking ball movement ability*) or be a primary target at the end of scoring sequences (*scoring ability*). It may be of greater importance to target players with superior scores in these metrics as the derivatives of these sum scores have previously being associated with successful outcomes likely due to their ability to provide the best opportunity to score.[19, 34] Further, in study five, both these sum scores positively contributed to *scoring opportunity* which demonstrated the strongest association with *quarter margin*. Developing tactical strategies that promote superior scores for these metrics may increase chances of success. For example, tactical strategies or training manipulations that provide multiple target player options inside the 50m zone that can receive possession may increase opportunities to successfully transfer possession inside the 50m zone and provide scoring attempts. Further, multiple key receivers will likely lead to lower *in-degree variability* scores which appear to have implications for *ball movement* and *quarter margin*.

11.1.3 Physical characteristics

In Australian Football, there are a wide array of GNSS derived variables available to physical performance coaches regarding the physical characteristics of match-play. While existing literature has provided valuable insight regarding these physical characteristics, the large number of variables makes it difficult to interpret the effect of physical performance indicators on match outcome and accordingly, which variables should be prioritised in training. The reduced subset of sum-score metrics derived in study three may provide a method for coaches and practitioners to further understand the influence of physical outputs on technical and tactical components (study five) and the specific physical requirements associated with varying contextual factors such as the phase of play (study six and seven). The results provide supporting data for performance analysts currently using GNSS technology and provide a way of objectively reviewing individual physical performance. This may subsequently facilitate the development of training interventions specifically tailored towards improving individual weaknesses or further developing existing strengths. Further, these metrics may allow coaches to longitudinally assess the development of an individual player's physical output over time.

The first three derived sum scores in study three pertain to different linear running demands at different intensities. *Game volume* is indicative of the general match characteristics with the total running volume an individual accumulates throughout the match as well as the volume of distance, number of efforts and number acceleration/deceleration efforts completed at low and moderate intensities included in this sum score. Resultant scores may reflect position specific roles with midfielders covering greater distances over the course of a game compared to other positions. This is likely due to position specific roles with midfielders covering a larger area of the field relative to the fixed positional characteristics of key position players. Alternatively, scores may be indicative of an individual's physical capacity with recent studies demonstrating that lower scores in the Yo-Yo Intermittent Recovery Test (level 2), an assessment of running capacity, corresponded with lower physical match outputs.[(231)] However, the ability to accumulate larger volumes in lower intensity metrics may not be as important as originally anticipated with study seven revealing no associations between this metric and success in any phase of play. Further, *game volume* loaded positively onto an endogenous variable labelled as *physical behaviour* in the model of performance (study five) which had no influence on *ball movement, scoring opportunity,* or *quarter margin*.

High speed, a sum score encapsulating higher velocity efforts and distances, along with *explosiveness,* comprised of moderate-high intensity acceleration metrics, may also be indicative of positional differences. Superior *high speed* and *explosiveness* scores may reflect the ability of a midfielder to rapidly reach possession that is in dispute (contested play) in different parts of the field which will increase chances of retrieving possession or reflect an ability to gain possession in dispute and rapidly accelerate into free space to then pass to other unopposed players. Alternatively, for key attacking players, superior *explosiveness* may allow an individual to decouple their own movements from the movements of a marking defender and move into free space to receive a pass. The importance of an attacker-defender decoupling has been associated with positive attacking outcomes in other footballing contexts.[123] While both these metrics loaded onto *physical behaviour* in study five, which had no association with *quarter margin*, in study seven these metrics were significantly associated with successful outcomes in offensive (*high speed* and *explosiveness*) and contested (*explosiveness*) phases of play. The examination of these metrics in these specific contexts, i.e., offensive, and contested phases of play, may validate these position specific theories, and indicate that relative to *game volume,* these metrics may be more relevant when associating physical output with performance. However, as with other derived variables, there are a multitude of ways to achieve high sum scores which practitioners must be aware of for correct interpretation of the outcomes.

While the first three physical sum scores pertain to linear movements of the individual at different intensities, *change of direction* and *impacts* are indicative of a player's ability to rapidly change direction, utilising inertial movement analysis. Like other sum scores, is helpful to conceptualise these by discussing with respect to the various positional roles, with certain players needing to navigate through congested phases of play or move erratically to evade or move past an opponent whilst attacking. As demonstrated in contextually similar sports such as soccer, the ability of attacking players to move quickly and unpredictably may assist in providing scoring opportunities.[28] This behaviour may help create decoupling with opposing defenders subsequently perturbing defensive formations or providing opportunities to move into available space to receive possession from teammates inside the forward 50 arc.[28] This may be justified with positive associations between these two metrics, and *high speed*, and successful outcomes in offensive phases of play (study seven). Alternatively, midfield players may need to change direction rapidly, physically shoving other players in the process, to be first to a loose ball or successfully follow the unpredictable movement of the ball. This may explain the positive associations revealed between *impacts* and successful outcomes in contested phases of play. Further, the positive association between *change of direction* and *high-pressure success* in a holistic model of performance (paper five) support this and provide novel implications for training and conditioning design proposing that these scores may have greater implications for performance in these phases than other physical metrics.

11.1.4 Spatiotemporal characteristics

Traditionally, collective tactical behaviour has been assessed using methods of notational analysis and/or coaches' subjective ratings of performance making it difficult to objectively assess performance acutely or longitudinally or to compare between different contexts. More recently, spatiotemporal behavioural analyses using the positional data from GNSS devices have provided objective measures for assessing tactical behaviour within team sports. Specifically, collective tactical behaviours can be determined by combining the positional data of each player to calculate metrics such as the on-field space occupied by the team, the centroid and stretch indices of each player, and the synchrony of movements between players. While many studies have attempted to describe tactical behaviour using spatiotemporal variables in team sports, study four was the first to describe and dimensionally reduce an array of spatiotemporal variables in Australian Football to facilitate their interpretation and practical application in varying contexts, such as different phases of play. Embedded in an ecological dynamics framework, these components facilitate the interpretation of spatiotemporal behaviour patterns and subsequently allow practitioners and coaches to design and implement training that promotes specific spatiotemporal behaviour. Further, this subsequently eases the integration of this information with other components of performance.

At the team level, spatiotemporal sum scores may help describe of the general behaviours that emerge or persist across an entire match. Derived sum scores provide insight into the coordination, synchronicity, and unpredictability (*dispersive coordination, lateral unpredictability and spacing, multidirectional synchrony,* and *longitudinal unpredictability*) as well as the dispersion (*lateral unpredictability and* spacing) and positioning (*longitudinal* behaviour) of a team's behaviour. Drawing on contextually similar sports such as soccer, it was anticipated that lower *dispersive coordination* and *multidirectional synchrony* coupled with *larger lateral unpredictability and spacing* scores may indicate that a team has spent a large amount of time in attack as moving asynchronously and in an unpredictable manner, with a dispersed shape, may be necessary to effectively perturb defensive lines and create scoring opportunities by misaligning defending players. In contrast superior *dispersive coordination*, *multidirectional synchrony,* and lower *lateral unpredictability and spacing* may persist when the team spend a significant proportion of the game defending as defensive structures are often characterised by a compact shape coupled with synchronised and predictable collective behaviour. In defence, the self-organisation into this resultant behaviour is deemed necessary to protect the team's goals from attacking perturbations. However, when specifically examining spatiotemporal behaviour in these phases of play (study six), these metrics were not significantly different in offensive or defensive phases. This similarity may be a result of defensive strategy with players mirroring the movements/patterns of the opposition team in offence. This may explain why most spatiotemporal metrics failed to associate with *quarter margin* in study five.

However, despite similarities between offensive and defensive phases of play across the course of a game, which may explain a lack of contribution to a holistic model (study five), the importance of spatiotemporal metrics may be more pronounced when investigating successful outcomes in specific phases of play. In study seven, reduced *duration* accompanied by superior physical output, as defined by *high speed*, *change of direction* and *collisions/impacts*, and reduced *multidirectional synchrony*, contributed substantially to a model predicting successful offensive phase outcomes. As demonstrated in contextually similar sports such as soccer, the ability of attacking players to move quickly and unpredictably may assist in providing scoring opportunities. This behaviour may help create misalignments with opposing defenders subsequently perturbing defensive formations or providing opportunities to get into free space to receive possession from teammates inside the forward 50 arc. Alternatively, these movement behaviours may emerge because of a direct style of play with attackers quickly playing on from marked possessions to sufficiently perturb defensive lines as it does not provide the defending team with enough time to modify their synergistic behaviours relative to the ball or the attacking team's movements. Coaches and practitioners may be able to facilitate or afford these behaviours in a training setting using small-sided games with more relative space per player (larger field sizes or lower player numbers) as this has shown to promote this style of behaviour in other contextually similar sports. Alternatively, teams that achieve performance outcomes comfortably utilising this style of play in a training setting can be challenged by decreasing the relative space per player or by using an outnumber scenario (e.g., 7 V 6 in defence and attack, respectively) as this may afford the offensive team with an environment whereby, they must exhibit more unpredictable behaviour to effectively exploit less space and receive possession.

In contrast to offensive behaviour, examining behaviour with reference to successful outcomes in defensive phases demonstrated that superior *multidirectional synchrony,* accompanied by reduced physical output, as marked by lower *change of direction* and *collisions/impacts* values, and a tendency for increased *duration* was associated with positive outcomes in defensive phases. These concurrent factors may have contributed to superior *multidirectional synchrony* and inferior *lateral unpredictability and spacing* with players easing movement to coordinate and synchronise movements to avoid being perturbed. The formation of a condensed defensive shape (*lateral unpredictability and spacing*) may help protect defensive zones and may also facilitate synchrony with smaller interpersonal distances between defenders providing favourable affordances to do so. These behavioural outcomes may also reflect an ability of the defending team to minimise the threat of direct offensive styles of play, holding players up on the mark and slowing down offensive passages of play. As per favourable behavioural patterns in offensive phases of play, these behaviours may be replicable in a training environment as coaches can incorporate small-sided games with less relative space per player to facilitate these favourable behaviours or alternatively, increase relative space per player to challenge the defensive unit.

Only *longitudinal behaviour* significantly contributed to a model predicting *quarter margin* with this measure weighting positively on *scoring opportunity.* Superior scores may indicate prevalent or regular attacking behaviour as higher scores may be a result of the team's frequent positioning in the attacking half coupled with greater end-to-end position variability. This variability may be a result of spatial exploration whereby players and teams explore the movement space or field looking for opportunities to score. This higher sum score may also reflect the ability of a team to secure repeat entries into the forward 50 metre arc (the attacking zone) and prevent the opposition team from leaving their defensive half. This information can be utilised to inform training design with specific constraints being imposed in small-sided games to facilitate these behaviours. For example, in contextually similar sports, instructing defenders to defend conservatively through use of a zone defence have revealed increases in the number of passes between field zones in offence. This signifies that incorporating a conservative defensive pattern in small-sided games may force attacking players to explore different areas of the field with greater dispersion of ball passing trajectories in the search for goal scoring opportunities.[99]

At the individual level of analysis, sum scores may reveal favourable position specific movement patterns that align with tactical guidelines, allow comparison between players in similar positions, or provide means to assess longitudinal changes in performance. As per the team level of analysis, sum scores provide an indication of synchrony, predictability, and player movement. While sum scores are yet to be validated with reference to performance at the individual level, findings from studies five and seven may provide insight into desirable patterns of behaviour. Based on successful offensive phases of play, attacking players may move asynchronously and unpredictably to perturb defensive lines and create goal scoring opportunities. Attacking players would therefore likely achieve lower *multidirectional and spacing synchrony* and *player positioning* scores coupled with larger *unpredictability* and *player movement* scores as they place themselves primarily in the forward half, probing for scoring opportunities which was demonstrated in study five. However, intra-position differences may be evident due to different tactics or playing styles. For example, smaller forwards, positioned closer to the team's centroid, may favour the movement of teammates and the ball to guide movements resulting in larger *multidirectional and spacing synchrony* and *player positioning* sum scores. It is therefore important to consider position-specific tasks and goals as well as tactics.

In contrast, defenders would likely spend a large proportion of the match moving synchronously with surrounding teammates and in a predictable manner and may therefore display superior *multidirectional and spacing synchrony* and *player positioning* scores coupled with lower *unpredictability* and *player movement* scores. As seen in successful defensive phases of play (study seven), synergistic movement is theorised to be important for resisting attacking perturbations and may also result from affordances provided by the movement of the ball and fellow teammates. However, as with attacking players, defenders who demonstrate different scores to what might be expected may be fulfilling an alternate tactical role. For example, defenders who disregard the movement of teammates and tactically choose to mimic opposing tackers who tend to move erratically in offence (study seven), may present with lower *multidirectional and spacing synchrony* and *player positioning* sum scores. Certain scores may also reveal differences in position specific tasks. For example, small defenders who attempt to win and transfer contested possession may demonstrate higher *player movement* scores as they attempt to evade opposition players when in possession or when providing a target for teammates.

11.2 Practical Application and Contribution of the Thesis

While many studies have attempted to describe the technical, physical, and tactical characteristics of sport, including cooperative network and spatiotemporal behaviours, studies one to four of this thesis were the first to describe and dimensionally reduce, and apply appropriate weightings of importance to, an array of associated features in an Australian Football context to facilitate their practical integration, application, and interpretation. The new components derived in these studies help to reduce the complexity of analysing and interpreting multiple facets of performance in Australian Football, while retaining a high level of variability. This subsequently makes it easier for performance analysts and practitioners to provide relevant feedback and information which may subsequently allow coaches to design and implement training programs that emulate specific features of match play and develop tactical strategies that promote favourable behavioural outcomes. Further, the integration of these metrics in relation to performance outcomes (studies five and seven) and contextual influences such as the phase of play (studies six and seven), may allow coaches to tailor training and provide specific information to players on all individual aspects of performance which may guide individual player development.

11.2.1 Changes Embedded in Industry

The findings from this thesis contributed to several positive changes at the Australian Football club involved in this research. The metrics derived in studies one, two, and three are all utilised in the game review process with the metrics derived in studies one and two also used in opposition analysis process. The metrics from the first three studies were utilised in a stepwise logistical regression (not published) to derive key performance indicators for match review (Figure 11.1). Further, findings from study one provided coaches with an alternative perspective on player involvement highlighting the contribution and level of involvement of individual players to the cooperative network of a team. This subsequently guided training drill design, altering constraints present in small-sided games to bring about desirable network behaviours, and informed tactical decisions with the ability to highlight key opposition players. Similarly, the metrics from study two allowed coaches to identify the technical contribution of players throughout the match and again informed drill design and tactical strategies. The physical metrics derived in study three were primarily used by the medical and conditioning staff to help manage player loads on a weekly basis, as well as inform conditioning bouts to be implemented in training. Further, findings from studies five, six, and seven provided novel implications for physical preparation during the pre-season period. The importance of *high speed, explosiveness* and *change of direction* were highlighted in these studies with training drills implemented throughout the pre-season in a periodised manner to reflect the progression of these characteristics.

2020 Match KPI's					
Metrics	**Win/Lose**	**Scoring Ability**	**Low Pressure Success**	**High Pressure Success**	**Change of Direction**
Target KPI	**WIN**	**105**	**104**	**98**	**100**
Quarter 1	LOSE	67	97	92	105
Quarter 2	WIN	88	104	89	111
Quarter 3	WIN	119	72	130	113
Quarter 4	LOSE	90	84	97	99

KPI Matches Outcome:	
YES	**NO**

Figure 11.1: KPI's derived from logistic regression modelling used to review quarter performance with respect to winning and losing. Green squares indicate that the KPI aligned with the expected outcome while the orange square indicates that the KPI did not match the outcome.

The practical applications listed in the following section are not simply recommendations, they also include examples of how the findings in the seven studies have been applied in a professional Australian Football club. The real-world implementation of these findings highlights the applied nature of this research. In summary, the understanding of the cooperative network, technical, physical, and spatiotemporal behavioural demands of Australian Football match play are imperative for the design of evidence-based training programs that lead to improvements in athletic performance. Coaches and conditioning staff can use this data to design position-specific training programs that contextualise network, technical, physical, and spatiotemporal performance.

11.2.2 Strategic Implications

The metrics derived in studies one to four, along with their performance validation in studies five to seven, provide means for coaches and practitioners to further understand the influence of cooperative network, technical, and tactical characteristics on performance outcomes. Further, the examination of spatiotemporal behaviour and physical characteristics exhibited in different phases of play, along with the outcome of these phases, provides novel insight into factors affecting performance. The results demonstrated in this line of research provides supporting data for performance analysts currently using technical indicators and GNSS data to analyse games and allow coaches to identify strengths and weaknesses in the opposition team that can be exploited through the implementation of game tactics. Team-derived metrics may reveal a team's tendency to adopt a specific style of play when successful (Figure 11.2) while individual metrics may identify key opposition players that are important for team success (Figure 11.3).

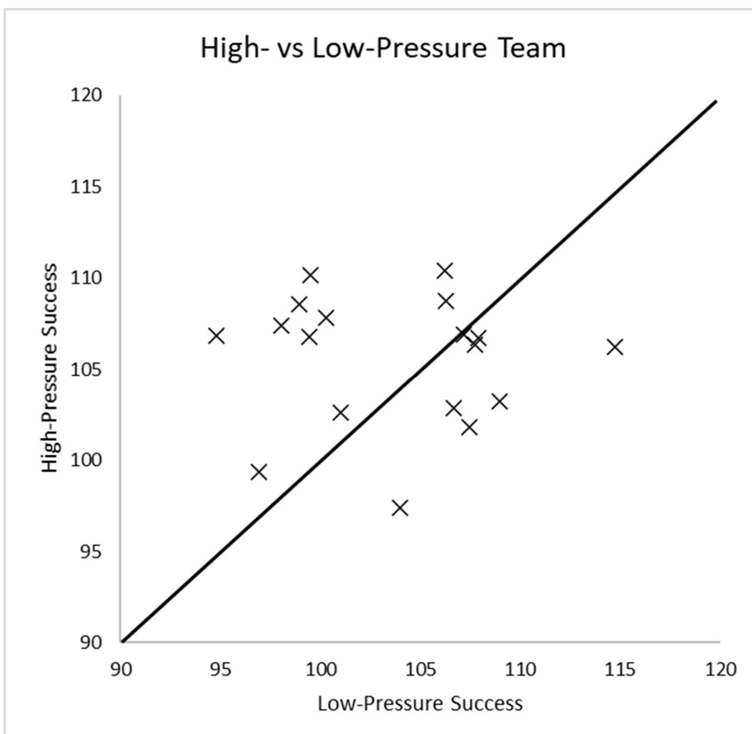

Figure 11.2: High- vs. Low Pressure for teams when they win revealing tendencies for team success. Teams centred around the black line are balanced whereas teams to the upper-left exhibit high-pressure tendencies when they win. Alternatively, teams in the lower-right exhibit low-pressure tendencies when they win

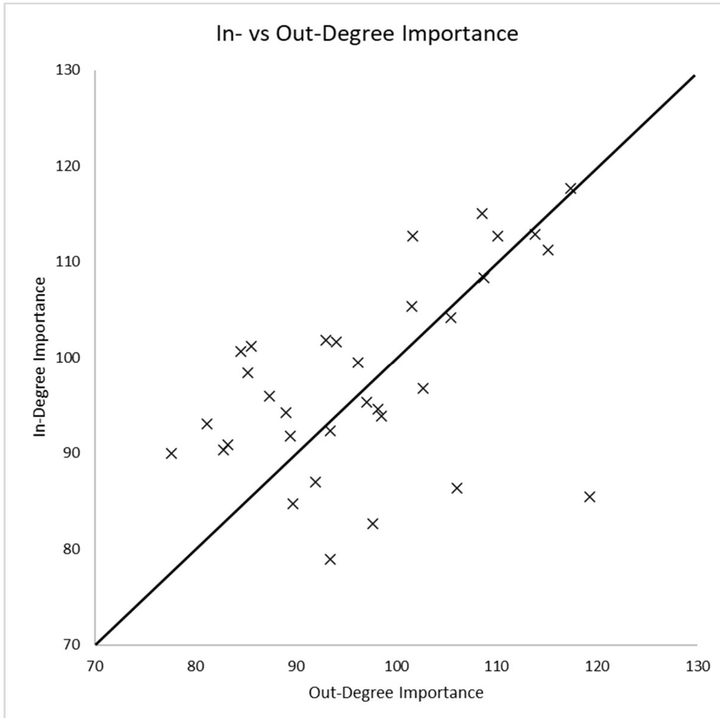

Figure 11.3: Individual cooperative network characteristics for players from a single team when they win. Players centred around the black line are equally important for receiving and distributing possession. Alternatively, players above and below the black line may act as more receiving or distributing players, respectively.

11.2.3 Training Design

While the factors that are causally related to changes in individual and team performance measures in Australian Football need to be examined further, the findings from this study have been used in training design in the club involved in this research. The newly derived information also allows coaching staff to develop training interventions that are representative of competition demands as they can now quantify and emulate the complex network structures, technical indicators, physical demands, and spatiotemporal behaviours evident in game scenarios. Further, their validation with reference to performance outcomes subsequently allows practitioners and coaches to design, implement, and prioritise training programs that develop favourable components. For example, until recently, linear distances accumulated at different velocities have been a primary focus of research investigating performance outcomes. However, integrating the metrics derived in study three with reference to performance (study five-seven) provided insight into an alternate component that may assert a stronger indirect influence on performance outcomes and suggest a focus for physical preparation.[49, 244, 245] *Change of direction* may be of greater relevance than other physical components in relation to successful match outcomes. Furthermore, *change of direction* ability may be particularly important during contested passages of play and for optimising *high-pressure success*.

Further, findings from study six and seven may guide coaches and practitioners as how to best manipulate small-sided games to bring about a desired behavioural outcome. Research utilising small-sided games in soccer have been utilised to develop training interventions which have subsequently resulted in an improvement in a team's ability to quickly and effectively reciprocally compensate when perturbed.[97] Use of small-sided games as a form of training has been extensively utilised to mimic and encourage favourable patterns of play, akin with the aforementioned behaviours. Further, assessing the impact of contextual factors such as the phase of play, along with the outcomes of these phases, has appropriately guided training design in these similar contexts with the emulation of these specific factors affording teams, and players, with an opportunity to coordinate and co-adapt to specific situations in a representative environment. In the current context, coaches can manipulate the relative space per player (changing the field size or number of players) to help promote, or challenge, a specific behavioural outcome. For example, increased physical output along with unpredictable movements appear to be beneficial for offensive success (study six) as this behaviour may help create decoupling with opposing defenders subsequently perturbing defensive formations or providing opportunities to move into available space to receive possession from teammates inside the forward 50 arc. In a small-sided game format, providing more relative space per player (Figure 11.4) or a positive outnumber scenario (e.g., 7 V 6 in attack and defence, respectively) has shown to increase these metrics in contextually similar sports. Alternatively, teams that achieve performance outcomes comfortably utilising this style of play in a training setting may be challenged by decreasing the relative space per player or by using an outnumber scenario (e.g., 7 V 6 in defence and attack, respectively) as this may afford the offensive team with an environment whereby, they must exhibit more unpredictable behaviour to effectively exploit less space and receive possession.

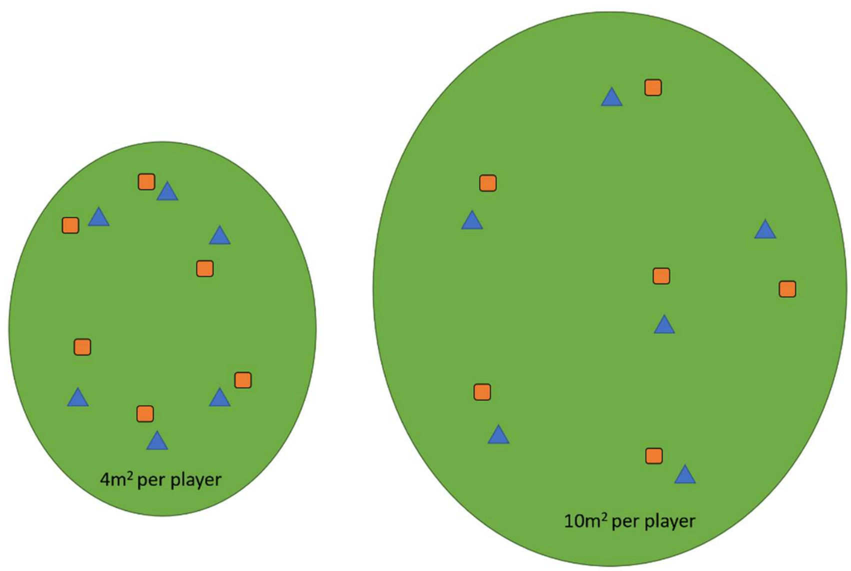

Figure 11.4: Alternating the relative space per player in a small-sided game format to either challenge (left) or facilitate (right) offensive favourable patterns of behaviour.

Further, the examination of behaviour in specific phases of play implicated duration as an important factor for delineating between phases of play (study six) as well as a contributing factor to success in offensive and defensive phases of play (study seven). The timescale or length of a drill may be an important consideration for training design as the manipulation of this component may afford more/less time for favourable behaviours to emerge and may facilitate or challenge players with respect to their physical requirements, synchrony, and coordination. For example, extending the duration or time allowed to achieve a task outcome, such as kicking a goal during a small-sided game may allow more time for players to self-organise into a stable pattern of behaviour that allows the achievement of that task outcome. Alternatively, reducing task time may challenge players to form these patterns of behaviour at a faster rate and via a different solution with a different state of coordination (Figure 11.5). Further, the duration can also be manipulated to encourage favourable patterns of play in offensive and defensive phases of play. Results from study seven suggest that reduced duration, accompanied by superior physical output and lower measures of synchrony and predictability, appear to be important for success in offensive phases of play due to the ability of attacking players to move quickly and unpredictably to perturb defensive formations and provide scoring opportunities. Alternatively, increased duration accompanied by lower physical output and increased measures of synchrony and predictability may be important for defensive success and reflect an ability to slow opposition offensive sequences of play and coordinate movement to avoid disruptions in defensive formations. The information derived from studies five, six, and seven can allow coaches and practitioners to design drills that promote favourable patterns of intra-team behaviour which may subsequently lead to improved team performance and the number of matches won.

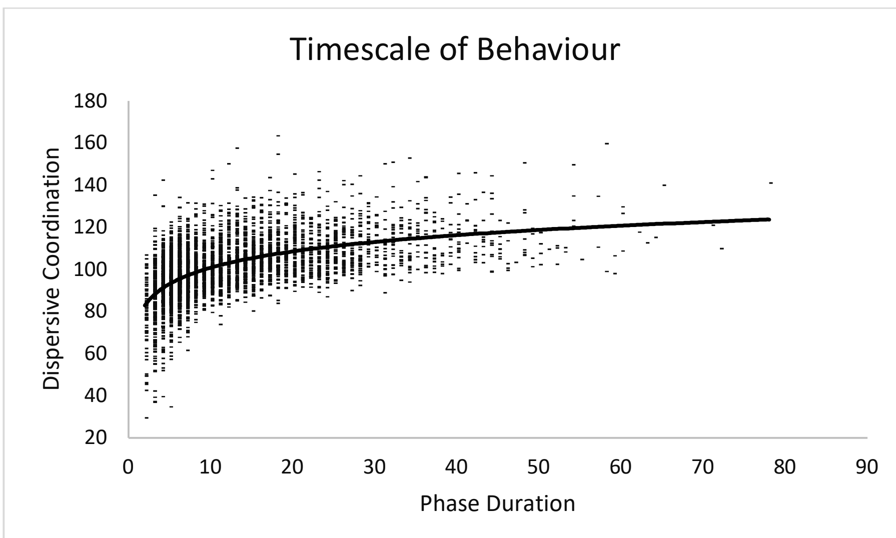

Figure 11.5: Profile of the changes in dispersive coordination (spatiotemporal sum score derived in study four) as the duration of offensive and defensive phases of play increase (study six)., i.e., coordination increases with time.

11.2.4 Player Monitoring and Development

The derived component scores can facilitate and simplify the information and feedback coaches provide to players. On an individual level, the examination of the individually derived metrics may highlight favourable task-specific characteristics associated with different positions in a team and provide an additional objective means of assessing player match-performance (Figure 11.6). This information could therefore facilitate weekly team selection or the recruitment of new players that can be a valuable addition to the team. These metrics may also allow coaches to longitudinally assess the development of an individual player’s role within the team over time (Figure 11.7). The ensuing improvement in an individual’s match performance indicators may have an effect at two levels. Firstly, for the individual, improved performance may lead to contract extensions, promote career longevity, and provide enhanced entertainment for spectators of the sport while secondly, on a club level, may lead to more wins.

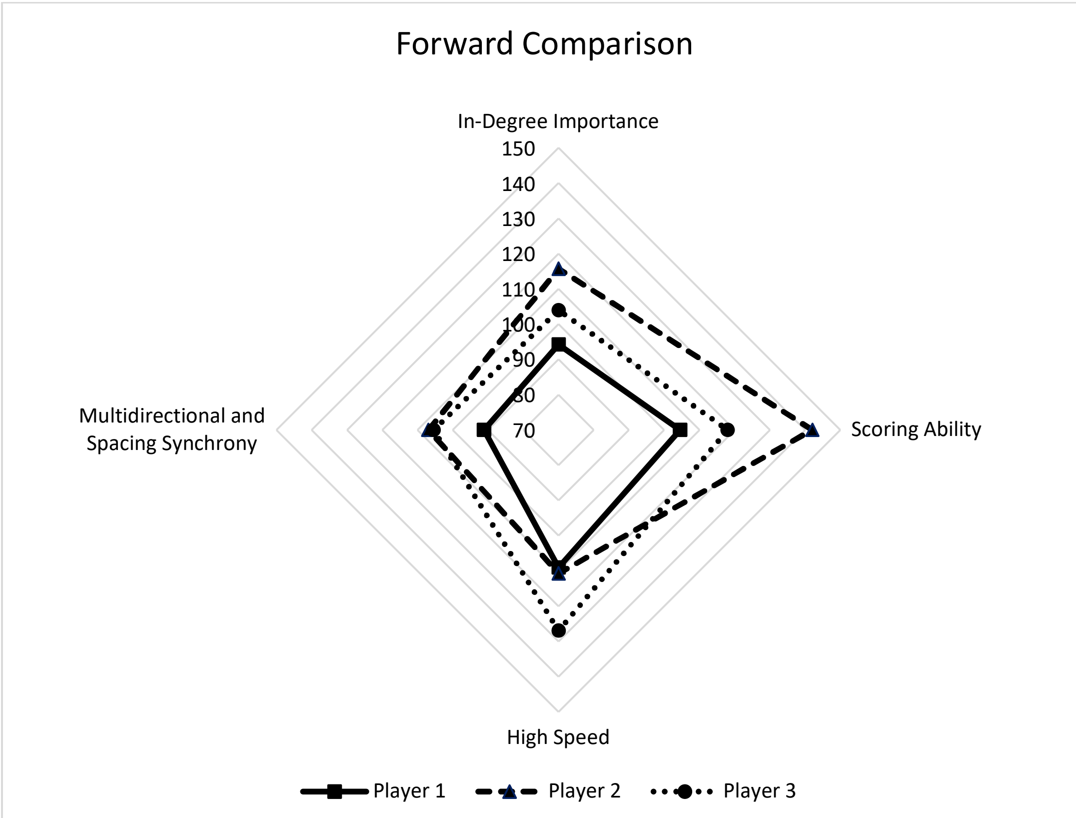

Figure 11.6: Comparison of three forward players from a given team examining four key indicators associated with successful outcomes in offensive phases.

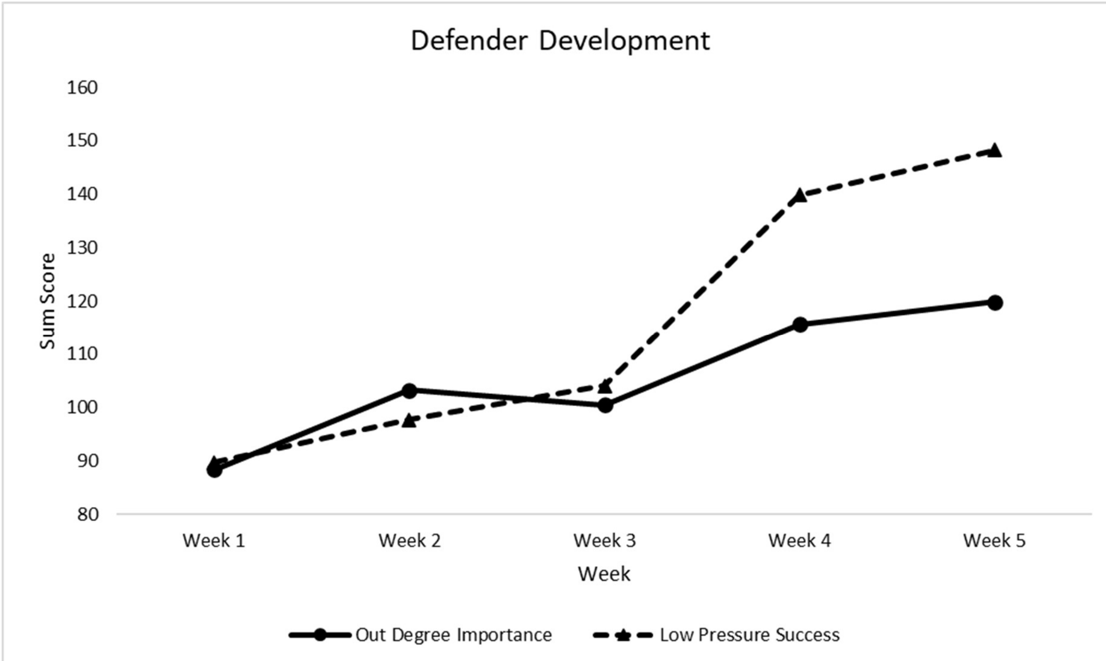

Figure 11.7: A real-life example of a 5-week period visualising the development of a defender using metrics theoretically associated with defender success.

Along with the proposed fiduciary benefits from the current line of research, there will likely be improvements in player workload monitoring and welfare. The simplified physical load measures developed in study three provide supporting data for performance analysts and practitioners currently using GNSS technology to monitor player workloads (Figure 11.8) which may allow conditioning and medical staff to better manage players and reduce the risk of injury. A heightened understanding of not only the physical demands, but also the technical, and tactical demands associated with playing football at the highest level will contribute to the optimised prescription of training to cope with such demands.

