Athlete monitoring in professional Australian football: Measurement characteristics, parsimony and relationships with performance

by Samuel Ryan

Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of

Distinguished Professor Aaron Coutts
Professor Franco Impellizzeri
Dr Thomas Kempton

University of Technology Sydney
Faculty of Health

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Certificate of Authorship and Originality of Thesis

I, Samuel Ryan, 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.

This document has not been submitted for qualifications at any other academic institution.

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Samuel Ryan

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Date Submitted

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My PhD journey often seemed difficult for many reasons, but upon reflection I appreciate that it was actually made very easy for me by the support and encouragement provided by many people. I am thoroughly proud of my achievement and am equally proud in acknowledging the people that helped me to the finish line.

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If we could give every individual the right amount of nourishment and exercise, not too little and not too much, we would have found the safest way to health.

Hippocrates.

The more comfortable we become with being stupid, the deeper we will wade into the unknown and the more likely we are to make big discoveries.

Schwartz M. The stupidity of scientific research. *Journal of Cell Biology*. 2008;121:1771.

Preface

This thesis is for the degree of Doctor of Philosophy and is in the format of conventional thesis. The thesis abides by the ‘Procedures for Presentation and Submission of Theses for Higher Degrees – University of Technology, Sydney; Policies and Directions of the University’.

The data collected by the candidate has resulted in five manuscripts being published in peer-reviewed journal articles. In addition, the thesis contains two manuscripts that have not been submitted for peer-review. The thesis begins with an introduction to provide a background to the research problem, followed by two literature reviews which in combination provide an overview of training monitoring and measurement characteristics of athlete monitoring tests in professional Australian football, and highlight gaps in current research pertinent to the stated research problems to be addressed in the thesis. Each study that follows is presented in manuscript form, including an introduction section, methods section, statistical analyses section, results section, discussion section and conclusion with practical applications. Figures and tables appear in the thesis within each manuscript as they appear in publication. A general discussion chapter is presented following the final study, reviewing and integrating the main findings of the thesis with previous research and associated limitations of the investigations. The final chapter provides a summary of the contribution of the thesis and directions for future research. Journal of the American Medical Association (JAMA) referencing style is used throughout the thesis, with a list of references provided in Chapter Eleven.

List of manuscripts submitted for publication

Ryan, S., Kempton, T., Impellizzeri, F., & Coutts, AJ. (2020). Training monitoring in professional Australian football: theoretical basis and recommendations for coaches and scientists. Journal of Science and Medicine in Football. 4(1);52-58. Doi:10.1080/24733938.2019.1641212.

Ryan, S., Pacecca, E., Kempton, T., & Coutts, AJ. (2019). Measurement properties of an adductor strength-assessment system in professional Australian footballers. International Journal of Sports Physiology and Performance. 14(2), 256-259. Doi: 10.1123/ijspp.2018-0264.

Ryan, S., Pacecca, E., Tebble, J., Hocking, J., Kempton, T., & Coutts, AJ. (2020). Measurement characteristics of athlete monitoring tools in professional Australian football. International Journal of Sports Physiology and Performance. 15(4); 457-463. Doi: 10.1123/ijspp.2019-0060.

Ryan, S., Kempton, T., & Coutts, AJ. (2020). Data reduction approaches to athlete monitoring in professional Australian football. International Journal of Sports Physiology and Performance. 16(1); 59-65. Doi: 10.1123/ijspp.2020-0083.

Ryan, S., Crowcroft, S., Kempton, T., & Coutts, AJ. (2020). Associations between refined athlete monitoring measures and individual match performance in professional Australian football. Journal of Science and Medicine in Football. Published Ahead of Print. Doi: https://doi.org/10.1080/24733938.2020.1837924

Conference proceedings and abstracts

Ryan, S., Pacecca, E., Tebble, J., Hocking, J., Kempton, T., & Coutts, AJ. (2019, June 4-7). Measurement characteristics of athlete monitoring tools in professional Australian football. *Presented at the 9th World Congress of Science and Football, Melbourne, Australia.*

Statement of candidature contribution

Table 1.1: *Percentage contribution of authors to peer-reviewed manuscripts of thesis.*

	Study One (Chapter Four)			
Author	**Sam Ryan**	**Emidio Pacecca**	**Thomas Kempton**	**Aaron Coutts**
Research design	70%	10%	10%	10%
Ethics application	70%			30%
Data collection	80%	20%		
Data cleaning	100%			
Statistical analysis	90%			10%
Manuscript preparation	100%			
Manuscript revision	50%		20%	30%

	Study Two (Chapter Five)					
Author	**Sam Ryan**	**Emidio Pacecca**	**Jye Tebble**	**Joel Hocking**	**Thomas Kempton**	**Aaron Coutts**
Research design	70%	5%			5%	20%
Ethics application	70%					30%
Data collection	65%	5%	20%	10%		
Data cleaning	100%					
Statistical analysis	100%					
Manuscript preparation	100%					
Manuscript revision	50%				20%	30%

	Study Three (Chapter Six)		
Author	**Sam Ryan**	**Thomas Kempton**	**Aaron Coutts**
Research design	80%	10%	10%
Ethics application	70%		30%
Data collection	90%	10%	
Data cleaning	100%		
Statistical analysis	90%		10%
Manuscript preparation	100%		
Manuscript revision	50%	20%	30%

	Study Five (Chapter Eight)			
Author	**Sam Ryan**	**Stephen Crowcroft**	**Thomas Kempton**	**Aaron Coutts**
Research design	80%		10%	10%
Ethics application	70%			30%
Data collection	90%		10%	
Data cleaning	100%			
Statistical analysis	60%	30%	10%	
Manuscript preparation	100%			
Manuscript revision	50%	20%	10%	20%

Thesis Abstract

Australian football (AF) is a physically-demanding, high-intensity field-based sport with players competing in the presence of performance-related psychological stress. This requires detailed monitoring of players for training and competition to maximise their readiness for high-level performance. Historically, monitoring team sport athletes has been based on the theoretical 'fitness-fatigue' model whereby performance can be deduced with knowledge of fitness (positive effects of training completed) and fatigue (residual impairments of function due to an acute training dose) over acute (~15 days) and chronic timeframes (~50 days). However, in practice, individual training load is prescribed to players over acute timeframes of ~7 days prior to competition matches, dictated by scheduling of matches every 6-8 days during the competition season. The prescription of acute training load is informed by a range of athlete monitoring data measuring training load completed, training response and neuromuscular performance. However, despite anecdotal evidence of the use of individual acute training load prescription in professional AF, it has not been presented empirically. This thesis contains five studies that aim to build a novel conceptual model of acute training load prescription using a refined collection of monitoring tests with suitable measurement characteristics that relate to competition performance in professional AF. *Study One* and *Study Two* evaluated the measurement characteristics of reliability and sensitivity of common tests of training response, neuromuscular performance and aerobic fitness using test-retest and signal-to-noise ratio methods. The results showed that perceived wellness questionnaires, countermovement jump tests, eccentric hamstring force tests, isometric adductor force tests and heart rate recovery tests possess acceptable reliability and sensitivity, allowing confident identification of meaningful test results for practitioners. *Study Three* and *Study Four* addressed the issue of monitoring data overload for team sport practitioners by applying principal component analyses (PCA) to the monitoring tests established in *Study One* and *Study Two* in addition to measures of training

load and extended this analysis to propose two practical methods of using the results of PCA to enhance efficiency in team sport monitoring systems. *Study Three* demonstrated that external load, internal load and perceived wellness represent statistically separate constructs of the training process, across acute (7-day) and chronic (28-day) timeframes commonly used to categorise athlete monitoring data. *Study Four* identified components to represent isometric adductor force, eccentric hamstring force and countermovement jump power. These findings indicate that many individual measures commonly collected and analysed in professional team sport monitoring systems assess similar aspects of the training process, and hence some variables can be excluded from monitoring systems to enhance efficiency in the use of financial and human resources. *Study Five* analysed the effect of a refined collection of measures of training load, training response and neuromuscular output from previous studies in the thesis and showed that z-score increases in individual acute training load associated with an 18-23% increase in performance z-score. This finding indicates that team competition schedule may have a confounding effect on acute load completed prior to a match as longer between-match periods provide for opportunity and flexibility for greater load completion. *Study Five* also found no significant relationships between a range of other commonly collected monitoring variables and performance change. Collectively, the thesis populated a novel conceptual model of acute training load prescription with individual adjustments of acute load informed by a refined range of reliable and sensitive monitoring measures that relate to individual performance changes.

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Abbreviations

AF	Australian football
AFL	Australian Football League
AU	arbitrary units
AUC	area under the curve
β	beta
bpm	beats per minutes
CI	confidence interval
cm	centimetres
CMJ	countermovement jump
CV	coefficient of variation
d	day
ES	effect size
Exp(β)	beta exponent
GPS	global positioning system
h	hours
HRex	heart rate during exercise
HRR	heart rate recovery
HSR	high-speed running
Hz	hertz
ICC	intraclass correlation coefficient
IMA	inertial movement analysis
Kg	kilograms
$km \cdot h^{-1}$	kilometres per hour

LPS	local positioning system
m	metres
m/s	metres per second
MCIC	minimal clinically important change
mm	millimetres
MTP	mid-thigh pull
N	Newtons of force
N/kg	Newtons per kilogram
PC	principal component
PCA	principal component analysis
QIC	quasi-likelihood independence model criterion
ROC	receiver operating characteristic
RPE	rate of perceived exertion
RSImod	reactive strength index modified
s	second
SD	standard deviation of the mean
SNR	signal-to-noise ratio
SRPE	session rate of perceived exertion
SWC	smallest worthwhile change
TD	total distance
TE	typical error
TRIMP	training impulse
VHSR	very high-speed running
W/kg	watts per kilogram

Chapter One | Introduction

Background

Australian football (AF) is a high-intensity field-based sport with regular collisions and intense activities such as jumping, tackling and grappling, resulting in acute neuromuscular fatigue and soreness.[1] Professional AF players also experience other performance-related psychological stress and have external demands on their time which can impact on their fatigue and recovery status and hence influence their responses to training stimuli and readiness for competition. In a professional AF context, 'readiness' refers to a player's acute readiness to complete tactical and physiological training activities designed by coaches and scientists.[1]

Information is obtained from a variety of sources to evaluate individual player readiness to train, which informs subsequent planning and delivery of acute training stimuli at an individual level. These include changes in constructs such as internal and external training load,[2,3] training response,[4] neuromuscular performance and fitness tests,[5] often expressed in acute (~7-day) and chronic (~28-day) terms.[6] Due to environmental constraints such as time and cost (human and financial) and risk of injury in fatigued athletes, it is impractical for professional team sport athletes to complete maximal physical capacity tests during the season to determine changes in fitness and fatigue.[7] Therefore, practitioners rely on monitoring tools that are submaximal in nature and easily administered and can identify changes in constructs training load completed, response to load and neuromuscular performance regularly throughout training and competition to assess the readiness of their players. To provide useful information to coaches and scientists, these tools should display measurement characteristics of validity (the ability of a test to measure what it is designed to measure), reliability (the consistency of results from a test) and sensitivity (the extent to which a test can detect changes beyond the typical error in results).[8,9] Moreover, these data should display an ability to detect changes in important outcomes measures including training availability and match performance. A further important consideration for practitioners working in professional sport to ensure efficient use of human and financial resources. The increased accessibility of monitoring technology for practitioners over recent years has resulted in relatively large amounts of time spent collecting monitoring data but often scarce time available to analyse, communicate and action information derived from these data, i.e. data overload.[10] Indeed, monitoring systems should include valid, sensitive and reliable measurements of elements of the training process, and these data should be collected and interpreted efficiently and according to their relationships with outcome measures (i.e. performance).