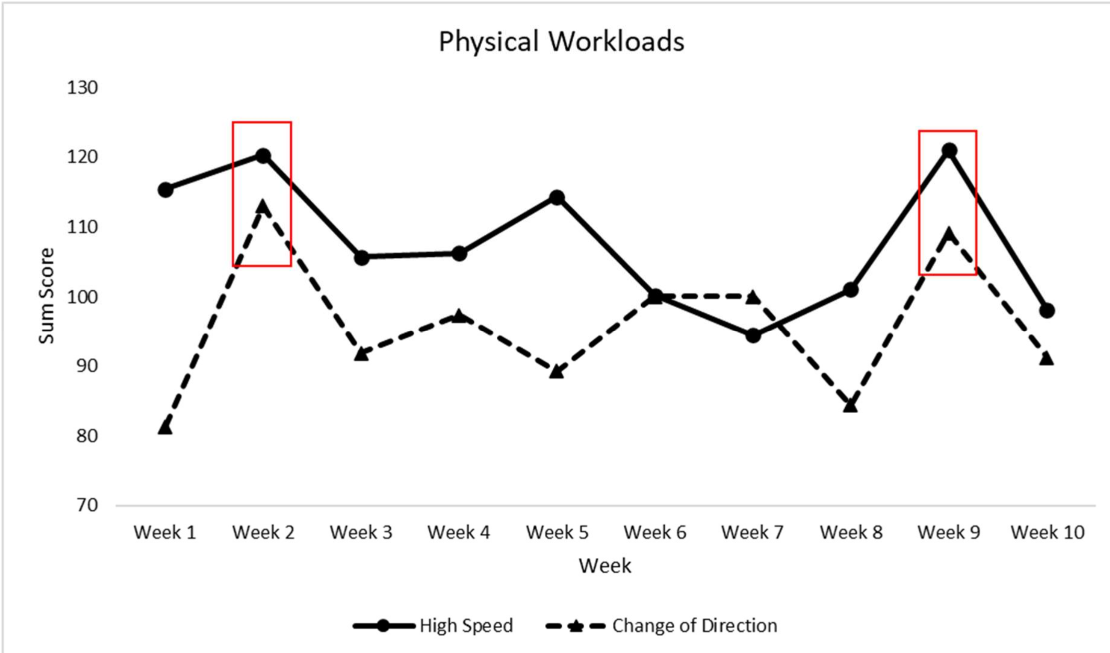

Figure 11.8: An example of player game loads over the course of ten consecutive rounds. Red squares indicate two weeks where game loads were relatively larger than other weeks. This may have training load implications for the individual.

11.2.5 Integration and Other Sports

Results of studies one and two provide supporting data for performance analysts currently using technical indicators to analyse performance in games. Further, studies three and four provide a small subset of spatiotemporal and physical sum scores that may provide supporting data for practitioners currently using GNSS technology. Findings from these studies may also prove useful in sports other than Australian Football, following its validation in these other sports. With performance validation in studies five, six, and seven, the findings and methodological approach utilised in studies one, two, three, and four may also prove useful in sports other than Australian Football following the calculation of components and respective weightings. The methodology provided in these studies can be followed by practitioners working with technical indicators and GNSS data in any sport, to help them understand the technical and physical characteristics of match play. Further, the use of structural equation modelling to help conceptualise and statistically examine the relationships between various areas of sports performance in study five provides a framework for sports scientists and coaches looking to explore the relationship between technical, tactical, and physical behaviour in any sport.

11.3 Research Limitations

The studies that comprise this thesis were primarily designed to impact on current practice by:

i. Improving knowledge about the interpretation of physical, technical, and tactical data in Australian Football.
ii. Identifying key factors that influence success in Australian Football.
iii. Contextualising the technical, tactical (cooperative network and spatiotemporal behaviour), and physical components of match-play to provide greater insight into factors that lead to improved training specificity.
iv. Developing evidence-based information that contributes to the improvement, development, and monitoring of players.
v. Providing supporting data for performance analysts and sports scientists using technical indicators as well as GNSS technology. It also aimed to develop a methodological framework to direct future research studies.

While these objectives have been realised within the immediate football club, the ability to transfer these results across different clubs within the AFL requires caution due to some inherent limitations associated with the research. While cooperative network and technical indicators could be collected and analysed for every player/team in the competition, physical and spatiotemporal data could only be collected for the involved club. Further, only data pertaining to the reference club was utilised in the examination of the aforementioned components with reference to phase of play and quarter outcomes with the results of this project being based on 43 professional Australian Football players from one team. Therefore, the suggested implications may only apply to this group and may not be representative of athletes from different teams, levels of competition (e.g., applicable to players from sub-elite Australian Football competitions), or sporting contexts. Further, with the findings from the collection of studies primarily being observational and longitudinal in nature, some criticisms of the work presented here may be that the set of studies lack generalisability or experimental control that provides objective data. Each club also imposes its own tactics that will differ based on coaching staff, experience, team selection, rotations, and the physical/technical ability of individual players along with uncontrollable factors such as environmental factors, player motivation, injuries, and the opposition team influence. Ideally, experimental training studies that lead to performance improvements in competitive matches would be ideal to provide proof of concept, for example, assessing whether successful outcomes in offensive phases of play are more prevalent following a training intervention that focuses on *change of direction*, a predictor of success in this phase (study seven). There is an absence of research in professional Australian Football in which the effects of controlled interventions on actual competitive performance have been definitively shown. Further, while there were no significant rule changes during the research data window, future rule changes may subsequently influence individual and team behaviour which may limit the ability to translate current findings to future contexts.

There are also practical limitations due to technology and processing requirements used in the data collection process. As GNSS data is not freely available between clubs, like technical indicators provided by ChampionData®, this makes it difficult to provide a complete picture of performance with only the reference team having all data available. The only possibility of overcoming these limitations is through collaboration between clubs that have a mutual interest in the research or if GNSS data is made available to all clubs. Due to privacy and commercial agreements, the latter appears less likely, thus collaborative research is required to provide a more complete picture of performance and subsequently achieve somewhat of a proof on concept. Further, the GNSS devices utilised in this research (Catapult S5) have since been superseded with a newer model now available. This would make it difficult to compare physical characteristics from the current season with findings for the data derived in this research due to differences in processing and sampling methods. With increasing use of computer vision technology to track player positions in team sports, future research opportunities may arise to facilitate multi-club physical and spatiotemporal analysis.

Another practical limitation of the work presented here may be the time-consuming nature of integrating the four different datasets (cooperative network data [ChampionData® coding], technical indicators [ChampionData® coding], physical data [GNSS data], and spatiotemporal data [GNSS data]), as well as the coding of individual phases of match play (Sportscode® video analysis). The lengthy process and post-hoc nature of the analysis and collation of this data also limits the application of this data in real-time. In the upcoming chapter 'Directions for Future Research', some suggestions are made that may allow this data to be collected and collated in real-time allowing the findings of this research to be considered and inform the decision-making process throughout the course of a game. Regardless, future research is needed to validate the findings of this research and its potential to perpetuate successful outcomes following immediate intervention in real-time.

There are also statistical limitations that should be acknowledged in the current project. While a principal components analysis in studies one-five were used for the sole purpose of dimension reduction in this paper, there may be discrepancies between the theoretical rationale for using a principal components analysis and its practical application. While this method derives principal components that explain most of the variance in the original data, original granular variables may equally provide valuable insights to coaches and performance staff. Further, the naming of these variables is subject to interpretation and demonstrates that a PCA may not be the sole means of dimensional reduction with other methods such as expert guided dimension reduction presenting as an option. Future studies may need to examine whether dimension reduction, or less-dimensional approaches (i.e., reducing performance down to a few separate metrics using expert guidance) offer the best approach to interpreting complex and multifaceted behaviours. Nonetheless, the current studies provide a guide for how these data can be analysed, interpreted, and implemented in a professional organisation. Further, in studies six and seven, incorporating team-based measures may have reduced the sensitivity of classifying each phase of play as while some phases of play may incorporate every player, other phases may require only 'a few key players'. Future investigations that analyse behaviour at the individual level with only involved 'key players' may provide additional insight.

The definitions of success in studies five and seven, may also present as a limitation. While quarter margin was used as a proxy for success in study five, it should be acknowledged that a team does not need to win every quarter to win a match and that a team could be losing until the final seconds of a quarter, giving a potentially inaccurate representation of what occurred within the quarter. While utilising quarter margin as a proxy for success in study five enabled a larger sample size, the assessment or concurrent analysis of indicators of performance with match outcome may provide additional insight as the primary aim is to win the match, not just the quarter. Further, while definitions of successful phases in study seven were derived from discussions with experienced coaching staff (Average AFL coaching experience = 6.8 years; Average professional playing experience = 11.5 years), there may be additional ways to delineate success and therefore model the data.

Finally, while an ecological dynamics framework may provide a suitable method for interpreting and examining resultant behaviour in a complex system such as Australian Football, there are inherent limitations associated with the use of this framework. While this framework may provide an upgrade to more operational methods of analysis, acknowledging the 'how' and 'why' successful behaviours occur as opposed to just 'when' they occur, its application in the current line of studies can only hypothesise about possible relationships that may exist between an athlete/team's direct and indirect perception during certain tactical situations or phases of play. Future experimental studies should consider a research design that allows for reflection (e.g., questionnaires on tactical intention), or consideration of tactical game plans, on decisions made over the course of a game or during specific tactical situations or phases of play. This information, when combined with complex network, skill, spatiotemporal, and physical analyses, may provide further context and insight into factors influencing behaviour.

Impact Statement

While a plethora of information is available on the physical and technical components of Australian Football, objective methods of assessing the tactical demands (spatiotemporal and cooperative network characteristics) have been scarcely examined in general, or indeed at the specific club involved in this sequence of research. Further, despite enhancements in the quantity and quality of data available for assessing the technical, physical, and tactical characteristics of match play, it is not common that all these aspects are combined in statistical models of sports performance. Advancements in the scale of data availability for reviewing match performance have simultaneously increased the complexity of identification and interpretation of relevant information and the consequential association with performance.

In order to overcome these shortcomings in current processes, the sequence of research projects presented in this thesis was able to successfully simplify an array of physical, technical, and tactical variables utilised in Australian Football. Specifically, the simplification refers to variable reduction via principal component analysis followed by confirmation that stakeholders found the new metrics and subsequent statistical models easier to interpret. While limited to the analysis of one club in the premier competition, the impact at the involved club was substantial, with specific outcomes realised pertaining to the effect of each of these components on performance outcomes. These simplified metrics were utilised to simultaneously examine the relationship between technical, physical, and tactical performance and quarter outcome as determined by point differential. Further, novel metrics were also utilised to investigate differences in spatiotemporal and physical behaviour exhibited during specific phases of play as well as behaviours exhibited in successful and unsuccessful phases of play.

The new components derived in this sequence of research projects assisted in the reduction of complexity when analysing and interpreting multiple facets of performance in Australian Football, while retaining most of the variance in the original data sources. This has subsequently simplified the process for the performance analysis team and high-performance department to provide relevant feedback and information, subsequently allowing coaches to design and implement training programs that emulate specific features of match play. For example, *low pressure success*, a component derived from passing network data and associated with quarter success, was utilised in the match review process as a key performance indicator. It follows that the development of unique tactical strategies, such as those fostering *low pressure success,* that promote favourable behavioural outcomes can be subsequently implemented. Further, the integration of these metrics in relation to performance outcomes (quarter point differential and success in different phases of play) and contextual influences such as the phase of play, has enabled performance coaches to tailor training and provide specific information to players on all individual aspects of performance, thus guiding individual player development. For example, *change of direction*, a measure derived from multiple GPS metrics, was found to be an important characteristic of contested and offensive phases of play. Accordingly, conditioning blocks have subsequently been tailored for these demands in an attempt to develop this specific capacity with shuttle running replacing straight line running. Along with the impact on coaching strategies, the physical metrics derived in the current project have been used by medical and conditioning staff to assist with the chronic management of training loads throughout the season, as well as informing conditioning bouts implemented in specific training sessions. For example, the longitudinal assessment of *change of direction* and *high-speed* metrics has allowed physical performance staff to identify individuals who have had successive weeks of heightened physical load. As a result, extra recovery or longer periods between subsequent training sessions may be scheduled for individual players who require it.

The development and application of new knowledge has been a collaborative effort involving staff from the University of Technology Sydney and the Sydney Swans Football Club. The personnel include Mark Watsford, Job Fransen, Andrew Novak, Rhys Tribolet, Tom Harley, Charlie Gardiner, John Longmire, Rob Spurrs, Michael Rennie, Dean Cox, members of the Coaching department and staff from the High-Performance Department. Each of these individuals played a significant role in the project.

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Charlie Gardiner
Sydney Swans | Head of Football

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Rob Spurrs
Sydney Swans | Head of Physical Performance

Chapter 12

Summary & Recommendations

12.1 Summary

While there is an abundance of cooperative network, technical indicators, physical and spatiotemporal variables available for coaching staff and practitioners to assess player performance in Australian Football, the large number of variables makes it difficult to identify and interpret relevant information associated with performance success and relevant to monitor in training. Furthermore, little attempt has been made to objectively quantify and integrate, tactical behaviour with technical and physical indicators of performance in this context. To address this, studies one to four reduced the dimensionality of commonly reported cooperative network, technical indicators, physical and spatiotemporal behaviours obtained from AFL games to facilitate their practical use and interpretability. Using a principal components analysis, this approach was able to reduce the dimensionality of all variables whilst maintaining most of the variance in the dataset. These newly derived components were utilised in an applied setting as part of review sessions in the professional football context as well as in modelling performance outcomes in studies five, six, and seven.

Due to the inter-relationships between cooperative network, technical, physical, and spatiotemporal behaviour demonstrated in similar sporting contexts, study five utilised the metrics derived in studies one, two, three and four to examine the relationships between these constructs and performance as determined by *quarter margin*. Study five was the first of its kind to concurrently examine differences in cooperative network, technical, physical, and spatiotemporal behaviours with respect to performance in professional Australian Football. This study revealed that *scoring opportunity* and *ball movement ability* had positive association with *quarter margin* highlighting the need to promote superior levels of mutual interaction in an attacking manner. Further, while no direct relationship was established between *uncontested behaviour* or *physical behaviour* with *quarter margin*, these two components may elicit an indirect effect on performance. For example, negative associations between *uncontested behaviour* and *scoring opportunity* suggest that elevated high-pressure success and a lack of synchrony (i.e., greater unpredictability) may positively influence this component, which in turn is associated with *quarter margin.* Additionally, negative associations emerging between *physical behaviour* and *ball movement ability* suggests that reducing movement may make it easier to synchronise and coordinate actions so that the team can function as a cohesive unit and make it easier to mutually interact with teammates and subsequently improve *ball movement.* Lastly, the association between *change of direction* and *high-pressure success* may have novel implications for athlete conditioning. For example, this may implicate the inclusion of shuttle-based running in conditioning drills over straight line running. The findings from study five provide novel insights for coaches and practitioners as well as subsequent implications for training and game plan design.

The physical metrics derived in study three and the spatiotemporal metrics developed in study four, derived from various measures of dispersion, variability, synchrony, and regularity, were used to assess match-play behaviour in a professional Australian Football club. Study six assessed the relationship between physical and intra-team spatiotemporal behaviour, via GNSS microtechnology, and phase of play. *Duration, game volume, high speed, explosiveness, change of direction, decelerations/impacts, dispersive coordination,* and *multidirectional synchrony* were able to delineate between the different phases of play, providing novel insight for coaches and practitioners and subsequently providing direction for conditioning and training design. For example, offensive and defensive phases were characterised by greater *game volume* than other phases of play with defensive phases also revealing stronger affiliations with decelerations/impacts. Contested plays demonstrated superior explosiveness and change of direction likely leading to lower values of synchrony and coordination. Contested phases of play were strongly associated with high-speed metrics which may be due to players trying to be first to the ball or place themselves in a position to receive possession. As expected, likely due to their lower physical characteristics, set shots, goal resets and umpire stoppages demonstrated greater dispersive coordination and multidirectional synchrony than other phases. Duration was also a delineating factor in classifying each phase of play. This suggests that the timescale may be an important consideration for training design as the manipulation of practice drills to afford more/less time in each phase of play may challenge players with respect to their physical requirements, synchrony, and coordination.

Finally, study seven sought to examine differences in physical and spatiotemporal behaviour with respect to successful outcomes in different phases of play. Reduced duration accompanied by superior physical output, as defined by *high speed*, *change of direction* and *collisions/impacts*, and reduced *multidirectional synchrony* were deemed meaningful for explaining some successful offensive phase outcomes. This may be a result of a direct style of play with players moving erratically and unpredictability to misalign defenders or providing passing opportunities for teammates. In contrast, defensive success was characterised by reduced physical output, as demonstrated by *change of direction* and *collisions/impacts*, lower *lateral unpredictability and spacing* and increased *multidirectional synchrony*. This may be a result of players slowing movement to coordinate and synchronise movements to avoid being perturbed. Similar to other studies in this thesis, findings from the present study provide novel insight for coaches and practitioners and potentially implicating training and game plan designs.

The sequencing and integration of each of the studies is presented in Figure 12.1. This research project was the first to elucidate and integrate a wide variety of cooperative network, technical indicators, physical, and spatiotemporal variables and examine their association with performance success. Findings from this research may subsequently guide training design and drill implementation fostering an improvement in individual and team performance.

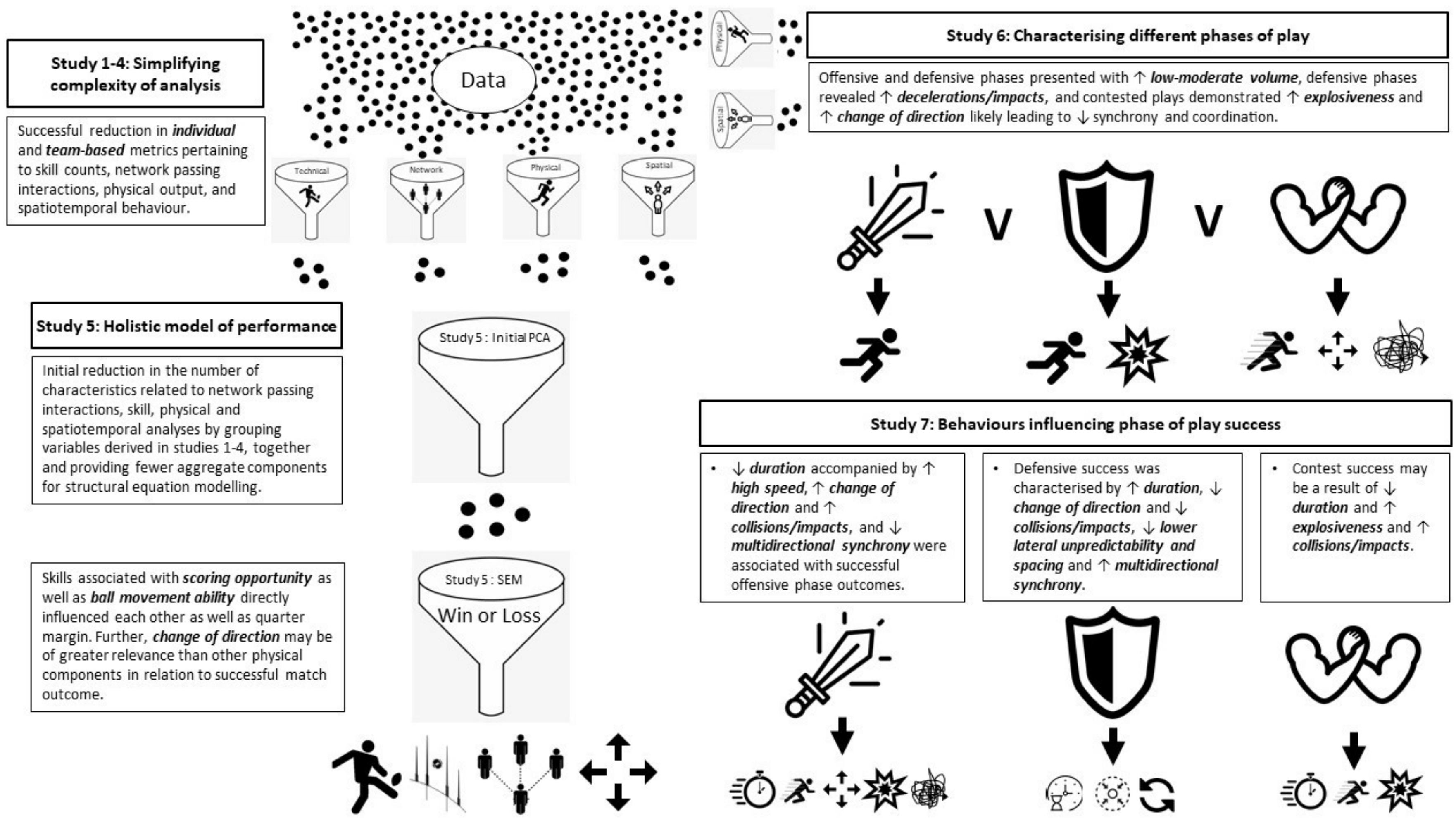

Figure 12.1: The inter-relationships and flow of studies one-seven

12.2 Directions for future research

Throughout the development of this thesis there have been several research questions that have formed from discussion with coaching staff, current developments in team sport research and results of prior studies. The seven research studies aimed to contribute to a multi-faceted conceptual model of performance and therefore future studies should aim to expand on these findings and contribute to the holistic model of performance in Australian Football.

- Data reduction techniques: While the use of a principal components analysis in studies one-four was a viable technique to reduce the dimensionality of the data, this method also presents some limitations. While PCAs are used for the sole purpose of dimension reduction in these studies, there may be discrepancies between the theoretical rationale for using a principal components analysis and its practical application. While this method derives principal components that explain most of the variance in the original data, original granular variables may provide valuable insight. Further, the naming of these variables is subject to interpretation and demonstrates that a PCA may not be the sole means of dimensional reduction with other methods such as expert guided dimension reduction presenting as an option. Future studies may need to examine whether dimension reduction, or less-dimensional approaches (i.e., reducing performance down to a few separate metrics using expert guidance) offer the best approach to modelling most of the variance in complex behaviour.
- Live analysis: While resultant sum scores derived in studies one-four provide a means for retrospectively assessing behaviour from games, quarters, and phases of play, the methods used to derive these sum scores may limit the capacity of these metrics to provide information for live tracking and analysis. Currently, raw data is retrospectively converted to z-scores and normalised to have the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)). While this is intended to facilitate interpretation, future research exploring avenues of live analysis may subsequently inform real-time decision making and offer an opportunity to intervene and alter emerging behaviour which may subsequently have implications for match success.
- Multi-team analysis: Currently in the AFL, technical data on all clubs is provided by ChampionData®, whereas GNSS data is not freely available between clubs making it difficult to provide a complete picture of performance with only the reference team having all data available. From an ecological dynamics perspective, opposition team and player movements provide perceivable information that subsequently inform the decision-making process and behaviours. Therefore, to provide a more in depth and complete model of performance, examination of all components from both teams is necessary. However, the only possibility of overcoming these limitations is through collaboration between clubs that have a mutual interest in the research or if GNSS data is made available to all clubs. Due to privacy and commercial agreements, the latter appears less likely, thus collaborative research is required to provide a more complete picture of performance and subsequently achieve somewhat of a proof on concept. Future lines of enquiry should explore the possibility for collaborative projects

subsequently providing a more complete picture of performance with behaviour from both teams assessed.

- Granular analysis: Though study five provides a comprehensive analysis encompassing network, technical, physical, and spatiotemporal components of performance in an Australian Football context, examination of all these components at a more granular level, i.e., during successful and unsuccessful phases of play, may further clarify the influence of these components on performance outcomes and match success. Further, as team behaviour in a complex system is an outcome of the interaction between its constituents, it may be important to examine behaviours of, or between, individual players and positional groups when analysing performance particularly during specific sub phases of the game, e.g., 1v1 marking contests. While contextually similar sports have examined spatiotemporal dyadic behaviour during critical moments, e.g., lead up to a successful pass in soccer,[95, 142] physical, technical or network attributes were not concurrently examined, potentially omitting important facets of match play.
- Tactical strategy prominence: In study five, the random effect (competition round) failed to meaningfully account for any additional variance in the models which may be indicative of tactical 'strengths' or 'habits' that are likely coached and remain stable across the season. Future investigations in AFL should consider pre-conceived tactical/coaching strategies and the influence this may have on behaviour on different phases of play and match outcomes. For example, in soccer, analyses showed that counterattacking tactical strategies employed by teams were more effective than elaborate attacks while playing against imbalanced defences. The assessment of specific tactics and opponent interactions is critical to evaluate the effectiveness of offensive playing tactics on the probability of scoring goals, and improves the validity of team match-performance analysis in soccer.[6]
- Training optimal behaviour: Future research should assess the influence of specific drill designs and training programs on behaviour and sum scores. Manipulating drill components such as field size, number of players, rules or incorporating vignettes may provide an effective means for improving the components shown to be of value in studies five-seven. For example, in study five, *connectedness* (a cooperative network variable derived in study one) contributed to *ball movement* which exerted a positive effect on *quarter margin* implicating this sum score for performance. Superior team *connectedness* scores are generated when most players connect bi-directionally and are easily reachable for others. In a training format, incorporating specific rules within a drill or SSG may aid in developing *connectedness* values and therefore have an influence on performance outcomes. For example, implementing a rule where all players must touch the ball at least once before scoring a goal may force teams to search for different movement solutions and passing interactions subsequently fostering greater connectedness. Alternatively, from a physical standpoint, it may also be of interest to see if improvements in traditional 'fitness tests' such as a 2km time trial following a conditioning program elicits changes in physical game metrics such as *game volume.* It would be of interest to monitor these components across a specific training period in the lead up to competition. Other contextually similar sports such as soccer have demonstrated improvements in inter-player lateral and

longitudinal synchronisation (spatiotemporal metrics) following a 9-a side, half-pitch, pre-season training protocol with professional football players.[150] This highlights that the use of training programs, and more specifically small-sided games, are an appropriate choice to promote the simultaneous development of physical, technical and tactical skills for football players and should be considered for future research in this context.[150]

- Application in differing contexts: With the scope and capacity of the newly derived metrics from studies one-four to contribute to the monitoring, review, and assessment of player performance and development, it would be of interest for these indicators and methods to be employed at different levels of competition within Australian Football, i.e., NAB league or AFLW. This may help translate existing findings generated from the elite level and subsequently lead to improvements in the development pathway and facilitate with player recruitment and drafting. Further, incorporating the methods used in this research, particularly the dimensional reduction and performance analysis techniques, in other contextually similar sports such as soccer, hockey, water polo, or basketball may further validate the approach utilised in this thesis and help establish a viable model of performance in those contexts.

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Appendix

Ethics Approval

-----Original Message-----
From: research.ethics@uts.edu.au <research.ethics@uts.edu.au>
Sent: Monday, 12 November 2018 3:28 PM
To: Research Ethics <research.ethics@uts.edu.au>; William Sheehan <William.Sheehan@uts.edu.au>; Mark Watsford <Mark.Watsford@uts.edu.au>
Subject: Neg Risk approval - ETH18-3126

This is an automated email

Dear Applicant

Project title: A constraints-led approach to the measurement and acquisition of team tactical behaviour

You have declared your research as Nil/Negligible Risk and that it DOES NOT include any of the following:
* Establishment of a register or databank for possible use in future research projects
* Collection, transfer and/or banking of human biospecimens
* Any significant alteration to routine care or health service provided to participants
* Interventions and therapies, including clinical and non-clinical trials, and innovations
* Targeted recruitment or analysis of data from any of the participant groups listed in Chapter 4 of the National Statement (or where any of these participants are likely to be significantly over-represented in the group being studied) including:
  - Women who are pregnant and the human fetus
  - Children and young people (under 18 years)
  - People in dependent or unequal relationships
  - People highly dependent on medical care who may be unable to give consent
  - People with a cognitive impairment, an intellectual disability, or a mental illness
  - People who may be involved in illegal activities (including those affected)
  - Aboriginal and Torres Strait Islander Peoples
* Collection, use or disclosure of personal information (except where expert opinion is being canvased with full disclosure, consent and identification for use in the public domain)
* Collection, use or disclosure of health information
* Collection, use or disclosure of sensitive information
* Covert observation, active concealment, or planned deception of participants
* Activity that potentially infringes the privacy or professional reputation of participants, providers or organisations (except where expert opinion is being canvased with full disclosure, consent and identification for use in the public domain)
* Potential for participants to experience harm (e.g. physical, psychological, social, economic and/or legal)
* Direct contact with UTS staff/students, patients, consumers or members of the public (except where expert opinion is being canvased with full disclosure, consent and identification for use in the public domain)
* Participants who have a pre-existing relationship with the researcher (except where expert opinion is being canvased with full disclosure, consent and identification for use in the public domain)

* People unable to give free informed consent due to difficulties in understanding the Information Sheet or Consent Form
* People in other countries

PLEASE NOTE: If at any time, the scope of your research changes to include one or more of the above categories, you are immediately required to submit a new application.
To access the National Statement on Ethical Conduct in Human Research, visit the NHMRC webpage: https://www.nhmrc.gov.au/guidelines-publications/e72

Please keep a copy of your ethics application form and approval letter on file to show you have considered the risks associated with your research. You should consider this your official letter of approval.
For tracking purposes, you have been provided with an ethics application number, which is UTS HREC ETH18-3126N.

I also refer you to the AVCC guidelines relating to the storage of data, which require that data be kept for a minimum of 5 years after publication of research. However, in NSW, longer retention requirements are required for research on human subjects with potential long-term effects, research with long-term environmental effects, or research considered of national or international significance, importance, or controversy. If the data from this research project falls into one of these categories, contact University Records for advice on long-term retention.

Instructions for saving the application form can be downloaded from: https://staff.uts.edu.au/howdoi/Pages/Researching/Research%20ethics%20and%20Integrity/Human%20research%20ethics/download-a-copy-of-my-application.aspx

To access this application, please follow the URLs below:
* if accessing within the UTS network: https://rm.uts.edu.au
* if accessing outside of UTS network: https://vpn.uts.edu.au, and click on ""RM6 - Production"" after logging in.

If you have any queries about this approval, please do not hesitate to contact your local research office or Research.Ethics@uts.edu.au.

Kind regards

UTS HREC Ethics Secretariat
C/- Research & Innovation Office
University of Technology Sydney
E: Research.Ethics@uts.edu.au
https://staff.uts.edu.au/topichub/Pages/Researching/Research%20Ethics%20and%20Integrity/Human%20research%20ethics/human-research-ethics.aspx
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REF: Ethics 2 -Neg Risk approved (c)

Study One: Using cooperative networks to analyse behaviour in professional Australian Football

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Original research

Using cooperative networks to analyse behaviour in professional Australian Football

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ABSTRACT

Objectives: Reducing the dimensionality of commonly reported complex network characteristics obtained from Australian Football League (AFL) games to facilitate their practical use and interpretability.
Design: Retrospective longitudinal design where individual players' interactions, determined through the distribution and receipt of kicks and handballs, during official AFL games were collected over three seasons.
Methods: A principal component analysis was used to reduce the number of characteristics related to the cooperative network analysis.
Results: The principal component analysis derived two individual-based principal components pertaining to in- and out-degree importance and three team-based principal components related to connectedness and in- and out-degree centralisation.
Conclusions: This study is the first to provide a simplified, novel method for analysing complex network structures in an Australian Football context with both the team- and individual-derived metrics revealing useful information for coaches and practitioners. This may consequently guide opposition analysis, training implementation, player performance ratings and player selection.

Practical implications

- The simplified complex network measures developed in this study provide supporting data for performance analysts currently using video and skill involvement counts to analyse games.
- The derived metrics allow coaches to identify strengths and weaknesses in the opposition team that can be exploited through the implementation of game tactics.
- This information enables coaching staff to develop training interventions that are representative of the skill demands of competition needed for successful team performance.

1. Introduction

Australian Football is a contact-based, team invasion sport played on an oval-shaped field by two teams of 22 players, with 18 players on the field, over four 20-min (in-play time) quarters, where the aim is to score as many points as possible by kicking between goal posts on each end of the oval. It involves phases of ball possession, contested play and stoppages of varying durations. In the Australian Football League (AFL), the pinnacle of Australian Football, the physical element of the game is characterised by intermittent high-speed running coupled with frequent collisions and changes of direction and speed.[1,2] Playing in the AFL requires high skill proficiency with players utilising hand and foot skills for passing, scoring and gaining ball possession.[3] Players also have certain position specific roles that lead to differences in performance outcomes. For example, nomadic players, such as midfielders, small forwards and small defenders, tend to have more skill involvements (touches of the football) and cover greater distance throughout the game than fixed position players, such as tall forwards and tall backs.[2] Teams also utilise a variety of tactical strategies depending on their own personnel, coaching philosophies, opposing team and environmental conditions during the match.[3]

Collectively, players adapt their physical abilities, skills and tactical strategies to cope with the ever-changing demands of the game. However, most team sport performance research has adopted a reductionist approach investigating these factors in isolation. Previously, performance analysts have largely related discrete technical on-field actions such as the frequency of kicks, handballs,

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possessions and marks,[4] in association with variables incorporating these skills such as disposal efficiency, shot efficiency, and passing rate to performance outcomes.[5,6] However, the excessive emphasis placed on performance outcome rather than process measures presents an underlying issue that primarily focuses on 'who did what, when' failing to provide a meaningful understanding of the underlying factors of successful performance in complex team invasion games. This stresses the need for a theoretical rationale that can provide insight into performance behaviours.[7] By utilising appropriate tactical analysis techniques, in association with a viable framework to explain behaviour in team sports, further insight as to 'why' or 'how' certain behaviours emerge can be elucidated and provide an understanding into the process characteristics underpinning successful performance.[8]

The ecological dynamics framework focuses on the performer-environment relationship and may provide a viable basis for understanding performance in team sport.[9] From an ecological dynamics perspective, Australian Football is a complex performance-environment sub-system where players and teams perceive opportunities for action which guide decision-making and subsequent actions. The perception of relevant environmental information sources allows players to self-organise into stable states of coordination that allows the achievement of task goals.[9] In this complex system, task-constraints such as field dimensions and passing rules, along with physical and informational constraints such as player size and opposition player movements, provide information and boundaries that govern behaviour. The resultant behaviour in a complex system is the interaction between its constituents. Therefore, it is important to examine the role played by player interactions when analysing performance from an ecological dynamics perspective. While passing interactions between players have been extensively researched in other football codes such as soccer,[10,11] minimal research exists in Australian Football.[5]

The implementation of complex network analysis can provide additional information that captures the dynamic nature of team sport performance.[12] The analysis of passing sequences within a team allows practitioners to map and quantify the interactions between different players during a game. Complex network analyses can reveal the local structure of organisation among players. In professional soccer, network analyses have revealed common tendencies in successful teams, with minimal reliance on key players (i.e. decentralisation) being a common characteristic associated with successful team performance.[11] It is suggested that decentralised teams foster interdependence whereby players do not solely rely on one or two key players. This encourages coordination and cooperation which is beneficial to a team's performance, as determined by match outcome.[11] When correctly implemented, a complex network analysis can identify key players, i.e. those that display high connectivity within a team such as midfielders in soccer, who link defenders and attackers through transfer of possession.[13] Such analysis may also be relevant in Australian Football as certain positions, similar to soccer, may have role-specific technical, tactical and physical demands that may influence inter-player interaction.[14]

Only one study has examined complex network structures in the context of Australian Football.[5] This study investigated how the complex network structures of different teams in the AFL competition self-organised into purposeful behaviour and how the characteristics of these complex networks were related to successful performance outcomes. The current manuscript revealed similar relationships to those in soccer, suggesting that successful offensive strategies were varied but frequently decentralised with the majority of players being well connected in successful teams. However, the array of complex network variables presented in this study, similar to soccer research, makes it difficult to delineate and interpret the effect of specific network structures on performance outcomes for its goal audience (i.e. coaches, recruiters, and performance analysts). Therefore, in order for complex networks to be adopted for practical performance analysis in sport, their analysis and interpretation should be simplified. This will also facilitate how researchers further investigate the relationship between complex network structures and performance outcome measures such as winning or losing games and contextual factors such as opposition team strength and playing at home or away. Therefore, the aim of this study was to reduce the dimensionality of commonly reported complex network characteristics obtained from AFL games in order to facilitate their practical use and interpretability. It was hypothesised that a factor analysis would successfully reduce the number of variables obtained from individual and team-based complex network analyses in Australian Football.

2. Methods

The study sample consisted of 48 male professional Australian Football players (age: 24.97 ± 3.78 years; playing experience: 5.22 ± 3.44 years) from one AFL team. Each participant played at least one game over the three-year (2016–2018) analysis window. Data from seventy-three senior matches were used for analysis. This sample provided 73 team-based files with 1605 individual files (33.4 ± 25.6 per player) from the designated AFL team. Furthermore, data was collected on each opposition team for all 73 matches used in this study, providing an additional 73 team-based files (4.3 ± 1.4 per team) and 1603 individual files (2.5 ± 1.5 per player). The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

The study followed a retrospective longitudinal design where individual players' interactions, as determined through the distribution and receipt of kicks and handballs, during official AFL games were collected over a period of three seasons. A Principal Component Analysis (PCA) was used to reduce the number of characteristics related to the complex network analysis.

Data was obtained from ChampionData®, the official data provider to the AFL.[5] ChampionData® code all AFL matches for a myriad of skill involvements[15] and are commonly used in Australian Football research.[15–17] A selection of statistical indicators have been empirically reviewed, including an array of disposal and possession-related statistics used in the current study, reporting a high level of reliability (ICC range = 0.980–0.998 RMSE range = 0.0–4.5).[18] The only other reliability information provided about ChampionData® statistics states that "quantity-based statistics are logged at better than 99% accuracy".[15] ChampionData® match statistics were used to create a weighted and directed, 22×22 adjacency matrix for each game, which reveals the number of interactions between certain players.[13] An interaction was counted if a handball or kick reached the intended target player. This matrix was then used to create a weighted directed graph with the graphed nodes representing individual players and weighted edges signifying the direction and number of passes between players. The adjacency matrices and graphs were subsequently used for analysis using MatLab routines.[19]

Table 1 identifies the variables that were included for analysis, the method of calculation, and their relevance and interpretation of outcome. The complex network variables describe the interaction between players such as the number of passes (kicks and handballs) that a player produces or receives along with the metrics that can be derived from that data such as a player's relative importance within the entire network. Additionally, all measures were derived from the matrix at the individual as well as the team-based level.

Table 1
Complex network variables.

Variable (source)	Calculation	Relevance and interpretation of outcome
Global player network summary statistics[11]		
Network density	$Density = \frac{\sum Column(nnz) + \sum Row(nnz)}{(n^2 - n)}$	With n equalling the number of players, and nnz equalling non-zero elements in the matrix, density signifies the global level of interaction within the network with values closer to 1 showing a more complete network whereby most players interact with the majority of the team.
Network intensity	$Intensity = \frac{\sum Column + \sum Row}{2}$	Indicative of the amount of ball movement in the network with higher values demonstrating a greater amount of ball movement.
Individual interaction level (source)[5,28]		
In- and out-degree node centrality	$In - Degree\ Node\,(i) = \sum Column(nnz)(i)$ $Out - Degree Node\,(i) = \sum Row(nnz)(i)$	Represents the number of incoming or outgoing connections at each node or player (i) with higher values signifying that players interact with more players via reception of a pass (in-degree) or interact more with other players via distribution of a pass (out-degree).
In- and out-degree node centrality proportion	$In - Node\ Proportion\,(i) = \frac{In - degree Node(i)}{(n-1)}$ $Out - Node\ Proportion\,(i) = \frac{Out - degree Node(i)}{(n-1)}$	Signifies how well connected a certain player (i) is within the network relative to the total number of players in the network. Values closer to 1 signify that the player is well connected and interacts with the majority of other players in the network.
Node ratio	$Node\ Ratio\,(i) = \frac{In - Degree Node(i)}{Out - Degree Node(i)}$	Identifies whether a specific player (i) is either connected with or connects with more players in the network. Values greater than 1 signify that the number of players an individual receives possession from is greater than the number of players they distribute to.
In- and out-degree pass centrality	$In - Degree\ Pass\,(i) = \sum Colum(i)$ $Out - Deegree\ Pass\,(i) = \sum Row(i)$	Reveals the total number of passes a player (i) receives or distributes
In- and out-degree pass centrality proportions	$In - Pass\ Proportion\,(i) = \frac{In - degree Pass(i)}{Intensity}$ $Out - Pass\ Proportion(i) = \frac{Out - degree Pass(i)}{Intensity}$	Indicates the proportion of all network passes that are either received (in-degree) or distributed (out-degree) by a specific player (i). As per node proportions, scores closer to 1 signify that a player is well connected or important in the network.
Centrality pass ratio	$Pass Ratio\,(i) = \frac{In - Degree Pass(i)}{Out - Degree Pass(i)}$	Identifies whether a player (i) receives or distributes more passes within the network. Values greater than 1 signify that a player receives a greater number of passes than they distribute.
Individual proximity[10,19,29]		
In- and out- closeness	$Closeness\,(i) = \left(\frac{A(i)}{n-1}\right)^2 \frac{1}{C(i)}$	With $A(i)$ as the number of reachable players from player i (not counting i), n as the number of players in the network, and $C(i)$ is the sum of distances from player i to all reachable players, closeness signifies how easy is it for a given player to reach (out-closeness) or be reached (in-closeness) by other players in the network. Higher values assume a positive meaning in the node's proximity and indicate that a player requires a shorter number of passes to connect with other players.
Betweenness centrality	$Betweenness\,(i) = \sum_{s,t \neq i} \frac{n_{st}(i)}{N_{st}}$	Indicative of how often a player appears on a shortest path between two players in the network. A player with a higher value is crucial to maintain team passing connections by acting as a connecting bridge and is important for passing flow in the network. $n_{st}(i)$ is the number of shortest paths from player s to player t that pass-through player i, and Nst is the total number of shortest paths from s to t.
Individual Importance[29,30]		
Pagerank centrality	$Pagerank\,(i) = p \sum_{j \neq i} \frac{A_{ij}}{L_j^{out}} x_j + q$	Ability to identify important players within the network. This measure holds that a player is of importance if they receive passes from other important players. Assigns to each player the probability that they will have the ball after a reasonable number of passes being made in the network. $L_j^{out} = \sum_k A_{jk}$ is the total number of passes made by player j, p is a heuristic parameter representing the probability that a player will decide to give the ball away, and q is a parameter awarding a 'free' popularity to each player.
Team equality statistics[11,31]		
In- and out-degree node centrality variability	$Node Variability = \frac{\frac{\sum i_{max} - i_n}{n}}{(n-1) \times Density}$	With i_{max} being the maximum value in the network and i_n representing every value in the network, this parameter reveals global centralisation characteristics of the team with lower values signifying that all players interact with the same number of players and, conversely, larger values suggesting that certain players connect more with other players.

Table 1 (Continued)

Variable (source)	Calculation	Relevance and interpretation of outcome
In- and *out-degree pass centrality variability*	$PassVariability = \frac{\sum_{n} i_{max} - i_n}{(n-1) \times Intensity}$	Assess centralisation tendencies with lower variability signifying that all players receive and/or distribute the same amount of possession through passing. Conversely, higher variability suggests that certain players receive or distribute more possession than other players.
Global In-Closeness	$GlobalMean = \frac{\sum_{n} i_n}{n}$	Individual player values were used in the calculation of team complex network values, both providing information regarding network equality, or centralisation, within the team. Indicates the average value in the given measure.
Global Out-Closeness *Global Betweenness* *Global Pagerank*		
In-Closeness Variability *Out-Closeness Variability* *Betweenness Variability Pagerank Variability*	$GlobalVariability = \frac{\sum_{n} i_{max} - i_n}{n-1}$	Lower values signifying equality, or decentralisation in the network. Indicates the variability within the team in the given measure.

All network values were converted to z-scores and normalised to the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score= 100+(z-score*15)). This subsequently facilitated dimensional reduction using a factor analysis.[20]

A data reduction technique was used to reduce the number of characteristics related to the network analysis by grouping network characteristics at the individual and team level. More specifically, an exploratory factor analysis was conducted through a PCA to reduce the dimensionality of the data into a smaller set of variables whilst maintaining most of the variance in the original data set.[21,22] As a result of PCA, no correlation exists between the principal components, but each contain their own highly correlated variables that measure an underlying, yet independent construct. This method ensures only distinct information remains within the data set.[23] A PCA involves the removal of the mean, calculation of the covariance of the data, determination of the eigenvalues and eigenvectors of the covariance matrix, and a varimax rotation of the original data onto a coordinate system spanned by the eigenvectors of the covariance matrix.[22] Two separate exploratory PCAs were executed using SPSS for Windows (Version 25)[24] where the aim was to determine whether common underlying constructs were present in the fourteen individual-derived variables, and in the fourteen team-derived variables. Linear relationships were initially assessed using a correlation matrix while the Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction.[24] In both data sets, all network variables were initially included, upon which variables with communalities (relative importance for inclusion in the factor) lower than 0.40 were excluded.[25] Each PCA was subsequently rerun using only variables of significant importance and consequentially used to derive factor loadings associated with each of the variables in the PCA. These factor loadings were then used to calculate summed variables for each component.

3. Results

Only one variable, *global pagerank*, was excluded from the PCA due to a communality below 0.40. Upon inspection of the subsequent correlation matrix, linear relationships existed between all variables at the individual and team-based level. An examination of the KMO measure of sampling adequacy suggested that the sample was factorable for both the team (KMO= 0.805) and individual (KMO = 0.756) data set. Additionally, Bartlett's test of sphericity was significant for both data sets ($p < 0.001$).[24] Table 2 reveals the total explained variance from the individual and team PCA, respectively.

The rotated component matrix produced factor weightings for each variable in their respective principal component. The five equations were derived from the analysis are displayed in Table 3.

4. Discussion

Australian Football match performance is a complex network, consisting of many independent and interacting degrees of freedom that show the potential for self-organisation into states of coordination. While many studies have attempted to describe the features of complex networks in sports, the present study was the first to describe and dimensionally reduce an array of network features in an Australian Football context to facilitate their practical application, interpretation, and reporting to performance staff. Fourteen individual and fourteen team-based variables were reduced to two individual and three team-based components, respectively. These principal components adequately represent different constructs whilst maintaining a large amount of the variability from the original data (Table 2).[24] These new components facilitate the interpretation of complex network features and subsequently allow practitioners and coaches to design and implement training that emulates specific network features and consequentially promotes favourable outcomes.

Equation 1 provides an indication of a player's level of interaction regarding incoming network relationships such as receiving a kick or handball (in-degree). Resultant sum scores from this equation provide insight regarding the level of possessions received (*in-degree pass* and *in-degree pass proportion*), ease of reachability (*in-closeness centrality*), the incoming level of connectivity within the network (*in-degree node*, *in-degree node proportion* and *pagerank*) and a player's importance for linking specific players within the network (*betweenness centrality*). Higher values may signify that a player is located centrally and is used by more players within a team. Furthermore, this sum score highlights a player's ability to link other players together or obtain possession of the ball and score. Accordingly, this may reflect a player's positional role with the specific task of receiving and distributing possession, such as a midfielder.[5,26] Alternatively, specific players such as key attackers may be relied upon to score goals in key attacking positions and therefore would display a high level of in-degree importance.[26]

In contrast, equation 2 provides an indication of a player's level of interaction regarding outgoing network relationships such as performing a kick or handball (out-degree). Higher sum scores are reflective of an individual's ability to distribute possession. This is influenced by the ability of a player to connect with other players (*out-degree node* and *out-degree node proportion*), distribute a large amount of possession (*out-degree pass* & *out-degree pass*

Table 2
Total variance explained from individual- and team-derived variables.

Initial eigenvalues				Extraction sums of squared loadings			Rotation sums of squared loadings		
Component	Total	Explained variance	Cumulative %	Total	Explained variance	Cumulative %	Total	Explained variance	Cumulative %
Individual									
1	8.770	62.642	62.642	8.770	62.642	62.642	7.057	50.407	50.407
2	3.451	24.648	87.290	3.451	24.648	87.290	5.164	36.883	87.290
Team									
1	6.401	49.242	49.242	6.401	49.242	49.242	4.960	38.152	38.152
2	2.400	18.463	67.705	2.400	18.463	67.705	3.008	23.135	61.287
3	1.728	13.290	80.994	1.728	13.290	80.994	2.562	19.707	80.994

Table 3
Resultant equations from principal components analysis.

Equation number	Variable	Calculation
1	In-Degree Importance	0.960 × In Degree Node + 0.960 × In Degree Node Proportion + 0.923 × In Closeness Centrality + In Degree Pass × 0.915 + 0.915 × Pagerank Centrality + 0.909 × In Degree Pass Proportion + 0.681 × Betweenness Centrality
2	Out-Degree Importance	0.849 × Out Degree Node + 0.848 × Out Degree Node Proportion + 0.848 × Out Closeness Centrality – 0.846 × Centrality Ratio Node – 0.820 × Centrality Ratio Pass + 0.792 × Out Degree Pass Proportion + 0.792 × Out Degree Pass
3	Connectedness	0.964 × Network Density – 0.949 × Team Betweenness Centrality + 0.939 × Team Out Closeness Centrality + 0.935 × Team In Closeness Centrality + 0.931 × Network Intensity
4	In-Degree Variability	0.925 × Team In Degree Node Variability + 0.925 × Team In Closeness Centrality Variability + 0.714 × Pagerank Centrality Variability + 0.613 × In Degree Pass variability
5	Out-Degree Variability	0.945 × Team Out Closeness Centrality Variability + 0.895 × Team Out Degree Node Variability + 0.626 × Out Degree Pass variability + 0.523 × Team Betweenness Centrality Variability

proportion), and easily reach other players within the network (*out-closeness centrality*). Additionally, if a player receives more possession than they distribute, this will negatively impact upon the resultant sum score, as would be the case in players in terminal positions such as goal scoring attackers or in players who frequently lose ball possession. Superior scores may also reflect positional roles. For example, defenders have the primary role of disrupting opponent offensive movements, ideally in the form of an intercept. This may lead to greater out-degree values as these players intercept opposition possession and then distribute to players around them.[5] Alternatively, midfield or ruck players who obtain possession without receiving the ball directly from teammates or interception, by winning the ball in contested play, may also display higher values due to their positional role. Collectively, the relationship between in-degree and out-degree importance is also relevant, as it highlights where the linking players are within a unit/team. While theoretical insight can be drawn from other similar sporting contexts, such as soccer, association between these metrics and position specific roles requires validation.

From a team perspective, equations 3–5 reveal global characteristics of the network. Equation 3 provides insight into the level of connectedness within the team with higher values signifying that most players connect bi-directionally (*network density*) and are easily reachable for others (team *in-* and *out-closeness centrality*). Additionally, the negative contribution of team *betweenness centrality* indicates that lower scores benefit overall connectedness. A lower team *betweenness centrality* score signifies that most players within the network can connect with one another without relying on a linking individual. As measures of possession are a determinant of success in Australian Football[5,6] and soccer,[27] superior displays of connectedness will likely be associated with positive outcomes. However, future studies are required to validate the use of the above metric in relation to match outcomes in Australian Football.

In conjunction with equation 3, equations 4 and 5 provide information regarding the mutuality of involvement from all players within the network. Lower values imply that the network is decentralised with all players interacting and contributing equally to the network. Conversely, greater values suggest that specific players are relied upon for receiving (equation 4) or distributing (equation 5) possession, resulting in the network being more centralised. While variability is yet to be examined in an Australian Football context, successful teams have demonstrated decentralised characteristics in soccer whereby adept teams often do not rely on a single player. From equations 3, 4 and 5, it is expected that in a decentralised network, sum scores would reveal a high connectivity score (equation 3), with low variability scores in both the in- and out-degree direction (equation 4 & 5). While the three outputs from these equations are capable of revealing the structure of complex team networks, future studies are required to validate their use in an Australian Football context and their association with successful performance.

Complex networks in Australian Football are multi-layered with the varying individual dynamics influencing the overall structures that emerge at the team level and, consequentially, inter-team match behaviour. The metrics derived in this study may provide means for coaches and practitioners to further understand the influence of these varied structures and the influence of varying contextual factors. While the present study is the first to provide a simplified, novel method for analysing complex network structures in an Australian Football context, these metrics are yet to be validated in relation to individual and team performance. The results of this study provide supporting data for performance analysts currently using video and skill involvement counts to analyse games and could allow coaches to identify strengths and weaknesses in the opposition team that can be exploited through the implementation of game tactics. This new information also allows coaching staff to develop training interventions that are representative of competition demands as they can now quantify and emulate complex network structures evident in game scenarios. At an individual level, the examination of the individually-derived metrics may highlight favourable task-specific characteristics associated with different positions in the network and provide an additional objective means of assessing player match-performance. This information could therefore facilitate the recruitment of new players that can be a valuable addition to the existing network. These metrics may also allow coaches to longitudinally assess the development of an individual players role within the network over time. Lastly, findings from this study may also prove useful in other sports other than Australian Football, following its validation in these other sports.

5. Conclusion

This study is the first to provide a simplified, novel method for analysing complex network structures in an Australian Football context with both the individual and team-based metrics revealing useful information for coaches and practitioners. While theoretical insight can be drawn from similar sporting contexts, future studies are required to validate the use of these new metrics in association with individual and team performance outcomes. This may consequently guide opposition analysis, training implementation, player performance ratings and player development, selection and recruitment. Further, if proven valid, the findings from the current study may provide a viable framework of analysis in other contextually similar sports.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jsams.2019.09.012.

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Study Two: Improving the interpretation of skill indicators in professional Australian Football

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Original research

Improving the interpretation of skill indicators in professional Australian Football

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Objectives: This study aimed to provide a simplified, novel method for analysing technical skill involvements in an Australian Football context by reducing the dimensionality of commonly reported skill counts obtained from Australian Football League (AFL) games. This may facilitate their practical use and interpretability.
Design: Retrospective longitudinal design where individual players' technical skill counts were collected over three seasons of official AFL games.
Methods: Seventy-three skill count values provided publicly by ChampionData® were collected for each match over a three-year analysis period. A principal component analysis was used to reduce the dimensionality of a large number of correlated technical skill indicators into a smaller set of uncorrelated components whilst maintaining most of the variance from the original data set.
Results: The principal component analysis derived four principal components pertaining to *high-pressure success*, *low-pressure success*, *attacking ball movement ability* and *scoring ability*.
Conclusions: This study is the first to provide a simplified, novel method for analysing technical skill counts in Australian Football. The derived metrics reveal useful information for coaches and practitioners. This may consequently ease the interpretation of skill count data available to coaches from games, guide opposition analysis, help in the design of representative practice and inform player performance ratings.

Practical applications

- The simplified measures of technical skill involvement developed in this study provide supporting data for performance analysts currently using video and technical skill counts to analyse games.
- The derived metrics can limit the potential misinterpretation that arises from dealing with a vast array of technical count data that is obtained from every game. Accordingly, they can allow coaches to identify individual strengths, weaknesses and roles within a team. This can subsequently guide player development and list-management decisions.
- These derived principal components also allow performance analysts and coaches to quantify the strengths and weaknesses of opposition players which may be exploited through the implementation of game tactics.
- This method of data reduction can be used in other team sports, where technical skill counts are commonly recorded.

1. Introduction

Professional Australian football is a complex team invasion sport consisting of two teams of 22 players with 18 taking the field and four interchange. Match play consists of four 20-min quarters of in-play time, with time stopping when the ball leaves the field of play or is deemed unplayable by the umpire. The game is played on an oval-shaped field that varies in length (149–175 m) and width (122–136 m), with two central 'goal' posts and two outer 'behind' posts at each end.[1] If the ball is kicked between the two goal posts by the attacking team, a goal worth six points is awarded. If the ball passes between the goal posts in any other way, hits a goal-post or passes between a goal post and a behind post, one point is awarded.[2] In the Australian Football League (AFL), the pinnacle of Australian football, players must utilise an array of technical skills in order to score more points than the opponent.[1] Teams also utilise a variety of tactical strategies depending on their own play-

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ers' strengths and weaknesses, coaching philosophies, opposing team tactics and environmental conditions during the match.[3]

In the last decade, performance analysts have successfully quantified a plethora of physiological and technical skill demands to derive practical applications for improving team performance. Specifically, physiological demands have been extensively researched using Global Positioning Systems (GPS)[4] while the assessment of discrete, technical, on-field actions such as frequency of *kicks, handballs, possessions* and *marks*[5] have been able to contribute to models predicting performance outcomes.[6–9] Further, though scarcely examined in Australian football, recent lines of inquiry have sought to objectively quantify tactical behaviour using cooperative network analyses that examine passing interactions between teammates,[2,10] as well as spatiotemporal analyses assessing dispersion, synchrony and regularity.[11] Whilst the examination of these components, often in isolation, have provided valuable insight into the physical, technical and, to a lesser degree, the tactical requirements of the game, discrepancies exist when associating these components with successful and unsuccessful performance outcomes.[6,9,12–14] These discrepancies may occur as players need to collectively adapt their physical abilities, technical skills and tactical strategies to perform successfully as the demands of the game evolve. Integrating and collectively analysing all these components may provide insight into existing discrepancies and provide a greater indication into factors affecting performance.[15,16]

Players require high levels of technical skill proficiency to perform successfully in the AFL and cope with the evolving game demands.[9] Accordingly, the technical skill demands of professional Australian Football have been quantified using methods of manual notational analysis.[3,17] ChampionData® code all AFL matches for a variety of technical skill indicators and the validity of these data have been investigated previously.[7,12,17] Such data reveals particular playing styles and contributes to models predicting performance outcome.[2,7,18] Technical skill count data presents the most common indicator of technical performance with the information provided allowing coaches and practitioners to understand which technical skills to develop during training and consequently improve performance.

While the large volume of information provided by ChampionData® regarding the technical skill demands are useful, inconsistencies and discrepancies exist in the literature between indicators of successful and unsuccessful performance. For example, one study highlighted that the number of handballs and turnovers had no significant effect on match outcome.[8] Conversely, other researchers reported the same indicators to be significant contributors to performance.[7] These discrepancies may partially be a result of researchers only incorporating a select number of indicators, accounting for a small portion of variance, to quantify performance outcomes. The extensive array of technical skill variables available to analysts and practitioners potentially makes it difficult to delineate and interpret the effect of specific technical skill variables on performance outcomes. For practical performance analysis in sport, the interpretation of these variables needs to be objectively simplified. Previous research methods have attempted to address this by focussing on a select number of variables and statistics primarily associated with possession,[5,8,9] ChampionData® ranking[5,6,12] or a coaches subjective rating of performance.[12,13] While this reductionist approach has facilitated the interpretation of technical skill count data, it fails to incorporate all available technical skill components that relate to performance success in Australian Football. Therefore, an approach that incorporates all relevant variables, holistically capturing technical skill performance, is required. The objective simplification of a wider variety of technical variables previously provided by ChampionData® may facilitate subsequent integration with physical and tactical components making it easier to interpret the effect of these components on performance outcome. This may further guide coaching staff in developing training programs where these performance elements are trained simultaneously.

In order for technical skill indicators to be adopted for practical performance analysis in sport, and integrated with other performance components, their analysis and interpretation needs to be objectively simplified through feature reduction techniques such as a principal component analysis.[19,20] This further facilitates investigation into the relationship between these technical components and performance outcome measures such as winning or losing games and contextual factors such as opposition team strength or playing at home or away. Accordingly, the aim of this study was to reduce the dimensionality of commonly reported technical skill indicators obtained from AFL games to facilitate their practical use and interpretability. It was hypothesised that a principal component analysis would reduce the number of variables obtained from individual-based skill counts in Australian football. Since technical performance is an integral contributor to success in Australian Football, the derived principal components will have a theoretical underpinning which will aid and simplify the interpretation of technical skill involvements associated with AFL match play. Given the modifiable nature of these components, subsequent implementation of training programs may enable the optimisation of physical performance.

2. Methods

The study sample consisted of 48 male professional Australian Football players (age: 24.97 ± 3.78 years; playing experience: 5.22 ± 3.44 years) from one AFL team. Each participant played at least one game over the three-year (2016–2018) analysis window. Seventy-three senior matches were used for analysis providing a sample of 1605 individual files (33.4 ± 25.6 per player) from the designated AFL team. Furthermore, data was collected on each opposition team for all 73 matches used in this study, providing an additional 1603 individual files (2.5 ± 1.5 per player). The procedures used in this study were conducted with approval from the Human Research Ethics Committee of the local institution.

The study followed a retrospective longitudinal design where all players' technical skill counts during AFL games were collected over three seasons. Data were obtained from ChampionData®, the official data provider to the AFL.[2] ChampionData® code all AFL matches for a variety of skill involvements[17] and are commonly used in Australian Football research.[14,17,21] A selection of statistical indicators have been empirically reviewed, reporting a high level of reliability (ICC range = 0.947–1.000; RMSE range = 0.0–4.5).[22] Other reliability information provided about ChampionData® statistics states that "quantity-based statistics are logged at better than 99% accuracy".[17]

Seventy-three skill count values provided publicly by ChampionData® were collected for each individual for each match (see Appendix A for Table A1). Specific variables were removed if they had a mean and standard deviation <1. This was deemed appropriate as skill involvements that occur less than once per game by players were unlikely to influence match outcome.[23] Further, collective variables that were made up of other smaller variables in the data set were removed to mitigate duplication while retaining granularity in the analysis. For example, an individual's *effective disposal* count was a direct result of summating a player's *effective kick* and *effective handball* count. As the latter two technical skill count variables had a mean and standard deviation >1 and were not initially removed, the *effective disposal* variable was removed from the dataset. Fig. 1 identifies the variables that were removed prior to analysis and Table 1 contains definitions of the included variables.

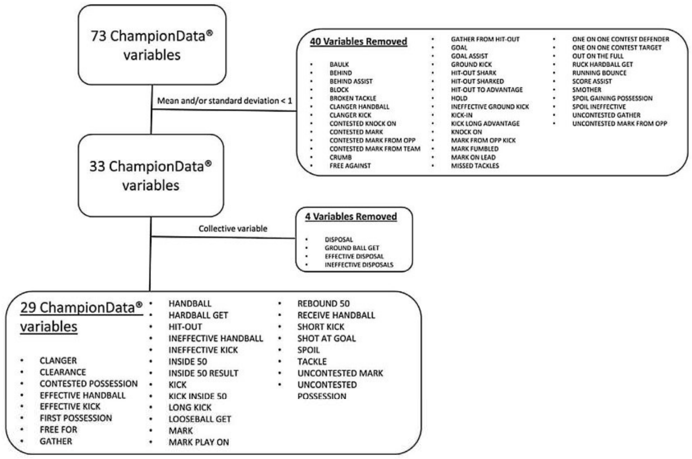

Fig. 1. Skill indicator selection criteria.

Table 1
Technical involvement indicators included in the principal component analysis.

Technical indicator	Description
Clanger	A handball or kick that give possession directly to the opposition.
Clearance	Credited to the player who has the first effective disposal in a chain that clears the stoppage area, or an ineffective kick or clanger kick that clears the stoppage area.
Contested Possession	A possession which has been won when the ball is in dispute. Includes looseball-gets, hardball-gets, contested marks, gathers from a hit-out and frees for.
Effective Handball	A handball to a teammate that hits the intended target.
Effective Kick	A kick of more than 40 m to a 50/50 contest or better for the team or a kick of less than 40 m that results in the intended target retaining possession.
First Possession	The initial possession that follows a stoppage, including a looseball-get, hardball-get, intended ball-get (gather), free kick or ground kick.
Free For	When a player is interfered with and is awarded a free kick by the umpires.
Gather	Possessions that were a result of a teammate deliberately directing the ball in the player's direction, via a hit-out, disposal or knock-on, excluding marks and handball receives. Gathers from a hit-out are contested possessions the rest are uncontested.
Handball	Disposing of the ball by hand.
Hardball Get	A disputed ball at ground level under direct physical pressure or out of a ruck contest, resulting in an opportunity to effect a legal disposal.
Hit-Out	Knocking the ball out of a ruck contest following a stoppage with clear control, regardless of which side wins the following contest at ground level.
Ineffective Handball	Handballs that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Ineffective Kick	Kicks that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Inside 50	Moving the ball from the midfield into the forward zone. Excludes multiple entries within the same chain of possession.
Inside 50 Result	Successful reception of an inside-50
Kick	Total number of times a player disposes the ball by foot
Kick Inside 50	When a player records an inside 50 for his team by kicking the ball from the midfield zone into the forward line.
Long Kick	A kick of more than 40 m to a 50/50 contest or better for the team.
Looseball Get	A disputed ball at ground level not under direct physical pressure that results in an opportunity to record a legal disposal.
Mark	When a player cleanly catches (is deemed to have controlled the ball for sufficient time) a kicked ball that has travelled more than 15 m without anyone else touching it or the ball hitting the ground.
Mark Play On	Playing on immediately without retreating behind the mark.
Rebound 50	Moving the ball from the defensive zone into the midfield.
Receive Handball	An uncontested possession that is the result of a teammate's handball.
Short Kick	A kick of less than 40 m that results in the intended target retaining possession. Does not include kicks that are spoiled by the opposition.
Shot at Goal	A kick directed at goal
Spoil	Knocking the ball away from a marking contest preventing an opponent from taking a mark.
Tackle	Using physical contact to prevent an opponent in possession of the ball from getting an effective disposal.
Uncontested Mark	Marks taken under no physical pressure from an opponent. Includes marks taken on a lead and from opposition kicks.
Uncontested Possession	Possessions gained whilst under no physical pressure, either from a teammate's disposal or an opposition's clanger kick. Includes handball receives, uncontested marks (including lead marks) and intended ball gets from a disposal.

Remaining skill counts were converted to z-scores and normalised to the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)). This subsequently facilitated dimensional reduction.[24] A data reduction technique was used to reduce the dimensionality of technical skill indicators. More specifically, a principal component analysis (PCA) was conducted to reduce the dimensionality of the correlated technical skill indicators into a smaller set of uncorrelated components whilst maintaining most of the variance from the original dataset.[19,20] Indeed, as a result of PCA, while the principal

Table 2
Total variance explained for each derived component from the principal component analysis.

Initial eigenvalues				Extraction sums of squared loadings			Rotation sums of squared loadings		
Component	Total	Explained variance	Cumulative %	Total	Explained variance	Cumulative %	Total	Explained variance	Cumulative %
1	7.928	27.337	27.337	7.928	27.337	27.337	6.082	20.972	20.972
2	4.882	16.834	44.171	4.882	16.834	44.171	4.469	15.410	36.382
3	2.704	9.324	53.495	2.704	9.324	53.495	3.253	11.216	47.599
4	1.580	5.449	58.944	1.580	5.449	58.944	2.231	7.693	55.291

Table 3
Resultant equations from principal component analysis.

Equation	Variable	Calculation
1	High-Pressure Success	0.867 × Handball + 0.865 × Contested Possession + 0.844 × First Possession + 0.805 × Clearance + 0.781 × Hardball Get + 0.771 × Effective Handball + 0.629 × Ineffective Handball + 0.586 × Gather + 0.515 × Looseball Get + 0.455 × Tackle
2	Low-Pressure Success	0.922 × Uncontested Mark + 0.909 × Mark + 0.749 × Mark Play On + 0.727 × Short Kick + 0.677 × Effective Kick + 0.655 × Uncontested Possession + 0.563 × Kick
3	Attacking Ball Movement Ability	0.902 × Kick Inside 50 + 0.882 × Inside 50 + 0.620 × Long Kick + 0.416 × Ineffective Kick
4	Scoring Ability	0.853 × Shot at Goal + 0.837 × Inside 50 Result

components that are derived are uncorrelated, each contain their own highly correlated variables that measure an underlying, independent construct. This method ensures only distinct information remains within the dataset.[20,25] The PCA was undertaken using SPSS for Windows (Version 25)[26] where the aim was to determine the presence of underlying constructs in the remaining 29 technical skill variables. Linear relationships were initially assessed using a correlation matrix while the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction.[26] All 29 variables were initially included, upon which variables with communalities (relative importance for inclusion in the component) lower than 0.40 were excluded.[27] The PCA was subsequently reprocessed using a varimax rotation method with only the variables of significant importance. The number of principal components to be retained was determined using a scree plot displaying the derived component eigenvalues.[28] The scree plot was assessed for a break resembling an 'elbow' shape between components, with relatively large eigenvalues and those with similar eigenvalues with the components that occur before the break assumed to be meaningful and are retained.[29] These components were subsequently used to derive component loadings associated with each variable in the PCA. These component loadings were then used to calculate summed variables for each component by treating them as coefficients in a linear regression model.

3. Results

No variables were excluded from the PCA as all communalities were greater than 0.40. Upon inspection of the subsequent correlation matrix, linear relationships existed between all variables. An examination of the KMO measure of sampling adequacy suggested that the sample was factorable (KMO = 0.578). Additionally, Bartlett's test of sphericity was significant ($p < 0.001$).[26] Upon inspection of the scree plot, four components occurred before the break in eigenvalues and were subsequently retained and accounted for 55% of the variance. Table 2 reveals the cumulative explained variance for each component from the PCA. The rotated component matrix produced component weightings for each variable in their respective principal component. The four equations derived from the analysis are displayed in Table 3.

4. Discussion

Australian Football is a complex sport where an array of physical, tactical and technical skills are needed to achieve success. While many studies have attempted to delineate the influence of technical skill demands on performance outcomes, often in isolation of other components, the present study was the first to describe and dimensionally reduce an array of technical skill indicators in an Australian Football context to facilitate their practical application, interpretation, and reporting to performance staff. The 29 individual-derived skill count variables were reduced to four components which adequately represent different constructs whilst maintaining 55% of the variance in the original data set (Table 2).[26] Whilst some of the explained variance in the original dataset was lost, not all indicators provided by ChampionData® are reportedly relevant when assessing performance outcome.[7,8] By reducing a large number of variables into four new variables, each with a different theoretical underpinning, these new components facilitate the interpretation of technical skill indicators. This may subsequently allow practitioners and coaches to assess and monitor individual player performance and development in addition to guiding list-management decisions that may subsequently lead to favourable performance outcomes.

Equation 1, *high-pressure success*, provides an indication of a player's ability to succeed in congested passages or high-pressure phases of play in which ball possession is in dispute (contested play). Resultant sum scores from this equation provide insights into an individual's ability to attain possession (*contested possession, first possession, hardball get, looseball get* and *gather*) and subsequently move the ball through (*handball* and *effective handball*) and away from (*clearance*) these congested passages of play. Larger scores may also reflect an individual's ability to shut down opposition players during congested phases of play with *tackles* positively contributing to this sum score. Higher values for this variable signify that a player is important for winning a ball that is in dispute and subsequently securing possession for the team to attack. This could be indicative of a player's positional role within the team, such as a midfielder, who has the specific task of winning disputed possession and then subsequently moving it forward to provide attacking opportunities.[2,30]

In contrast, equation 2, *low-pressure success*, provides an indication of a player's ability to succeed in uncongested, attacking passages of play. Higher sum scores are reflective of an individual's ability to successfully receive possession in the absence of pressure (*mark, uncontested mark* and *uncontested possession*) and continue to move the ball (*mark play on, kick, short kick* and *effective kick*) in an attempt to maintain possession. This may also reflect a position-specific role such as key or roaming defenders who are responsible for moving possession out of the defensive half without risking a turnover in possession.[30]

Equation 3, *attacking ball movement ability*, reflects an individual's ability to move the ball in the attacking direction. A *kick inside 50* and an *inside 50* both reflect movement of the ball, for the attacking team, inside the opposition's 50 m arc, a requirement for creating scoring opportunities. Further, conducting a *long kick* will also increase resultant sum scores and may result from an attempt to cover large distances to move the ball away from an individual's defensive half or alternatively shift the movement of play to areas of the ground that are not occupied by the defensive team, in turn providing opportunities to advance the ball. Additionally, while it may be considered as a negative attribute, the contribution of an *ineffective kick* to resultant sum scores is appropriate as kicks entering an attacking team's forward half, or that are deemed as threatening, are often heavily defended in an attempt to turn possession over. Midfielders or small forwards who demonstrate superior *ineffective kick* values may be responsible for attacking movements and setting up attacking passages of play.[2,30]

Finally, equation 4, *scoring ability*, reveals a player's ability to receive possession inside the attacking 50 m arc (*inside 50 result*) and attempt to score points (*shot at goal*). As with equations 1–3, higher sum scores may reflect positional roles with key forwards, who are positioned in the forward half, receiving a larger amount of possession in the forward 50 and ideally performing more shots at goal.[30] Conversely, attacking players who possess low sum scores for this metric may reflect an inability to successfully receive possession inside the attacking portion of the field consequently resulting in less shots on goal. Alternatively, lower scores may be indicative of a defensive player and having little direct involvement with ball movement and scoring opportunities.