Research Question

Information pertaining to measurement characteristics of commonly used monitoring tools in professional AF is scarce. Secondly, despite the issue of data overload in athlete monitoring acknowledged elsewhere,[11,12] no research has provided a practical method of refining athlete monitoring data to collect, analyse and action information about elements of the training process efficiently. Lastly, no studies have examined the effect of a refined collection of training load, training response and neuromuscular output on subsequent changes in individual match performance in professional AF.

Research Objectives

A series of studies were conducted to address the research problems mentioned above. *Review One* will present current evidence supporting the use of common athlete monitoring tools in professional Australian football and identify limitations of existing research to highlight avenues for future investigations. *Review Two* will discuss necessary measurement properties of athlete monitoring tools and how they can be established within a professional AF club environment. Guided by the findings of *Review One* and *Review Two,* Chapters Four to Eight of the thesis will present a series of original investigations that address substantial gaps in current understanding of monitoring test measurement characteristics, methods to enhance efficiency of athlete monitoring, and relationships between a refined collection of training load, response and neuromuscular output measures on individual match performance.

Study One will assess the reliability and sensitivity of a common method of isometric adductor force in professional Australian football via signal-to-noise ratio analysis. *Study Two* will further apply this method of analysis to other common monitoring tests in professional Australian football. *Study Three* will apply a data reduction technique to commonly used measures assessing acute and chronic derivations of training load and training response in professional Australian football and use the findings of this analysis to further enhance monitoring efficiency based on statistical contribution and practical efficacy. *Study Four* will apply the methods presented in *Study Three* to commonly used neuromuscular performance measures in professional Australian football. The combination of *Study Three* and *Study Four* will provide a reduced collection of monitoring variables to be examined in the final study of the thesis. *Study Five* will assess the relationship between monitoring measures established in *Study One, Study Two, Study Three and Study Four* and changes in individual match performance in professional Australian football. A schematic representation of the thesis is provided in Figure 1.1.

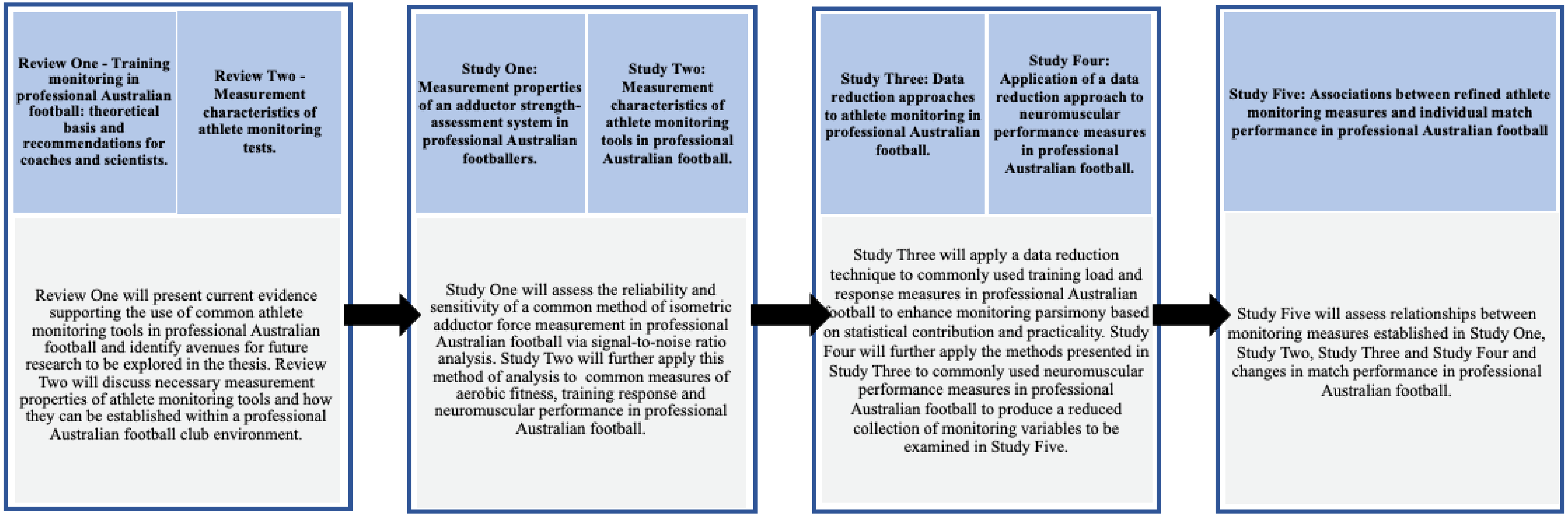

Figure 1.1: *Schematic representation of the thesis.*

Chapters Two, Four, Five and Eight have been accepted for publication or are under review in peer-reviewed journals, with a summary of their aim and significance detailed below. Chapters Three and Seven form part of the thesis but will not be submitted for publication in peer-reviewed journals.

Study One (Chapter Four) – Measurement properties of an adductor strength-assessment system in professional Australian footballers.

Purpose: To examine the reliability and sensitivity of an adductor strength assessment system and enhance interpretation of test results for practitioners of professional Australian footballers.

Significance: This study will establish the reliability and sensitivity of a commonly used test for assessing adductor strength of professional Australian footballers during a competition season. The findings will also assist practitioners to contextualise changes in adductor strength of their players at major time points following professional Australian football match-play with knowledge of typical test error and normal weekly variation in adductor strength. The study will present and apply a novel and unobtrusive method of assessing measurement reliability and sensitivity within a typical professional team sport training environment.

Study Two (Chapter Five) – Measurement characteristics of athlete monitoring tools in professional Australian football.

Purpose: To examine the measurement properties of commonly used monitoring tests in professional Australian football.

Significance: Research suggests that perceptual wellness questionnaires, eccentric hamstring strength tests, countermovement jump (CMJ) tests and submaximal heart rate tests possess varying levels of reliability among a range of athlete cohorts. However, the extent to which changes in these tests exceed their typical error remains unknown, limiting interpretability of test results for coaches and scientists. This study will employ the methods used in *Study One* to establish the reliability and sensitivity of common athlete monitoring tools and provide thresholds for meaningful changes in individual test results.

Study Three (Chapter Six) - Data reduction approaches to athlete monitoring in professional Australian football.

Purpose: To apply data reduction methods to athlete monitoring data to address the issue of data overload for practitioners of professional Australian football teams.

Significance: Previous research has acknowledged data overload to be problematic for time and resource-poor practitioners of professional Australian football teams. Indeed, monitoring data is only useful if coaches and scientists have adequate time to collect, analyse and communicate the information derived from these data to other coaches and players. This study will be the first to apply a data reduction method (PCA) to training load and training response data collected from professional Australian footballers to identify measures that are collinear and assess similar elements of the training process. The study will also propose two novel methods of applying the findings of a PCA to enhance efficiency in the monitoring of professional Australian footballers.

Study Five (Chapter Eight) – Associations between refined athlete monitoring measures and individual match performance in professional Australian football

Purpose: To establish relationships between a refined collection of athlete monitoring measures in detecting individual changes in match performance in professional Australian footballers.

Significance: Isolated relationships have been reported between athlete monitoring measures and physical, technical and tactical performance markers. However, no research has attempted to establish associations between a refined collection of acute and chronic measures of training load, training response and neuromuscular output with changes in individual match performance in professional Australian footballers. This study will highlight relationships between monitoring measures and in combination with *Study One, Study Two, Study Three and Study Four* help guide the selection of athlete monitoring tests based on their statistical contribution to elements of the training process, measurement characteristics and association with changes in performance.

Chapter Two | Review One | Training monitoring in professional Australian football: theoretical basis and recommendations for coaches and scientists

Ryan, S., Kempton, T., Impellizzeri, F., & Coutts, AJ. (2020). Training monitoring in professional Australian football: theoretical basis and recommendations for coaches and scientists. Journal of Science and Medicine in Football. 4(1);52-58. Doi:10.1080/24733938.2019.1641212.

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Abstract

Australian football (AF) is a demanding, high-intensity field-based sport with regular collisions and intense physical demands such as jumping, tackling and jostling, resulting in neuromuscular fatigue and soreness, combined with external stressors (i.e. commercial, sponsorship, education, family). These can influence an athlete's fatigue and recovery status and their readiness for training and competition, requiring an individualised approach to monitoring to maximise training readiness. In the case of professional team-sport, the term of athlete readiness is often used by practitioners to describe the athlete's capacity to complete training and competition. Optimal readiness would reflect a condition where an athlete has no impairment of physical performance, no mental fatigue or excessive psychological distress. A theoretical framework exists for athlete monitoring that includes the quantification of training load and understanding individual ability to tolerate the training demands imposed by coaches. However, while this approach is thought to ultimately determine the readiness of a player for training and competition, it has not been tested empirically. The purpose of this narrative review is to describe the theoretical basis that underpins athlete monitoring systems, and to provide an overview of their contribution to decision-making processes in planning and delivery of training in professional AF. This review can assist coaches and scientists to gain a better understanding of commonly used monitoring measures and how the information derived from these sources is applied in a professional AF environment.

Introduction

Australian football (AF) is a demanding, high-intensity field-based sport with regular collisions and intense activities such as jumping, tackling and jostling, resulting in neuromuscular fatigue and soreness.[1] In addition to these heavy physical demands, professional AF players also experience other performance-related psychological stress and have external demands on their time (i.e. commercial obligations, media, education, family). These stressors can impact on an athlete's fatigue and recovery status and influence their responses to the training stimulus and readiness for competition. In the case of professional team-sport, the term of athlete readiness is often used by practitioners to describe the athlete's capacity to complete training activities and perform during competition. Optimal readiness would reflect a condition where an athlete has no impairment of physical performance, no excessive mental fatigue or psychological distress. Indeed, to enhance performance readiness and attempt to reduce the risk of injury and illness, training load should be adjusted on an individual level based upon training goals combined with an athlete's current fitness and fatigue status. A theoretical framework exists for athlete monitoring that includes the quantification of training load and understanding individual fitness and fatigue responses to the training dose at an individual level.[13] While this approach is thought to ultimately determine the readiness of a player for training and competition, it has not been tested empirically.

Quantification of training load and assessments of fitness and fatigue status can be provided using athlete monitoring tools. Recent technological advancement has increased the number of tools available, such as internal and external training load measures,[2,3] training response measures including psychometric markers,[4] neuromuscular fatigue assessments[14] and fitness tests.[5] Data obtained from these tools can support decision-making regarding the planning and delivery of training load at an individual level to optimise player readiness for training and matches. In practice, the objective information provided by these tools are often combined with expert opinion (i.e. from coaches and scientists) to make decisions about future training. Specifically, practitioners often consider information relating to previous training and match load completed and the players' response to this load (commonly assessed via short psychometric questionnaires and neuromuscular performance tests) when deciding appropriate future training volume and content for individual players. Alterations in individual training load are typically achieved through manipulation of training duration, intensity and content. These changes are made with the intent of reducing injury risk and maximising player readiness for training and competition. However, despite the widespread use of this approach, no research has established the efficacy of this method in a professional AF environment. Therefore, the purpose of this narrative review is to describe the theoretical basis that underpins athlete monitoring systems, and to provide an overview of their contribution to decision-making processes in planning and delivery of training in professional AF players. This review will assist coaches and scientists to gain a better understanding of the evidence supporting commonly used monitoring measures and how the information derived from these sources is applied in a professional AF environment.