The metrics derived in this study provide a method for coaches and practitioners to further understand the influence of technical aspects and the influence of varying contextual factors on technical skill counts, along with the relationship with physical and tactical components. These metrics provide specific insight into the technical skill demands of the game, specifically pertaining to the use of possession. While this study is the first to provide a simplified, novel method for analysing technical skill indicators in an Australian Football context, these metrics are yet to be validated in relation to team performance outcomes.

The results of this study provide supporting data for performance analysts currently using video and technical skill counts to analyse games and could allow coaches to identify strengths and weaknesses in the opposition team that can be exploited through the implementation of game tactics. This new information also allows coaching staff to develop training interventions that are representative of competition demands as they can now quantify and emulate technical skill demands evident in game scenarios. Further, the derived component scores can facilitate and simplify the information and feedback coaches provide to players. At the individual level, examination of the derived metrics may highlight favourable role-specific characteristics associated with different positions in the team and provide an additional objective means of assessing player match-performance. This information could therefore facilitate weekly team selection or, alternatively, the recruitment of new players that might be of particular value to the team. These metrics may also allow coaches to longitudinally assess the development of an individual player's role within the team over time. Lastly, the findings and methodological approach utilised in this study may also prove useful in sports other than Australian Football following the calculation of components and respective weightings. Additionally, as the results from this study are not generalisable to other sporting contexts, it is recommended that those who are adopting this form of methodology continue to update component loadings as new data is acquired each season. This will ensure that factor loadings remain accurate and stable throughout the season. The methodology provided in this study can be followed by practitioners working with technical skill indicators in any sport, to help them understand the technical characteristics of match play.

5. Conclusion

This study is the first to provide a simplified, novel method for analysing technical skill indicators in an Australian Football context, providing useful information with reduced dimensionality for coaches and practitioners. The derived components provide specific insight into individual player performance and the technical skill demands of match play, particularly the movement of possession. This may consequently guide opposition analysis, training implementation, player performance ratings and player development, selection and recruitment. Further, if proven valid, the findings from the current study may provide a viable framework of analysis in other contextually similar sports.

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Appendix A.

Table A1
Complete list of technical involvement indicators considered for analysis.

Technical indicator	Description
Baulk	Using deception as the ball carrier to beat an opponent, by sidestepping or feigning disposal.
Behind	A minor score, as judged by the goal umpire. Behinds are worth one point to a team's total score.
Behind Assist	Creating a behind by getting the ball to a teammate either via a disposal, knock-on, ground kick or hit-out, or by winning a free kick before the advantage is paid.
Block	Effectively shepherding an opponent out of a contest to the benefit of a teammate.
Broken Tackle	Evading a tackle attempt by an opponent and legally disposing of the ball in space.
Clangers	Number of handballs or kicks that give possession directly to the opposition.
Clanger Handball	Handballs that give possession directly to the opposition.
Clanger Kick	Kicks that give possession directly to the opposition.
Clearance	Credited to the player who has the first effective disposal in a chain that clears the stoppage area, or an ineffective kick or clanger kick that clears the stoppage area.
Contested Knock On	Using the hand to knock the ball to a teammate's advantage rather than attempting to take possession from a contested situation.
Contested Mark	When a player takes a mark under physical pressure of an opponent or in a pack.
Contested Mark from Opposition	When a player takes a mark under physical pressure of an opponent or in a pack from an opposition kick.
Contested Mark from Team	When a player takes a mark under physical pressure of an opponent or in a pack from a teammates kick.
Contested Possession	A possession which has been won when the ball is in dispute. Includes looseball-gets, hardball-gets, contested marks, gathers from a hit-out and frees for.

Table A1 (*Continued*)

Technical indicator	Description
Crumb	A type of groundball-get that is won by a player at ground level after a marking contest. The player must not be involved in the original contest. Crumbing Possessions can be either hardball or looseball-gets.
Disposal	Legally getting rid of the ball, via a handball or kick.
Effective Disposal	Legally getting rid of the ball, via a handball or kick, and reaching an intended target.
Effective Handball	A handball to a teammate that hits the intended target.
Effective Kick	A kick of more than 40 m to a 50/50 contest or better for the team or a kick of less than 40 m that results in the intended target retaining possession.
First Possession	The initial possession that follows a stoppage, including a looseball-get, hardball-get, intended ball-get (gather), free kick or ground kick.
Free Against	When an infringement occurs resulting in the opposition receiving a free kick from the umpires.
Free For	When a player is interfered with and is awarded a free kick by the umpires.
Gather	Possessions that were a result of a teammate deliberately directing the ball in the player's direction, via a hit-out, disposal or knock-on, excluding marks and handball receives. Gathers from a hit-out are contested possessions the rest are uncontested.
Gather from Hit-Out	A possession gained from a teammate's hit-out to advantage. Counted as a contested possession.
Goal	A major score, as judged by the goal umpire. Worth six points to a team's total score.
Goal Assist	Creating a goal by getting the ball to a teammate either via a disposal, knock-on, ground kick or hit-out, or by winning a free kick before the advantage is paid to the goal scorer.
Ground Ball Get	Contested possessions won at ground level, excluding free kicks. Groundball gets can either be hardball gets or looseball gets.
Ground Kick	A deliberate kick without taking possession that gains either significant distance from the point of contact or an uncontested possession for a teammate.
Handball	Disposing of the ball by hand.
Hardball Get	A disputed ball at ground level under direct physical pressure or out of a ruck contest, resulting in an opportunity to effect a legal disposal.
Hit-Out	Knocking the ball out of a ruck contest following a stoppage with clear control, regardless of which side wins the following contest at ground level.
Hit-Out Shark	Winning clear possession of the ball from the opposition ruck's hit-out.
Hit-Out Sharked	A hit-out that directly results in an opponent's possession.
Hit-Out to Advantage	A hit-out that reaches an intended teammate.
Hold	Holding the ball in when the umpire calls for a ball up.
Ineffective Disposals	Kicks or handballs that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Ineffective Ground Kick	Ground kicks that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Ineffective Handball	Handballs that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Ineffective Kick	Kicks that are not advantageous to the team, but do not directly turn the ball over to the opposition.
Inside 50	Moving the ball from the midfield into the forward zone. Excludes multiple entries within the same chain of possession.
Inside 50 Result	Successful reception of an inside-50
Kick	Total number of times a player disposes the ball by foot
Kick-In	When a player kicks the ball back into play after an opposition behind. Kick-ins are regarded as a function of the team and do not count as kicks, although they are similarly graded for quality.
Kick Inside 50	When a player records an inside 50 for his team by kicking the ball from the midfield zone into the forward line.
Kick Long Advantage	A long kick that results in an uncontested possession by a teammate. If an error is made by the player 'receiving' the kick, a 'kick long to advantage' is still recorded for the player kicking the ball.
Knock On	When a player uses his hand to knock the ball to a teammate's advantage rather than attempting to take possession within his team's chain of play.
Long Kick	A kick of more than 40 m to a 50/50 contest or better for the team.
Looseball Get	A disputed ball at ground level not under direct physical pressure that results in an opportunity to record a legal disposal.
Mark	When a player cleanly catches (is deemed to have controlled the ball for sufficient time) a kicked ball that has travelled more than 15 m without anyone else touching it or the ball hitting the ground.
Mark from Opposition Kick	As per above but from an opposition kick.
Mark Fumbled	Unsuccessful reception of a kick.
Mark on Lead	An uncontested mark taken after outsprinting an opponent.
Mark Play On	Playing on immediately without retreating behind the mark.
Missed Tackles	Attempted tackles that are missed, allowing the ball carrier to break into space.
One on One Contest Defender	Being isolated in a one-on-one contest as the defender.
One on One Contest Target	Being isolated in a one-on-one contest as the target of the kick.
Out on the Full	A kick that travels over the boundary line on the full.
Rebound 50	Moving the ball from the defensive zone into the midfield.
Receive Handball	An uncontested possession that is the result of a teammate's handball.
Ruck Hardball Get	Taking possession of the ball directly out of the ruck.
Running Bounce	Touching the ball to the ground, either directly or via a bounce, to allow a player to avoid being penalised for running too far.
Score Assist	Creating a score by getting the ball to a teammate either via a disposal, knock-on, ground kick or hit-out, or by winning a free kick before the advantage is paid to the goal scorer.
Short Kick	A kick of less than 40 m that results in the intended target retaining possession. Does not include kicks that are spoiled by the opposition.
Shot at Goal	A kick directed at goal
Smother	Suppressing an opposition disposal by either changing the trajectory of the ball immediately after the disposal or by blocking the disposal altogether.
Spoil	Knocking the ball away from a marking contest preventing an opponent from taking a mark.
Spoil Gaining Possession	Spoils directed straight to a teammate.
Spoil Ineffective	Spoils directed straight to an opposition player.
Tackle	Using physical contact to prevent an opponent in possession of the ball from getting an effective disposal.
Uncontested Gather	Winning possession of the ball uncontested at ground level.
Uncontested Mark	Marks taken under no physical pressure from an opponent. Includes marks taken on a lead and from opposition kicks.
Uncontested Mark from Opposition	Marks taken from an opposition kick under no physical pressure from an opponent.
Uncontested Mark from Team	Marks taken from a teammate's kick under no physical pressure from an opponent.
Uncontested Possession	Possessions gained whilst under no physical pressure, either from a teammate's disposal or an opposition's clanger kick. Includes handball receives, uncontested marks (including lead marks) and intended ball gets from a disposal.

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jsams.2020.01.016.

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Study Three: Simplifying the complexity of assessing physical performance in professional Australian football

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Simplifying the complexity of assessing physical performance in professional Australian football

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ABSTRACT

Purpose: To provide a simplified, novel method for analysing the physical demands in an Australian Football context by reducing the dimensionality of commonly reported physical characteristics obtained from match play. This may facilitate their practical use and interpretability.

Methods: A retrospective longitudinal design was utilised with individual players' physical outputs, measured via global navigation satellite system devices, collected during official Australian Football League matches over three seasons. A principal component analysis was used to reduce a large number of correlated physical characteristics related to the analysis of physical match demands into a smaller set of uncorrelated components.

Results: Forty-six variables were reduced to five principal components whilst maintaining 56% of the variance in the original dataset. The principal component analysis derived five individual-based principal components pertaining to *low-moderate movement volume, high speed running volume, accelerations, change of direction* and *impacts*.

Conclusions: Utilising factor loadings (eigenvectors) derived from a principal component analysis, this study is the first to provide a simplified, novel method for analysing the physical demands in an Australian Football context with the derived metrics revealing useful information for coaches and practitioners. This may consequently guide training implementation, player performance ratings and player selection. Further, these new values may facilitate the monitoring of physical player loads.

ARTICLE HISTORY
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KEYWORDS
Performance analysis; physical demands; GPS; GNSS; principal component analysis

Introduction

Professional Australian Football is the most popular form of football in Australia and is classified as a contact, team sport. (Gray and Jenkins 2010) The game takes place on an oval-shaped field that varies in length (149–175 m) and width (122–136 m), with two larger central 'goal' posts and two outer 'behind' posts. (Gray and Jenkins 2010) If the ball is kicked between the two goal posts by the attacking team, a goal worth 6 points is awarded. If the ball passes between the goal posts in any other way, hits a goalpost, or passes between a goal post and a behind post, a behind worth 1 point is awarded. (Braham and Small 2018) The primary aim is to score more points than the opposing team. Match play is carried out by two teams of 22 players, with 18 on the field at a time who contest play over four 20-minute quarters of 'in-play', with the clock stopping every time a goal is scored, the ball goes out of play, or play is ceased by the officiating umpires. Match play involves phases of ball possessions, contested play (where both teams compete for possession) and stoppages of varying durations. (Gray and Jenkins 2010) The physical element of the game is characterised by intermittent high-speed running coupled with frequent collisions and changes of direction. (Gray and Jenkins 2010) Additionally, competing at this level requires a high level of skill proficiency with players utilising a myriad of hand and foot skills for passing, scoring and gaining possession of the ball. (Johnston et al. 2016) Teams also utilise a variety of tactical strategies depending on player availability, coaching philosophies, the opposing team and environmental conditions during the match. (Costa et al. 2010)

Collectively, players require superior physical abilities, technical skills and tactical strategies to cope with the ever-changing demands of the game. (Sullivan et al. 2014b) Team success in Australian Football is a culmination of the aforementioned variables with superior performance allowing teams to fulfil the main objective of the game, to score the most points through goal kicking. Accordingly, in the past decade applied research in this context has investigated these factors, each with a wide array of variables, to derive practical applications aimed at improving a team's performance. Through the analysis of games played in the Australian Football League (AFL), the technical and physical characteristics of professional Australian Football have been adequately quantified using notational analysis techniques (Johnston et al. 2016) and microtechnology such as global navigation satellite system (GNSS) and accelerometers. (Sullivan et al. 2014b) Further, whilst scarcely examined in Australian football, recent lines of inquiry have sought to objectively quantify tactical behaviour using cooperative network analyses, (Braham and Small 2018; Sheehan et al. 2019) passing interactions between teammates, as well as

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window. Sixty-three senior matches were used for analysis providing a sample of 1376 individual files (28.7 ± 21.8 per player) from the designated AFL team. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

Study design

The study followed a retrospective longitudinal design where individual players' physical match loads, as measured via GNSS technology, during official AFL games were collected over a period of three seasons. A principal component analysis was used to reduce the number of characteristics related to the analysis of physical match characteristics whilst maintaining most of the variance in the original dataset.

Data collection

Data was collected via the use of GNSS units sampling at 10 Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia). Currently in the AFL, all elite teams evaluate the physical characteristics of game play using this technology. (Sullivan et al. 2014b) The GNSS units were worn by the players within a custom-built pouch sewn into the rear of the player's jersey. The device sits superior to the player's shoulder blades at the base of the neck and records data pertaining to physical match characteristics. While GNSS provider vests may provide enhanced validity and reliability, gplayer jerseys were fit tightly and were used as an alternative. (McLean et al. 2018) Intra-class correlation coefficients (ICCs) for Catapult GNSS devices have demonstrated high to very high reliability (r = 0.86–0.99) for distances covered at low-, high-, and very high-speed running intensities. (Johnston et al. 2014) Additionally, the same study utilising the typical error of measurement (TEM) demonstrated good reliability (TEM = 0.8–4.8%) for low- and high-speed running variables but poor reliability (TEM = 11.5–11.7%) for very high-speed running variables. (Johnston et al. 2014) Utilising a coefficient of variation (CV), other studies demonstrated good reliability (CV < 5%) for variables pertaining to banded inertial movement analyses (IMA) and moderate reliability (CV 5-10%) for direction specific IMA counts (Luteberget et al. 2017) and good to moderate reliability for acceleration measures (CV 1.-8–9.1%). (Akenhead et al. 2014)

Physical variables

Table 1 identifies the variables that were included for analysis, their description, and associated bands used for analysis. These variables have previously been used in Australian Football to quantify the physical match characteristics at the individual level of analysis. (Gray and Jenkins 2010; Mooney et al. 2011, 2013; Johnston et al. 2012, 2015, 2016; Hiscock et al. 2012; Sullivan et al. 2014a, 2014b; Bauer et al. 2015)

Statistical analysis

A data reduction technique was used to reduce the dimensionality of physical load characteristics at the individual level. More specifically, a factor analysis was conducted through a principal component analysis to reduce the dimensionality of the physical load variables into a smaller set of uncorrelated components whilst maintaining most of the variance from the original data set. (Kaiser 1960; Federolf et al. 2014) As a result of the selected analysis technique, no correlation exists between the principal components, but each contain their own highly correlated variables that measure an underlying, yet independent construct. This method ensures only distinct information remains within the data set. (Weaving et al. 2014) A principal component analysis involves the removal of the mean, calculation of the covariance of the data, determination of the eigenvalues and eigenvectors of the covariance matrix, and a varimax rotation of the original data onto a coordinate system spanned by the eigenvectors of the covariance matrix. (Federolf et al. 2014) The analysis was executed using SPSS for Windows (Version 25) (IBM SPSS Statistics for Windows [computer program] 2017) where the aim was to determine whether common underlying constructs were present in the 46 physical load variables. Linear relationships were initially assessed using a correlation matrix while the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction. (IBM SPSS Statistics for Windows [computer program] 2017) All 46 variables were initially included, upon which variables with communalities (relative importance for inclusion in the factor) lower than 0.40 were excluded. (Stevens 2002; Howard 2016) The principal components analysis was subsequently re-run using only variables of significant importance. The number of principal components to be retained was determined using the scree plot which is a line plot of the derived factor eigenvalues. (Lewith et al. 2010) The scree plot was assessed for a break or separation, resembling an 'elbow' shape, between factors with relatively large eigenvalues and those with similar eigenvalues. The components that occur before the break are assumed to be meaningful and are retained. (Dmitrienko et al. 2007) These components were subsequently used to derive factor loadings (eigenvectors) associated with each of the variables in the analysis. These factor loadings (eigenvectors) were then used to calculate summed variables (sum scores) for each component by treating them as coefficients in a linear regression model. For interpretation, sum scores are calculated by multiplying the factor loadings (eigenvectors) with the associated standardised physical GNSS variables (Table 3). (Weaving et al. 2019) Sum scores can then be converted to z-scores and normalised to the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)) to facilitate interpretation. (Henderson et al. 2018)

Results

Four variables, *band 1 deceleration duration* and *band 1, 2* and *3 acceleration duration*, were excluded from the PCA due to communalities below 0.40. Upon inspection of the subsequent correlation matrix, linear relationships existed between all variables. An examination of the KMO measure of sampling adequacy suggested that a considerable proportion of the variance in the dataset is a result of underlying factors (KMO = 0.77). Additionally, Bartlett's test of sphericity was significant (p < 0.001) (IBM SPSS Statistics for Windows [computer program] spatiotemporal analyses assessing measures of space and shape. (Alexander et al. 2018) Despite providing valuable insight into the physical, technical and, to a lesser degree, the tactical requirements of the game, discrepancies exist when associating these components with successful and unsuccessful performance outcomes. (Mooney et al. 2011; Johnston et al. 2012; Hiscock et al. 2012; Sullivan et al. 2014b; Bauer et al. 2015) These discrepancies may occur as players need to collectively adapt their physical abilities, skills and tactical strategies to cope with the ever-changing demands of a game. Attempts to ease the integration of all these components for collective analysis may provide insight into existing discrepancies as well as provide a greater indication into factors affecting performance. (Silva et al. 2013)

In an attempt to objectively quantify the underpinnings of successful performance, sports scientists have focused on identifying associated physiological characteristics using GNSS devices with a plethora of ensuing research quantifying the external physical characteristics of the game. (Mooney et al. 2011; Johnston et al. 2012; Hiscock et al. 2012; Sullivan et al. 2014b; Bauer et al. 2015) Currently in the AFL, all professional teams evaluate the physical characteristics of game play using this technology which are capable of providing a wide array of associated variables. (Sullivan et al. 2014b) Specifically, speed-based running indices and accelerometry data have led to many publications that have quantified the physical components of Australian Football using a combination of these variables. (Mooney et al. 2011; Johnston et al. 2012; Hiscock et al. 2012; Sullivan et al. 2014b; Bauer et al. 2015) These studies revealed that Australian Football match-play involves higher running volumes compared to any other team sport, with players performing frequent intermittent bouts of high-speed running, accelerations, decelerations, changes of direction and frequent collisions with opposing players. (Gray and Jenkins 2010)

While microtechnology data have provided valuable information regarding the physical characteristics of the game, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance. (Mooney et al. 2011; Johnston et al. 2012; Hiscock et al. 2012; Sullivan et al. 2014b; Bauer et al. 2015) One study of a cohort of elite players revealed that higher rated players, as determined by Coaches' subjective ratings, covered a greater percentage of distance at high speed and greater sprint distance than lower rated players. (Bauer et al. 2015) On the contrary, another study revealed that more proficient players spent a greater percentage of time at low speed and covered less distance than less proficient players. (Johnston et al. 2012) While this research examined performance using a select number of variables to measure technical and physical performance, there are inherent limitations present when using Coaches' ratings of performance, as these are subjective in nature, making it difficult to translate or compare findings in different contexts. (Johnston et al. 2012; Bauer et al. 2015) Further, manually selecting a small number of the available physical metrics may have failed to holistically capture physical performance.

Literary inconsistencies are further exemplified when assessing the relationship between objectively quantified technical and physical performance indicators. Previous literature demonstrated a negative relationship between ChampionData® Player Rank (a holistic measure of technical performance), and physical output measures. (Sullivan et al. 2014b; Bauer et al. 2015) On the contrary, another study revealed a positive relationship between the number of high speed efforts conducted per minute, and the number of disposals (a positive indicator of technical performance). (Mooney et al. 2011) While this line of work attempts to delineate the simultaneous influence of physical and technical indicators on team performance success, limitations when implementing only a select number of technical and physical GNSS output variables in the study design are evident.

Furthermore, when examining the relationship between GNSS derived data, quarters won and lost, and contextual variables such as weather, ground location and game turnaround time, inconsistencies in research findings are also evident. One study associated lower physical output with quarters won, (Sullivan et al. 2014a) while conversely another failed to identify any relationship between physical derived metrics, quarter success, or contextual variables. (Hiscock et al. 2012) These studies may have failed to fully account for the physical, technical and tactical components, selecting only a few GNSS derived variables, or, with the latter, neglecting to include a sufficient number of variables to adequately quantify physical performance. Accordingly, including and simplifying a wider array of physical variables, through use of dedicated statistical techniques, such as principal component analysis, (Weaving et al. 2014, 2017; Williams et al. 2017) may facilitate the use and integration of these data with technical and tactical information. This may subsequently allow performance analysts and coaches to collectively evaluate these components and the relationship with contextual factors and performance outcomes. Additionally, despite the widespread use of GNSS technology in sport, confusion still remains around the most appropriate metrics to use, and how information generated can be most effectively reported back to key stakeholders. (Malone et al. 2019) Therefore, the aim of this study was to reduce the dimensionality of commonly reported physical load indicators obtained from AFL games in order to facilitate their practical use and interpretability. It was hypothesised that a principal component analysis would reduce the number of physical characteristics associated with Australian Football match play whilst maintaining most of the variance in the original dataset. Since physical performance capacity is an integral contributor to success in Australian Football, the derived principal components will have a theoretical underpinning which will aid and simplify the interpretation of the physical characteristics associated with AFL match play. Given the modifiable nature of these components, subsequent implementation of training programs may enable the optimisation of physical performance.

Methods

Participants

The study sample consisted of 48 male professional Australian Football players (age: 25.0 ± 3.8 years; playing experience: 5.2 ± 3.4 years) from one AFL team. Each participant played at least one game over the three-year (2016–2018) analysis

Table 1. GNSS derived physical variables.

Physical Variable	Description	Bands
Total Duration	The total amount of time spent on-field. Does not include time on the bench.	-
Total Distance	Total distance covered during time spent on field. Does not include distance covered while on the bench.	-
Banded Velocity Distance	The total amount of distance covered in a designated velocity band.	B1: 0–6 km·hr^{1}; B2: 6–14.4 km·hr^{1}; B3: 14.4–18 km·hr^{1}; B4: 18–22 km·hr^{1}; B5: 22–25 km·hr^{1}; B6: >25 km·hr^{1}
Banded Velocity Efforts	Counts the number of times an athlete reaches the designated velocity band for a specific amount of time. Effort must be sustained within the band for at least 1 s.	B1: 0–6 km·hr^{1}; B2: 6–14.4 km·hr^{1}; B3: 14.4–18 km·hr^{1}; B4: 18–22 km·hr^{1}; B5: 22–25 km·hr^{1}; B6: >25 km·hr^{1}
Banded Acceleration & Deceleration Distance	The total amount of distance covered accelerating or decelerating in the designated band.	Acceleration: B1: 1.36–2.15 m·s^{2}; 2.151–2.75 m·s^{2}; > 2.751 m·s^{2} Deceleration: B1: −1.36- −2.15 m·s^{2}; −2.151- −2.75 m·s^{2}; < −2.751 m·s^{2}
Banded Acceleration & Deceleration Duration	The total amount of time spent accelerating or decelerating in a certain range.	Acceleration: B1: 1.36–2.15 m·s^{2}; 2.151–2.75 m·s^{2}; > 2.751 m·s^{2} Deceleration: B1: −1.36-−2.15 m·s^{2}; −2.151- −2.75 m·s^{2}; < −2.751 m·s^{2}
Banded Acceleration & Deceleration Efforts	Counts the number of times an athlete reaches the designated acceleration or deceleration band for a specific amount of time. Effort must be sustained within the band for at least 0.4 s	Acceleration: B1: 1.36–2.15 m·s^{2}; 2.151–2.75 m·s^{2}; > 2.751 m·s^{2} Deceleration: B1: −1.36-−2.15 m·s^{2}; −2.151- −2.75 m·s^{2}; < −2.751 m·s^{2}
Banded Inertial Movement Analysis (IMA)	Using raw accelerometer and gyroscope data to create a non-gravitational acceleration vector, reveals the magnitude and the direction of an agility action. It can classify events within intensity, and distinguish between forward (acceleration), backward (deceleration), vertical (jump) and left and right lateral events.	Low: 1.5–2.5 m·s^{1}; Medium: 2.5–3.5 m·s^{1}; High: >3.5 m·s^{1}

2017). Figure 1 reveals the total explained variance from the PCA.

he rotated component matrix produced factor weightings for each variable in their respective principal component (Table 2). All variables, except one, were assigned to the component in which they had the strongest weighting. Despite having a slightly higher weighting factor (0.524) in the fourth component, *IMA change of direction left low* was placed in component two due to the theoretical and logical association with the existing variables in the component. The following equations that were subsequently derived are presented in Table 3.

Discussion

Australian Football is a highly demanding sport in terms of the physical requirements. While many studies have attempted to quantify the physical characteristics of the game and the associated underpinnings of successful performance, this study was the first to describe and dimensionally reduce an array of physical load variables in a professional-level context to facilitate their practical application and interpretation. Forty-six variables were reduced to five components in the principal component analysis. These new components help to reduce the complexity of analysing and interpreting the physical characteristics of Australian Football. These principal components adequately represent different constructs whilst maintaining 56% of the variance from the original data (Figure 1). (IBM SPSS Statistics for Windows [computer program] 2017) Whilst some of the explained variance in the original dataset was lost, not all physical indicators are reportedly relevant when assessing performance outcomes. (Bauer et al. 2015) These new components may firstly ease interpretation of GNSS derived variables and subsequently enable coaches and practitioners to assess and monitor individual player performance with greater certainty. Further, the new metrics derived in this study may allow coaches to develop training drills that emulate the physical characteristics of the game in a more representative manner.

Equation 1 is indicative of the general match characteristics with the total running volume an individual accumulates throughout the match (*total distance*) as well as the volume completed at low and moderate intensities included in this sum score. This is appropriate as the majority of the time spent running during matches is at lower intensities. (Johnston et al. 2018) Sum scores are a combination of the distance and number of efforts accumulated at low (*velocity band 2* and *velocity band 3*) and moderate (*velocity band 4*) velocities. Further, the intermittent nature of the sport, at low-moderate intensities, is captured by the number of acceleration and deceleration efforts (*band 1* and *band 2*) and accumulated acceleration and deceleration distances (*band 1*). The resultant sum scores from equation 1 may reflect position specific roles or individual physical capacities. Compared to key attackers and defenders, midfielders cover the greatest distances and have the highest work rates. (Johnston et al. 2018) This is likely due to position specific roles with midfielders covering a larger area of the field relative to the fixed positional characteristics of key position players. (Johnston et al. 2018) Alternatively, lower scores may be indicative of an individual's physical capacity. Recent studies have demonstrated that lower scores in the Yo-Yo Intermittent Recovery Test (level 2), an assessment of running capacity, corresponded with lower physical match outputs. (Mooney et al. 2013) Therefore, lower scores may reflect an inability to complete work throughout the match.

Similarly, equation 2 provides an indication of a player's ability to accumulate distance running and complete repeated

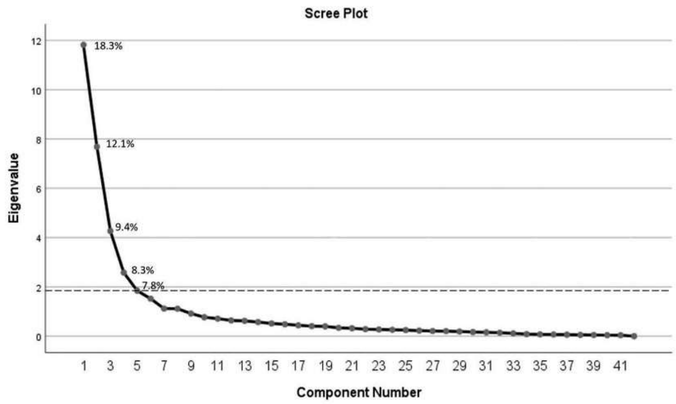

Figure 1. Scree plot for principal component analysis demonstrating the components, and the explained variance, that occur before the break and therefore assumed to be meaningful and are retained.

Table 2. Data-reduction procedure: rotated component matrix of GNSS variables with factor loadings (eigenvectors) >0.4.

	Component				
	1	2	3	4	5
Velocity Band 3 Distance	**.869**				
Total Distance	**.835**				
Deceleration Band 1 Efforts	**.807**				
Acceleration Band 1 Efforts	**.805**				
Velocity Band 3 Efforts	**.772**				
Velocity Band 4 Efforts	**.727**				
Velocity Band 2 Total Distance	**.713**				
Velocity Band 4 Total Distance	**.652**		.473		
Acceleration Band 1 Distance	**.649**				.408
Deceleration Band 2 Efforts	**.621**				
Deceleration Band 1 Distance	**.605**				
Acceleration Band 2 Efforts	**.560**				.446
IMA Acceleration High		**.899**			
IMA CoD Right High		**.885**			
IMA CoD Left High		**.862**			
Ima Acceleration Medium		**.738**			
Ima Cod Right Medium		**.712**			
Ima Cod Left Medium		**.706**		.492	
IMA Acceleration Low		**.526**		.468	
IMA CoD Right Low	.414	**.455**		.417	
Velocity Band 6 Total Distance			**.833**		
Velocity Band 6 Efforts			**.830**		
Velocity Band 5 Total Distance			**.823**		
Velocity Band 5 Efforts			**.701**		
Ima Deceleration Medium				**.740**	
IMA Deceleration Low				**.654**	
Ima Jump Count Low Band				**.617**	
IMA Deceleration High				**.607**	
IMA CoD Left Low	.407	**.415**		.524	
Acceleration Band 3 Efforts					**.878**
Acceleration Band 3 Distance					**.858**
Acceleration Band 2 Distance					**.823**

Factor loadings assigned to component appear in **bold**.

efforts at higher velocities (*velocity band 5* and *6*). Greater sum scores are indicative of an individual's physical capacity (Mooney et al. 2013) and may also partly reflect positional demands. Similar to equation 1, midfielders may demonstrate larger scores as the ability to rapidly reach possession that is in dispute in different parts of the field will increase chances of retrieving possession. (Johnston et al. 2018) Alternatively, superior scores may reflect offensive or defensive movements with individuals utilising high velocities to intercept opposition chains of possession or to position themselves in favourable spaces of the field where they can receive possession from a teammate. Lower scores may be an indicator of efficiency with higher calibre players being able to positively impact the game without excessively exerting themselves. This would align with previous literature that revealed that players who were perceived to have performed superiorly demonstrated lower physical outputs. (Sullivan et al. 2014b; Bauer et al. 2015)

Table 3. Resultant equations from principal components analysis.

Variable	Calculation
Low-Moderate Volume	0.869 × Velocity Band 3 Distance + 0.835 × Total Distance + 0.807 × Deceleration Band 1 Efforts + 0.805 × Acceleration Band 1 Efforts + 0.772 × Velocity Band 3 Efforts + 0.727 × Velocity Band 4 Efforts + 0.713 × Velocity Band 2 Distance + 0.652 × Velocity Band 4 Distance + 0.649 × Acceleration Band 1 Distance + 0.621 × Deceleration Band 2 Efforts + 0.605 × Deceleration Band 1 Distance + 0.560 × Acceleration Band 2 Efforts
High Speed Running	0.833 × Velocity Band 6 Distance + 0.830 × Velocity Band 6 Efforts + 0.823 × Velocity Band 5 Distance + 0.701 × Velocity Band 5 Efforts
Explosiveness	0.878 × Acceleration Band 3 Efforts + 0.858 × Acceleration Band 3 Distance + 0.823 × Acceleration Band 2 Distance
Change of Direction	0.899 × IMA Acceleration High + 0.885 × IMA Change of Direction Right High + 0.862 × IMA Change of Direction Left High + 0.738 × IMA Acceleration Medium + 0.712 × IMA Change of Direction Right Medium + 0.706 × IMA Change of Direction Left Medium + 0.526 × IMA Acceleration Low + 0.455 × IMA Change of Direction Right Low + 0.415 × IMA Change of Direction Left Low
Collisions/ Impacts	0.740 × IMA Deceleration Medium + 0.654 × IMA Deceleration Low + 0.617 × IMA Jump Low + 0.607 × IMA Deceleration High

Aligning with equation 1 and 2, equation 3 reflects the acceleration of a player with this score comprising of moderate-high intensity acceleration variables (*Acceleration Band 2* and *3 Distance* and *Acceleration Band 2 Efforts*). Sum scores reflect the ability of a player to rapidly change velocity and may be a result of position-specific tasks. For example, rapid acceleration may allow key forwards to misalign themselves with a marking defender and move into free space to receive a pass. The importance of an attacker-defender misalignment has been associated with positive attacking outcomes in other footballing contexts. (Vilar et al. 2012, 2014) Alternatively, higher scores may reflect an ability of a midfielder or defender to gain possession in dispute and rapidly accelerate into free space to then pass to other unopposed players. (Johnston et al. 2015, 2018) As with other derived variables, there are a multitude of ways to achieve high sum scores which practitioners must be aware of for correct interpretation of the outcomes.

While equations 1, 2 and 3 pertain to the linear movement of the individual at different intensities, equations 4 and 5 are indicative of a player's ability to change direction. Solely derived from IMA measures, these sum scores may reflect positional roles with certain players needing to navigate through congested phases of play or move erratically to evade or move past an opponent whilst attacking. (Johnston et al. 2015, 2018) Alternatively, larger scores may be indicative of a defender's ability to block attacking movements and to increase pressure on the attacker with the aim of causing a turnover. (Young et al. 2015) Equation 5 may also provide an indication of the number of collisions or impacts an individual is subjected to as this score is characterised by rapid decelerative movements, commonly associated with sudden stoppages. Accordingly, it may be expected that midfielders demonstrate greater scores due to a greater involvement in contested passes of play. With all available sum scores, it is important to examine outputs for each component in the context of playing position and/or specific role assigned to certain players as this may strongly influence result scores.