Theoretical basis of athlete monitoring

Athlete monitoring is now common practice in professional team sports.[15] Monitoring systems are reliant on being able to accurately quantify the training dose completed by the athlete, and the individual athlete's response to that dose. Once this dose-response relationship is understood at the level of the individual athlete,[16] targeted prescription of training and recovery activities can be provided in order to optimise training outcomes. The 'fitness-fatigue' model underpins the theoretical basis of this approach, whereby performance may be modelled from the positive (i.e. fitness) and negative (i.e. fatigue) responses that arise from training load delivered to the athlete.[17] Fitness was initially represented by the positive adaptations generated by training completed by an athlete over a chronic time period, while fatigue is the result of an acute training dose.[16] Whilst the 'fitness-fatigue' model has not consistently been shown to describe or predict performance,[3,18] the theoretical and conceptual basis (balance between positive and negative training-induced effects) can be used as a generic framework to develop athlete monitoring systems.

According to the conceptual 'fitness-fatigue' model, the appropriate balance between training and recovery should be attained to maximise physical adaptations.[16] The balance of 'fitness' and 'fatigue' is achieved by careful prescription of training to allow for higher training loads over chronic time periods to maximise physiological adaptations, but lower training loads in the days closer to competition to reduce acute residual fatigue. However, achieving an appropriate balance of fitness and recovery can be difficult in AF competition periods, as there are often relatively short periods between matches, and the training loads during these periods are typically influenced by the nature of the technical and tactical training prescribed by coaches. Moreover, training may be completed in the presence of acute fatigue to achieve physiological adaptions during preseason training periods. Indeed, training activities are derived from a combination of technical and tactical requirements determined by coaches and also physiological requirements determined by strength and conditioning and sport science staff, as training must be targeted to the systems that influence performance.[19]

Training delivery in professional Australian football

The aim of athletic training is to provide a stimulus that improves physical performance while also attempting to protect an athlete from injury and illness during competition.[6] In professional AF, training usually includes tactical skills training designed by technical coaches (drills that are congruent with aspects of the team's game plan or specific technical skills that require improvement or focus), conditioning (running or cross-training) and resistance training.[20] Recent case studies describing the training load completed by professional AF players have shown that training load (total and high-intensity running distances and session rating of perceived exertion load) is greater during the preseason period (i.e. November to February) compared to in-season (i.e. March to September), with the majority of total training load obtained from skills and conditioning sessions.[20] During in-season, approximately half the total training load (session-RPE) is derived from matches, while the other half is typically generated from technical-tactical sessions and upper body weight sessions.[20] The overall intensity of training is at least of moderate intensity (assessed via session-RPE), which is likely due to the nature of training being focused on tactical capabilities as opposed to physical.[21] However, whilst these studies have described the training load completed by professional AF players across typical training microcycles, they provide little insight into the methodology and decision-making process used to plan and deliver training in practice.

A contemporary approach to planning and delivering training load combines consideration of objective and subjective monitoring measures with tactical requirements of coaches. The specific nature and content of most training sessions (field-based skills sessions) in AF is typically determined by technical or tactical coaches, designed to meet specific strategies of the team and individual players. However, at an individual player level, the volume and nature of training load is often manipulated based on their readiness for training with consideration of factors such as upcoming match location, opposition strength and days between matches.[22,23] The process of acute training load periodisation has theoretical support and is common in professional practice,[22,23] however there have been few reports of the specific information used to underpin decision-making regarding acute training periodisation at an individual level in professional AF.

Monitoring player readiness in professional Australian football

Coaches and scientists obtain information from a variety of sources to inform planning and delivery of acute training stimuli at an individual level. These include internal and external training load measures[2,3] and acute and chronic responses to training load such as heart rate variability, perceptions of neuromuscular fatigue and fitness tests.[4,5,24,25] While some of these tests have established validity and reliability, practitioners must consider their association with training load, injury risk and performance in addition to their practical limitations to properly interpret the information they provide.

External training load refers to the physical work prescribed and delivered in training,[19] and is often assessed using microtechnology devices which provide locomotive measures (e.g. total distance, distance covered at speed thresholds, number of accelerations and decelerations) and mechanical measures (e.g. tackles, jumps and impacts) of training demands.[26,27] Given the complexity of the physical requirements of AF,[28] a combination of these external load measures is necessary to provide a comprehensive understanding of training demands. In practice, external load is typically reported in terms of 'locomotive load' as these measures have some evidence of validity and reliability.[27,29] However, few studies have established a valid or reliable measure of other technical activities that produce substantial mechanical load such as kicking, tackling, jumping and change of direction in AF,[30,31] possibly explaining why these measures are not widely reported. Future research may examine the validity of these measures to provide a more complete understanding of AF training and match demands.

While external load variables are used to describe training and competition loads, they do not provide information on player tolerance and adaptation to those stimuli. This necessitates the assessment of internal training load, which refers to the psychological and physiological responses to the external load.[13,19] A common method of measuring internal load is the session-RPE method,[32,33] where players are shown a category-ratio RPE scale and asked to provide a number rating the overall perception of exertion relating to the whole training session shortly after completion.[32] The rating is multiplied by the duration of the session in minutes to determine a total session training load in arbitrary units. The session-RPE method permits quantification of training load across any modality, hence it is a practically useful method for measuring internal load in AF.[32,34] However, caution is needed when comparing the load measured via session-RPE generated by exercises of different nature, as athletes may use previous sessions of a similar nature as a reference point for their perception rating. An additional measure of internal load is heart rate during training, extended to training impulse (TRIMP) where training intensity can be determined by calculating the average level of heart rate reserve (the difference between recorded heart rate and heart rate maximum), with a lower heart rate reserve indicative of greater training intensity and therefore greater load.[35] However, heart rate monitors are not permitted to be worn by AF players during competition, therefore session-RPE is the most practical method of measuring internal load during competition in these athletes.[32]

Information from external load measures can provide practitioners with objective information regarding the intensity and nature of training and match-play, however it is the internal training load that ultimately determines the training outcome, as athletes are likely to respond differently to the same external workload.[19] The individual response is due to the influence of many factors such as nutrition, psychological status and genetics which are not accounted for by external load measures.[19,36] Therefore, a combination of external and internal load measures is vital for a better understanding of the dose-response relationship derived from training and competition.[36,37] Indeed, research in AF has reported associations between external load (total distance covered during a session) with session-RPE, suggesting that changes in external load may be indicative of training response.[37] This relationship between external and internal load allows coaches and scientists to derive information about how an athlete is tolerating training stressors without intervention (i.e. fitness tests or questionnaires), which is an avenue for further empirical investigation in professional AF.[38]

External and internal load measures both provide useful information on the demands of training and matches, however meaningful relationships between these measures and match performance in professional AF are not well-established. Research has shown running performance during simulated team-sport match activity (i.e. sprint velocity and total distance covered) to decrease following high acute training loads,[39] while acute running distances in training have demonstrated small positive effects (effect size: 0.13) on subsequent match running performance in professional AF players.[40] Additional research has shown that both running distances and session-RPE load during training are associated ($r = 0.76$ and 0.73, respectively) with changes in relative running distances during matches.[18] However, this study found trivial relationships between training load and an objective measure of overall football match performance derived from match statistics (Player Rank, Champion Data).[18] Similarly, investigations into the relationship between training load and AF performance measures have reported small positive effects of weekly total and high-speed running volumes on objective and subjective ratings of performance.[40,41] Collectively, this research indicates that training load may influence subsequent match running performance in AF players, however this relationship is likely influenced by other elements of a player's preparation for competition.[40] Moreover, training load appears to only associate with relative running performance during matches, and these measures have been found to relate poorly with coach ratings of performance and statistical performance measures.[41] Longitudinal investigations of large cohorts (using multiple teams) are required to establish associations between aspects of in-season training load (locomotive load, resistance training load and measures of training completion) and measures of football performance in professional AF players.

Measuring training response professional Australian football

It is important that athletes are monitored for their response to training, as individual athletes may respond to the same training dose differently.[42] One way to assess training response is through player perceptual wellness, which is typically measured by short psychometric questionnaires.[6] In practice, assessments of wellness are usually collected several times during a training week, with players providing a subjective rating of their muscle soreness, fatigue, stress and sleep quality.[43] These responses are often compared to an individual's normal response (z-score) and can be viewed in the form of a 'traffic light system' to alert practitioners to a meaningful change (i.e. a change that exceeds the typical variation) in a player's perceived wellness).[15] For this reason (simplicity), these self-reports are quite common in research and practice. However, evidence of validity for most of these questionnaires is lacking and apparently none have been developed using valid and well-established psychometric methods.

Indeed, the concept of wellness has not been defined and it is prone to various and different interpretations, and the use of single items is theoretically limited to unidimensional constructs and not complex constructs such as stress and motivation.[44] Future work is required to develop appropriately validated short questionnaires that can be applied in professional AF and athletes in general. However, despite these limitations this measure of training response is considered by practitioners to be a useful and inexpensive method of determining an athlete's perception of their training readiness, provided the limitations of these instruments are considered.

Although a precise and shared definition of wellness is not available, research in professional AF has shown perceived wellness responses to be associated with changes in training load, with poorer perceptions of wellness associated with higher training load.[45] However, a study investigating player wellness during an AF competition season found no significant relationship between match load and subsequent wellness,[46] indicating that the commonly used measure of wellness may only provide an acute assessment of training readiness and limited insight into a player's readiness to perform in a match. Few studies have examined associations between wellness elements and football performance measures, however research has shown perceived muscle soreness 48 hours prior to a game to have a small, positive effect on a statistical indicator of match performance (Player Rating, Champion Data).[40] These findings suggest that wellness responses may provide some insight into a player's capacity for subsequent match performance,[40] however until studies examine the validity of these instruments, their utility and sensitivity is difficult to ascertain. Therefore, caution is need in their interpretation while it is acknowledged that practitioners find information derived from these measures as useful.

Measuring fitness and neuromuscular performance in professional Australian football

Individual monitoring of training response is often achieved by neuromuscular performance and fitness tests. These include but are not limited to isometric adductor force tests, eccentric hamstring force tests, countermovement jump tests, mid-thigh pull tests and submaximal heart rate tests.[47-49]

Adductor force assessment

Adductor force of professional AF players is typically assessed via isometric adductor muscle contractions with the aim of detecting pain and decrements or limb imbalances in force output following training and matches.[50] A study of professional AF players found adductor force assessed two to three days post-match was not sensitive to internal training load (session-RPE), indicating it to be a poor indicator of training responsiveness.[51] Nonetheless, a recent study examining the reliability of an adductor force assessment system in professional AF players reported a very likely moderate negative effect of reported adductor pain on adductor strength,[48] indicating that this measure is useful in detecting adductor pain and can prompt further investigation to establish a player's readiness for training. Other research in AF showed adductor force to remain below baseline values at four days post-match, suggesting it is a useful measure of match recovery. Collectively, adductor force measurement appears to be a suitable indicator of adductor pain and rate of lower limb neuromuscular recovery but displays poor sensitivity to training load. Future work is required to assess associations between changes in adductor force during in-season periods and match performance to enhance the utility of this test.

Eccentric hamstring force assessment

Eccentric hamstring force is commonly assessed using the Nordic hamstring exercise to evaluate limb force reductions or imbalances.[52] The Nordic hamstring test has been shown to be a reliable measure of eccentric hamstring force, and can also discriminate between previously injured and uninjured athletes.[52] However, few studies have examined the association between eccentric hamstring force and training completion or match performance in professional AF players. A recent study in professional AF that examined the influence of session-RPE training load on hamstring flexibility found higher training loads to have a trivial association with lower hamstring flexibility,[51] indicating that a change in this measure is not sensitive to changes in training load. However, while the diagnostic accuracy of this test in detecting injury has not been demonstrated, research has shown that relatively low levels of eccentric hamstring force measured during a preseason training period are associated with an increased risk of hamstring strain injury in a subsequent competition season.[53] Collectively, eccentric hamstring force appears to have limited utility in assessing a player's readiness to train (over acute timeframes), however it may provide practitioners with useful information regarding subsequent injury risk during a competition season. Future research examining associations between acute changes in eccentric hamstring force and both mechanical load (i.e. acceleration, deceleration, change of direction during training) and injury risk is warranted.

Countermovement jump performance and mid-thigh pull

Countermovement jump (CMJ) performance has been shown to be responsive to match load, with substantial reductions in CMJ flight time following AF competition matches,[25] while decreases in CMJ performance have also been related to increases in low-speed movement and reduced accelerations during competition matches.[14] These findings support the use of CMJ tests as an indicator of post-match recovery in AF players, and suggest it to be a useful test to prompt altered training loads during a 96-hour period following competition. Additionally, mid-thigh pull (MTP) has been proposed as an isometric alternative to CMJ for assessing lower limb neuromuscular fatigue in professional AF.[54] Previous research has established MTP to be a valid, reliable and practical method of assessing lower limb neuromuscular fatigue in team sport athletes,[55,56] however no research has examined relationships between CMJ or MTP and training completion or match performance in professional AF.

Submaximal heart rate measures

Research has established associations between heart rate measures and changes in training status in endurance athletes[57] which have subsequently been applied to cohorts of AF athletes.[49] Heart rate is typically expressed by heart rate during exercise (HRex), with lower values indicative of greater cardiac efficiency,[57] and heart rate recovery (HRR) with faster return to pre-exercise heart rate reflective of better aerobic fitness.[57] Previous research in professional AF has reported a submaximal heart rate recovery test to be a valid and reliable measure of training status.[5] Additionally, research investigating training response during a preseason training camp in AF reported lower HRex following intense periods of training, indicating it provides a useful index of aerobic fitness in AF players over short timeframes.[24] However, future work is required to establish meaningful changes (via reliability and sensitivity assessment) in HRex and HRR in order to enhance interpretation of these measures when evaluating training readiness in AF players.

Current evidence shows that neuromuscular performance tests provide practitioners with limited information to forecast the training readiness and injury risk status of their athletes in isolation, hence we suggest caution when interpreting results from these tests. While adductor force and elements of CMJ performance are reduced following competition matches, their sensitivity to changes in training load are unknown, hence they should be used in conjunction with other measures when assessing a player's readiness to train. In contrast, eccentric force measures can provide practitioners with insight into subsequent risk of hamstring injury during a competition season, however the responsiveness of this measure to alterations in acute training load remains unclear. A HRR test can provide an index of aerobic fitness during preseason and competition periods, however further research is needed to establish meaningful changes in this measure to enhance interpretability of test results for practitioners. Nonetheless in practice, changes in these and similar measures administered regularly (during between-match training cycles) can prompt further examination of other monitoring data when assessing an individual player's readiness to train. However, research establishing relationships between monitoring test results and match performance and training completion is required to enhance the interpretability of test results for coaches and scientists.

Acute training periodisation and delivery in professional Australian football

The theoretical model of athlete monitoring presented in this review indicates that preparing an athlete for competition is multi-factorial, and to do so effectively requires inputs of information from a range of objective and subjective sources. There are a range of factors that influence an athlete's readiness to train demanding individual monitoring and alteration of acute training load. In practice, coaches design training based on tactical and strategic requirements to best equip players with the knowledge and capabilities to perform against a given opposition team each week during a competition season. Subsequently, coaches and scientists consider information relating to previous training and match load completed and response to this load to deliver appropriate training load to individual players that allows them to be physically and psychologically 'ready' for competition. Acute training load alterations are typically achieved through manipulation of running volume at different speed thresholds, instances of maximum speed exposure, and volume of mechanical load, among others. The aim of this approach is to minimise risk of injury and enhance individual player readiness for training and competition, however no research has established the efficacy of this approach in a professional AF environment. Moreover, the utility of many of the monitoring measures described in this review in detecting meaningful changes in training completion and match performance remains unknown. Therefore, accurate acute training load prescription continues to be reliant on the collaboration of coaches and scientists, supported by objective monitoring measures of player readiness.

Practical Applications

- Coaches and scientists should use locomotive and mechanical load derived from external load measures, and session-RPE load when assessing individual player readiness for training based on load completed.
- Perceptual wellness responses are widely used in professional AF club settings to prompt further investigation of player readiness for training, however further work is required using established psychometric methods to determine their validity.
- Adductor force and countermovement jump performance are useful neuromuscular fatigue measures following AF matches and should be administered to guide acute prescription of training load during between-match microcycles
- Submaximal heart rate measures (HRex and HRR) are unobtrusive and non-fatiguing methods of assessing aerobic fitness over short periods in AF players.

- External and internal training load measures show strong associations with subsequent running performance but not football performance measures in competition matches.
- Measurement characteristics (validity and reliability) of monitoring measures specific to the protocols used in AF clubs should be established to provide practitioners with the most useful information when assessing a player's training readiness.

Conclusions

Monitoring measures used to inform decisions about future training load prescription should be based on a proof of concept and strong theoretical support. These elements can be derived from high-quality research that establishes the validity and reliability of monitoring measures to allow proper interpretation of data collected. Only measures that can provide meaningful information (i.e. a meaningful change in a measure) on the tolerance or adaptation of an athlete to training and life stressors should be considered when assessing player readiness. In the case of professional team-sport, the term of athlete readiness is often used by practitioners to describe the athlete's capacity to complete training and competition. Optimal readiness would reflect a condition where an athlete has no impairment of physical performance, no mental fatigue or excessive psychological distress. Additionally, collection of monitoring information needs to be cost-efficient and refined for practitioners to allow timely feedback to coaches on the training readiness of their player. The feedback should be integrated with the expert knowledge and experience of coaches and scientists to allow holistic assessments of a player's readiness to train and compete.

Chapter Three | Review Two | Measurement properties of athletic testing

Abstract

Athlete monitoring systems are now common in professional team sports. The aim of these systems is to maximise training adaptations and athlete availability for competition via regular evaluations of athlete readiness. In the case of professional team sport, readiness can refer to an athlete's current physiological and psychological capacity to complete training activities and perform at their best during competition. Many monitoring tests are available to practitioners to infer the readiness of their athletes for training and competition. However, to be the most useful, these tests must possess measurement characteristics of validity, reliability and sensitivity. Validity refers to the ability of a test to measure what practitioners intend it to measure. Reliability is defined as the consistency of results from a test. Sensitivity is a measure of the extent to which a test consistently produces results that exceed the typical test error. Establishment of these measurement characteristics allows practitioners to confidently interpret test results when evaluating the readiness of their athletes for training and competition. The purpose of this review is to provide clear definitions of validity, reliability and sensitivity in the context of professional sport and provide simple methods of assessing each characteristic within normal training environments without the need for intervention.

Introduction

Athlete monitoring systems are commonly used in professional team sports to provide coaches and scientists with an understanding of player readiness to train and their injury risk.[16] Information from these systems is used to plan training load to maximise physical adaptations whilst maintaining player availability for competition.[6] Recent research and technological advances has increased the number of tests available to practitioners to assess elements of the training process, including submaximal heart rate tests,[58] countermovement jump tests,[14] lower limb muscular strength tests[59] and perceptual wellness questionnaires.[50]

Due to environmental constraints and risk of injury in fatigued athletes, it is impractical for professional team sport athletes to complete maximal physical capacity tests during the season to determine changes in training load and training response.[7] Therefore, practitioners rely on simply-administered and unobtrusive monitoring tests to provide regular indexes of training load, response and neuromuscular performance. Information from these tests is used to evaluate a player's readiness to train and partake in competition. However, the most useful monitoring tools for coaches and scientists must possess validity, reliability and sensitivity.[6]

The aim of this brief review is to provide clear definitions of measurement characteristics in athlete monitoring tests. Due to the range of monitoring tests now available to practitioners, it is important that test validity, reliability and sensitivity be established and considered when selecting monitoring tools to use in evaluating individual athlete readiness to train and perform during competition. This review will also present simple methods of establishing these test characteristics without the need for intervention or heightened risk of fatigue and injury to athletes.

Validity

Validity is defined as the ability of a test to measure what it is designed to measure.[8] There are two types of validity relevant to athlete monitoring tests; criterion validity (the level of agreement between test results and the "gold standard" method or measurement) and construct validity (the extent to which a tests result corresponds with expected results given the knowledge of the construct being assessed, in the absence of a "gold standard).[60] Indeed, in the field of exercise science, there is an absence of "gold standard" measures for some monitoring tools commonly used by practitioners, for example perceptual wellness assessments. In this case, wellness measures do not possess criterion validity and indeed are poorly defined as unidimensional constructs,[6] but may demonstrate construct validity and are therefore useful to practitioners. For instance, perceptions of wellness such as fatigue and soreness have been reported to decrease following periods of high training load, suggesting they possess construct validity.[45] This type of research (longitudinal observation) does not require intervention and allows practitioners to be confident that a monitoring tool is measuring what is intended.

Reliability

Reliability refers to the consistency of results in a test.[60] This characteristic can be assessed via test-retest analysis, where measurements are collected from the same individuals under identical test conditions[48] to produce a typical error measure, often expressed as a coefficient of variation percentage (CV%).[61] Knowledge of typical test error is important for practitioners as it allows interpretation of a change in a test result as meaningful; if a result does not exceed the typical test error, it cannot be considered meaningful. Reliability testing via test-retest analysis can be conducted unobtrusively within a normal training environment and provides a threshold for individual changes in test results to enhance interpretation for practitioners. An alternative measure of reliability is a smallest worthwhile change (SWC), which has historically been calculated by multiplying the standard deviation of results from a cohort of athletes by 0.2, with 0.2 said to represent a small, non-trivial effect.[62] However, in some cases the SWC is less than the CV%, therefore changes in test results must exceed both the SWC *and* the CV% for practitioners to interpret them as meaningful. Both the CV% and SWC can be calculated easily to provide an interpretable index of the typical error in monitoring tests.

An alternative method of assessing measurement reliability is determining a minimal clinically important change (MCIC), which may be greater than the CV% or SWC value established via reliability testing.[63] Indeed, a change that exceeds the typical measurement error may represent a statistically meaningful change, but depending on a range of factors in a team sport context (i.e. the physical characteristics of the individual from whom the result was derived), it may not be clinically or practically important.[63] For example, a change in a test result may exceed the CV% or SWC, but not have a meaningful effect on an outcome measure of interest, i.e. training completion or performance. In the case of training load prescription, a statistically meaningful change in a monitoring test may not alter the type, nature or intensity of training delivered to an athlete, or their training completion or subsequent performance. To date, no research has presented a uniform method of calculating a MCIC as it is dependent on the cohort of athletes being tested.