In Australian football, there are a wide array of GNSS derived variables available to physical performance coaches regarding the physical characteristics of match-play. While existing literature has provided valuable insight regarding these physical characteristics, (Mooney et al. 2011; Johnston et al. 2012; Hiscock et al. 2012; Sullivan et al. 2014b; Bauer et al. 2015) the large number of variables makes it difficult to interpret the effect of physical performance indicators on match outcome and accordingly, which variables should be prioritised in training. The metrics derived in this study may provide a method for coaches and practitioners to further understand the influence of physical outputs and the specific physical requirements associated with varying contextual factors such as weather, ground location and game turnaround time. The results provide supporting data for performance analysts currently using GNSS technology and provide a way of objectively reviewing individual physical performance. This may subsequently facilitate the development of training interventions specifically tailored towards improving individual weaknesses or further developing existing strengths. Further, these metrics may allow coaches to longitudinally assess the development of an individual player's physical output over time. While the principal components were derived from one team and may not be generalisable to other teams and styles of play, these aggregate metrics may highlight favourable role-specific characteristics associated with different positions in the team and provide an additional objective means of assessing player match-performance. Resultant scores, potentially accompanied by appropriate visualisations, (Weaving et al. 2019) may highlight any positional differences (Figure 2) and can subsequently facilitate and simplify the information and feedback coaches provide to players post-match. Lastly, while theoretical insight can be drawn from previous research examining a wide array of physical variables, future studies are required to validate the use of these new metrics in association with individual and team performance outcomes. Findings from this study may also prove useful in sports other than Australian Football utilising GNSS technology, following the calculation of components and weightings (eigenvectors) in these other sports. Additionally, as the results from this study are not generalisable to other teams or sporting contexts, it is recommended that those who are adopting this form of methodology continue to update factor loadings (eigenvectors) as new data is acquired. This will ensure that factor loadings remain accurate. The methodology provided in this study can be followed by practitioners working with GNSS systems in any sport, to help them understand the plethora of physical variables available from their GNSS provider.

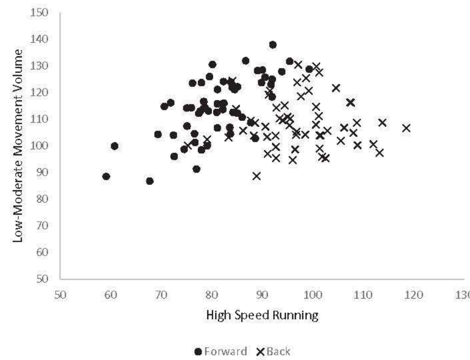

Figure 2. Visualisation highlighting differences in physical match characteristics between two different positions.

Practical implications

- The simplified physical load measures developed in this study provide supporting data for performance analysts and practitioners currently using GNSS technology to monitor player workloads and physical output.
- These new metrics facilitate the practical use and interpretability of GNSS derived variables and allow coaches to

identify individual strengths and weaknesses which can subsequently guide player development.

- The newly derived variables may ease integration of physical load data with technical and tactical related data by reducing the complexity of the available information. This may help to determine the influence of this component on performance outcomes.

Conclusion

Utilising factor loadings (eigenvectors) derived from a principal component analysis, this study is the first to provide a simplified, novel method for analysing physical match characteristics in an Australian Football context providing useful information for coaches and practitioners. This may consequently guide training implementation, player performance ratings and player development, selection and recruitment. Further, if proven valid, the findings from the current study may provide a viable framework of analysis in other contextually similar sports.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Study Four: Tactical analysis of individual and team behaviour in professional Australian Football

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Tactical analysis of individual and team behaviour in professional Australian Football

Original investigation

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ABSTRACT

Introduction: This study sought to reduce the dimensionality of commonly reported spatiotemporal characteristics obtained from Australian Football games to facilitate their practical use and interpretability.
Methods: A retrospective longitudinal design was utilised with team and individual spatiotemporal variables, measured via global navigation satellite system devices, collected during official Australian Football League matched over three seasons. Two separate principal component analyses were conducted at the team and individual level to reduce correlated spatiotemporal characteristics into a smaller set of uncorrelated components.
Results: At the team level, eighteen variables were reduced to five components pertaining to dispersive coordination, lateral predictability and spacing, multidirectional synchrony, longitudinal predictability and longitudinal behaviour whilst maintaining 69% of variance in the original dataset. At the individual level, fifteen variables were reduced to four components pertaining to *multidirectional and spacing synchrony, unpredictability, player movement* and *player positioning* whilst maintaining 64% of variance.
Conclusion: This study is the first to provide a simplified, novel method for analysing spatiotemporal behaviour in an Australian Football context with both the team- and individual- derived metrics revealing useful information for coaches and practitioners. Components may provide insight into behaviours that emerge and persist throughout a game and allow coaches to distinguish between different playing/ behavioural styles

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Introduction

Australian Football is a contact team sport involving 18 players per side on an oval-shaped field.Gray and Jenkins 2010 The professional Australian Football League (AFL) is characterised by its physical demands, involving intermittent high-speed running, collisions and changes in direction;(Gray and Jenkins 2010)'(Johnston et al. 2018) high levels of hand and foot skill proficiency for passing, scoring and gaining ball possession;(Johnston et al. 2016) and specific tactical strategies, i.e., intention of preparing a player or team for certain situations in a match,(Peráèek and Peráèková 2018) that vary depending on team personnel, coaching philosophies, opposing team and environmental conditions.(Johnston et al. 2016) While existing information regarding the technical and physical demands of Australian Football provides valuable insight into factors that contribute to team performance, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance.(Bauer et al. 2015),(Johnston et al. 2012),(Sullivan et al. 2014),(Hiscock et al. 2012), (Mooney et al. 2011) The excessive emphasis placed on performance outcome measures focussing on 'who did what, when' fails to fully elucidate the underlying factors of successful performance in such a complex game and emphasises the need for a theoretical rationale that can provide insight into performance behaviours.(Araújo et al., 2014) To enhance understandings of match performance, notational analysis and/or coaches' subjective ratings of performance have been used to assess and describe tactical behaviours, i.e., specific intentional behaviours in an attempt to achieve a goal, of performers during match-play.(Vilar et al. 2012) This has typically occurred through verbal descriptions of lived experiences or game observation.(Araújo and Bourbousson 2016) While this may offer valuable insight, the reliance on subjective impressions and procedural knowledge of expert performers are clear limitations.(Memmert et al. 2017) Subjective analysis presents particular issues when comparing performance between teams or players acutely or longitudinally across a season. To assess performance in differing contexts the use of objective assessments of tactical performance embedded within a viable theoretical framework are essential.

With recent technological advancements, such as an increase in sensitivity of GNSS devices and application of novel statistical approaches, it is possible to objectively quantify collective team behaviour. Practitioners can quantitatively model and predict performance outcomes in team sports, particularly during critical in-game events.(Travassos et al. 2013) Further, embedding appropriate spatiotemporal analysis techniques within a viable framework to help explain behaviour may also provide further insight as to 'why' or 'how' certain behaviours emerge in conjunction with common analyses. This approach deepens the understanding of the process characteristics underpinning successful performance.(Silva et al. 2013)An ecological dynamics

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framework that focuses on the performer-environment relationship is a viable framework that provides a basis for understanding such performance in team sport.(Davids et al. 2013) From an ecological dynamics perspective, Australian Football is a complex performance-environment sub-system where players and teams perceive opportunities, also known as affordances, for action which guide decision-making and subsequent actions. The perception of mutual relevant environmental information creates shared affordances, allowing players to self-organise into stable states of coordination and form synergies that enable the achievement of collective task goals.(Davids et al. 2013) In this complex system, task-constraints such as field dimensions and passing rules, along with physical and informational constraints like player size and opposition player movements provide boundaries that govern behaviour. Resultant behaviour in a complex system is an outcome of the interaction between its constituents, therefore, it is important to examine spatiotemporal behaviours between players and teams when analysing performance.

Spatiotemporal analyses can provide additional information that captures the dynamic nature of team sport.(Araujo and Davids 2016) While scarcely examined in Australian Football,(Alexander et al. 2018) this approach has provided insight into the behaviour that characterises successful attacking and defensive phases of play in soccer.(Tenga et al. 2010)' (Clemente et al. 2013) Spatiotemporal analyses involve the calculation of metrics relating to spacing and formations of players, using their geo-spatial position, often recorded via GNSS devices. Metrics reported in the literature can categorised as being related to dispersion of players (i.e., the spread of players within a team or positional group which is assessed using a stretch index or effective area), synchrony (i.e. describing whether players are moving at the same rate and/or in the same direction which is captured using cluster phase and correlation methods), variability (magnitude of change in a variable across a specific time period and is measured using a coefficient of variation), and predictability (regularity of player movements assessed using entropy measures). Only one study has utilised these metrics in Australian Football demonstrating greater team dispersion during offensive phases compared to defensive and contested phases.Alexander et al. 2018) These higher values may indicate players attempting to spread the opposition defensive players to create a greater effective playing space allowing easier passage towards the goals. In contrast, lower values of dispersion may indicate a defensive mechanism to contract rapidly if the opposition gained possession of the ball.(Alexander et al. 2018) While these measures provide new insight into tactical mechanisms influencing team success, the utilisation of two 20-minute halves in a 15v15-match simulation drill does not fully represent the collective behaviour exhibited by teams during competitive match-play due to the increase in relative space per player. Further research investigating these metrics in AFL matches may deepen the understanding of the influence of tactical behaviour on performance.

While a variety of objective measures quantifying dispersion,(Frencken and Lemmink 2008)' (Moura et al. 2013) synchrony,(Duarte et al. 2012) variability(Silva et al. 2014) and predictability(Couceiro et al. 2014) have sought to provide insight into behaviour associated with successful performance, the vast array of spatiotemporal variables presented in the literature convolutes their relationship with performance outcomes. For example, one line of enquiry in federation football demonstrated that lower measures of dispersion led to more goal scoring opportunities for the opposition.(Bartlett et al. 2012) This contradicts original ideas that defensive teams need to contract to protect the goal and limit goal-scoring opportunities for the attacking team.(Clemente et al. 2013) For spatiotemporal analysis to be adopted for practical performance analysis in sport, the analysis and interpretation should be simplified. Accordingly, this study aimed to reduce the dimensionality of commonly reported spatiotemporal variables obtained from AFL games to facilitate their practical use and interpretability. In accordance with previous literature that has dimensionally reduced network,(Sheehan et al. 2020b) technical(Sheehan et al. 2020a) and physical(Sheehan et al. 2020) variables, it was hypothesised that a principal component analysis (PCA) would successfully reduce the number of variables obtained from individual- and team-based spatiotemporal analyses in Australian Football, while maintaining a large proportion of its variance.

Methods

Participants

48 male professional footballers (age: 25.0 ± 3.8 years; playing experience: 5.2 ± 3.4 years) from one AFL team were analysed over a three-year (2016–2018) analysis window. Fifty senior matches were used for analysis providing a sample of 50 team files and 1099 individual files (22.9 ± 17.6 per player) from the designated AFL team. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

Study design

Retrospective longitudinal design where individual players' and the teams' spatiotemporal behaviours were collected during official AFL games over three seasons. A PCA reduced the number of variables related to the analysis of both individual and team spatiotemporal behaviour whilst maintaining most of the variance in the original dataset.

Data collection

Data were collected via the use of GNSS units sampling at 10 Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia). Intra-class correlation coefficients (ICCs) for Catapult GNSS devices have demonstrated high to very high reliability (r = 0.-86–0.99) for distances covered at low-, high-, and very high-speed running intensities.(Johnston et al. 2014) Additionally, the same study utilising the typical error of measurement (TEM) demonstrated good reliability (TEM = 0.8–4.8%) for low- and high-speed running variables but poor reliability (TEM = 11.5–11.7%) for very high-speed running variables.(Johnston et al. 2014)

Spatiotemporal variables

Spatiotemporal variables were calculated from raw individual player latitudinal and longitudinal positional data via MATLAB software.(The MathWorks I 2018a) Prior to analysis, all geospatial coordinates were rotated into a standardized 2D space so that longitudinal movements (y_i; towards each of the goals) and lateral movements (x_i; perpendicular to the line connecting the two goals) could be analysed together.(Fong 2003) Further, as teams change their direction of play at the beginning of each quarter, coordinates from alternating quarters were rotated 180 degrees to ensure attacking direction was consistent. For each field, the boundary coordinates (x_f,y_f) were collected by walking around the outside of the oval, half a metre from the boundary line, with a GPS device. Subsequently, MATLAB's *inpolygon* function was utilised to return indices identifying whether player coordinates (x_n,y_n) were inside or outside the region specified by the boundary coordinates of the field. Using these values, all player data points that fell outside the field region (i.e. benched players) were omitted from the following calculations.(The MathWorks I 2018a) Further, due to the input of units being in degrees, post-calculation results for stretch indices and displacement were converted using MATLAB's *distdim* function which takes angular units (degrees or radians) and converts to linear distance (metres).(The MathWorks I 2018a) This conversion is made along a great circle arc on a sphere with a radius of 6371 km, the mean radius of the Earth.(The MathWorks I 2018a) While the construct validity of this function was assessed using GNSS data from a known area and by calculating the field width and length using this method, it is worth noting that when using this function as the linear distances associated with radians of longitude changes with latitude may vary slightly. Table 1 identifies the team and individual variables included for analysis, their description and method of calculation. These variables have been used in soccer and, to a lesser degree, Australian Football to quantify team and individual spatiotemporal movement behaviours.(Clemente et al. 2013)' (Duarte et al. 2012') (Silva et al. 2014') (Duarte et al. 2013),(Moura et al. 2016),(Rodrigues and Passos 2013),(Frencken et al. 2013),(Bourbousson et al. 2010)

Statistical analysis

A PCA was implemented to reduce the dimensionality of spatiotemporal characteristics at the team and individual levels. Two separate analyses (team and individual values) were utilised to reduce the dimensionality of the included variables into a smaller set of uncorrelated components whilst maintaining most of the variance from the original dataset.(Kaiser 1960') (Federolf et al. 2014) As a result of the analysis technique, no correlation exists between the principal components while each contain their own highly correlated variables that measure underlying, independent constructs. This method ensures only distinct information remains within the dataset.(Weaving et al. 2014) While this method does not identify which measures are most related to performance, it dimensionally reduces available metrics into components that describe the underlying structure of those metrics. A PCA involves the removal of the mean, calculation of the covariance of the data, determination of the eigenvalues and eigenvectors of the covariance matrix, and a varimax rotation of the original data onto a coordinate system spanned by the eigenvectors of the covariance matrix. (Federolf et al. 2014)

The analysis was executed using SPSS for Windows (Version 25)(IBM Corp. IBM SPSS 2017), factoring the correlation matrix, to determine whether common underlying constructs were present in the 18 team- and 15 individual-derived spatiotemporal variables. Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction.(IBM Corp. IBM SPSS 2017) All variables were initially included, upon which variables with communalities (relative importance for inclusion in the factor) lower than 0.40 were excluded.(Stevens 2002)' (Howard 2016) The PCA was subsequently re-run using only variables of significant importance. The number of principal components to be retained was determined using the scree plot which is a line plot of the derived factor eigenvalues.(Lewith et al. 2010) The scree plot was assessed for an inflection point between factors with relatively large eigenvalues and those with similar eigenvalues. The components that occur before the break are deemed meaningful and are retained.(Dmitrienko et al. 2007) These components were subsequently used to derive factor loadings associated with each of the variables in the analysis. These factor loadings were then used to calculate summed variables (sum scores) for each component by treating them as coefficients in a linear regression model. For interpretation, sum scores are calculated by multiplying the factor loadings (eigenvectors) with the associated standardised spatiotemporal variables (Table 2).(Weaving et al. 2019) Sum scores were then converted to z-scores and normalised to the same unit and magnitude, with a set mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)) to facilitate interpretation.(Henderson et al. 2018)

Results

No variables were excluded from the team analysis while two variables, *individual longitudinal coefficient of variation* and *individual longitudinal correlation* were removed due to communalities below 0.40. An examination of the KMO measure of sampling adequacy suggested that a considerable proportion of the variance in the dataset was associated with the underlying factors (Team KMO = 0.58; Individual KMO = 0.62). Bartlett's test of sphericity was significant in both analyses ($p < 0.001$).IBM Corp. IBM SPSS 2017)

The scree plots revealed that the team analysis provided five components and the individual analysis provided four components prior to the break in eigenvalues. The nomenclature adopted for these was based on detailed discussions among the author team relating to the constituents of each component and the facet of match-play they represented. These components accounted for 69% and 64% of the variance in the team and individual dataset, respectively. Figure 1 reveals the cumulative explained variance for each component from the analyses. The rotated component matrix produced component weightings for each variable in their respective principal

Table 1. GNSS-derived spatiotemporal tactical variables.

Individual	
Variable	Description
Lateral: - Lateral Displacement- Lateral CV- Lateral Correlation- Lateral SaEn (Computed from lateral displacement)- Lateral Rho	Position of a player in the side-to-side direction of the playing field. Positive values are movements to the left of the field's centre respective to the attacking direction. *Lateral coefficient of variation* is the variability in player displacement in the side-to-side direction; *Lateral correlation* is a relationship between the lateral movements of the individual player and lateral movements of the team centroid; *Lateral sample entropy* is a measure of the individual's lateral movement predictability; *Lateral rho* is a measure of individual lateral phase synchronisation with respect to the rest of the team.
Longitudinal: - Longitudinal Displacement – Longitudinal CV- Longitudinal Correlation - Longitudinal SaEn (Computed from longitudinal displacement)- Longitudinal Rho	Position of a player in the end-to-end direction of the playing field. Positive values are movements away from the field's centre towards the defensive end and negative values are towards the attacking end. *Longitudinal coefficient of variation* is the variability in player displacement in the end-to-end direction; *Longitudinal correlation* is a relationship between the longitudinal movements of the individual player and longitudinal movements of the team centroid; *Longitudinal sample entropy* is a measure of the individual's longitudinal movement predictability; *Longitudinal rho* is a measure of individual Longitudinal phase synchronisation with respect to the rest of the team.
Stretch Index: - Stretch Index- Stretch Index CV- Stretch Index Correlation- Stretch Index SaEn- Stretch Index Rho	The distance of a player to the team centroid at a given time. It is calculated as the distances of a given player each (x_i, y_i) and the centroid of the team $(\bar{x}, \bar{y})$ at a given time. $StretchIndex(DistanceFormula) = \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}$ *Stretch index coefficient of variation* is the variability in the distance of a player to the team centroid; *Stretch index correlation* is a relationship between the stretch index of the individual player and the team stretch index value; *Stretch index sample entropy* is a measure of the predictability of an individual's distance to the team's centroid; *Stretch index rho* is a measure of individual's stretch index phase synchronisation with respect to the rest of the team.
Team	
Variable	**Description**
Centroid: - Lateral Centroid- Longitudinal Centroid	The geometrical centre of a team.Couceiro et al. 2014; Johnston et al. 2014 Calculated as the mean position $(\bar{x}, \bar{y})$ of all players on the field (x_n, y_n) and provides information on the global positioning of the team over time. Centroid measures provide lateral and longitudinal coordinates. Positive lateral values represent movements to the left of the field's centre and positive longitudinal values represent movements away from the field's centre towards the defensive end respective to the attacking direction.
- Surface Area	The total space covered by a team and calculated as the area within the convex hull.Howard 2016 It is calculated using MATLAB's *convhull* function which returns an index array of the outermost players at a given time.Frencken et al. 2013 The polygonal area can then be calculated using MATLAB's *areaint* function which calculates the spherical surface area of the polygon specified by the convex hull input vectors (x,y) Larger values indicate greater total field coverage but ignores player distribution.
- Stretch Index	The dispersion and contraction of the team in relation to the team centroid. Stevens 2002 It is calculated using the mean of the distances between each player (x_n, y_n) and the centroid of the team $(\bar{x}, \bar{y})$ at a given time. Larger values signify that players, on average, are further away from the team centroid.
Coefficient of Variation (CV): – Surface Area CV- Stretch Index CV- Lateral CV- Longitudinal CV	A form of linear analysis that uses the standard deviation (s_k) and mean $(\bar{k})$ to quantify the overall variability of the team's spatiotemporal characteristics during specific time periods. Lower values represent lower overall variability in the selected measure.The MathWorks I 2018a $CoefficientofVariation = \frac{s_k}{\bar{k}}$
Pairwise Correlations: - Stretch Index Correlation - Lateral Correlation - Longitudinal Correlation	Assesses the synchronicity of players. Can be calculated using MATLAB's *corrcoef* function (pairwise option) to correlate the time-series of displacement (x_i, y_i) and stretch index measures of player *i* with the time-series of the team's centroid $(\bar{x}, \bar{y})$ and stretch index, respectively. For the team-derived value, scores of each player were averaged to provide an indication of the level of synchronicity for the team for both displacement and dispersion. Values closer to one signify that players within the team, on average, demonstrate similar movements for the event period.Federolf et al. 2014; Weaving et al. 2014; IBM Corp. IBM SPSS 2017

(*Continued*)

Table 1. (Continued).

Individual	
Variable	Description
Sample Entropy (SaEn): - Surface Area SaEn- Stretch Index SaEn, - Lateral SaEn- Longitudinal SaEn	A non-linear measure of variability that provides an indication as to the regularity/predictability of behaviour. Calculated using *Sample Entropy* from MATLAB's File ExchangeLewith et al. 2010 and is defined as the negative natural logarithm for conditional properties that a series of data points a certain distance apart, *m*, would repeat itself at $m + 1$.Dmitrienko et al. 2007, Weaving et al. 2019 Given a time series $t(n) = t(1), t(2), \ldots, t(n)$ with n number of data points, a sequence of m-length vectors is formed. Comparisons are then made against each m-length vector within the time series. Vectors are considered alike if the tail or head of the vector fall within a certain tolerance level as determined by $r \times s$.The MathWorks I 2018a The sum of the total number of like vectors is then divided by $n - m + 1$ and is equal to *B*. Additionally, *A* is equal to the subset of *B* that also matched for $m + 1$. Sample entropy is then calculated:$SampEn = -ln\frac{A}{B}$ A time series with similar distances between data points would result in a lower sample entropy value and large differences would result in greater sample entropy values. Thus, sample entropy can determine the predictability and regularity of a time series, with values closer to zero signifying greater regularity/predictability. Dmitrienko et al. 2007, Weaving et al. 2019 Based on previous literature, the parameters to be used in this study are $m= 2$ and $r = 0.2$.Dmitrienko et al. 2007, Henderson et al. 2018, Braham and Small 2018
Cluster Phase (Rho): - Stretch Index Rho- Lateral Rho- Longitudinal Rho	Quantifies the collective spatiotemporal phase synchronisation, of oscillatory movement components (e.g. players' movement displacement trajectories) in a single collective parameter.Travassos et al. 2014 Calculated in MATLAB using Richardson's (2020) *ClusterPhase* toolbox.Moura et al. Prior to calculation, differential values (for each data point *i* in the time-series, the *i-1th* data point was subtracted) were created to determine whether players were synchronising their movements in the same direction, regardless of whether they were in line with each other. Values closer to 1 signify perfect synchrony. Kaiser 1960

component. All variables were assigned to the component in which they had the strongest weighting. The five team (1–5) and four individual (6–9) equations derived from the analysis are displayed in Table 2.

Discussion

Until recently, tactical behaviour has been assessed using methods of notational analysis and/or coaches' subjective ratings of performance making it difficult to objectively assess performance acutely or longitudinally or to compare between different contexts.(Vilar et al. 2012(, (Memmert et al. 2017) Alternatively, spatiotemporal behavioural analyses have recently provided objective measures for assessing tactical behaviour. (Memmert et al. 2017), (Alexander et al. 2018), (Tenga et al. 2010),(Clemente et al. 2013),(Braham and Small 2018) While many studies have attempted to describe tactical behaviour using spatiotemporal variables in team sports, this was the first to describe and dimensionally reduce an array of spatiotemporal variables in Australian Football to facilitate their practical application and interpretation. The derived principal components adequately represent different constructs whilst maintaining a large amount of the variability from the original data (Figure 1).(IBM Corp. IBM SPSS 2017) Embedded in an ecological dynamics framework, these components facilitate the interpretation of spatiotemporal behaviour patterns and subsequently allow practitioners and coaches to design and implement training that promotes specific spatiotemporal tactical behaviour.

At the macroscopic level of analysis, the constructs in equations 1–5 provide useful information regarding spatiotemporal behaviour that emerges collectively at the team level. Sum scores generated from the equations derived in this study describe patterns of behaviour which could be analysed with

Table 2. Resultant equations from two principal component analyses for team and individual measures.

Equation Number	Component	Calculation
Team		
1	Dispersive Coordination	− 0.923 × Stretch Index SaEn − 0.823 × Surface Area SaEn + 0.891 × Stretch Index CV + 0.684 × Surface Area CV + 0.850 × Team Stretch Index Correlation
2	Lateral Unpredictability and Spacing	− 0.933 × Centroid Lateral Correlation + 0.694 × Centroid Lateral SaEn + 0.923 × Surface Area + 0.832 × Stretch Index + 0.536 × Team Stretch Index Rho
3	Multidirectional Synchrony	0.955 × Centroid Longitudinal Rho + 0.936 × Centroid Lateral Rho
4	Longitudinal Unpredictability	− 0.815 × Centroid Longitudinal Correlation + 0.694 × Centroid Longitudinal SaEn
5	Longitudinal Behaviour	0.694 × Centroid Longitudinal CV − 0.686 × Centroid Longitudinal Displacement
Individual		
6	Multidirectional and Spacing Synchrony	0.900 × Individual Stretch Index Rho + 0.900 × Individual Lateral Rho + 0.891 × Individual Longitudinal Rho
7	Unpredictability	0.845 × Individual Stretch Index SaEn + 0.839 × Individual Lateral SaEn + 0.747 × Individual Longitudinal SaEn +
8	Player Movement	− 0.926 × Individual Stretch Index + 0.771 × Individual Stretch Index CV + 0.741 × Individual Lateral Correlation
9	Player Positioning	0.806 × Individual Stretch Index Correlation + 0.656 × Individual Longitudinal Displacement

CV, Coefficient of Variation; SaEn, Sample Entropy; Rho, Cluster Phase.

respect to performance outcomes. As equations were derived from values that captured behaviour across the entire match, resultant sum scores provide insights into behaviours that persist or are the most prevalent throughout the game. Higher *dispersive coordination* (equation 1) and *multidirectional synchrony* (equation 3) coupled with lower *lateral unpredictability and spacing* (equation 2) scores emerge when a team spends a significant proportion of the game defending. Based on contextually similar sports,(Travassos et al. 2014)' (Moura et al.) defensive structures are often characterised by a compact shape coupled with synchronised and predictable collective behaviour. In defence, the self-organisation into this resultant behaviour is deemed necessary to protect the team's goals from attacking perturbations. Alternatively, from a defensive standpoint, larger scores generated from higher CV values in dispersion may suggest a different defensive style of play indicating that the team defensively shadows offensive teams as they attempt to spread and use large areas of the field.

Conversely, lower *dispersive coordination* (equation 1) and *multidirectional synchrony* (equation 3) coupled with larger *lateral unpredictability and spacing* (equation 2) scores may indicate that a team have spent a large amount of time in attack. Similarly, insights adopted from similar sporting contexts (Memmert et al. 2017)' (Tenga et al. 2010)' (Clemente et al. 2013) suggest that moving asynchronously and in an unpredictable manner, with a dispersed shape, may be necessary to effectively perturb defensive lines and create scoring opportunities by misaligning defending players. Additionally, larger *longitudinal behaviour* (equation 5) scores may further indicate the prevalence of attacking behaviour as higher scores may be a result of the team's frequent positioning in the attacking half coupled with greater end-to-end position variability as a result of spatial exploration looking for opportunities to score. This higher sum score may also reflect the ability of a team to secure repeat entries into the forward 50 metre arc (the attacking zone) and prevent the opposition team leaving their defensive half.

Furthermore, the team-derived sum scores may also reflect matches characterised by a large amount of disputed possession or that consisted of regular changes in possession, i.e., frequent changes from attack to defence and vice versa. For example, frequent changes from defence, or contested play, to attack may inhibit the ability for players to self-organise and result in larger *lateral unpredictability and spacing* (equation 2) sum scores due to an absence of unidirectional movement synchrony in the side-to-side direction concurrently with a synchronised increase in dispersion. This collective increase in dispersion when transitioning from defence into attack has also been demonstrated in contextually similar sports (Memmert et al. 2017)' (Tenga et al. 2010)' (Clemente et al. 2013) and provides favourable affordances over the initial movement of the ball or alignment with teammates. Similarly, match-play characterised by frequent transitions would likely reveal larger *longitudinal unpredictability* (equation 4) sum scores as lower unidirectional synchrony and predictability in the end-to-end direction is expected as teams move from attack to defence, or vice versa, attempting to re-organise with the change in possession. While sum score may indicate the prevalence of attacking, defending or transitioning behaviour, caution should be taken when interpreting sum scores from the entirety of a match as they emerge due to unfavourable patterns of behaviour. For example, a team may spend a large portion of the match attacking yet may not disperse effectively or move erratically enough to perturb defensive lines. As a result, the sum scores would likely reflect that of a match spent defending. Deriving sum scores from specific phases of play, i.e attack, defence or contested phases, would provide more detailed insight into the effectiveness of emergent defensive or attacking behaviour and may indeed enhance the validity of this type of analysis.

At the individual level, the assessment of sum scores may be useful when assessing longitudinal changes in performance or when comparing players in similar positions. Across a match, specific positions may demonstrate favourable or unfavourable characteristics that align with tactical guidelines. Based on contextually similar research,(Travassos et al. 2014)' (Moura et al. 0000) defenders would likely spend a large proportion of the match moving synchronously with surrounding teammates and in a predictable manner, positioning themselves furthest away from the team's centroid in the defensive half between the attacking team and the goals. As a result, key defenders may display superior *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) scores coupled with lower *unpredictability* (equation 7) and *player movement* (equation 8) scores. Unified, synergistic movement is theorised to be important for resisting attacking perturbations and may also result from affordances provided by the movement of the ball and fellow teammates. Alternatively, defenders who disregard the movement of teammates and tactically choose to mimic opposing tackers who tend to move erratically, may present with lower *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) sum scores. Certain scores may also reveal differences in position specific tasks. For example, small defenders who attempt to win and transfer contested possession may demonstrate higher *player movement* (equation 8) scores as they attempt to evade opposition players when in possession or when providing a target for teammates.

Alternatively, also demonstrated in contextually similar sports,(Memmert et al. 2017)' (Tenga et al. 2010)' (Clemente et al. 2013) attacking players may move asynchronously and unpredictably in an attempt to perturb defensive lines and create goal scoring opportunities. Attacking players would therefore likely reveal lower *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) scores coupled with larger *unpredictability* (equation 7) and *player movement* (equation 8) scores as they place themselves primarily in the forward half, probing for scoring opportunities. As with defenders, intra-position differences may be evident. For example, smaller forwards, positioned closer to the team's centroid, may favour the movement of teammates and the ball to guide movements resulting in larger *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) sum scores.

Finally, individual sum scores may be able to distinguish between player roles within specific positional groups. For example, wing midfield players may use information provided by ball movement and teammates to guide behaviour and self-organise throughout a match, resulting in superior *multidirectional and spacing synchrony* (equation 6) and *player positioning* (equation 9) sum scores. This behaviour is justified as occupying the lateral field corridors in a synchronised manner is the greatest destabilising factor of opponents' organisation during attacking phases, which is likely evident as critical transitional game periods are associated with changes in lateral distance between teams.(Gonçalves et al. 2014) Conversely, inside midfielders may demonstrate lower scores across a match as they move erratically to win contested possession or move into free space to create passing opportunities to teammates. Inside midfielders may also reveal higher *player movement* (equation 8) scores as they spend more time closer to the team's centre trying to win and subsequently transfer contested possession. In other contextually similar sports, the midfield is where transition play moves from defensive to offensive patterning and players disperse laterally to deal with the congestion of players, attempting to provide passing affordances for teammates in this area.Fradua et al. 2013)

The derived spatiotemporal metrics provide a method for coaches and practitioners to further understand tactical match-play behaviour exhibited by teams and individuals. While this is the first study to provide a simplified, novel method for analysing spatiotemporal behaviour in Australian Football, these metrics are yet to be investigated with respect to individual and team performance. Further, while principal components were derived from professional-level match-play over three-years, data was derived from one team only meaning the results may not be generalisable. Regardless, the results provide supporting data for performance analysts using GNSS technology to analyse games and could allow coaches to identify strengths and weaknesses in movement patterns and exploit these through the implementation of game tactics. Collectively, at the team level, while future research is required to validate the use of these metrics with different phases of play, the derived sum scores may provide insights into behaviours that persist over the course of a game, particularly with reference to attack, defence and disputed/contested possession. Individually, scores may provide insight into positional tasks/roles or reveal how players use surrounding information to guide behaviour. Whether at the individual or team level of analysis, the five team and four individual equations provide a detailed analysis of movement behaviour in a simplified manner.

Practical implications

- The simplified spatiotemporal metrics provide supporting data for performance analysts and practitioners currently using GNSS technology.
- Team-derived components provide insight into spatiotemporal behaviours or styles of play that emerge and persist throughout the game. Resultant values can be analysed with respect to performance outcomes and may provide further insight as to 'why' or 'how' these certain outcomes occur or implicate certain styles of play for performance. For example, it could be hypothesised that greater coordination in the movements of team-mates during defensive phases of play would be associated with concession of fewer goals i.e., higher *dispersive coordination* (equation 1) and *multidirectional synchrony* (equation 3) coupled with lower *lateral unpredictability and spacing* (equation 2).
- Individual-derived metrics provide an objective appraisal of different player styles or roles. Additionally, position-specific sum scores may demonstrate favourable or unfavourable characteristics that align with tactical guidelines. For example, an attacking player who has the primary role of probing for scoring opportunities may have fulfilled their role when they reveal lower multidirectional and spacing synchrony (equation 6) and player positioning (equation 9) scores coupled with larger unpredictability (equation 7) as these states of asynchronous movement behaviour may be necessary to perturb defensive formations.
- This information may improve the integration of spatio-temporal data with physical, technical and tactical metrics by reducing the complexity of the available information and allow coaching staff to develop training interventions representative of competition movement demands. In match simulation drills that are designed to emulate favourable attacking behaviour, coaches may concurrently utilise spatiotemporal, physical, and technical indicators to assess behaviour. For example, it has been theorised that superior change of direction (physical) would likely lead to a reduction in synchronous behaviour (spatiotemporal) and may provide a sufficient perturbation to the defensive team and subsequently provide an opportunity for an inside 50, a positive technical indicator of performance.(Rennie et al. 2017)

Conclusion

This study is the first to provide a simplified, novel method for assessing spatiotemporal behaviour in the context of Australian Football match-play. Both the team and individual metrics provided specific movement insights for coaches and practitioners. This information can consequentially guide training implementation, player development and enable comparisons between playing styles. Further, the current findings may provide a viable framework for analysis in other contextually similar sports.

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Study Five: A holistic analysis of collective behaviour and team performance in Australian Football via structural equation modelling

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A holistic analysis of collective behaviour and team performance in Australian Football via structural equation modelling

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ABSTRACT
Despite awareness of the importance of quantifying technical, tactical, and physical characteristics of match play, few studies have examined the structural relationship of these aspects in professional sport. Accordingly, this study concurrently examined these components in relation to quarter outcome (n = 272) in Australian Football. The study followed a retrospective longitudinal case study design where one teams' cooperative passing network, skill counts, physical loads, and spatiotemporal behaviours during official Australian Football League games were collected from a period spanning four seasons (2016–2019). A principal components analysis (PCA) and structural equation modelling were used to explore the structural relationships between components and examine the influence on quarter outcome as determined by the point differential (*quarter margin*). *Scoring opportunity* and *ball movement* had direct associations with *quarter margin*, while *unpredictability, uncontested behaviour* and *physical behaviour* did not. Negative associations between *uncontested behaviour* and *scoring opportunity* suggest that elevated high-pressure success and a lack of synchrony may positively influence *scoring opportunity*, a determinant of *quarter margin*. Further, negative associations between *physical behaviour* and *ball movement* suggest that with less physical work, a team's collective ability to transfer possession between teammates is facilitated, offering an interesting dichotomy between skill and physical demands of Australian Football. While hundreds of different metrics are available, the present study was the first to concurrently examine the influence of a variety of match play components on performance outcomes in Australian Football. These results may provide direction for coaches and practitioners when contemplating practice design, tactical strategies, or the development of behaviour through specific training exercises. Game plans and training drills that focus on optimising attacking and low-pressure ball movement coupled with high levels of mutual interaction between teammates may be beneficial for performance.