Sensitivity

Sensitivity is defined as the extent to which a test can detect changes beyond the typical error in results consistently.[8] Sensitivity is typically assessed via intervention studies, where a cohort of participants are provided with an intervention following pre-testing, and subsequent to the intervention are tested again, where the difference between pre- and post-test results represents the sensitivity or responsiveness of the measurement.[64] However, this type of investigation is not possible in professional team-sport environments due to time, cost and risk of fatigue and injury to athletes. An alternative to the intervention method is to combine typical test error and test result variation as a proxy for sensitivity. Specifically, sensitivity can be quantified using signal-to-noise ratio (SNR) analysis. In the case of athlete monitoring, "signal" refers to individual changes in a monitoring test in response to training stimuli while "noise" is represented by the typical error in the measurement (from test-retest reliability analysis). Measurement signal and noise can be combined to produce a SNR, providing practitioners with an index of responsiveness in a measure relative to the typical error in the test. This analysis allows practitioners to confidently interpret test results as meaningful or unimportant.[50] In professional team sport athlete monitoring, results from a monitoring test must exceed the typical test error consistently during a given period to be considered sensitive. If results are generally not exceeding the normal test error, the level of error is too high for practitioners to detect meaningful changes. Previous research in professional Australian football has reported SNRs of above 1 to represent acceptable sensitivity and above 1.5 to represent "good" sensitivity,[50] however ultimately this form of sensitivity analysis provides a dichotomy. Indeed, if a monitoring test displays a SNR of below 1, it indicates that the test cannot consistently detect meaningful changes in the test, whereas a SNR of above 1 shows that a results from a test are consistently greater than the typical error (CV%) and hence can be interpreted as meaningful. Therefore, SNR analysis is a relatively simple and unobtrusive method of assessing monitoring test sensitivity within a normal training environment of professional sporting teams.

Diagnostic Accuracy

After establishment of monitoring test validity, reliability and sensitivity, the utility of a monitoring test in detecting meaningful changes in an outcome measure should be examined. This is commonly assessed via establishment of the sensitivity (true positive rate) and specificity (true negative rate) of a test against a gold standard of measurement, quantified as a Youden Index.[65,66] Previous research has presented this concept in a confusion matrix that illustrates definitions of true positive and true negative results in an outcome measure following change in an independent variable (i.e. a monitoring test), shown below in table 3.1.[65]

Table 3.1: *Definitions of monitoring tool diagnostic characteristics.*

Measurement characteristic	Quantification	What does it tell us?
(1) Sensitivity	True positive rate	Does this test consistently detect meaningful changes in performance?
(2) Specificity	True negative rate	Does this test consistently detect unmeaningful changes in performance?
Diagnostic Accuracy	Sensitivity + Specificity - 1	An index of diagnostic accuracy; 0 = no accuracy, 1 = perfect accuracy

Conclusion

Monitoring tests must possess validity, reliability and sensitivity to provide valuable and interpretable information to practitioners of professional sporting teams. Given these measurement characteristics, practitioners can be confident that the tests they are using are (1) measuring the construct they intend to measure, (2) yielding consistent results, regardless of tester and test subject and (3) producing results that exceed the typical test error and can hence be interpreted as meaningful or unimportant. Observational research, test-retest analysis and SNR analysis represent simple and practical methods of determining validity, reliability and sensitivity of monitoring tools within professional team sport environments. These measurement characteristics should be established specific to the protocols used by professional sporting teams to ensure they are providing practitioners with the most useful information to inform decisions regarding their athletes.

Chapter Four | Study One | Measurement properties of an adductor strength-assessment system in professional Australian footballers

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Abstract

Objectives: To examine the measurement properties of an adductor strength assessment system for professional Australian footballers.

Design: Observational, longitudinal.

Methods: Test-retest reliability data were collected from 18 professional Australian footballers from one club on the same day during the 2017 AFL competition. Week-to-week variation data were collected on 45 professional Australian footballers from one club during the same season at 48 h, 72 h and 120 h post-match. Players lay beneath a GroinBar Hip Strength Testing System in supine position with their knee joint at an angle of 60 degrees. Players provided a pain score from 0-10 (0=no pain, 10=maximum pain). Force (N) was extracted for left and right limbs of each player. Coefficient of variation (CV) and smallest worthwhile change (SWC) were calculated on test-retest data. Signal-to-noise ratio (SNR) was calculated for each major time point by CV. Mean difference between force scores in a subgroup of players with and without groin pain (n=18) were collected as evidence of construct validity for the system.

Results: Test CV was 6.3% [4.9, 9.0]. CV exceeded the SWC on both limbs. Overall intraclass correlation coefficient (ICC) was 0.94. The SNR ranged from 1.6 and 2.6 on average for 48, 72 and 120 hours post-match. Groin pain had a very likely moderate negative effect on adductor strength (ES: 0.41).

Conclusions: The system possesses greater measurement precision compared to other methods of assessing adductor strength within professional Australian footballers. Increased groin pain reduced groin squeeze force production. Practitioners may interpret changes exceeding 6.3% in adductor strength as meaningful.

Key Words: training monitoring, reliability, sensitivity

Introduction

Functional movement screening and force tests are used to regularly assess movement quality in professional team sport athletes. One common test used on Australian footballers is adductor force assessment.[67,68] Previous studies have shown that chronic adductor pain (osteitis pubis) can be attributed to a combination of altered pelvic integrity and changes in adductor force production following intense exercise such as competition match-play.[67,68] Similarly, studies in professional rugby league players reported decreased adductor force 24 to 48 hours (h) post-match.[69] This reduction was associated with greater high-speed running load in the preceding game, indicating that match activity profile influences adductor force output. Collectively, this association with injury and changes in match load provides basis for regular adductor force output monitoring in professional Australian footballers.

For an athlete monitoring tool to provide useful information, it should be reliable and display an appropriate signal-to-noise ratio.[16] Reliability may be assessed using a test-retest method, where typical test error is assessed within a normal training environment.[47] This measure of reliability can be used in conjunction with weekly variation to produce a signal-to-noise ratio[66] to indicate if a change in a measure from an individual (signal) exceeds the normal variation of the measure. A lower ratio is preferable, as it indicates a change in the measure is able to be detected, given the measurement noise associated with the test.[66]

Adductor force production in Australian footballers has been previously been measured using handheld dynamometry and sphygmomanometers.[68,70] Research has reported this method to have an acceptable level of reliability, with ICC (intraclass correlation coefficient) ranging from 0.70 to 0.90[68,70] and minimal test-retest variance (<6%) in general population participants.[71] Other research has shown adductor pain to significantly reduce adductor force when assessed using a sphygmomanometer.[72] However, measurement error is potentially increased by these techniques being dependent on the tester following a consistent method of test administration. A system has recently been developed for adductor force assessment via hip adduction for the left and right limb. This requires custom load cell placement to correspond with individual player height, ensuring the position of the player's limbs and hip and knee joint angle is identical for every assessment, allowing for greater standardisation of results. These elements theoretically minimise measurement error, however information regarding the measurement characteristics of the system has not been investigated.

The aim of this study was therefore to examine the measurement characteristics of reliability and sensitivity of a standardised adductor force assessment system for professional Australian footballers. This information will assist practitioners to contextualise changes in adductor force of their players at major time points following professional Australian football match-play and provide a threshold for meaningful changes in adductor force test results.

Methods

Reliability testing was completed on 18 professional Australian footballers from one club on the same day during the 2017 AFL competition season (age: 23.14 ± 2.06 y; height: 1.86 ± 0.04 m; weight: 78.14 ± 8.79 kg). Week-to-week variation data was collected on 45 professional Australian footballers from one club during the 2017 AFL competition season (age: 24.58 ± 4.03 y; height: 1.88 ± 0.07 m; weight: 86.04 ± 9.07 kg). Informed consent and institutional ethics approval were obtained (HREC: ETH17-1942). All testing was conducted within 30 minutes in the morning prior to a main on-field training session. All players participating in the study were free of injury and trained fully during the session following the testing. Players were familiar with testing procedures, having completed the assessment a minimum of five times previously. Assessment time points were chosen to correspond with the club's typical weekly system of player monitoring. These coincided with a recovery day post-match (+48 h) and main skills training sessions (+72 to 120 h) during the week. Week-to-week variation data was collected from the week prior to the first competition match of the season until the week prior to the final competition match of the season. Data collected from players not in full training were excluded from further analysis.

Players were required to lie beneath the GroinBar Hip Strength Testing System (Vald Performance, Albion, Australia) in a supine position with their knee joint at an angle of 60 degrees. Bar height was customised for each player to ensure they maintained a knee joint angle of 60 degrees while being in the appropriate position beneath the apparatus. Placing the femoral medial condyle of both knees on load cells (sample rate of 50Hz), players were given a verbal cue to complete a warm-up of one repetition at 80% of their maximum effort. After a short break they were asked to complete a maximum repetition, pushing their femoral medial condyles against the pads as hard as possible for five seconds, providing a measure of force (N) for left and right limbs.[68] Following the test, players were asked to provide a score out of 10 on a visual analogue scale for pain felt during the squeeze, with 0 indicating no pain and 10 indicating maximum pain. Live data was captured via the GroinBar iPad application and uploaded to a personalised cloud account and exported into a customised Microsoft Excel spreadsheet (Microsoft, Redmond, USA) for analysis. All tests were administered by the same individual.

Statistical Analyses

A single figure of force (N) was collected for the left and right limbs of each player, in addition the combined force of both limbs divided by two. The intrarater reliability of the test was assessed using Hopkins reliability spreadsheets,[62] calculating a coefficient of variation percentage (CV%) and smallest worthwhile change (SWC). Week-to-week variation was assessed using the same Hopkins reliability spreadsheets.[62] A signal-to-noise ratio (SNR) was also calculated by dividing the week-to-week variation of each major time point (48 h, 72 h and 120 h post-match) by the reliability CV. SWC was calculated as 0.2 x between-subject standard deviation, corresponding with previous research.[47,68] Intraclass correlation coefficients were calculated for comparison with previous analyses. Mean, standard deviation and 90% confidence intervals were calculated for all tests to determine the precision of values calculated.[47,68] To determine the effect of reported groin pain on adductor strength, mean differences between those with reported groin pain (yes or no) among the test-retest group (n=18) were assessed using Hopkins validity spreadsheets.[62]

Results

Reliability results are shown in Table 4.1. Overall, the test had a CV% of 6.3% [4.9, 9.0] and an intraclass correlation coefficient (ICC) of 0.94, with CV exceeding the SWC on both limbs. Week-to-week variation results for 48 h, 72 h and 120 h post-match are shown in Table 4.2. The SNR ranged from 1.6 and 2.6 on average for 48 h, 72 h and 120 h post-match. All CV% values exceeded the corresponding SWC for both limbs at all major time points. Reported groin pain had a very likely moderate negative effect on adductor strength (effect size: 0.41 [0.26, 0.55]).

Table 4.1: *Test-retest reliability of GroinBar Hip Strength Testing System.*

Variable	**Left**	**Right**	**Average**
Mean (N)	382.3	380.6	381.5
SD (N)	94.3	91.1	92.0
SWC% (90% CI)	5.0 [3.4, 6.3]	5.0 [3.4, 6.3]	5.0 [3.4, 6.4]
CV% (90% CI)	6.3 [4.9, 9.0]	6.7 [5.2, 9.4]	6.3 [4.9, 8.9]
Intraclass correlation coefficient	0.95 [0.89, 0.97]	0.94 [0.88, 0.97]	0.94 [0.87, 0.96]

SD: standard deviation of the mean; SWC: smallest worthwhile change; CV: coefficient of variation; SNR: signal-to-noise ratio; N: Newtons.

Table 4.2: *Signal-to-noise ratio of adductor strength at 48 h, 72 h and 120 h post-match.*

	48 hours (n=249)			**72 hours (n=299)**			**120 hours (n=277)**		
	Left	Right	Average	Left	Right	Average	Left	Right	Average
Mean (N)	381.0	377.9	379.0	381.1	383.2	378.8	377.1	375.5	375.4
SD (N)	100.2	95.0	97.5	96.0	91.3	94.3	90.4	85.3	86.3
SWC% (N)	5.0 [2.8, 6.5]	5.2 [3.2, 6.5]	5.0 [2.8, 6.5]	4.4 [3.0, 9.2]	4.4 [1.8, 5.5]	6.3 [3.2, 8.9]	4.5 [2.0, 5.9]	3.7 [-0.6, 5.4]	4.4 [0.3, 6.2]
CV% (N)	12.7 [11.2, 4.8]	11.5 [9.5, 15.0]	12.6 [10.3, 16.6]	10.5 [8.1, 15.4]	13.5 [9.7, 24.0]	16.2 [11.2, 36.7]	11.3 [8.2, 25.9]	3.8 [9.3, 35.3]	9.9 [6.4, 27.7]
SNR	2.0	1.7	2.0	1.7	2.0	2.6	1.8	2.1	1.6

SD: standard deviation of the mean; SWC: smallest worthwhile change; CV: coefficient of variation; SNR: signal-to-noise ratio; N: Newtons.

Discussion

The present study demonstrated a relatively high level of reliability of the adductor force assessment system (CV <10%).[47] The system also showed sensitivity to changes in training and competition demands, with SNR of at least 1.6 at 48 h, 72 h and 120 h post-match. Additionally, adductor pain showed a very likely moderate negative effect on subsequent adductor force. These results allow practitioners to confidently interpret changes in adductor force as meaningful within professional Australian footballers at major time points during a typical training week following competition matches.

Results showed an intrarater ICC of 0.94, indicating excellent reliability,[73] particularly in comparison to previous research assessing adductor force using hand-held dynamometry[68] and sphygmomanometer[72] methods (ICC=0.70-0.90). The difference in ICC between studies is unsurprising, given the enhanced standardisation of data collection procedures in the current system. The use of hand-held dynamometry and sphygmomanometer assessment involves estimates of hip and knee joint angle, and in the case of the sphygmomanometer method, force values are collected via visual inspection of a monitor, making standardisation of testing difficult.[68,70] In this study, standardisation was enhanced with all tests conducted with limbs in the same location and knees in the 60-degree position, allowing for differences in player limb length. We found a CV of 6.3% via test-retest reliability analysis, lower than reported values for the sphygmomanometer method (7.6%).[68] Collectively, our results indicate that the system examined in this study possesses greater measurement precision in comparison to the dynamometry and sphygmomanometer methods of assessing adductor force in professional Australian footballers.

A monitoring tool is deemed sensitive if the variation in test results consistently exceed the normal variation in results, with a higher SNR indicative of greater test sensitivity.[66] Our results showed the system to be sensitive to changes in adductor strength, with a SNR of at least 1.6 at 48 h, 72 h and 120 h post-match. Notably, the greatest sensitivity was found at 72 h post-match compared to the other time points, illustrating the post-match period of greatest change in adductor force. However, other research in Australian football reported trivial differences in adductor strength assessed via a sphygmomanometer between 48 and 72 h post-match,[51] suggesting caution should be applied when interpreting changes in adductor force as a direct measure of recovery following a match. Future research may examine the relationship between match activity profiles and subsequent adductor force to fully explore the efficacy of this test as a measure of neuromuscular fatigue.

The results of the present study also showed a very likely moderate negative effect of reported adductor pain on adductor force ouput.[62] This is in agreement with other research in Australian footballers that reported a significant negative association between adductor pain and adductor force via sphygmomanometer assessment.[72] This suggests that the system examined here is capable of discriminating between players with and without reported adductor pain, establishing further efficacy as an adductor force assessment tool in professional Australian footballers.

While this study was the first to examine the measurement properties of an adductor force assessment system in professional Australian footballers, some limitations should be considered when applying our findings. The test relies on maximal efforts from subjects and despite the cues given to players to provide a maximal adductor contraction, their motivation may have fluctuated and influenced their test result. Further, variation in adductor force following matches (72 and 120 h post-match) are likely mediated by individual recovery strategies and match loads not reported in this study.

Conclusion

This study examined the measurement properties of an adductor force assessment system in professional Australian footballers. Our results demonstrated an appropriate level of reliability (CV of 6.3%) and sensitivity (SNR of 1.6-2.6 and very likely moderate effect of groin pain on adductor strength) for the system, establishing a useful tool for detecting changes in adductor force within professional Australian footballers at major time points following competition matches.

Practical Applications

- The system examined in this study possesses greater measurement precision in comparison to the dynamometry and sphygmomanometer methods of assessing adductor force within professional Australian footballers.
- Practitioners of professional Australian football teams may interpret changes in adductor force exceeding 6.3% as meaningful and reported groin pain to have a very likely negative effect on adductor force.

Chapter Five | Study Two | Measurement characteristics of athlete monitoring tools in professional Australian football

Ryan, S., Pacecca, E., Tebble, J., Hocking, J., Kempton, T., & Coutts, AJ. (2020). Measurement characteristics of athlete monitoring tools in professional Australian football. International Journal of Sports Physiology and Performance. 15(4);457-463. Doi: 10.1123/ijspp.2019-0060.

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Abstract

Purpose: To examine the reliability and sensitivity of common athlete monitoring tools in professional Australian football players.

Methods: Test-retest reliability (noise) and weekly variation (signal) data were collected from 42 professional Australian footballers from one club during the 2018 competition season. Perceptual wellness was measured via questionnaires completed before main training sessions (48, 72 and 96 h post-match), with players providing a rating (1-5 Likert scale) regarding their muscle soreness, sleep quality, fatigue level, stress and motivation. Eccentric hamstring force and countermovement jumps were assessed via proprietary systems once per week. Heart rate recovery (HRR) was assessed via a standard submaximal run test on a grass-covered field with players wearing a heart rate monitor. The HRR was calculated by subtracting average heart rate during final 10 seconds of rest from average heart rate during final 30 seconds of exercise. Typical test error was reported as coefficient of variation (CV% and TE) and intraclass correlation coefficient (ICC). Sensitivity was calculated by dividing weekly CV by test CV to produce a signal-to-noise ratio (SNR).

Results: All measures displayed acceptable sensitivity. SNRs ranged from 1.3-11.1. ICCs ranged from 0.30 to 0.97 for all measures.

Conclusions: The HRR test, CMJ test, eccentric hamstring force test and perceptual wellness all possess acceptable measurement sensitivity. SNR analysis is a novel method of assessing measurement characteristics of monitoring tools for professional AF players. These data can be used by coaches and scientists to identify meaningful changes in common monitoring tests in professional Australian football.

Key Words: athlete monitoring, reliability, sensitivity

Introduction

Athlete monitoring systems are commonly used in professional team sports to provide coaches and scientists with an understanding of player performance readiness and injury risk.[6] Information from these systems is used to prescribe training load to maximise adaptations whilst maintaining player availability for competition. Recent research and technological advances have increased the number of tools available to assess constructs of the training process. These include submaximal heart rate tests,[58] countermovement jump tests,[74] lower limb muscular force tests[59] and perceptual wellness questionnaires.[45]

Due to environmental constraints and risk of injury in fatigued athletes, it is impractical for professional team sport athletes to complete maximal physical capacity tests during the season to determine changes in fitness and fatigue.[7] Therefore, practitioners rely on monitoring tools that are submaximal in nature and easily administered that can identify changes in training load, response and neuromuscular performance regularly throughout training and competition to assess the readiness of their players. To provide useful information to coaches and scientists, these tools should display measurement characteristics of validity (the ability of a test to measure what it is designed to measure), reliability (the consistency of results from a test) and sensitivity (the extent to which a test can detect changes beyond the typical error in results).[8] Reliability can be assessed via test-retest analysis, where measurements are collected from the same individuals under identical test conditions.[48] This produces a typical error measure, often expressed as a coefficient of variation percentage (CV%) that indicates the level of error to be accounted for when interpreting changes in that test.[61] Using the CV%, the sensitivity of a test can be established via signal-to-noise anlysis.[48] Indeed, measurement signal is often assessed via intervention studies where responsiveness (i.e. a change in performance) is measured following the intervention,[64] however this is not possible in professional team sport environments due to time and cost constraints. Therefore, in the case of team sport athlete testing, “signal” refers to individual changes in a monitoring test in response to training stimuli (provided by a valid test), while “noise” is represented by the typical error in the measurement (derived from test-retest reliability analysis). Measurement signal and noise can be combined to produce a signal-to-noise ratio (SNR), providing practitioners with an index of responsiveness in a measure relative to the typical error in the test. This information is important to coaches and scientists as it allows confident interpretation of athlete monitoring data by identifying meaningful changes (i.e. those results that exceed the “noise” in the test).

Studies in professional Australian football (AF) have shown perceptual wellness questionnaires are sensitive to weekly change in training load[45] and match load,[46] suggesting they are valid measures of training response in this athletic population. However, the measurement characteristics of perceptual wellness questionnaires has received little research attention. A study of collegiate basketballers reported a total perceptual wellness questionnaire CV% of 6.9,[74] while research in professional AF reported a Cronbach’s alpha of 0.87 as a measure of reliability on a composite scale of nine wellness constructs.[45] These findings indicate that perceived wellness questionnaires possess acceptable reliability as measured by CV%,[48] however the capability of these questionnaires to detect changes that exceed the typical error is unknown. Moreover, while changes in perceived wellness are typically expressed as z-scores,[46] no research has examined the reliability of perceived wellness using this method. Additionally, while the Nordic eccentric hamstring strength test possesses acceptable reliability as a measure of hamstring force production and can discriminate between previously injured and uninjured athletes,[52] the sensitivity of this test in professional AF players has not been established.

Separately, submaximal heart rate tests may be administered at regular intervals to provide practitioners with a non-fatiguing assessment of changes in aerobic fitness in team sport athletes.[49] Previous research in professional AF reported a submaximal heart rate recovery test to be a valid and reliable measure of training status.[49] However, the capacity of this test to detect changes exceeding the typical error has not been examined in this athletic population. Additionally, countermovement jump (CMJ) tests are commonly used to assess neuromuscular fatigue in professional AF players.[14,25] Countermovement jump performance has been shown to be responsive to match load, with substantial reductions in CMJ flight time following competition matches,[25] while another study reported decreases in CMJ performance were related to increases in low-speed movement and reduced accelerations during competition matches.[14] Moreover, CMJ performance has been shown to demonstrate acceptable measurement reliability in team sport athletes, with CV ranging from 1.1% to 7.1% across a range of CMJ variables.[47] However, no research has investigated if weekly variation in CMJ performance consistently exceeds the typical error in this test among professional AF players.

Collectively, research suggests that perceptual wellness questionnaires, eccentric hamstring force tests, CMJ tests and submaximal heart rate tests possess varying levels of reliability among a range of athlete cohorts. However, the extent to which changes in these tests consistently exceed their typical error remains unknown, limiting interpretability of test results for coaches and scientists. Therefore, the purpose of this study was to establish the reliability and sensitivity of common monitoring tests in a professional AF population. This information will allow coaches and scientists of professional AF teams to confidently identify and interpret meaningful changes in commonly collected monitoring data.

Methods

Subjects

Data were collected from 45 professional Australian footballers (age: 24.6 ± 4.0 y; height: 1.88 ± 0.07 m; body mass: 86.0 ± 9.0 kg) from one club during the 2018 AFL competition season (week prior to round 1 to round 23). Informed consent and institutional ethics approval were obtained (UTS HREC: ETH17-1942). Reliability and weekly variation testing protocols were identical for all four tests. The number of subjects varied between measurement tests and is reported in Table 5.2 and Table 5.3.