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Introduction

Australian Football (AF), like other invasion games such as field hockey, water polo, soccer, and basketball, is characterised by its 360-degree nature with the ability for players to distribute the ball in all directions. Players require superior physical abilities, technical skills and tactical strategies to cope with the ever-changing demands of the game (Sullivan et al. 2014b). Team success in AF is more than the sum of its parts with a culmination of the aforementioned variables with superior performance allowing teams to fulfil the main objective of the game, to score the most points through goal kicking. In these contexts, the scientific analysis of performance aims to integrate objective, reliable and relevant data to create knowledge, and translate this by designing learning opportunities so that key stakeholders can utilise this information to advance understanding of game behaviour, guide decisions, and subsequently improve future outcomes (McGarry 2009; Martin et al. 2021). Accordingly, applied research in this context has often adopted a reductionist approach, investigating these factors (each with a wide array of variables) in isolation to derive practical applications aimed at improving a team's performance.

In an effort to deepen the level of understanding of match performance, performance analysis has been utilised to subjectively audit and describe the behaviours of performers during different sub-phases of play, i.e., attack and defence, to provide additional information for practitioners (Vilar et al. 2012; Rennie et al. 2018). This has typically occurred through verbal descriptions of lived experiences or game observation (Araújo and Bourbousson 2016). While these processes may offer insight, such methods are often not sufficiently objective and are less systematic, relying on subjective impressions and procedural knowledge of expert performers, subsequently making it difficult to translate or compare findings in different contexts (Memmert et al. 2017) as well as increase the likelihood of confirmation bias (Martin et al. 2021). As these methods likely do not provide sufficient objectivity, new objective, systematic and open-minded approaches for gathering and interrogating data need to be explored in order to make it possible to assess performance in differing contexts.

In an attempt to objectively quantify the underpinnings of successful performance, analysts have often focused on identifying associated physiological demands such as workload, total

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distance covered or distances covered at different intensities as measured by a global navigation satellite system (GNSS) (Casamichana et al. 2013). For example, in AF, the physical element of the game is characterised by large volumes of running, partly due to the large oval shaped playing field, with players covering ~12–17 km of distance and completing bouts of intermittent high-speed running coupled with frequent collisions and changes of direction (Gray and Jenkins 2010). Furthermore, through the assessment of discrete on-field actions such as the number of completed passes, time spent in possession of the ball, or the amount of tackles made, researchers have endeavoured to provide reliable technical descriptions of game demands as predictors of success (Travassos et al. 2013). In AF, skill count analyses have emphasised the importance of skill proficiency with players utilising a myriad of hand and foot skills for passing, scoring and gaining possession of the ball (Johnston et al. 2016). While the extensive information regarding the physical and technical actions is useful, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance (Mooney et al. 2011; Hiscock et al. 2012; Johnston et al. 2012; Sullivan et al. 2014b; Bauer et al. 2015). This has also been demonstrated in other team invasion games (Novak et al. 2021). The excessive emphasis placed on performance outcome measures in research contexts presents an underlying issue that primarily focuses on 'who did what, when' which fails to provide a meaningful understanding of the underlying factors of successful performance in complex team sports. An absence of detailed understanding exemplifies the need for a theoretical rationale that can provide insight into performance behaviours that may emerge over time (Glazier and Robins 2013; Araújo et al. 2014). Additionally, the vast dimensions of analysis somewhat complicates their interpretation, which limits the practical relevance of the research.

With technological advancements, such as an increase in sensitivity and application of GNSS devices, in conjunction with analytical approaches such as spatiotemporal analysis and cooperative passing network analysis, practitioners are able to more precisely measure team behaviour and quantitatively model, infer and predict performance outcomes in team sports such as AF (Travassos et al. 2013). For example, by analysing passing sequences within a team, practitioners can map the relationship between different players during a game and reveal the local structure of organisation among players. This form of cooperative network analysis can provide additional information that captures the dynamic nature of team sport performance (Araujo and Davids 2016) and provide additional insight into factors influencing success (Braham and Small 2018). Further, while scarcely examined in AF (Sheehan et al. 2021b) spatiotemporal analysis of collective variables such as team or positional-group displacement and dispersion and inter-player levels of synchronicity and predictability can provide additional information that helps capture the dynamic nature of team sport (Araujo and Davids 2016). This approach has provided insight into the behaviour that characterises successful attacking and defensive phases of play in soccer (Tenga et al. 2010; Clemente et al. 2013a) as well as AF (Alexander et al. 2018; Sheehan et al. 2021a, 2021b). For example, one study utilising these metrics in AF demonstrated greater team dispersion during offensive phases compared to defensive and contested phases (Alexander et al. 2018). These higher values likely reveal players spreading the opposition's defensive players to create a greater effective playing space allowing easier passage towards the goals. In contrast, lower values of dispersion may indicate a defensive mechanism to contract rapidly if the opposition gained possession of the ball (Alexander et al. 2018). While these metrics provide objective insight into theoretical mechanisms influencing success, the concurrent examination of the structural relationships between these indicators and other behavioural components, i.e., network, skill, and physical behaviour, and performance is yet to be explored. Further, the utilisation of two 20-minute halves in a 15v15-match simulation drill, adopted in previous studies (Alexander et al. 2019), does not fully represent the collective behaviour exhibited by teams during competitive match-play due to the increase in relative space per player. Further research investigating these metrics in AF League (AFL) matches alongside other components of match-play may deepen the understanding of the influence of tactical behaviour on performance.

There is plethora of information available for sports scientists and practitioners regarding network, technical, physical, and spatiotemporal behaviour. Nonetheless, the complexity associated with the reporting of these methods, and the absence of a sound conceptual framework that can appropriately contextualise and describe behaviour, makes the application of this information difficult. Ecological dynamics has been considered as a viable framework for analysing and understanding individual team behaviour as it actively focuses on the performer–environment relationship, and may provide a basis for understanding performance in team sports such as AF (Davids et al. 2013). In AF, task-constraints, such as field dimensions and passing rules, along with physical and informational constraints, such as player size and opposition player movements, provide perceptual information and boundaries that guide and govern behaviour and allows players to self-organise into stable states of coordination that enables the achievement of task goals (Davids et al. 2013). Accordingly, as resultant behaviour is the result of the interaction between its constituent components, it is important to examine the influence of interactions and behaviour exhibited by, and between, players when analysing performance in team sports from an ecological dynamics perspective. Appropriate application of statistical techniques rationalised using an ecological dynamics approach makes it possible to assess and monitor coordinative behaviour that emerges within and between teams. Further, utilising dimensional reduction techniques may help simplify and elucidate the most appropriate metrics and allow the information generated to be more effectively reported back to key stakeholders (Malone et al. 2019; Sheehan et al. 2020, 2020a, 2020b, 2021b).

Investigating the interrelationship between cooperative networks and team spatiotemporal measures, alongside physical and technical data within an ecological dynamics framework, may provide insight into 'how' and 'why' successful behaviours in AF occur as opposed to just 'when' they occur (Vilar et al. 2012). While several studies in AF have revealed that technical and tactical constructs are more closely related to successful quarter outcomes when compared to physical performance measures (Sullivan et al. 2014a; Kempton and Coutts 2016), the adoption of an integrated approach to the reporting of physical and technical construct data has been suggested (Carling 2013; Kempton et al. 2017). Additionally, with the objective analysis of tactical performance, the inclusion of this information using an integrated approach may provide valuable insight as all these constructs are closely linked and do not occur in isolation (Figure 1). For example, in contextually similar sports such as soccer the physical demands appear to be associated with positional information, technical and tactical performance (Moura et al. 2013; Clemente et al. 2013b). While running demands have not been concomitantly assessed with tactical measures, team dispersion measures typically reduce in the second half (i.e., in offence players are less dispersed in the second than in the first half of a game), which could be attributed to the onset of fatigue in the second half of a game (Clemente et al. 2013b), demonstrating the inter-relationship between the physical and tactical domains of performance in football. With diminished physical capacities, the ability of players to explore the whole width and length of field while trying to unbalance an opposing team is compromised (Clemente et al. 2013b). The concurrent examination of a myriad of physical, technical, and tactical variables may help elucidate the role of certain variables in relation to performance and team success.

Team dispersion measures typically reduce in the second half (i.e., in offence players are less dispersed in the second than in the first half of a game), which could attributed to the onset of fatigue in the second half of a game (Clemente et al. 2013b), demonstrating the inter-relationship between the physical and tactical domains of performance in football. With diminished physical capacities, the ability of players to explore the whole width and length of field while trying to unbalance an opposing team is compromised (Clemente et al. 2013b).

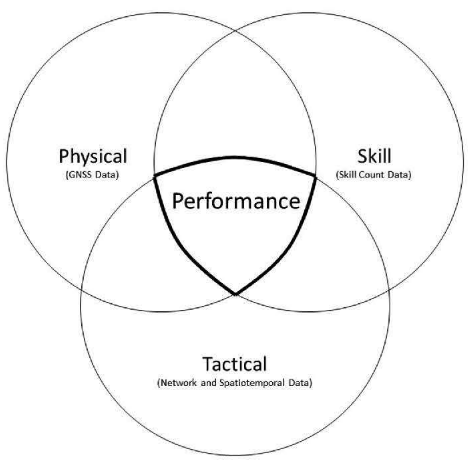

Figure 1. Integrated theoretical model of performance.

Due to the inter-relationships between physical, technical, and tactical characteristics the aim of the present study was to utilise aggregate metrics derived by Sheehan and colleagues (Sheehan et al. 2020, 2020a, 2020b, 2021b) to examine the relationships between these characteristics and performance as determined by match *quarter margin* (point differential) in AF. This theoretical model of performance was assessed through the use of a combined PCA and structural equation model as these techniques can reduce dimensionality and concurrently model relationships between each component and an outcome variable (Lomax and Schumacker 2004). Based on existing literature, it was hypothesised that an interplay of physical, technical, spatiotemporal and network features would provide a detailed model of performance for AF with the latter three aspects contributing to a greater degree than the physical characteristics. Due to their inextricable link, it was also hypothesised that physical behaviour would exhibit an association with spatiotemporal behaviours while network characteristics would be associated with skill indicators.

Methods

Participants

Fifty-six male professional Australian footballers (age: 24.8 ± 4.5 years; professional playing experience: 5.8 ± 4.3 years) from one AFL team were analysed over a four-year (2016–2019) period. Sixty-eight senior matches were used for analysis providing a sample of 272 quarters from the designated AFL team. This provided a sufficient sample size for the analysis as a ratio of 5–10 samples per expected free parameter in the model (27) is recommended (Bentler and Chou 1987; Bollen 1989). The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the Authors' academic institution.

Study design

The study followed a retrospective longitudinal case study design where one team's passing interactions (cooperative network), skill counts, physical loads, and spatiotemporal behaviours during official AFL games were collected from a period spanning four seasons. Network (Sheehan et al. 2020b), skill(Sheehan et al. 2020a), physical (Sheehan et al. 2020), and spatiotemporal (Sheehan et al. 2021b) sum scores were subsequently derived according to the methods outlined by Sheehan and colleagues which have been used to provide insight into factors influencing behavioural outcomes in AFL matchplay (Sheehan et al. 2021a). A preliminary analysis was conducted using a PCA to explore relationships between these scores and reduce the number of individual and correlated variables for modelling with respect to an outcome variable. Structural equation modelling (SEM) was subsequently used to explore relationships between these newly derived component scores and to examine the influence of these components on quarter outcome as determined by point differential.

Data collection

Network and skill analysis. Network indicators, derived from player interactions as determined through the distribution and receipt of kicks and handballs (Sheehan et al. 2020b), and skill counts were obtained from ChampionData® (supplementary Table 1), the official data provider to the AFL (Braham and Small 2018). ChampionData® code all AFL matches for a variety of skill involvements (O'Shaughnessy 2006) and are commonly used in AF research (O'Shaughnessy 2006; Mooney et al. 2011; Rennie et al. 2018). A selection of statistical indicators have been empirically reviewed, reporting a high level of reliability (ICC range = 0.947–1.000; RMSE range = 0.0–4.5) (Robertson et al. 2016b). Other reliability information provided about ChampionData® statistics states that 'quantity-based statistics are logged at better than 99% accuracy' (O'Shaughnessy 2006). As stated, network (Sheehan et al. 2020b) and skill (Sheehan et al. 2020a) sum scores were generated using weightings derived by Sheehan and colleagues (Table 1).

Physical and spatiotemporal analysis

Data was collected via the use of GNSS units sampling at 10 Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia) which have shown to be suitably reliable at low-, high-, and very high-speed running intensities (Johnston et al. 2014). Further, variables pertaining to banded inertial movement analyses (IMA) and accelerations have also demonstrated suitable reliability (Akenhead et al. 2014; Luteberget et al. 2017). As stated, physical (Sheehan et al. 2020) and spatiotemporal (Sheehan et al. 2021b) sum scores were generated using weightings derived by Sheehan and colleagues (Table 2).

Table 1. Network and skill sum score equations.

Network Variable (Sheehan et al. 2020b)	Calculation
In-Degree Variability	0.925 × Team In Degree Node Variability + 0.925 × Team In Closeness Centrality Variability + 0.714 × Pagerank Centrality Variability + 0.613 × In Degree Pass variability
Out-Degree Variability	0.945 × Team Out Closeness Centrality Variability + 0.895 × Team Out Degree Node Variability + 0.626 × Out Degree Pass variability + 0.523 × Team Betweenness Centrality Variability
Connectedness	0.964 × Network Density – 0.949 × Team Betweenness Centrality + 0.939 × Team Out Closeness Centrality + 0.935 × Team In Closeness Centrality + 0.931 × Network Intensity
Skill Variables (Sheehan et al. 2020a)	**Calculation**
High-Pressure Success	0.867 × Handball + 0.865 × Contested Possession + 0.844 × First Possession + 0.805 × Clearance + 0.781 × Hardball Get + 0.771 × Effective Handball + 0.629 × Ineffective Handball + 0.586 × Gather + 0.515 × Looseball Get + 0.455 × Tackle
Low-Pressure Success	0.922 × Uncontested Mark + 0.909 × Mark + 0.749 × Mark Play On + 0.727 × Short Kick + 0.677 × Effective Kick + 0.655 × Uncontested Possession + 0.563 × Kick
Attacking Ball Movement Ability	0.902 × Kick Inside 50 + 0.882 × Inside 50 + 0.620 × Long Kick + 0.416 × Ineffective Kick
Scoring Ability	0.853 × Shot at Goal + 0.837 × Inside 50 Result

Table 2. Physical and spatiotemporal sum score equations.

Physical(Sheehan et al. 2020)	Calculation
Low-Moderate Volume	0.869 × Velocity Band 3 Distance + 0.835 × Total Distance + 0.807 × Deceleration Band 1 Efforts + 0.805 × Acceleration Band 1 Efforts + 0.772 × Velocity Band 3 Efforts + 0.727 × Velocity Band 4 Efforts + 0.713 × Velocity Band 2 Distance + 0.652 × Velocity Band 4 Distance + 0.649 × Acceleration Band 1 Distance + 0.621 × Deceleration Band 2 Efforts + 0.605 × Deceleration Band 1 Distance + 0.560 × Acceleration Band 2 Efforts
High Speed Running	0.833 × Velocity Band 6 Distance + 0.830 × Velocity Band 6 Efforts + 0.823 × Velocity Band 5 Distance + 0.701 × Velocity Band 5 Efforts
Explosiveness	0.878 × Acceleration Band 3 Efforts + 0.858 × Acceleration Band 3 Distance + 0.823 × Acceleration Band 2 Distance
Change of Direction	0.899 × IMA Acceleration High + 0.885 × IMA Change of Direction Right High + 0.862 × IMA Change of Direction Left High + 0.738 × IMA Acceleration Medium + 0.712 × IMA Change of Direction Right Medium + 0.706 × IMA Change of Direction Left Medium + 0.526 × IMA Acceleration Low + 0.455 × IMA Change of Direction Right Low + 0.415 × IMA Change of Direction Left Low
Collisions/Impacts	0.740 × IMA Deceleration Medium + 0.654 × IMA Deceleration Low + 0.617 × IMA Jump Low + 0.607 × IMA Deceleration High
Spatiotemporal (Sheehan et al. 2021a)	**Calculation**
Dispersive Coordination	– 0.923 × Stretch Index SaEn – 0.823 × Surface Area SaEn + 0.891 × Stretch Index CV + 0.684 × Surface Area CV + 0.850 × Team Stretch Index Correlation
Lateral Unpredictability and Spacing	– 0.933 × Centroid Lateral Correlation + 0.694 × Centroid Lateral SaEn + 0.923 × Surface Area + 0.832 × Stretch Index + 0.536 × Team Stretch Index Rho
Multidirectional Synchrony	0.955 × Centroid Longitudinal Rho + 0.936 × Centroid Lateral Rho
Longitudinal Unpredictability	– 0.815 × Centroid Longitudinal Correlation + 0.694 × Centroid Longitudinal SaEn
Longitudinal Behaviour	0.694 × Centroid Longitudinal CV – 0.686 × Centroid Longitudinal Displacement

Performance

Quarter margin, also known as point differential, was used as a performance outcome/dependent variable. This was calculated as the reference team's final quarter score, minus the oppositions final quarter score. This metric has previously been used in AF as a measure of performance.(Sullivan et al. 2014a)

Statistical analysis.

Part I: preliminary analysis

PCA was used to reduce the number of characteristics related to network, skill, physical and spatiotemporal analyses by grouping characteristics together and providing fewer aggregate components for regression. A PCA has the ability to reduce the dimensionality of the data into a smaller set of variables whilst maintaining most of the variance in the original data set (Kaiser 1960; Federolf et al. 2014). As a result of PCA, no correlation exists between the principal components, but each contain their own highly correlated variables. This method ensures each component is uncorrelated and can be regressed together (Weaving et al. 2014). An exploratory PCA was executed using SPSS for Windows (Version 25) (IBM Corp 2020) where the aim was to determine a suitable number of components present in the 17 variables pertaining to cooperative network interactions, skill counts, physical, and spatiotemporal characteristics. Linear relationships were initially assessed using a correlation matrix while the Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to ensure the data was suitable for data reduction (IBM Corp 2020). All variables were initially included, upon which variables with communalities (relative importance for inclusion in the components) lower than 0.40 were excluded (Stevens 2002). The PCA was subsequently re-run using only variables of significant importance. The number of principal components to be retained was determined using the scree plot which is a line plot of the derived factor eigenvalues (Lewith et al. 2010). The scree plot was assessed for a separation between factors with relatively large eigenvalues and those with similar eigenvalues. The components, consisting of their individually assigned variables and associated weightings, that occur before the break are assumed to be meaningful and are retained (Dmitrienko et al. 2007). Outliers were also investigated for each variable via an outlier labelling rule of the interquartile range multiplied by 2.2 (Hoaglin and Iglewicz 1987).

Part II: structural equation modelling

Maximum likelihood estimation in SEM was used to investigate associations between a performance outcome (*quarter margin*), network, technical, physical, and spatiotemporal characteristics (Figure 2). SEM was used to model paths from *quarter margin* through the components. The components were tested by analysing associations between independent variables (principal components) and a dependent variable (*quarter margin*). To determine the appropriateness of the SEM model, the normed chi-square index (χ^2/df) was selected over the traditional chi-square statistic as this nearly always rejects the model when large samples are used (Bentler and Bonett 1980) with indices below three representing a parsimonious fit (Joreskog and Sorbom 1993). The Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and standardised root mean square residual (SRMR) indices were also assessed with indices >0.90, <0.10, and <0.08, respectively, signifying an acceptable model fit (Jaakkola et al. 2019). Finally, due to the complexity of the model, the Parsimonious Normed Fit Index (PNFI) was also calculated with indices >0.50 representing a parsimonious fit (Joreskog and Sorbom 1993). Laavan (Rosseel 2012) and PiecewiseSEM (Lefcheck and Freckleton 2016) statistical packages were used in RStudio to conduct the analysis. Direct effects were classified as either *small* = 0.10, *medium* = 0.30, or *Large* >0.50 (Suhr 2006).

Results

Part I: preliminary analysis

Only one variable, out-degree variability, was excluded from the PCA due to communalities below 0.40. Outliers were detected with 19 quarters subsequently being removed. This subsequently left data from 253 quarters for inclusion. An examination of the KMO measure of sampling adequacy suggested that a considerable proportion of the variance that can be considered 'common variance' (KMO = 0.74). Additionally, Bartlett's test of sphericity was significant (p < 0.001) (IBM Corp 2020). Figure 3 reveals the total explained variance from the

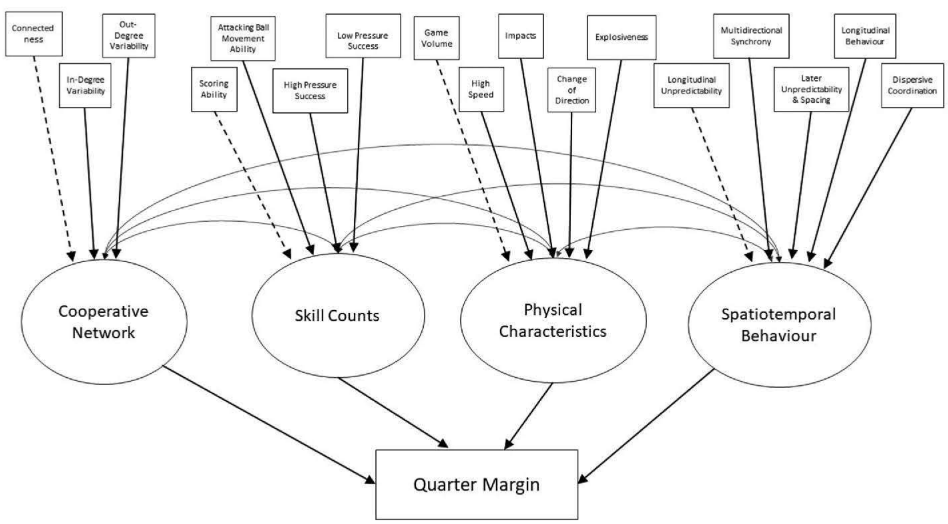

Figure 2. Example of an SEM model examining associations between a performance outcome (*quarter margin*) and performance components.

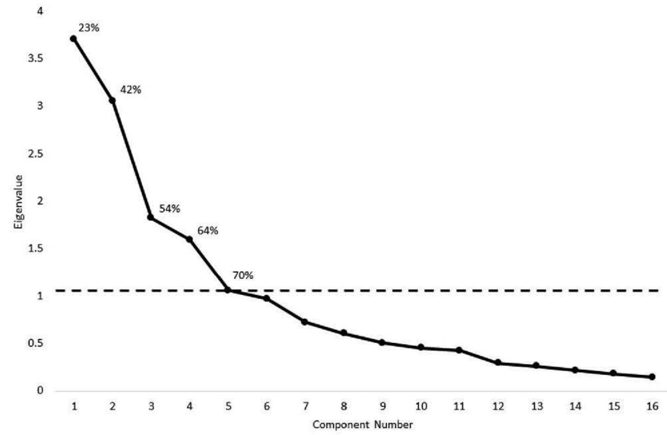

Figure 3. Scree plot for principal component analysis demonstrating the components, and the explained variance, that occur before the break and therefore deemed to be meaningful and are retained.

Table 3. Resultant constructs and variable weightings from principal components analysis.

Component/ Construct	Variables
Physical Behaviour	Game Volume (.878) + Change of Direction (.846) + Impacts (.839) + Explosiveness (.700) + High Speed (.600)
Scoring opportunity	Attacking Ball Movement Ability (.913) + Scoring Ability (.908) + Longitudinal Behaviour (.858)
Ball Movement	Connectedness (.835) + Low Pressure Success (.807) – In Degree Variability (.679)
Unpredictability	Longitudinal Unpredictability (.831) + Lateral Unpredictability and Spacing (.726) – Dispersive Coordination (.697)
Uncontested Behaviour	Multidirectional Synchrony (.823) – High Pressure Success (.550)

PCA. All variables were assigned to the component in which they had the strongest weighting. Resulting components (Table 3) were then entered into the SEM model (Part II).

Part II: structural equation modelling

In the initial model, *Physical behaviour* (r = –.01), *scoring opportunity* (r = .59), *ball movement* (r = .20), *unpredictability* (r = –.08), and *uncontested behaviour* (r = –.05) were combined and loaded onto *quarter margin*. An initial model of performance failed to satisfy all model fit criterion suggesting an adequate model fit to the data: $\chi^2(105) = 377.734$; $p = 0.001$; $\chi^2/df = 3.597$; CFI = 0.858; RMSEA = 0.101; SRMR = 0.084; PNFI = 0.631. Accordingly, modification indices were utilised to refine the model, with largest indices added first, until an adequate model was fitted as per the model fit criteria: χ^2 (101) = 283.282; p = 0.001; χ^2/df = 2.698; CFI = 0.905; RMSEA = 0.084; SRMR = 0.080; PNFI = 0.641. Figure 4 demonstrates the final model of performance with *scoring opportunity* (r = .60), *ball movement* (r = .20), *unpredictability* (r = –.08), *uncontested behaviour* (r = –.03), and *physical behaviour* (r = –.00) combining and loading onto *quarter margin*.

Discussion

Hundreds of different metrics are available for performance analysts for reporting to key stakeholders, facilitating feedback to athletes and service the review and evaluation processed in AF (Martin et al. 2021). However, only recently have these been objectively simplified with sum scores from analyses such as PCA representing different constructs of match play which simplify the interpretation of the available information (Sheehan et al. 2020, 2021b). This is particularly important as the volume of data available to coaches, athletes and performance directors, who are often time-poor, continues to grow exponentially (Martin et al. 2021). Despite recent studies delineating between different phases of play (Sheehan et al. 2021a) and offering insight into factors influencing success using physical and spatiotemporal metrics (Sheehan et al. 2021b), the concurrent influence of all match play components, i.e. network, skill, physical and spatiotemporal, has scarcely been examined in team sport contexts and is yet to be investigated in an AF. Accordingly, the present study addressed this shortcoming providing insight into the influence of these components on performance outcomes (*quarter margin*) in professional AF. These results may subsequently provide direction for coaches and practitioners when contemplating training design focus or tactical strategies to be used during competitive games or the development of tactical behaviour through specific training exercises.

Scoring opportunity (r = .60) and *ball movement* (r = .20) were the only two components to have associations with *quarter margin* (Figure 4). This was anticipated as the constituents of each of these components (Table 1 and Table 3) have previously been associated with successful performance in AF (Braham and Small 2018 ; Robertson et al. 2016a). Scoring ability (consisting of shots on goal and inside 50 results), attacking ball movement ability (calculated from inside 50s, long

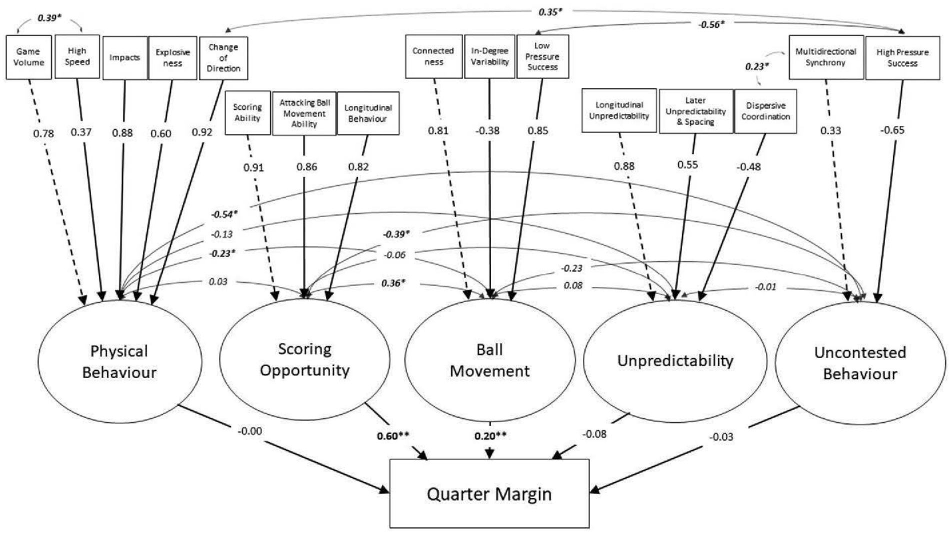

Figure 4. Complete SEM model of performance visualising parameter estimates and fixed parameters (dashed line). *$p < .05$ for covariances; ** $p < .05$ for regression coefficients.

kicks, ineffective kicks) and longitudinal behaviour (being positioned inside the attacking half and showing greater variability in end-to-end displacement, therefore potentially exploring movement space for attacking opportunities), all positively weighted on *scoring opportunity*. Several of these aspects have previously been associated with successful performance outcomes likely due to their ability to contribute to scoring opportunities (Robertson et al. 2016a; Alexander et al. 2019). Further, the association between ball movement and *quarter margin*, characterised by higher levels of low-pressure success (uncontested marks, marks, playing on from a mark, effective kicks, short kicks and kicks) and a superior passing network (delineated by a large amount of possession as measured by connectedness that is mutually shared by the majority of players (in-degree variability)) has also previously been associated with success (Robertson et al. 2016a; Braham and Small 2018; Fransen et al. 2021). This suggests that offensive strategies that are varied but frequently decentralised, with minimal reliance on key players and the majority of players being well-connected may be important for quarter success. Decentralised teams, where players do not solely rely on one or two key players, foster interdependence and encourage coordination and cooperation which are beneficial to a team's performance, as determined by match outcome (Grund 2012). Further, both of these constructs demonstrated a positive association with each other, emphasising the need to focus on these components in tandem when considering tactical strategies or training methodologies that will optimise performance.

Interestingly, *uncontested behaviour* (comprised of multidirectional synchrony and negatively weighted high-pressure success) did not reveal any influence on *quarter margin*. However, *uncontested behaviour* demonstrated a negative association with *scoring opportunity* which may indicate that elevated high-pressure success (negatively weighted on *uncontested behaviour*) and a lack of synchrony may positively influence *scoring opportunity*, a determinant of *quarter margin*. This negative association may have implications for increasing *scoring opportunity* as it has been suggested that moving asynchronously may help perturb opposition defensive formations which can help provide scoring opportunities (Tenga et al. 2010; Clemente et al. 2013a; Memmert et al. 2017). Using this rationale and results from previous literature (Alexander et al. 2019) it would be expected that *unpredictability* would also influence *scoring opportunity* or *quarter margin* in some capacity, however, this was not evident in the present study. It is therefore likely that this prior association is a result of contextual influences. For example, when higher *scoring opportunities* arise, opposition defensive efforts to prevent this may subsequently lead to chaotic movement or higher levels of contested behaviour (i.e., lower *uncontested behaviour*) in attempts to spoil/compete for possession. This rationale may also be more likely as previous lines of enquiry examining the influence of contested play skill indicators similar to the constituents that make up high-pressure success (e.g., handballs, contested possessions and tackles) failed to significantly contribute to models of success (Robertson et al. 2016a).

As hypothesised, *physical behaviour* had a negligible influence on *quarter margin*. This may explain the discrepancies demonstrated in previous lines of enquiry looking to associate physical metrics with performance outcomes (Johnston et al. 2012; Bauer et al. 2015). However, their importance may not be completely discounted with negative associations emerging between this construct, *ball movement* and *uncontested behaviour* (Figure 4). Reducing movement, and subsequently *physical behaviour*, may be a result of attempts to synchronise and coordinate actions so that the team can function as a cohesive unit. This may make it easier to mutually interact with teammates and subsequently improve *ball movement* (Sheehan et al. 2021b). Alternatively, as per the theoretical relationship between *uncontested behaviour* and *scoring opportunity*, reductions in *physical behaviour* may be a by-product of contextual match factors rather than intentional action per se. For example, implementing low-pressure ball movement tactics and controlling possession (uncontested marks, uncontested possessions, short kicks) in a manner that the opposition team does not deem as threatening, may subsequently result in a reduction in *physical behaviour*. With minimal pressure being applied or pressure to compete, as required during contested phases of play or during a lead up to a scoring opportunity (Sheehan et al. 2021b), *physical behaviour* may remain reduced. Positive associations between change of direction scores and high-pressure success in the present study may also illuminate the physical demands of high-pressure or contested phases of play. This may also indicate that change of direction scores may have greater implications for performance in these phases than other physical metrics. Until recently, linear distances accumulated at different velocities have been a primary focus of research looking at performance outcomes, however, the current findings provide insight into an alternate component that may assert a stronger indirect influence on performance outcomes and suggest a focus for physical preparation (Rennie et al. 2018; Sheehan et al. 2021a, 2021b).

While the present study provides a comprehensive analysis encompassing multiple components of performance in an AF context, examination of these components at a more granular level, i.e., during successful and unsuccessful phases of play, may further clarify the influence of network, technical, physical, and spatiotemporal components on performance outcomes. Further, as team behaviour in a complex system is an outcome of the interaction between its constituents, it may be important to examine behaviours of, or between, individual players and positional groups when analysing performance. While the data was collected in the highly ecologically valid environment of professional football over a four-year period providing 253 quarters for analysis, only the reference team's behaviour were recorded, neglecting opposition behaviour. Accordingly, the results may not be generalisable to other teams or fully encapsulate the influence of these components. Further, final models will likely change as PCA results, those derived in part I of the analysis, may differ when conducted with different team data as this technique is capable of differentiating n team characteristics and playing styles in contextually similar sports such as soccer (Casal et al. 2021). Future lines of enquiry should explore the possibility for collaborative projects subsequently providing a more complete picture of performance with behaviour from both teams assessed. Finally, the use of a PCA also presents some limitations. While PCAs are used for the sole purpose of dimension reduction in this paper, there may be discrepancies between the theoretical rationale for using a PCA and its practical application. While this method derives principal components that explain most of the variance in the original data, original granular variables may provide valuable insight. Further, the naming of these variables is subject to interpretation and demonstrates that a PCA may not be the sole means of dimensional reduction with other methods such as expert guided dimension reduction presenting as an option. Future studies may need to examine whether dimension reduction, or less-dimensional approaches (i.e., reducing performance down to a few separate metrics using expert guidance) offer the best approach to modelling most of the variance in complex behaviour. It is also worth noting that within this study, original principal components were not classified together. Regardless, the present study provides novel insights into the interplay of factors influencing quarter success. This provides coaches and practitioners with information that may help guide the decision-making process, provide actionable insights, develop tactical behaviours, or manipulate training environments to afford specific behavioural outcomes that optimise opportunities for performance success (Martin et al. 2021).