Perceptual wellness questionnaire

Players completed a short questionnaire on a smartphone device before the main field training session (7:00 to 9:00) prior to each competition match, prompting them to provide a rating from 1 to 5 (1 representing a low or poor rating and 5 representing a high or good rating) in relation to their perception of muscle soreness, sleep quality, fatigue level, stress and motivation. The questionnaire used in this study was customised for the observation group based on a common protocol used in previous research.[75] Test-retest reliability was conducted using an identical protocol on a main training day (96 h post-match in the final week of competition), approximately 30 minutes after their initial completion of the questionnaire, consciously avoiding recall of their previous responses. This method of reliability assessment was based on previous research in elite athletes.[66] All perceptual wellness responses were reported relative to players' individual mean and standard deviation as a z-score.[46]

Eccentric hamstring force test

Eccentric hamstring force was assessed once per week (72 hours post-match) in the afternoon following the main skills training session of the week (~ two hours post-training following food intake) using a proprietary hamstring force assessment system (Nordbord, Vald Performance, Albion, Australia). The timing of testing aligned with players' main resistance training session of the week following a match to allow at least 72 hours recovery prior to the next match. Players placed their feet inside two hooks containing two uniaxial strain gauges at the back of the Nordbord (superior to the lateral malleolus of each ankle) at a sample rate of 50 Hz and resolution of 0.25 Newtons and slowly moved their torso forward, with their bodyweight eliciting contraction of the hamstring muscle group. Once in a near-flat prone position, players placed their hands in front of themselves and gently fell toward the floor. Verbal cues were provided to prompt a 50% warm-up repetition (i.e. not a maximal effort), followed by three maximum effort repetitions. Test results were analysed by peak eccentric force for both limbs in Newtons (left, right and average). This protocol was based on a previous study using a customised apparatus,[52] however no research has established specific protocols for the system used in this study. Test-retest reliability was conducted using an identical protocol in the afternoon of a typical training day, with maximal tests separated by three minutes of static recovery.[52]

Countermovement jump test

CMJ performance was assessed once per week (72 hours post-match) during a strength training session in the afternoon following the main skills session of the week during the competition season (i.e. the same session as eccentric hamstring testing occurred). Players were allowed approximately two hours recovery following the morning training session where fluid and food was provided. Players held a wooden rod (12 x 1200 mm) across their shoulders and were instructed to choose a depth where they felt they could jump as high as possible. Verbal cues were provided to prompt a 50% warm-up repetition, followed by three maximum effort repetitions from the same starting position. This protocol was based on previous research using similar testing systems.[76-78] Peak force and jump height were measured by a proprietary force plate system (ForceDecks, Vald Performance, Albion, Australia) with a sampling rate of 1000 Hz. Vertical force range was 0 to 1000 kg and resolution of the force platform was 15 grams per 15 Newtons. Test-retest reliability was conducted using an identical protocol in the afternoon of a main training day, with tests separated by five minutes of passive recovery.[77] Variables chosen for analysis were based on previous studies in professional AF players[47] and collegiate athletes,[77] including peak jump height (via impulse momentum method), mean concentric force, reactive strength index modified (RSImod), relative peak power (highest power value recorded during one jump) and relative peak force (highest force value recorded during one jump). Calculations of these measures were adapted from previous research.[78]

Submaximal heart rate test

Submaximal heart rate tests were conducted on eight occasions throughout the competition season (48 hours post-match) as part of a warm-up for the main skills session of the week. Players were instructed to run back and forth on a grass-covered field over 80-m intervals for five minutes at a submaximal speed (12 $km \cdot h^{-1}$) while wearing a heart rate monitor (Polar T31 Wireless Heart Rate Monitor, Polar Australia). Players were prompted by a beep at the end of each running interval to ensure they maintained the correct running speed. Following the exercise protocol, players were instructed to sit on the ground and remain still for 60 seconds. Heart rate data was captured using 10 Hz Global Positioning System (GPS) units worn by each individual player between their scapulae within a small pouch in their training jersey, and downloaded using proprietary software (Openfield 1.20.0, Catapult Sports, Melbourne, Australia) following each test. The average heart rate (beats per minute) of each player in the final 30 seconds of the test period (HRex) and in the final 10 seconds of the 60 second recovery period (HRR) were collected.[49] Heart rate recovery was calculated by subtracting the average heart rate during the final 10 seconds of the 60 second rest period from the average heart rate (beats per minute) during the final 30 seconds of the heart rate test. Individual maximum heart rate values were derived from maximal testing (2-km time trial) conducted during the preseason training period.[79] Test-retest reliability was conducted using an identical protocol, with tests separated by a non-training day (48 hours) during the preseason training period.

Statistical Analyses

Data were exported from proprietary software and collated in a customised Microsoft Excel spreadsheet (Microsoft, Redmond, USA). Test-retest reliability was assessed using customised spreadsheets[62] to calculate the typical error, expressed as a coefficient of variation percentage (CV%), and intraclass correlation coefficient (ICC) for CMJ test, eccentric hamstring test and HRR test. ICCs >0.80 were considered acceptable.[80] Perceived wellness reliability was calculated using the same spreadsheets to generate a TE (typical error) value, as z-scores did not require log-transformation. Normality of wellness data was confirmed via inspection of histograms. Typical weekly variation was assessed using the same custom spreadsheets (CV%).[62] Weekly perceptual wellness was categorised by number of hours post-match (48, 72 and 96 hours) as it was the only measure collected at multiple time points within a training week. The SNRs for the four tests at each time point were calculated by dividing weekly variation CV or TE by the CV or TE established via test-retest reliability. Mean, standard deviation and 90% confidence intervals were also calculated.[48] SNRs were assessed as "poor" if <1.0, "acceptable" if 1.0-1.5, and "good" if >1.5, adapted from research in other professional sports.[66,81]

Results

Test-retest reliability results for perceptual wellness, eccentric hamstring force test, CMJ test and heart rate recovery test are shown in Table 5.1. Weekly variation and SNRs are shown in Table 5.2 and 5.3. All monitoring measures at all time points displayed acceptable to good SNRs. ICCs ranged from 0.30 to 0.97 across all measures.

Table 5.1: *Test-retest reliability of heart rate recovery, perceptual wellness, countermovement jumps and eccentric hamstring force tests.*

Monitoring measure	**Mean**	**SD**	**Subjects**	**CV/TE (90% CI)**	**ICC**
Heart Rate					
HRex (bpm)	88.8	5.3	16	1.2% (0.9, 1.7)	0.95
HRR (bpm)	28.7	7.0	16	5.0% (3.9, 7.3)	0.60
Perceptual Wellness					
Perceived stress (z-score)	0.0	0.1	14	0.07 (0.06, 0.11)	0.45
Perceived soreness (z-score)	0.2	0.5	14	0.29 (0.22, 0.43)	0.77
Perceived motivation (z-score)	-0.1	1.0	14	0.60 (0.46, 0.89)	0.72
Perceived sleep quality (z-score)	-0.1	1.1	14	0.71 (0.54, 1.05)	0.64
Perceived fatigue (z-score)	0.2	0.8	14	0.65 (0.50, 0.97)	0.30
Countermovement Jumps					
Jump height (cm)	38.2	5.2	18	3.9% (3.1, 5.5)	0.93
Mean concentric force (N)	1792.9	195.4	18	2.1% (1.7, 3.0)	0.97
Reactive strength index modified (m/s)	0.56	0.11	18	7.0% (5.4, 9.9)	0.90
Relative peak mechanical power (W/kg)	54.1	5.4	18	3.5% (2.8, 5.0)	0.89
Relative peak force (N/kg)	25.3	2.1	18	2.6% (2.0, 3.6)	0.92
Peak Eccentric Hamstring Force					
Left limb hamstring peak force (N)	391.4	63.4	18	4.2% (3.3, 5.9)	0.89
Right limb hamstring peak force (N)	401.1	67.5	18	3.3% (2.6, 4.7)	0.87
Average limb hamstring peak force (N)	396.4	63.9	18	2.9% (2.2, 4.0)	0.92

HRex: exercise heart rate; HRR: heart rate recovery; bpm: heart beats per minute; cm: centimeters; N: Newtons; W/kg: watts per kilogram of body weight; N/kg: Newtons per kilogram of body weight; m/s: metres per second; SD: standard deviation; CV: coefficient variation percentage; CI: confidence interval; ICC: intraclass correlation coefficient.

Table 5.2: *Weekly variation and signal-to-noise ratio of heart rate recovery, countermovement jumps and eccentric hamstring force tests.*

Monitoring measure	Mean	SD	Subjects	CV (90% CI)	SNR	SNR Rating
Heart Rate Recovery Test (n = 176)						
HRex (bpm)	81.6	6.2	41	7.4 (6.5, 8.9)	5.3	Good
HRR (bpm)	35.4	10.6	41	23.9 (16.2, 28.6)	1.4	Acceptable
Countermovement Jumps (n = 206)						
Jump height (cm)	38.0	4.4	35	5.9 (5.4, 6.6)	1.5	Acceptable
Mean concentric force (N)	1806.4	225.8	35	4.9 (4.5, 5.5)	2.3	Good
Reactive strength index modified (m/s)	0.50	0.10	35	13.5 (12.2, 15.2)	1.9	Good
Relative peak mechanical power (W/kg)	53.7	5.1	35	5.4 (4.9, 6.1)	1.5	Good
Relative peak force (N/kg)	25.3	2.5	35	6.4 (5.8, 7.2)	2.5	Good
Peak Eccentric Hamstring Force (n = 543)						
Left limb hamstring peak force (N)	378.2	78.1	39	8.4 (7.9, 8.9)	2.0	Good
Right limb hamstring peak force (N)	387.1	74.6	39	7.9 (7.4, 8.4)	2.4	Good
Average limb hamstring peak force (N)	382.6	74.0	39	7.0 (6.6, 7.4)	2.4	Good

SNR: signal-to-noise ratio; HRex: exercise heart rate; HRR: heart rate recovery; bpm: heart beats per minute; cm: centimeters; N: Newtons; W/kg: watts per kilogram of body weight; N/kg: Newtons per kilogram of body weight; m/s: metres per second; SD: standard deviation; CV: coefficient variation percentage; CI: confidence interval.

Table 5.3: *Weekly variation and signal-to-noise ratio of perceptual wellness measures.*

Monitoring measure	Mean	SD	Subjects	TE (90% CI)	SNR	SNR Rating
48 hours post-match (n = 576)						
Perceived stress (z-score)	0.0	0.7	42	0.78 (0.73, 0.83)	11.1	Good
Perceived soreness (z-score)	0.0	0.9	42	0.94 (0.88, 1.03)	3.2	Good
Perceived motivation (z-score)	0.0	0.8	42	0.78 (0.73, 0.83)	1.3	Acceptable
Perceived sleep quality (z-score)	0.0	0.9	42	0.92 (0.87, 0.97)	1.3	Acceptable
Perceived fatigue (z-score)	0.0	0.9	42	0.91 (0.87, 0.97)	1.4	Acceptable
72 hours post-match (n = 511)						
Perceived stress (z-score)	0.0	0.7	42	0.72 (0.68, 0.78)	10.2	Good
Perceived soreness (z-score)	0.0	0.9	42	0.91 (0.86, 0.98)	3.1	Good
Perceived motivation (z-score)	0.0	0.9	42	0.85 (0.80, 0.91)	1.4	Acceptable
Perceived sleep quality (z-score)	0.0	0.9	42	0.92 (0.87, 0.98)	1.3	Acceptable
Perceived fatigue (z-score)	0.0	0.9	42	0.92 (0.87, 0.98)	1.4	Acceptable
96 hours post-match (n = 431)						
Perceived stress (z-score)	0.0	0.1	42	0.09 (0.09, 0.10)	1.3	Acceptable
Perceived soreness (z-score)	0.0	0.8	42	0.86 (0.81, 0.93)	2.9	Good
Perceived motivation (z-score)	0.0	0.7	42	0.76 (0.71, 0.93)	1.3	Acceptable
Perceived sleep quality (z-score)	0.0	0.9	42	0.89 (0.83, 0.95)	1.3	Acceptable
Perceived fatigue (z-score)	0.0	0.9	42	0.95 (0.89, 1.02)	1.5	Good

SNR: signal-to-noise ratio: SD: standard deviation; TE: typical error; CI: confidence interval.