Practical implications

- Skills associated with *scoring opportunity* and longitudinal team movement appear most relevant for directly assessing performance outcomes in professional AF. Training that focuses on positioning the team in the attacking half, varying movement in the end-to-end direction and optimising ball movement and possession inside the attacking 50 m arc may be important for exploring the movement space and subsequently provide attacking opportunities.
- Coaches should consider game plans and training that foster low-pressure ball movement (uncontested marks, marks, playing on from a mark, effective kicks, short kicks, and kicks), positive outnumbers in offence (e.g., 12v10), and high levels of mutual interaction between players (e.g., limiting the number of times certain players can receive possession). This may promote decentralisation encouraging interdependence, coordination and cooperation and ultimately improving performance.
- Change of direction may be of greater relevance than other physical components in relation to successful match outcome. Furthermore, change of direction ability may be particularly important during contested passages of play and optimising high-pressure success and therefore should be considered when planning/reviewing training and drill designs.
- The theoretical approach and methodology utilised in this study provides a framework for sports scientists and coaches looking to explore the relationship between skilfulness, tactical, and physical behaviour in other contextually similar sports.

Conclusion

This was the first study to concurrently examine differences in network, technical, physical, and spatiotemporal characteristics with respect to quarter outcome in professional AF.

Scoring opportunity, characterised by scoring ability, attacking ball movement behaviour and longitudinal behaviour, and *ball movement ability*, characterised by connectedness, negatively weighted in-degree, and low-pressure success, directly influenced *quarter margin*. These two components also revealed a positive association with each other implicating these components for performance success. While no direct relationship was established between *physical behaviour* or *uncontested behaviour* with *quarter margin*, these two components may elicit an indirect effect on performance. Furthermore, the association between change of direction and high-pressure success may have novel implications for athlete conditioning. It appears that the ability to promote superior levels of mutual interaction in an attacking manner, subsequently increasing *ball movement*, is beneficial for success. The findings from the present study provide novel insights for coaches and practitioners as well as subsequent implications for training and game plan design. Future research should examine the influence of individual and positional group behaviours, as well as opposition behaviours, on performance outcomes in different phases of play.

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An assessment of physical and spatiotemporal behaviour during different phases of match play in professional Australian football

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ABSTRACT
Despite advancements in the scale of data available for quantifying the physical and spatiotemporal characteristics of match play, there is an absence of research combining these aspects in professional sport. This study sought to differentiate between phases of play in professional Australian football using novel physical and spatiotemporal metrics. Data was obtained from Australian Football League games to provide new insight into the specific characteristics of each phase of play. A retrospective cross-sectional design was utilised with team's physical and spatiotemporal variables, measured via global navigation satellite system devices. A multinomial logistic regression was conducted to determine which physical and spatiotemporal measures were associated with each phase of play (contested play, defence, offence, set shot, goal reset, umpire stoppage). The addition of the predictors to a model that contained only the intercept significantly improved the fit between the model and data, with the logistic model correctly predicting the phase of play for 63.7% of the cases. This was the first study to concurrently examine differences in physical and spatiotemporal characteristics with respect to phase of play in an Australian football context. Differences in duration, physical and spatiotemporal properties were observed, providing new insight for coaches and subsequently providing direction for conditioning and practice design.

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Performance analysis; tactical analysis; phase of play; GPS; GNSS

Introduction

Australian football is an intense, intermittent team sport where players require physical prowess to deal with the repeated high-speed running and collisions (Gray & Jenkins, 2010), high levels of skill proficiency to utilise a myriad of hand and foot skills for passing, scoring and gaining possession of the ball (R. J. Johnston et al., 2016). Teams must also utilise a variety of tactical strategies that depend on the availability of team personnel, coaching philosophies, opposing team characteristics and environmental conditions during the match (Costa et al., 2010; Tenga et al., 2010). Australian football is a complex performance-environment sub-system where players and teams perceive opportunities for action which guide decision-making and subsequent action. Perception of relevant information allows players to self-organise into functional states of coordination that subsequently allows the team to fulfil the main objective of the game, to score the most points through goal kicking Davids et al. (2013).

In this complex system, task-constraints, such as field dimensions and passing rules, individual constraints, such as players' action capabilities and informational constraints, such as opposition player movements, provide information and boundaries that govern individual and collective behaviour. Individually, players require superior technical skills, physical abilities and tactical strategies to be able to co-adapt to the dynamic nature of match play as well as cope with the ever-changing demands of the game from season to season (Sullivan et al., 2014b). In the past decade, applied research in this context has investigated these factors, each with a wide array of variables, to derive practical applications aimed at improving team performance. Through the analysis of games played in the Australian Football League (AFL), the assessment of discrete, technical, on-field actions, such as frequency of kicks, handballs, possessions and marks (Kempton et al., 2015) have contributed to models predicting performance outcomes (Hiscock et al., 2012; Robertson et al., 2016; Sullivan et al., 2014a, 2014b). Further, the physical characteristics of the game have been extensively quantified using microtechnology, such as global navigation satellite system (GNSS) devices and accelerometers (Sullivan et al., 2014b). Currently, in the AFL, all professional teams make use of this technology and its array of associated variables (Kempton et al., 2015; Sullivan, et al., 2014b). Specifically, speed-based running indices, accelerometry data and estimates of metabolic power have led to several publications quantifying the physical components of Australian football using a combination of these variables (Coutts et al., 2015, 2010; Wisbey et al., 2010).

In addition to physical metrics, researchers have utilised GNSS devices to derive novel spatiotemporal metrics and to understand the complexity of time-series data via measures such as entropy. Spatiotemporal analyses using these metrics can reveal synergistic and co-adaptive behaviours that emerge at an intra-team level, i.e., between players of the same team (Araujo & Davids, 2016). This includes measurement of the

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team's geospatial centre (centroid), average distance to this centroid (stretch index), dispersion of the outermost players (effective area), and the variability (coefficient of variation) and regularity (entropy) in these measures. However, examining each of these spatiotemporal metrics in isolation does not capture the dynamic nature of performance, as elements that make up complex systems can be viewed as both independent and interacting (Vázquez-Guerrero et al., 2020). It is therefore important to assess these components concurrently. Further, while technical, physical and spatiotemporal components can provide a large amount of information to assess tactical strategies and describe the characteristics of match play, the sheer volume of information provided by a multitude of variables, along with the complexity of the outputs, likely hinders its uptake by practitioners and researchers. However, recently several studies have attempted to increase the practicality of these methods by dimensionally reducing a multitude of characteristics into principal components (Sheehan et al., 2020, 2020a, 2020b).

Across the entirety of a game, Australian football match play involves higher running volumes than any other team sport with players performing frequent intermittent bouts of high-speed running, accelerations, decelerations, changes of direction and frequent collisions with opposing players (Gray & Jenkins, 2010; Varley et al., 2014). While these lines of enquiry provided valuable insight into the physical characteristics of the game, and subsequently provided direction for conditioning and practice design, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance. Examining behaviour by summarising outputs over an entire game may fail to capture the variability in these metrics, as behaviour likely changes depending on varying contextual information such as the phase of play. This subsequently explains why it has been difficult to draw conclusions about the influence of certain physical characteristics on game success (Bauer et al., 2015; Hiscock et al., 2012; R. Johnston et al., 2012; Mooney et al., 2011; Sullivan et al., 2014b). To address this, Gronow et al. compared time spent in four different speed zones when the reference team was in possession (offence) or without possession (defence) (Gronow et al., 2014). This study demonstrated that in quarters won, there was less time spent >14 km/hr and more time <14 km/hr in offence and, in contrast, more time spent >14 km/hr and less time <14 km/hr in defence. The authors suggested that the ability to control the pace of the game by controlling possession, and subsequently creating more disposal options, may have attributed to the lower physical demands when in possession of the ball. However, this study was limited to the use of four physical variables, pertaining to linear velocities, which may fail to encapsulate all the physical requirements associated with Australian football (Gray & Jenkins, 2010; Varley et al., 2014). Additionally, contested plays and stoppages were both neglected from physical analysis despite being considered important components of Australian football match play (Rennie et al., 2020).

Attempts to overcome these limitations were addressed by Rennie et al. with the inclusion of additional four physical variables (total distance, relative distance, accelerations and decelerations) and the examination of contested plays and stoppages (Rennie et al., 2020). Offensive and defensive phases were relatively similar across all measured physical characteristics with both demonstrating greater high-speed running demands over all other phases of play. The physical characteristics of stoppages were lower in all areas, but this insight provided implications for the inclusion of match-specific recovery cycles in training designs (Rennie et al., 2020). Lastly, with the inclusion of accelerometry data and the analysis of contested plays, these phases accumulated the most total distance, number of accelerations and number of decelerations, again providing phase-specific insight for practitioners by highlighting the change of direction demands and general unpredictability (Rennie et al., 2020). However, as the spatiotemporal movement behaviour of players was not objectively quantified, nor could it be inferred validly from linearly derived metrics that disregard player displacement over time, mechanisms underpinning greater observed accelerometry metrics can only be theorised. Further, despite acknowledging that all phases, including stoppages, involve important tactical elements, this component was not assessed using objective spatiotemporal measures to examine tactical behaviour. While the description of physical characteristics associated with each phase of play provided novel insight and highlighted the need for specificity when designing conditioning and training drills, the study was delimited to eight physical variables potentially neglecting other important physical characteristics associated with Australian football match play (Gray & Jenkins, 2010; Varley et al., 2014).

Spatiotemporal analysis is yet to be extensively applied in Australian football with only two studies utilising these measures during specific phases of play (Alexander, Spencer, Mara et al., 2019; Alexander, Spencer, Sweeting et al., 2019). These studies demonstrated greater values in length, width, and surface area during offensive phases comparative to defensive and contested phases (Alexander, Spencer, Mara et al., 2019). It was suggested that greater values of dispersion may be indicative of players trying to spread the opposition defending players to create a greater effective playing space, which allows for an easier passage of the ball towards the goals. In contrast, lower values of dispersion may indicate a defensive mechanism to close down space quickly if the opposition gained possession of the ball (Alexander, Spencer, Mara et al., 2019). While these measures provide some insights into potential tactical mechanisms that influence team success, its findings are limited to two 20-minute halves in a 15v15-match simulation drill, which may not fully represent actual competitive game play. Therefore, their relevance to understanding collective behaviour needs confirmation. Further, only a limited number of spatiotemporal metrics were used, and stoppage phases were not available in the analysis. More detailed information about strategies used by teams during stoppages is essential as players often need to quickly organise offensive and defensive structures or jostle for superior position to win the ball (Rennie et al., 2020). Further, while the aforementioned studies investigated collective team behaviour during a competitive match, research into collective behaviour throughout a season remains absent. Also, investigations that aim to use spatiotemporal metrics to classify phase of play are yet to be reported (in any invasion sport). Further research investigating these metrics in AFL matches with a broader array of metrics, across a wider range of phases of competitive match play, may improve the understanding of the influence of spatiotemporal behaviour on performance outcomes and provide greater detail for practitioners responsible for training design.

Previous research designs have primarily relied on a select number of physical or spatiotemporal variables, in isolation from one another, to analyse emergent behaviour in specific phases of play. This approach makes it difficult to delineate and interpret the relationship of these parameters with each phase of play and risks neglecting valuable information that may provide insight into emergent behaviour in this sporting context. Recent lines of enquiry have successfully reduced a large number of physical variables (Sheehan et al., 2020) and spatiotemporal variables whilst maintaining a large proportion of variance from the original dataset, facilitating their practical use and interpretability. Accordingly, to address current shortcomings in the literature, the present study incorporated these newly derived metrics to examine the influence of phase of play on physical and spatiotemporal movement behaviour. It was hypothesised that offensive and defensive phases would be characterised by higher physical sum scores, particularly low-moderate game volume and high speed. Due to their unpredictability, contested phases of play would be characterised by high explosiveness and change of direction, which would also contribute to higher lateral and longitudinal unpredictability. Finally, it was hypothesised that set shots, goal resets and umpire stoppages would yield the lowest physical scores and consequentially greater dispersive coordination and multidirectional synchrony (Clemente et al., 2013; Memmert et al., 2017; Tenga et al., 2010).

Methods

Participants

The study sample consisted of 35 male professional Australian football players (age: 25.2 ± 3.9 years; playing experience: 5.7 ± 3.7 years) from one AFL team. Each participant played at least one game over one season. Seventeen senior matches from a regular season were used for analysis providing a sample of 9788 phases of play from the designated AFL team. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

Study design

The study followed a retrospective cross-sectional design where one team's physical and spatiotemporal behaviour, as measured via GNSS technology during official AFL games, was collected from a period spanning one season. Subsequently, physical and spatiotemporal measures were associated with each phase of play.

Data collection

Data were collected via the use of GNSS units sampling at 10 Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia) and recording data pertaining to the players' latitudinal and longitudinal positioning. Following each match, video footage was manually coded for phases of offence, defence, contested play, umpire stoppage, set shot, and goal reset using SportsCode (SportsTec Limited, version 9.4.1, Warriewood, Australia). The operational definitions for these phases of play are described in Table 1 in accordance with previous research (Rennie et al., 2020; Rennie et al., 2018).

Table 1. Operational definition for each phase of play coded during analysis (Rennie et al., 2020; Rennie et al., 2018).

Phase	Definition
Offence	The reference team has clear control of the ball via a hard ball get, a mark, handball, or an intercept during open play.
Defence	The opposition team has clear control of the ball via a hard ball get, a mark, handball, or an intercept during open play.
Contested Play	Neither team has clear control or possession of the ball due to tackling or opposition pressure. The ball is not secured via a mark or clean receive from a teammate.
Set Shot	Commences the moment a player marks the ball in a scoring position, executes the shot and the umpire indicates either a goal or behind. If an umpire requests a score review, the phase is defined as an umpire stoppage.
Goal Reset	Commences when the umpire signals a goal has been scored to the proceeding centre bounce.
Umpire Stoppage	Commences when the umpire signals a stoppage in play to indicate a ball up or boundary throw-in. Blood rules or stoppages due to injury were excluded from the analysis.

Spatiotemporal and physical variables

Data were collected from 50 senior matches and were used for analysis providing a sample of 50 team files. Spatiotemporal variables were calculated from raw individual player latitudinal and longitudinal positional data via MATLAB software (The MathWorks I, 2018). Table 2 identifies the team variables included for analysis, their description and method of calculation. These variables have been used in soccer and, to a lesser degree, Australian football to quantify team and individual spatiotemporal movement behaviours (Bourbousson et al., 2010; Clemente et al., 2013; Duarte et al., 2012, 2013; Frencken et al., 2013; Moura et al., 2016; Rodrigues & Passos, 2013; Silva, Aguiar et al., 2014). A principal component analysis was then conducted using SPSS for Windows (Version 25) (IBM Corp, 2017) to determine whether common underlying constructs were present in the 18 team-derived spatiotemporal variables. This approach has been used previously and aims to reduce the dimensionality of spatiotemporal characteristics (Sheehan et al., 2020, 2020a, 2020b). All variables were included in the analysis as all possessed communalities (relative importance for inclusion in the factor) greater than 0.4 (Howard, 2016; Stevens, 2002). Further, an examination of the KMO measure of sampling adequacy suggested that a considerable proportion of the variance in the dataset was associated with the underlying factors (KMO = 0.58). Bartlett's test of sphericity was also significant ($p < 0.001$) (IBM Corp, 2017). Scree plots were assessed for an inflection point between factors with relatively large eigenvalues and those with similar eigenvalues. The components that occur before the break are deemed meaningful and are retained (Dmitrienko et al., 2007). Five components, accounting for 69% of the variance in the original dataset, were subsequently used to derive factor loadings associated with each of the variables in the analysis. The factor loadings derived

Table 2. GNSS-derived spatiotemporal variables.

Variable	Description
Centroid: – Lateral Centroid – Longitudinal Centroid	The geometrical centre of a team (Clemente et al., 2013; Duarte et al., 2012) Calculated as the mean position ($\bar{x}$,$\bar{y}$) of all players on the field (x_n,y_n) and provides information on the global positioning of the team over time. Centroid measures provide lateral and longitudinal coordinates. Positive lateral values represent movements to the left of the field's centre and positive longitudinal values represent movements away from the field's centre towards the defensive end respective to the attacking direction.
- Surface Area	The total space covered by a team and calculated as the area within the convex hull (Frencken et al., 2011). It is calculated using MATLAB's *convhull* function which returns an index array of the outermost players at a given time (The MathWorks I, 2018). The polygonal area can then be calculated using MATLAB's *areaint* function which calculates the spherical surface area of the polygon specified by the convex hull input vectors (x,y) Larger values indicate greater total field coverage but ignores player distribution.
- Stretch Index	The dispersion and contraction of the team in relation to the team centroid (Bourbousson et al., 2010). It is calculated using the mean of the distances between each player (x_n,y_n) and the centroid of the team ($\bar{x}$,$\bar{y}$) at a given time. Larger values signify that players, on average, are further away from the team centroid.
Coefficient of Variation (CV): – Surface Area CV – Stretch Index CV – Lateral CV – Longitudinal CV	A form of linear analysis that uses the standard deviation and mean to quantify the overall variability of the team's spatiotemporal characteristics during specific time periods. Lower values represent lower overall variability in the selected measure (Silva, Aguiar et al., 2014).
Pairwise Correlations: – Stretch Index Correlation – Lateral Correlation – Longitudinal Correlation	Assesses the synchronicity of players. Can be calculated using MATLAB's *corrcoef* function (pairwise option) to correlate the time-series of displacement (x_i,y_i) and stretch index measures of player i with the time-series of the team's centroid ($\bar{x}$,$\bar{y}$) and stretch index, respectively. For the team-derived value, scores of each player were averaged to provide an indication of the level of synchronicity for the team for both displacement and dispersion. Values closer to one signify that players within the team, on average, demonstrate similar movements for the event period (Frencken et al., 2013; Moura et al., 2016; Rodrigues & Passos, 2013).
Sample Entropy (SaEn): – Surface Area SaEn – Stretch Index SaEn, – Lateral SaEn – Longitudinal SaEn	A non-linear measure of variability that provides an indication as to the regularity/predictability of behaviour. Calculated using *Sample Entropy* from MATLAB's File Exchange (Lee, 2012) and is defined as the negative natural logarithm for conditional properties that a series of data points a certain distance apart, m, would repeat itself at $m+1$ (Richman & Moorman, 2000; Yentes et al., 2013). Given a time series $t(n) = t(1), t(2), \ldots, t(n)$ with n number of data points, a sequence of m-length vectors is formed. Comparisons are then made against each m-length vector within the time series. Vectors are considered alike if the tail or head of the vector fall within a certain tolerance level as determined by $r \times s$ (Silva, Aguiar et al., 2014). The sum of the total number of like vectors is then divided by $n - m + 1$ and is equal to B. Additionally, A is equal to the subset of B that also matched for $m+1$. Sample entropy is then calculated:$SampEn = -ln\frac{A}{B}$ A time series with similar distances between data points would result in a lower sample entropy value and large differences would result in greater sample entropy values. Thus, sample entropy can determine the predictability and regularity of a time series, with values closer to zero signifying greater regularity/predictability (Richman & Moorman, 2000; Yentes et al., 2013). Based on previous literature, the parameters to be used in this study are $m = 2$ and $r = 0.2$ (Castellano et al., 2013; Richman, 2007; Yentes et al., 2013).
Cluster Phase (Rho): – Stretch Index Rho – Lateral Rho – Longitudinal Rho	Quantifies the collective spatiotemporal phase synchronisation, of oscillatory movement components (e.g., players' movement displacement trajectories) in a single collective parameter (Richardson et al., 2012). Calculated in MATLAB using Richardson's (2020) *ClusterPhase* toolbox (Richardson, 2018). Prior to calculation, differential values (for each data point i in the time-series, the *i-1th* data point was subtracted) were created to determine whether players were synchronising their movements in the same direction, regardless of whether they were in line with each other. Values closer to 1 signify perfect synchrony (Duarte et al., 2013).

from physical variables by Sheehan et al. were used to represent the physical characteristics (Sheehan et al., 2020). Physical and spatiotemporal sum scores were then generated from the raw data for each phase of play using factor loadings derived via principal component analyses (Table 3) (Sheehan et al., 2020). The sum scores were then converted to z-scores and normalised to the same unit and magnitude, with a mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score×15)) to facilitate interpretation of variables measured on different scales (Henderson et al., 2019).

Statistical analysis

A multinomial logistic regression was executed using SPSS for Windows (Version 25) (IBM Corp, 2017) to determine which physical and spatiotemporal measures (Table 3) were associated with each phase of play. A main effect model was produced with phase of play as the dependent variable and duration, physical and spatiotemporal variables as covariates. Contested plays were selected as the reference group as this was the most common phase of play. Statistical significance threshold was set at $p < 0.05$. Further, the AIC, Nagelkerke R^2, F and p values of the specified model were used to determine whether multinomial regression yielded a superior data fit than a null model or a model with no independent variables. Further, odds ratios (OR) and their confidence intervals (CI), and the percentage of correct classification were also utilised to provide insight into the results. Only phases with a duration of 2 seconds or more were included in the analysis as this is believed to be the minimum timescale required for interpersonal coordination to emerge in the context of team sports (Ric et al., 2016). Outliers were also investigated for each variable via an outlier labelling rule of the interquartile range multiplied by 2.2 (Hoaglin & Iglewicz, 1987). Outliers identified via this rule

Table 3. Resultant equations derived by Sheehan et al. (2020).

Component	Calculation	Interpretation
Physical		
Low-Moderate Volume	0.869 × Velocity Band 3 Distance + 0.835 × Total Distance + 0.807 × Deceleration Band 1 Efforts + 0.805 × Acceleration Band 1 Efforts + 0.772 × Velocity Band 3 Efforts + 0.727 × Velocity Band 4 Efforts + 0.713 × Velocity Band 2 Distance + 0.652 × Velocity Band 4 Distance + 0.649 × Acceleration Band 1 Distance + 0.621 × Deceleration Band 2 Efforts + 0.605 × Deceleration Band 1 Distance + 0.560 × Acceleration Band 2 Efforts	Superior scores indicate the accumulation of physical match load at low-moderate intensities.
High Speed Running	0.833 × Velocity Band 6 Distance + 0.830 × Velocity Band 6 Efforts + 0.823 × Velocity Band 5 Distance + 0.701 × Velocity Band 5 Efforts	Superior scores indicate that greater volume of high speed metrics have been accumulated.
Explosiveness	0.878 × Acceleration Band 3 Efforts + 0.858 × Acceleration Band 3 Distance + 0.823 × Acceleration Band 2 Distance	Superior scores reflect acceleration capability and an ability to rapidly change velocity.
Change of Direction	0.899 × IMA Acceleration High + 0.885 × IMA Change of Direction Right High + 0.862 × IMA Change of Direction Left High + 0.738 × IMA Acceleration Medium + 0.712 × IMA Change of Direction Right Medium + 0.706 × IMA Change of Direction Left Medium + 0.526 × IMA Acceleration Low + 0.455 × IMA Change of Direction Right Low + 0.415 × IMA Change of Direction Left Low	Superior scores reflect high intensity and frequent changes in direction.
Collisions/Impacts	0.740 × IMA Deceleration Medium + 0.654 × IMA Deceleration Low + 0.617 × IMA Jump Low + 0.607 × IMA Deceleration High	Superior scores indicate a higher number of collisions or impacts accumulated.
Spatiotemporal		
Dispersive Coordination	− 0.923 × Stretch Index SaEn − 0.823 × Surface Area SaEn + 0.891 × Stretch Index CV + 0.684 × Surface Area CV + 0.850 × Team Stretch Index Correlation	Superior scores indicate that players are dispersing in a varied but unison manner.
Lateral Unpredictability and Spacing	− 0.933 × Centroid Lateral Correlation + 0.694 × Centroid Lateral SaEn + 0.923 × Surface Area + 0.832 × Stretch Index + 0.536 × Team Stretch Index Rho	Superior scores indicate that the team is moving in an unpredictable manner in the side-to-side direction with a shape that is largely dispersed.
Multidirectional Synchrony	0.955 × Centroid Longitudinal Rho + 0.936 × Centroid Lateral Rho	Superior scores indicate that the change in player displacement in the end-to-end and side-to-side direction relative to the team is in-phase.
Longitudinal Unpredictability	− 0.815 × Centroid Longitudinal Correlation + 0.694 × Centroid Longitudinal SaEn	Superior scores be indicative of unpredictable behaviour and a lack of coordination in the end-to-end direction.
Longitudinal Behaviour	0.694 × Centroid Longitudinal CV − 0.686 × Centroid Longitudinal Displacement	Superior scores indicate greater range of displacement in the end-to-end direction with positioning in the reference teams' forward attacking half.

IMA, Inertial movement analysis; CV, Coefficient of Variation; SaEn, Sample Entropy; Rho, Cluster Phase.

Table 4. Classification table.

	Predicted						
Observed	Contested Play	Defence	Offence	Set Shot	Goal Reset	Umpire Stoppage	Percent Correct
Contested Play	2909	182	168	0	0	26	88.6%
Defence	872	593	483	13	4	50	29.4%
Offence	862	384	746	13	2	49	36.3%
Set Shot	4	5	7	258	34	76	67.2%
Goal Reset	0	1	2	28	310	1	90.6%
Umpire Stoppage	44	18	34	13	17	1130	90.0%
Overall Percentage	50.2%	12.2%	15.4%	3.5%	3.9%	14.3%	63.7%

Table 5. Predictors' unique contributions in the multinomial logistic regression.

Predictor	χ^2	Degrees of freedom	p
Duration	3954.83	5	<.001
Game Volume	908.99	5	<.001
High Speed	60.99	5	<.001
Explosiveness	266.99	5	<.001
Change of Direction	682.74	5	<.001
Collisions/Impacts	330.50	5	<.001
Dispersive Coordination	37.77	5	<.001
Lateral Unpredictability and Spacing	3.64	5	.602
Multidirectional Synchrony	16.11	5	.007
Longitudinal Unpredictability	4.67	5	.458
Longitudinal Behaviour	4.36	5	.499

χ^2 = amount by which −2 log likelihood increases when predictor is removed from the full model.

were then investigated manually to determine potential causes and assess whether they were realistic values or produced by measurement or other error.

Results

Outliers were detected, however, investigation revealed that these were realistic values and not errors. A select number of phases containing extreme values were visually assessed to see if the values were realistic. Further, there were a large number of them (n; 31% of the total observations) which can likely be attributed to the inclusion of threshold variables such as high-speed running which have a relatively small median and IQR. The addition of independent variables to a model that contained only the intercept significantly improved the fit between model and data (AIC for the null model and specified model was 29,031.9 and 16,448.7, respectively, χ^2 (55, N = 9339) = 12,693, Nagelkerke $R^2 = .78$, $p < .001$). Using the logistic model to predict phase of play based on physical and spatiotemporal characteristics resulted in 63.7% correct classification (Table 4). As shown in Table 5 and Figure 1, significant unique contributions were made by duration, game volume, high speed, explosiveness, change of direction, collisions/impacts, dispersive coordination and multidirectional synchrony. With contested plays as the reference group, each predictor has five parameters, one associated with membership in each of the respective phases of play rather than the contested phase of play. Further, the OR and associated 95% CIs are shown in Figure 1.

Discussion

Dedicated statistical providers (e.g., ChampionData), advances in microtechnology and novel statistical approaches have provided a large volume of information for advancing performance analysis in sport over the past decade. While a plethora of data is available for quantifying the technical, physical and spatiotemporal characteristics of match play, only recently have these been objectively simplified for practical implementation in AFL games with surrogate sum scores representing different constructs of the game (Table 2) and easing the interpretation of available information. In the present study, it was evident that the different phases of play in professional Australian football yielded different physical and spatiotemporal characteristics, providing unique insight into match play. Further, the ability of simplified novel metrics to adequately delineate and predict different phases of play may assist in describing and interpreting the differences in collective team behaviour in AFL. Understanding the cooperative behaviours in specific phases of play can enable coaches to assess the appropriateness of their training tasks with respect to these.

The results from the present study align with previous findings with set shots, goal resets and umpire stoppages being characterised by lower physical output (Rennie et al., 2018). The present study demonstrated markedly lower physical output for these phases of play over offensive, defensive, and contested phases for low-moderate game volume, explosiveness and change of direction. However, while these phases may not be characterised by their physicality, novel spatiotemporal metrics indicate they can be characterised by superior dispersive coordination and multidirectional synchrony over offensive, defensive and contested phases of play (reference group). This may be due to their markedly lower physical demands as well as longer durations with longer timescales potentially affording greater opportunities for players to coordinate and synchronise behaviours with one another (Ric et al., 2016). Despite limited discernible differences from a spatiotemporal perspective (Figure 1), subtle differences may still exist between set shots, umpire stoppages and goal resets. For example, physical characteristics specific to each phase of play may still provide valuable insight, with set shots revealing stronger associations with explosiveness and decelerations/impacts over umpire stoppages. Fellow teammates moving to afford the ball carrier a better goal scoring position during this phase may explain the heightened physical output. Rapid changes in velocity and movement, captured in explosiveness sum scores, may be a result of teammates trying to break away from their defensive counterpart or move into free space.

With contested phases of play as the reference group, the smaller ORs demonstrated by all other phases, particularly offence, set shots, goal resets and umpire stoppages, demonstrate that change of direction, explosiveness and

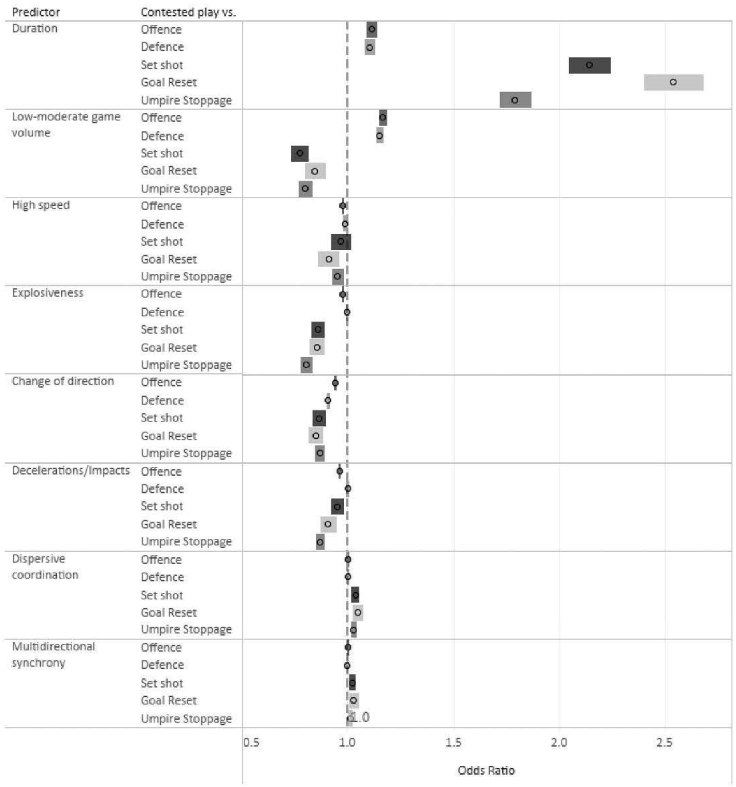

Figure 1. Visual representation of the odds ratios and 95% confidence intervals demonstrating the likelihood of classification and contrasting contested plays with each of the other phases.

decelerations/impacts characterise contested phases of play (Figure 1). This may be a result of unpredictable movements throughout this phase, trying to evade defenders in congested passages of play, attempts to follow unpredictable movements of the ball, or bump off opposing players to gain an advantage over opponents competing for the ball. Additionally, stronger links with high speed may be a result of players using higher velocities to get to the ball first or place themselves in a position to receive possession from a fellow player. While previous findings also demonstrated that contested play involves a greater number of accelerations and decelerations than other phases due to the erratic, unpredictable movement of players (Rennie et al., 2020), these metrics relied on linear changes in velocity neglecting side to side movements. Further, no spatiotemporal metrics were incorporated in these studies to further elaborate on this finding. In the present study, lower values of dispersive coordination and, to a lesser degree, multidirectional synchrony, in each phase increased the likelihood of being classified as a contested phase. This potentially validates previous theories. Additionally, the shorter duration of this phase may also contribute to lower values of dispersive coordination and multidirectional synchrony insufficient time may be available for players to co-adapt to one another and coordinate movement behaviours (Ric et al., 2016).

As observed in previous investigations (Rennie et al., 2020), offensive and defensive phases shared similar physical and spatiotemporal characteristics. This similarity may be a result of defensive strategy with players mirroring the movements/patterns of the opposition team in offence. Higher low-moderate game volume increases the likelihood of a phase being classified as defence or offence which is likely due to the offensive aim of the game, to advance the ball up the field to score, and the defensive aim to prevent this. While phases were not examined with reference to matches won or lost, the increased odds of being classified as a defensive phase over an offensive phase with reference to high-speed values aligns with previous findings (Gronow et al., 2014). As previously suggested, the ability to control the pace of the game by controlling possession, and subsequently creating more disposals may have contributed to lower high-speed scores in offence while alternatively, high speed in defence may be a result of trying to shut down offensive passages of play (Gronow et al., 2014). Further, the increased likelihood of being classified as a defensive phase with increased decelerations/impacts may be a result of the need to tackle or bump opposition players in an attempt to gain possession, while conversely in offence the aim is to avoid defenders whilst trying to move the ball up the field. Furthermore, in offence, superior change of direction may help advance the ball up the field and be of greater importance than high speed in offence with sudden changes in direction helping players evade defenders or misalign counterpart defenders to provide passing opportunities for teammates. Interestingly, while the current model produced a 63.7% correct prediction rate, the classification rates for each phase were varied, with erroneous classifications being most prevalent for offensive and defensive phases, each commonly being classified as one another or as contested phases of play. Incorporating team-based measures may have reduced the sensitivity of classifying each phase of play as while some phases of play may incorporate every player, other phases may require only "a few key players". Future investigations that include separate machine learning models, account for additional features, or analyse behaviour at the individual level with only involved "key players" may provide additional insight. However, it is also possible that offensive and defensive phases would appear similar due to the adaptation of the defending to and attacking team's collective behaviour. Additionally, the inclusion of set shots, goal resets and umpire stoppages may have also reduced the sensitivity of the model with such stark differences, specifically from a physical perspective, present between these phases and offensive, defensive, and contested phases of play.

While all physical components aided in the delineation of some phases of play, dispersive coordination and multidirectional synchrony were the only spatiotemporal characteristics to contribute to the model. While spatiotemporal differences, specifically pertaining to values of dispersion, have been demonstrated in other lines of enquiry (Alexander et al., 2018), lateral unpredictability and spacing (partly derived using measures of dispersion) did not significantly contribute to the model. However, previous studies demonstrating differences in dispersion utilised a non-representative design incorporating a 15v15 format on a full-sized field which may have failed to account for the relative space per player (Alexander et al., 2018). Lower player numbers competing on larger fields afford more relative space per player and may have exacerbated the differences demonstrated between offensive and defensive phases of play. The increase in relative space may have made it easier for the offensive team to disperse and explore passing/scoring opportunities while concurrently forcing the defending team to contract towards their defensive half in an attempt to minimise scoring opportunities (Silva, Duarte et al., 2014). Other contextually similar sports have revealed similar patterns by manipulating player numbers and field size to alter the relative space per player (Silva, Aguiar et al., 2014; Silva, Duarte et al., 2014). Also, of interest, longitudinal behaviour, which incorporates the team displacement, did not contribute significantly to the model or help differentiate between offensive and defensive phases of play. Since the offensive and defensive phases of play in Australian football are often short (~12 seconds on average in our sample), this may not provide enough time for players to flood certain parts of the field when a turnover occurs (i.e., flood the defensive half when a turnover in offence occurs). Further, this may not be the most efficient method due to the size of the field or may also reflect tactical strategies of players to remain on their opposition counterpart or hold their position/zone in case another turnover occurs. As the present study only analysed aggregated measures of phases, this may have limited the ability of these spatiotemporal measures to classify different team behaviours in AFL. For example, the current approach may have neglected behaviour that emerges over longer timescales or the capacity for a team to rapidly and successfully transition from one phase of play to another, i.e., lower physical scores coupled with higher synchrony during umpire stoppages to higher physical scores and lower synchrony during offensive phases, which may be of importance for team success. Future research should examine these transitions in greater depth along with their association with performance outcomes.

Despite these methodological considerations, the present study showcases an ecologically valid approach to the analysis of physical and spatiotemporal variables in a cohort of professional athletes. As hypothesised, offensive and defensive phases presented with greater low-moderate volume, defensive phases revealed stronger affiliations with decelerations/impacts and contested plays demonstrated superior explosiveness and change of direction likely leading to lower values of synchrony and coordination. Interestingly, contested phases of play were strongly associated with high-speed metrics, which may be due to players trying to be first to the ball or place themselves in a position to receive possession. As expected, likely due to their lower physical characteristics, set shots, goal resets and umpire stoppages demonstrated greater dispersive coordination and multidirectional synchrony than other phases. While this paper focused on detailing cooperative team behaviour in different phases of play, additional research that implements different machine learning models and features could determine whether individual phases of play can be more accurately classified. Regardless, while data were only collected from one team and therefore may not be generalisable to the rest of the competition, the current findings have implications for technical, tactical, and conditioning drill design in a range of team sports including, but not limited to Australian football.

Practical implications

- Certain phases of match play in professional Australian football were associated with physical and spatiotemporal sum scores and may be useful to interpret differences in team behaviours in these phases of play.
- The timescale of each phase of play is an important consideration for training design as the manipulation of practice drills to afford more/less time in each phase of play

may challenge players with respect to their physical requirements, synchrony and coordination. For example, extending the duration or time allowed to achieve a task outcome, such as kicking a goal during a small-sided game, may allow more time for players to self-organise into a stable pattern of behaviour that allows the achievement of that task outcome. Alternatively, reducing task time may challenge players to form these patterns of behaviour at a faster rate.

- This study is the first to examine the change in direction characteristics of each phase of play. This variable may be of greater importance than high speed in offensive phases of play, providing novel insight for conditioning drill design and influence values of coordination and synchrony.
- Contrary to previous findings, phases of play involving set shots appear to have an important physical component revealing heightened associations with explosiveness and decelerations/impacts. Drills that require a teammate to rapidly breakaway from a defensive counterpart in a set-shot simulation may help replicate this component.

Conclusion

This is the first study to concurrently examine differences in physical and spatiotemporal characteristics with respect to phase of play in the context of professional Australian football. Low-moderate game volume, high speed, explosiveness, change of direction, decelerations/impacts, dispersive coordination and multidirectional synchrony were able to delineate between the different phases of play, providing novel insight for coaches and practitioners and subsequently providing direction for conditioning and training design. Future research should further delineate the importance of each of these components by examining phase of play with reference to matches won and lost as well as incorporating skill indicators.

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Study Seven: An assessment of physical and spatiotemporal behaviour during different phases of match play in professional Australian football

Collective behaviours influencing phase of play success in Australian football.
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Original Scientific Research Study

COLLECTIVE BEHAVIOURS INFLUENCING PHASE OF PLAY SUCCESS IN AUSTRALIAN FOOTBALL.

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BLUF

The different physical and spatiotemporal characteristics associated with successful phases of play in professional Australian Football provide novel coaching implications for conditioning, practice, and game plan design.

ABSTRACT

Despite advancements in the scale of data available for quantifying the physical and spatiotemporal characteristics of match play, few studies combine these aspects in professional sport. This study related these components to behaviours associated with successful outcomes across various phases of play. A retrospective cross-sectional design was utilised with team physical and spatiotemporal variables obtained from professional Australian Football League games via global navigation satellite system devices. A binomial generalised mixed effects regression model was used to estimate the effects of phase duration, physical and spatiotemporal variables on the probability of a successful outcome in different phases of play (contested play, defence, offence, set shot, goal reset, umpire stoppage). From a physical perspective, the addition of fixed effects, namely duration, low-moderate volume, high speed running, explosiveness, change of direction, and impacts, to a model that contained only the random intercept were significantly improved between model and data for offensive, defensive, and contested phases of play. Further, the addition of spatiotemporal fixed effects including dispersive coordination, lateral unpredictability and spacing, multidirectional synchrony, longitudinal unpredictability, and longitudinal behaviour, also significantly improved the model for the same phases of play. This was the first study to concurrently examine differences in physical and spatiotemporal characteristics with respect to successful outcomes in different phases of play. These novel insights may provide coaching direction for conditioning, practice, and game plan design. For example, implementing reactive agility drills during conditioning bouts may assist in developing change of direction ability which may be important for offensive success. Alternatively, setting up training drills that provide less relative space per player in offence may force players to utilise change of direction ability over high speed running.

Key Words - Performance analysis; Tactical analysis; Team Sport; GPS; GNSS.

INTRODUCTION

Australian football is an 18 versus 18 (with 4 substitutions on each team) contact sport played on an oval shaped field. From an ecological dynamics perspective, Australian Football is a complex performer-environment subsystem where players and teams use information embedded within their performance environment to guide their actions and decision making. Information-rich environments consisting of teammates, opposition players, line markings, umpires, etc., afford opportunities for players to self-organise and coordinate behaviour in a way that allows the team to achieve the main objective of the game, to score the most points through goal-kicking. (9) To adequately achieve task goals while satisfying constraints, players require skilled behaviour, physical abilities and tactical strategies to co-adapt to the dynamic nature of match play as well as cope with the ever-changing demands of the game from season to season. (30) As a result, a thorough understanding of the complex interactions between the individual within their performance environment and the task at hand is required to capture the complexity of Australian football performance.

Performance analysis in professional Australian Football has progressively evolved over the last 40 years and has proven to be integral for understanding the different constituents of match play allowing practitioners to adequately capture the complexity of Australian Football by quantifying these components. (10) Analysis of these constituents has included the assessment of discrete, technical, on-field actions such as frequency of kicks, handballs, possessions and marks,(17) which have been able to contribute to models predicting performance outcomes. (13, 24, 29, 30) Additionally the physical characteristics of the game have been extensively quantified using microtechnology such as global navigation satellite system (GNSS) devices and accelerometers. (30) More recently, with recent technological advancements, including the increase in sensitivity and application of GNSS devices and the accessibility of novel statistical approaches, it is possible to objectively measure and quantify collective team movement (spatiotemporal characteristics) providing insight into tactical strategies and behaviours. Spatiotemporal analysis using these metrics can be undertaken to identify synergistic and co-adaptive behaviours that emerge on an intra-team level, i.e. between players of the same team. (3)

The technical, physical and tactical areas of analysis have provided guidance and direction for coaches and practitioners when it comes to the analysis of match performance and development of representative training tasks. In the past decade, applied research in Australian Football has investigated these factors, each with a wide array of variables, to derive practical applications aimed at improving a team's performance. Currently in the Australian Football League (AFL), the pinnacle of Australian Football, all professional teams evaluate the physical characteristics of game play using GNSS technology which are capable of providing a wide array of associated variables e.g. total distance, average speed, high-speed running, and acceleration characteristics. (30) As a result, the external physical characteristics of the game have been documented extensively. (5, 13, 15, 19, 30) Across the course of a match, players accumulate higher running volumes than any other team invasion sport whilst completing frequent intermittent bouts of high-speed running, accelerations, decelerations, changes of direction and frequent collisions with opposing players. (10, 34) While microtechnology data have provided valuable information regarding the physical characteristics of match play, inconsistencies and discrepancies exist between indicators of successful and unsuccessful performance. (13, 29) For example, when examining differences in quarters won and lost, one study associated lower physical output for quarters that were won, (29) while conversely another failed to identify any relationship between physically derived metrics and quarter outcome. (13) Discrepancies may arise as these studies may have failed to fully account for the physical characteristics of match play through the selection of only a few GNSS derived variables. Further, examining behaviour across the entirety of a match, or a quarter, may fail to fully account for the complexity of the sport or be specific enough to delineate the influence of physical components on match success. (11)

In an attempt to capture the complexity of Australian Football, Gronow and colleagues compared the amount of time spent in four different speed zones when the reference team was in offence or defence over the length of a quarter. (11) The results may explain previous discrepancies with contrasting behaviour demonstrated in offence and defence. For example, in quarters won, more time was spent below 14km/hr in offence and less time at speeds greater than 14km/hr while in defence more time was spent at speeds greater than 14km/hr and less time below 14km/hr. The authors suggested that the ability to control the pace of the game through the control of possession, and subsequent creation of more disposal options, may have attributed to the lower physical characteristics of offensive plays. (11)

Results from this line of enquiry highlight the importance of examining specific phases of play as this may provide greater insight than analysing behaviour over the course of a quarter or match. Theoretically, across the course of a game an equivalent amount of time spent attacking and defending may reveal minimal differences in physical output when comparing wins and losses as both these phases appear to elicit conflicting physical demands. While this study provided further insight for practitioners into the physical characteristics associated with offensive and defensive phases of play and the association with quarter success, this study was limited to the use of four physical variables, pertaining to linear velocities, which may fail to encapsulate all the physical characteristics associated with Australian Football. (10, 34) Additionally, contested plays and stoppages were both neglected from physical analysis despite being considered important components of Australian Football match play. Inclusion of these phases may further clarify the influence of physical output during specific match periods on quarter or game outcomes. (20)

The aforementioned limitations were addressed to some extent by Rennie and colleagues who assessed four additional physical variables (total distance, relative distance, accelerations and decelerations) during all phases including stoppages and contested phases of play. (20) As expected, there were differences across all phases of play with stoppages demonstrating markedly lower physical output in all areas providing implications for the inclusion of match specific recovery cycles in training designs. (20) While offensive and defensive phases were relatively similar across all variables, players accumulated more high speed running volume over all other phases. The inclusion of accelerometry data also offered novel insight into the physical characteristics of contested phases with this passage of play accumulating more total distance, number of accelerations and number of decelerations than all other phases potentially reflecting the change of direction demands and unpredictable nature of game play during contested phases of play. (20) However, as player geospatial positioning was not objectively assessed in the analysis, reasons for the greater observed accelerometry metrics can only be theorised. Only recently have the validity of these claims been supported with contested phases demonstrating lower values of synchrony and coordination. (25) Additionally, while the description of physical characteristics associated with each phase of play provided novel insight, the study was delimited to eight physical variables using a reductionist approach, potentially neglecting other important physical characteristics associated with Australian Football match play. (10, 34) Further, these characteristics were not concurrently assessed with respect to performance success such as quarter or match success.

To-date, only one paper has examined the spatiotemporal differences between phases of match play with respect to wins and losses in Australian Football. Incorporating spatiotemporal metrics, greater values in length, width, and surface area were observed during offensive phases comparative to defensive and contested phases. (2) This increase in dispersion may be indicative of players trying to spread the opposition defending players to create a greater effective playing space, which allows for an easier passage of the ball towards the goals to provide scoring opportunities. Alternatively, the lower values of dispersion may be indicative of a collective team movement to close down space and prevent the opposition team from maintaining or transferring possession. (2) While these measures provide some insights into potential tactical mechanisms that influence team success, only a limited number of spatiotemporal metrics were utilised limiting the analysis of tactical behaviour. Incorporating variables that can measure the dynamic properties of spatiotemporal metrics, such as how they change and persist over time are crucial in describing the dynamic nature of match play. Therefore, the inclusion of variables such as such variability, (28) synchrony (23) or predictability, (8) obtained from time series of spatiotemporal measures, may offer new insights into the tactical behaviour of Australian Football teams during competitive match play. Further, despite the important tactical elements associated with stoppage phases, these phases were neglected from the analysis. Information pertaining to this phase may still be of interest as often players need to quickly organise offensive and defensive structures and jostle for superior position to win the ball. (20) Finally, the study sample incorporated two 20-minute halves in a 15 versus 15 match simulation drill, and therefore the representativeness of the collective behaviour exhibited by teams during competitive match play is questionable. While this provides a foundational understanding, further research investigating these metrics in AFL matches with a broader array of spatiotemporal measures, including variables capturing the dynamics of tactical behaviour may enhance the understanding of the influence of spatiotemporal tactical behaviour on performance outcomes. This may subsequently provide useful applications for representative training design that incorporates physical and tactical behaviours reflective of match-play.

While technological advancements in GNSS technology and the accessibility of statistical techniques that can more readily capture the complexities of performance have drastically increased the amount of available information to quantify match characteristics, this has concurrently convoluted existing findings and made variable selection for performance analysis an arduous task. With many physical and spatiotemporal metrics available for practitioners, as demonstrated, study designs have only incorporated a select number of variables which may fail to encapsulate the full complexity of the game and lead to existing discrepancies in the literature. A viable option for overcoming this issue is to dimensionally reduce the large number of available variables using statistical procedures such as a principal component analysis in conjunction with domain expertise. These dimension reduction methods have no real pedigree in performance analysis science, but principal component analysis and exploratory or confirmatory factor analysis have been used extensively in other research areas such as the development and analysis of psychological questionnaires. (16) Recent lines of enquiry have successfully reduced a large number of physical variables (26) and spatiotemporal variables (27) whilst maintaining a large proportion of variance from the original dataset, facilitating their practical use and interpretability. This approach allows analysts to practically examine the different constituents of match play whilst minimising the risk of omitting important information. However, these metrics are yet to be examined in Australian Football with respect to performance outcomes.

Accordingly, this study used the physical (low-moderate volume, high speed, explosiveness, change of direction and collisions/impacts) (26) and spatiotemporal (dispersive coordination, lateral unpredictability and spacing, multidirectional synchrony, longitudinal unpredictability and longitudinal behaviour) (27) metrics derived by Sheehan and colleagues to examine behaviours associated with successful phase outcomes across the various phases of play (Table 1). It was hypothesised that successful offensive phases would reveal lower values than unsuccessful phases in all physical metrics as well as decreased multidirectional synchrony and increased lateral unpredictability and spacing, longitudinal unpredictability and longitudinal behaviour. Comparatively, successful defensive phases would exhibit higher physical demands than unsuccessful phases along with superior scores of multidirectional synchrony coupled with lower scores in all other spatiotemporal variables. Further, in contested phases, due to their unpredictable nature, it was expected that higher low-moderate game volume, change of direction and collisions/impact scores along with greater lateral unpredictability and spacing, longitudinal unpredictability and lower multidirectional synchrony would align with successful outcomes. Due to their relatively lower physical demands and predictable nature, set shots, goal resets and umpire stoppages were hypothesised to present lower lateral unpredictability and spacing, longitudinal unpredictability and superior multidirectional synchrony in phases with a successful outcome due to an enhanced ability to coordinate movements and self-organise.

Table 1 - Operational definition for each phase of play coded during analysis with definitions of successful outcomes for each phase of play as determined by coaching staff.

Phase	Definition
Offence	The reference team has clear control of the ball via a hard ball get, a mark, handball, or an intercept during open play. A turnover from penalty, infringement or behind also constitutes a change in possession. Successful phases lead to an entry inside the attacking 50 arc (inside 50) or a scoring opportunity (set shot or a goal or behind scored in general play).
Defence	The opposition team has clear control of the ball via a hard ball get, a mark, handball, or an intercept during open play. A turnover from penalty, infringement or behind also constitutes a change in possession. Successful phases lead to a direct turnover (interception) or a contested play/umpire stoppage further away from its origin in the attacking direction, i.e., further away from the defending goal.
Contested Play	Neither team has clear control or possession of the ball due to tackling or opposition pressure. The ball is not secured via a mark or clean receive from a teammate. Successful phases lead to possession of the ball, i.e. precedes an offensive phase.
Goal Reset	Includes the duration between the umpire signalling a goal has been scored to the proceeding centre bounce. Successful phases precede a contested play with a successful outcome.
Umpire Stoppage	The umpire signals a stoppage in play to indicate a ball up, boundary throw-in. Blood rules or stoppages due to injury were excluded from the analysis. Successful phases precede a contested play with a successful outcome.
Set Shot	Commences the moment a player marks the ball in a scoring position, executes the shot and the umpire indicates either a goal or behind. If an umpire requests a score review, the phase is defined as an umpire stoppage. Successful phases that occur in a quarter that is won.

METHODS

Approach to the Problem

The study followed a retrospective cross-sectional design where one team's physical and spatiotemporal behaviours, as measured via GNSS technology during official AFL games was collected from a period spanning one season.

Subjects

The study sample consisted of 35 male professional Australian Football players (age: 25.2 ± 3.9 years; playing experience: 5.7 ± 3.7 years) from one AFL team. 17 senior matches from one season (2018) provided 9788 observations (phases of play) from one designated AFL team. The procedures used in this study were conducted with ethics approval from the Human Research Ethics Committee of the local institution.

Procedures

Data pertaining to the players' latitudinal and longitudinal positioning were collected via the use of GNSS units sampling at 10Hz ('Optimeye S5', Catapult Sports, Melbourne, Australia). Following each match, video footage was manually coded for phases of offence, defence, contested play, umpire stoppage, set shot, and goal reset using SportsCode (SportsTec Limited, Warriewood, Australia). The operational definitions for these phases of play are described in Table 1 in accordance with previous research. (20, 21) Successful phase outcomes were also manually coded and are also defined in Table 1. These definitions were derived, and agreed upon, from discussions with the coaching group at the football club. Spatiotemporal variables were calculated from raw individual player latitudinal and longitudinal positional data via MATLAB software using methods previously outlined by Sheehan et al..(27, 32) Physical and spatiotemporal sum scores were then generated from the raw data for each phase of play using factor loadings previously derived via principal component analyses (Table 2). (26, 27) Sum scores were then converted to z-scores and normalised to the same unit and magnitude, with a mean of 100 and a standard deviation of 15 (quotient score = 100 + (z-score*15)) to facilitate interpretation of variables measured on different scales. (12)

Table 2 - Physical and spatiotemporal equations derived by Sheehan and colleagues.

Component	Calculation	Description
	Physical	
Low-Moderate Volume	0.869 × Velocity Band 3 Distance + 0.835 × Total Distance + 0.807 × Deceleration Band 1 Efforts + 0.805 × Acceleration Band 1 Efforts + 0.772 × Velocity Band 3 Efforts + 0.727 × Velocity Band 4 Efforts + 0.713 × Velocity Band 2 Distance + 0.652 × Velocity Band 4 Distance + 0.649 × Acceleration Band 1 Distance + 0.621 × Deceleration Band 2 Efforts + 0.605 × Deceleration Band 1 Distance + 0.560 × Acceleration Band 2 Efforts	Superior scores indicate the accumulation of physical match load at low-moderate intensities.
High Speed Running	0.833 × Velocity Band 6 Distance + 0.830 × Velocity Band 6 Efforts + 0.823 × Velocity Band 5 Distance + 0.701 × Velocity Band 5 Efforts	Superior scores indicate that greater volume of high speed metrics have been accumulated.
Explosiveness	0.878 × Acceleration Band 3 Efforts + 0.858 × Acceleration Band 3 Distance + 0.823 × Acceleration Band 2 Distance	Superior scores reflect acceleration capability and an ability to rapidly change velocity.
Change of Direction	0.899 × IMA Acceleration High + 0.885 × IMA Change of Direction Right High + 0.862 × IMA Change of Direction Left High + 0.738 × IMA Acceleration Medium + 0.712 × IMA Change of Direction Right Medium + 0.706 × IMA Change of Direction Left Medium + 0.526 × IMA Acceleration Low + 0.455 × IMA Change of Direction Right Low + 0.415 × IMA Change of Direction Left Low	Superior scores reflect high intensity and frequent changes in direction.
Collisions/Impacts	0.740 × IMA Deceleration Medium + 0.654 × IMA Deceleration Low + 0.617 × IMA Jump Low + 0.607 × IMA Deceleration High	Superior scores may indicate a higher number of collisions or impacts accumulated.
	Spatiotemporal	
Dispersive Coordination	− 0.923 × Stretch Index SaEn – 0.823 × Surface Area SaEn + 0.891 × Stretch Index CV + 0.684 × Surface Area CV + 0.850 × Team Stretch Index Correlation	Superior scores may indicate that players are dispersing in a varied but unison manner.
Lateral Unpredictability and Spacing	− 0.933 × Centroid Lateral Correlation + 0.694 × Centroid Lateral SaEn + 0.923 × Surface Area + 0.832 × Stretch Index + 0.536 × Team Stretch Index Rho	Superior scores may indicate that the team is moving in an unpredictable manner in the side-to-side direction with a shape that is largely dispersed.
Multidirectional Synchrony	0.955 × Centroid Longitudinal Rho + 0.936 × Centroid Lateral Rho	Superior scores may indicate that the change in player displacement in the end-to-end and side-to-side direction relative to the team is in-phase.
Longitudinal Unpredictability	− 0.815 × Centroid Longitudinal Correlation + 0.694 × Centroid Longitudinal SaEn	Superior scores may be indicative of unpredictable behaviour and a lack of coordination in the end-to-end direction.
Longitudinal Behaviour	0.694 × Centroid Longitudinal CV − 0.686 × Centroid Longitudinal Displacement	Superior scores may indicate greater range of displacement in the end-to-end direction with positioning in the reference teams' forward attacking half.

IMA, Inertial movement analysis; CV, Coefficient of Variation; SaEn, Sample Entropy; Rho, Cluster Phase.

Statistical Analysis

For offensive and defensive periods, only phases with a duration of 12 seconds or more were included in the analysis as this is believed to be the minimum timescale required for stable patterns of interpersonal coordination to emerge in the context of team sports. (22) Due to their unpredictable nature, a lower threshold was adopted for contested plays with phases spanning three seconds or more being included. (22) All set shot, umpire stoppage and goal reset phases were included, regardless of their duration. Outliers were also investigated for each variable via an outlier labelling rule of the interquartile range multiplied by 2.2. (14) Outliers identified via this rule were then investigated manually to determine potential causes and assess whether they were realistic values or produced by measurement or other error. Due to the inherent variability in behaviour that exists between matches, a binomial Generalised Mixed Effects Regression model was used to estimate the associations between phase duration, physical and spatiotemporal variables (table 2) and the probability of a successful outcome in different phases of play. The competition round was included as a random effect while physical and spatiotemporal sum scores along with duration were added as fixed effects. Duration was not included as a fixed effect in umpire stoppages, goal resets or set shots as time spent in these phases of play are not necessarily in the players' control. Model outputs (odds ratios and their confidence intervals), Aikaike Information Criterion (AIC) and pseudo 'variance explained' (R2) values were calculated to assess model goodness-of-fit. Goodness-of-fit was interpreted using Cohen's recommendations (r2: 0.02 = weak, 0.13 = moderate, 0.26 = substantial).(7) All statistical analyses were conducted using the lme4 (4) package in R statistical software (31) with significance values set at $p<0.05$.

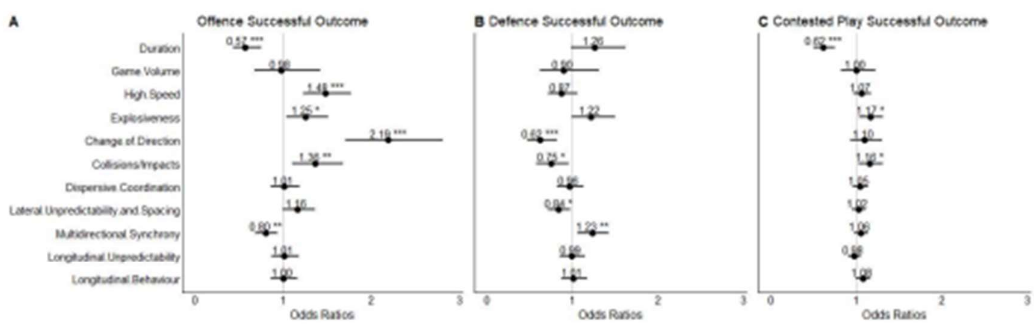
RESULTS

Outliers were detected, however, investigation revealed that these were realistic values rather than measurement errors. A select number of phases containing extreme values were visually assessed to determine whether values were realistic. Further, there were a large number of labelled outliers (n; 31% of total observations) which can likely be attributed to the inclusion of threshold variables such as high-speed running which have a relatively small median and interquartile range. The addition of fixed effects to a model that contained only the random intercept significantly improved the model fit for offensive, defensive, and contested phases of play but not for the other phases of play. Table 3 demonstrates the AIC for the null model and the specified model for each phase of play along with associated chi-square and p-values. Marginal r2 values (indicating explained variance from fixed effects only) and conditional r2 (indicating explained variance from both fixed and random effects) are also included in Table 3. Further, the odds ratios (OR) and associated 95% confidence intervals are demonstrated in Figure 1.

Table 3 - Model properties for each individual phase.

Model	AIC random effect only	AIC fixed and random effects	(χ^2)	df	p-value	Marginal r^2	Conditional r^2
Offence	1218.4	1038.8	201.6	11	< .001	.28	.28
Defence	1122.3	1069.3	75.0	11	< .001	.13	.13
Contested Play	3771.6	3749.2	44.4	11	< .001	.02	.02
Set Shot For	247.0	252.2	14.7	10	.142	.10	.30
Set Shot Against	234.0	243.2	10.7	10	.378	.07	.36
Umpire Stoppage	1622.5	1627.9	14.5	10	.150	.02	.02
Goal Reset	478.10	486.4	11.8	10	.300	.12	.12

χ^2 = chi-squared value; df = Model degrees of freedom.



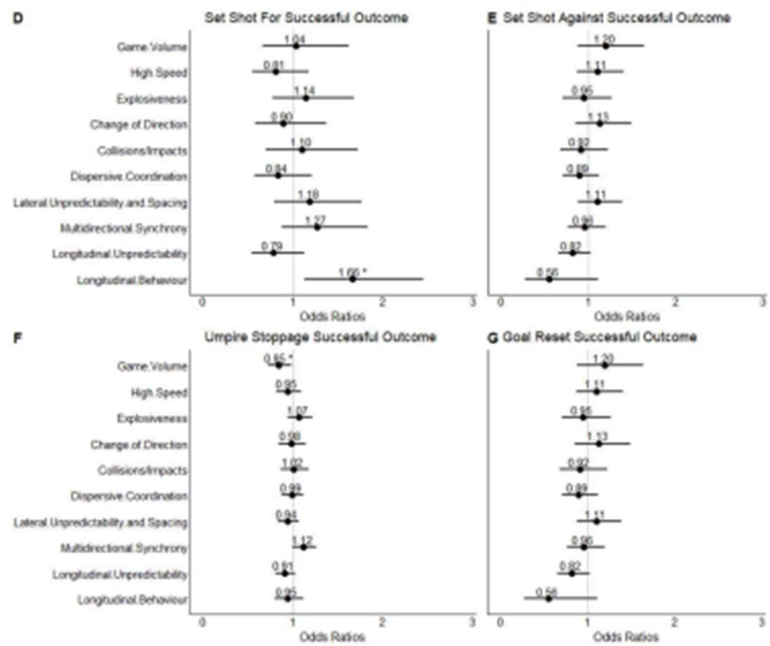


Figure 1 - Odds ratios and 95% confidence intervals demonstrating the likelihood of a successful outcome in each respective phase of play. Note: *< 0.05, **< 0.01, *** < 0.001.

DISCUSSION

While a plethora of physical and spatiotemporal data is available for performance analysis in Australian Football, only recently have these been objectively simplified with sum scores representing different constructs of Australian Football match play subsequently easing the interpretation of the available information. (26, 27) Despite these surrogate measures successfully delineating different phases of play and providing unique insights into match-play, (25) the influence of these metrics on performance outcomes was yet to be explored. Accordingly, the present study addressed this shortcoming providing insight into behavioural movement characteristics associated with successful outcomes in each phase of play. These results may subsequently provide direction for coaches and practitioners when contemplating tactical strategies to be used during competitive games or developing tactical behaviour through specific training exercises.

Reduced duration accompanied by superior physical output, as defined by high speed, change of direction and collisions/impacts, and reduced multidirectional synchrony and, to a lesser degree, lateral unpredictability and spacing, contributed substantially to a model predicting successful offensive phase outcomes. As demonstrated in contextually similar sports such as soccer, the ability of attacking players to move quickly and unpredictably may assist in providing scoring opportunities. (18) This behaviour may help create misalignments with opposing defenders subsequently perturbing defensive formations or providing opportunities to get into free space to receive possession from teammates inside the forward 50 arc. (18) Alternatively, these movement behaviours may emerge as a result of a direct style of play with attackers quickly playing on from marked possessions in an attempt to sufficiently perturb defensive lines as it does not provide the defending team with enough time to modify their synergistic behaviours relative to the ball or the attacking team's movements. (33) The use of a refined definition of offensive success in the present study may explain why the current study's findings contradict those of Gronow et al. who revealed that lower physical output at higher speeds was associated with quarter success, implicating the use of slower playing style and controlled possession. (11) However, only examining phases of play with reference to quarter success may be limiting as favourable behaviours leading to specific positive outcomes such as a scoring opportunity may be negated or diluted across the timespan of a quarter. In contrast, the findings from the present study indicate a direct style of play or intense, asynchronous movement patterns that can effectively perturb defensive formations. Coaches and practitioners may be able to facilitate or afford these behaviours in a training setting using small sided games with more relative space per player (larger field sizes or lower player numbers) as this has shown to promote this style of behaviour in other contextually similar sports (1). For example, utilising a 16 V 16 format, instead of the regular 18 V 18, in a match simulation drill on an Australian Football field would provide approximately 60m2 extra of relative space per player (~460m2 vs ~520m2). Alternatively, teams that achieve performance outcomes comfortably utilising this style of play in a training setting can be challenged by decreasing the relative space per player or by using an outnumber scenario (e.g. 7 V 6 in defence and attack, respectively) as this may afford the offensive team with an environment whereby they must exhibit more unpredictable behaviour to effectively exploit less space and receive possession. (1)

As revealed in other contextually similar sports, favourable defensive outcomes tend to contrast that of successful offensive behaviour. (18) In an Australian Football context, reduced physical output, as marked by lower change of direction and collisions/impacts values, and a tendency for increased duration contributed moderately to a model predicting favourable defensive outcomes. Subdued physical output, particularly alongside lower change of direction values, may also contribute to displays of superior multidirectional synchrony and inferior lateral unpredictability and spacing with players easing movement in an attempt to coordinate and synchronise movements to avoid being perturbed. (6) Further, the formation of a condensed defensive shape (lateral unpredictability and spacing) may help protect defensive zones and may also facilitate synchrony with smaller interpersonal distances between defenders providing favourable affordances to do so. (6) This condensed shape in defence was also implicated by Alexander et al. who revealed a positive association between reduced measures of dispersion and match outcome in a in 15 V 15 match simulation drill. (2) Alternatively, these behavioural outcomes may also reflect an ability of the defending team to minimise the threat of direct offensive styles of play, holding players up on the mark and slowing down offensive passages of play. Contrary to drill designs that promote favourable attacking behaviours, i.e. direct and unpredictable styles of play, coaches can incorporate small sided games with less relative space per player to facilitate these favourable behaviours or alternatively, increase relative space per player to challenge the defensive unit. (1)

While physical and spatiotemporal characteristics were able to model successful outcomes in offensive and defensive phases of play (i.e., moderate-substantial), despite reaching a $p<0.05$ threshold of significance, these characteristics were not as useful for explaining the variances evident in successful and unsuccessful outcomes in contested phases of play (R2 = weak). Regardless, as per offensive phases of play, success in this phase of play may be a result of heightened physical intensity as marked by reduced duration and increased explosiveness and collisions/impacts. This behaviour may be a result of players changing velocity rapidly, physically shoving other players in the process, to be first to a loose ball or successfully follow the unpredictable movement of the ball. However, given the unpredictable nature of the phase only 2% of the variance in successful outcomes could be attributed to the included physical and spatiotemporal characteristics. The seemingly random nature may make it difficult to provide distinct guidelines for achieving success in this phase or, alternatively, technical and skill components (not assessed in the current line of enquiry) may be of greater importance for success during these passages of play. Similarly, during set-shots, goal-resets and umpire stoppages, physical metrics were not associated with success which may be attributed to the lack of a technical skill assessment. Future lines of enquiry should look at concurrently incorporating physical, spatiotemporal, and technical characteristics of team performance, including how their interaction may influence performance, to provide a more holistic perspective on Australian Football Performance.

While the present study can be considered comprehensive (i.e. incorporating novel metrics derived from over 70 physical and spatiotemporal variables), inclusion of technical indicators such as the number of passes or specific player interactions through cooperative network analyses may provide additional insight into behaviour leading to successful and unsuccessful phase outcomes. (26) Further, while definitions of successful phases were derived from discussions with coaching staff (Average AFL coaching experience = 6.8 years; Average professional playing experience = 11.5 years) there may be additional ways to delineate success and therefore model the data. This study also falls short in its ability explore how movement behaviour evolves over different timescales with time providing unique affordances and likely influencing phase outcomes, which offers valuable avenues of research for future studies. (22) Lastly, while the random effect (competition round) failed to meaningfully account for any additional variance in the models, this may be indicative of tactical 'strengths' or 'habits' that are likely coached and remain stable across the season. Future investigations should consider pre-conceived tactical/coaching strategies and the influence this may have on behaviour on different phases of play. Regardless, the present study provides novel insights into factors influencing successful outcomes, particularly in offensive and defensive phases of play. Coaches and practitioners may use this information to develop tactical behaviour to optimise performance success and to manipulate training environments to afford specific behavioural outcomes.

PRACTICAL APPLICATIONS

- Reduced duration accompanied by superior physical output and lower measures of synchrony and predictability appear to be important for success in offensive phases of play due to the ability of attacking players to move quickly and unpredictability to perturb defensive formations and provide scoring opportunities. Alternatively, lower physical output and increased measures of synchrony and predictability may be important for defensive success and reflect an ability to slow opposition offensive sequences of play and coordinate movement to avoid disruptions in defensive formations. Accordingly, the association of specific physical and spatiotemporal sum scores with successful outcomes in certain phases of match-play indicate that these metrics may be useful for reviewing performance in these phases of play.
- Duration may be an important consideration for game plan design as this variable appears to influence offensive and, to a lesser degree, defensive outcomes. Time constraints applied in training drills may be manipulated to afford

more/less time in specific phases of play which may challenge players with respect to their physical requirements, synchrony and coordination. For example, implementing a 30-second shot clock whereby the attacking team only has 30 seconds to score when in possession of the ball may provide a suitable constraint to promote this direct behaviour.

- While there is little research examining change of direction characteristics in Australian Football, this variable may be of greater importance than traditional linear velocity-based variables. Change of direction appears to be a stronger factor influencing offensive and defensive success and thus has novel implications for conditioning and drill design. Incorporating reactive agility drills that help develop this component or manipulating match simulation drills to provide less relative space per player may encourage players to exploit change of direction ability, e.g., 11 V 11 instead of a 9 V 9 performed on half an Australian Football field and may be warranted given the association with success in the present study.

CONCLUSION

This was the first study to concurrently examine differences in physical and spatiotemporal characteristics with respect to successful outcomes in different phases of play in professional Australian football. Reduced duration accompanied by superior physical output, as defined by high speed, change of direction and collisions/impacts, and reduced multidirectional synchrony were deemed meaningful for explaining some successful offensive phase outcomes. This may be a result of a direct style of play with players moving erratically and unpredictability to misalign defenders or providing passing opportunities for teammates. In contrast, defensive success was characterised by reduced physical output, as demonstrated by change of direction and collisions/impacts, lower lateral unpredictability and spacing and increased multidirectional synchrony. This may be a result of players slowing movement in an attempt to coordinate and synchronise movements to avoid being perturbed. Findings from the present study provide novel insight for coaches and practitioners and potentially implicating training and game plan designs. Future research should consider including skill indicators into these models as well as the influence of specific player interactions (passing network characteristics).

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