Discussion

The aim of this study was to establish the reliability and sensitivity of common monitoring tests in professional AF players. Our findings show that the heart rate recovery test, variables from CMJ test, eccentric hamstring force test and perceptual wellness questionnaire all possess acceptable sensitivity and therefore can confidently be used by coaches and scientists of professional AF teams to identify meaningful changes in these monitoring measures.

The present results showed that all wellness measures displayed acceptable SNRs at 48, 72 and 96 hours post-match, with perceived stress displaying the greatest sensitivity (SNR: 1.3 to 11.1). Notably, perceived stress and perceived soreness were the only two elements to display SNRs of >2.0 at any time point, suggesting that these are the most responsive to training stressors of the five wellness elements examined in this study. Interestingly, perceived stress displayed the equal-lowest SNR at 96 hours post-match, suggesting that factors affecting player stress levels were most influential at 48 and 72 hours post-match, possibly related to the previous week's match. Overall, SNRs for all wellness elements were lower (i.e. a weaker signal) at 96 hours post-match than at earlier time-points, with perceived soreness the only element to display a SNR of >1.5, indicating that players had stable perceptions of stress, motivation, sleep quality and fatigue within 96 hours post-match. This is in agreement with previous research in professional rugby league that reported perceived fatigue, general wellbeing and soreness to return to pre-game values within four days post-match.[75] Other research in professional AF also reported perceived fatigue, stiffness, sleep quality, stress and general wellbeing to improve as gameday approached (i.e. as hours following the previous match increased).[45] Another notable finding of the current study was that perceived sleep quality, motivation and fatigue displayed relatively low SNRs at all time points (SNR: 1.3 to

1.4). This suggests that players perceive changes in these elements as relatively minimal throughout a typical training week, therefore coaches and scientists should interpret changes in sleep quality, motivation and fatigue with relative caution. Perceived sleep quality, fatigue and motivation also displayed the highest typical error of the five elements examined in this study, indicating relatively poor reliability. Collectively, our findings suggest that perceived stress and soreness provide the most useful information regarding a player's perceived readiness to train based on acceptable reliability and relatively good responsiveness to training and life stressors.

Submaximal heart rate tests are considered valid measurements of aerobic fitness in individual and team sport athletes.[24,82] We found the typical test error in HRex and HRR to be considerably higher than those reported in previous research using similar protocols,[49] with disparities possibly due to subtle differences in test protocols, the smaller sample of players and the different manufacturer of the heart rate monitors used in the present study. Moreover, the previous study performed testing on an artificial turf surface indoors in contrast to our testing being conducted outdoors, the latter being less of a controlled testing environment. Additionally, different temperatures on testing days in the present study (20.0 degrees Celsius and 25.5 degrees Celsius, respectively) may further explain the difference in findings. Nonetheless, despite the relatively high typical error reported in our study, HRex and HRR displayed acceptable SNRs, indicating that the test can identify changes that exceed the typical error. Notably, HRex displayed greater sensitivity than HRR (5.3 compared to 1.4), therefore we suggest using heart rate during submaximal exercise in preference to heart rate during recovery as a training monitoring test in professional AF. Indeed, our study demonstrates that this is a non-invasive test[83] and hence we recommend the inclusion of a submaximal heart rate recovery test in monitoring systems of professional AF players.

The eccentric hamstring force test in the present study demonstrated lower typical error (CV%: 2.9 – 4.2%) compared to previous research in recreational athletes (CV%: 5.8 – 8.5)[52] and professional footballers (CV%: 4.3 – 6.3).[7] In contrast with previous research, we assessed reliability using highly-trained athletes who were very familiar with testing protocols. Moreover, the apparatus used in the present study likely possesses higher resolution and sample frequency than that used in previous research. Notably, left limb peak eccentric force production displayed a poorer reliability (CV%: 4.2) and subsequently a lower SNR than right limb (CV%: 3.3) and average force (CV%: 2.9) respectively, which may be due to the specific bilateral force imbalances of the observation group. Our finding agrees with a previous study in professional footballers that reported a lower test error for force values collected from players' dominant leg (CV%: 4.3) compared to non-dominant leg (CV%: 5.4). This supports monitoring of individual changes in dominant and non-dominant leg hamstring force in professional football. Collectively, our findings suggest that the test examined in the present study is a reliable and sensitive method to assess peak eccentric hamstring force in professional AF players throughout a competition season.

Previous research has assessed the reliability of the CMJ test[47] and relationships between CMJ performance and external load[14] in team sport athletes, however no studies have determined the sensitivity of this test using SNR analysis in professional AF players. The present study examined reliability and sensitivity of five CMJ variables, with concentric mean force (SNR: 2.3) and relative peak force (SNR: 2.5) displaying the greatest capability to detect changes that exceed the typical test error. Interestingly, these two variables also displayed similarly low typical test error (CV%: 2.1 and 2.6, respectively) to those reported previously,[47] suggesting they may be the most responsive CMJ measures for coaches and scientists of professional AF teams to monitor. However, previous research in collegiate athletes reported lower inter-day

CVs than those identified in our study, with test CV% ranging from 2.7 – 4.3% in relative peak power, relative peak force and relative mean force.[77] The differences in findings may be explained by the design of the present study in measuring CMJ performance within a professional AF training environment in contrast to reliability research conducted in a laboratory setting on three occasions during a seven-day period used in previous research.[77] We also examined the reliability and sensitivity of reactive strength index modified (RSImod), which has been presented as a superior measure to jump height and other force and power variables in assessing the stretch-shortening cycle of athletes and therefore their explosiveness when jumping.[84,85] Research in professional rugby league reported players with a greater RSImod demonstrated superior force, power and impulse during both the concentric and eccentric phases of a CMJ in comparison to their lower RSImod counterparts.[85] We found RSImod to have relatively low typical error (CV%: 7.0%) and high sensitivity (SNR: 1.9), indicating it to be a useful global measure of CMJ performance in professional AF players. While these results demonstrate that these CMJ test methods have appropriate reliability and sensitivity, a limitation of the approach used in the present study was the timing of testing post-training and hence we cannot be sure that players completing the test were in a fully-rested state. Indeed, this approach makes it difficult to determine the causes for any observed changes in these measures, as they may be influenced by recent training (earlier in the day) or chronic training effects not explored here.

While the results of this study provide information on the reliability and sensitivity of common measures for monitoring professional AF players, caution should be taken when generalising these findings. The current study did not relate these monitoring data against outcome measures (injury or performance), therefore further work is required to establish their efficacy as monitoring tools. Additionally, while the wellness measures examined in this study were customised for the observation group as is typically the case in professional team sports, they were not developed using accepted psychometric validation approaches. Therefore, it is recommended that changes exceeding the typical error in the measures reported in this study be interpreted alongside other validated measures of training response. Further, a possible confounding factor affecting our results was the collection of test-retest data obtained for peak eccentric hamstring force and countermovement jump tests following a field training session. Due to practical constraints in a high-performance environment with competing interests for scheduling priorities, we were unable to collect CMJ and eccentric hamstring test data from athletes in a completely fully-rested state (i.e. after overnight rest), which is recommended for assessment of true reliability. However, the present study provides an example of how these types of data can be interpreted within similar training environments.

Conclusion

The present study examined the reliability and sensitivity of commonly used monitoring tools in professional AF. Our findings provide a framework for assessing reliability and sensitivity of monitoring tests, and this information can allow practitioners to identify meaningful changes in results of these tests. While we classified tests with a SNR of 1.0 – 1.5 as acceptable, those that display a SNR of >1.5 will provide practitioners with more useful information when assessing changes in constructs of fitness and fatigue.

Practical Applications

- Perceived wellness questionnaires, eccentric hamstring force tests, countermovement jump tests and submaximal heart rate recovery tests demonstrate acceptable to good sensitivity.
- Monitoring perceived sleep quality, motivation and fatigue via wellness questionnaires provides little insight into the fitness and fatigue status of professional AF players.
- SNR analysis is a novel method of assessing the capacity of a measure to detect changes that consistently exceed typical test error when monitoring professional AF players.

Chapter Six | Study Three | Data reduction approaches to athlete monitoring in professional Australian football

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Abstract

Purpose: To address the issue of data overload for practitioners of professional Australian football teams via Principal Component Analyses (PCA).

Methods: Data were collected from 45 professional Australian footballers from one club during the 2018 AFL competition season. External load was measured in training and matches by 10 Hz Optimeye S5 and ClearSky T6 GPS units. Internal load was measured via session-RPE method. Perceptual wellness was measured via questionnaires completed before main training sessions with players providing a rating (1-5 Likert scale) of muscle soreness, sleep quality, fatigue, stress and motivation. Percentage of maximum speed was calculated relative to individual maximum speed recorded during preseason testing. Derivative external training load measures (total daily, weekly and monthly) were calculated. PCAs were conducted for Daily and Chronic measures and components were identified via scree-plot inspection (eigenvalue >1). Orthogonal rotation was undertaken with a factor loading redundancy threshold of 0.70.

Results: Components were identified by the Daily PCA identified components representing external load, perceived wellness and internal load. The Chronic PCA identified components representing 28-day speed exposure, 28-day external load, 7-day external load and 28-day internal load. Perceived soreness did not meet the redundancy threshold.

Conclusions: Monitoring player exposure to maximum speed over chronic timeframes can capture variations in between-match training cycles. Perceived soreness represents a distinct element of a player's perception of wellness. Summed variable and single variable approaches are novel methods of data reduction following PCA of athlete monitoring data.

Key Words: athlete monitoring, data reduction, principal component analysis

Introduction

Athlete monitoring systems are commonly used in professional sport to provide insights into player training readiness and injury risk.[6] In the case of professional Australian football (AF), readiness refers to a player's ability to complete planned training activities with no excessive physical impairment, mental fatigue or psychological distress.[6] Evaluations of readiness are informed by objective and subjective sources including external training load measures,[11,86] internal load measures,[2] exposure to maximum sprint speed[87] and perceptual wellness assessments.[40] These data are typically analysed over short and longer timeframes to provide ongoing evaluations of how athletes are adapting to training and competition stimuli to inform acute training load prescription.

A challenge faced by coaches and scientists is synthesising and communicating actionable information from a broad range of data sources to support decision-making regarding a player's preparation for training and competition. Indeed, monitoring professional AF players is a complex process with inferences of player readiness derived from many data sources.[6] While extensive access to monitoring data allows practitioners to capture important information about the training process, this can lead to data overload, where data representing similar constructs (training load, response and neuromuscular performance) are analysed and reported.[11] This likely results in data collinearity, which can cause accentuation of relationships between monitoring variables and outcome measures when conducting observational analysis of athlete preparation data.[12] This can lead to erroneous conclusions when assessing the effect of monitoring measures on outcomes such as injury risk and performance.[12]

One approach to address the issue of data overload in athlete monitoring is to selectively reduce the number of variables that are collected and analysed to improve the efficiency of analysis without losing the veracity of the information provided by these data. One such method is Principal Component Analysis (PCA), a data reduction technique designed to evaluate the contribution of multiple variables to the variance of an entire dataset of correlated measures.[11,88]

Recent research has applied PCA to identify correlated training load measures in professional team sports. One study examining derivative measures of internal load (session-RPE) in professional rugby league players reported cumulative load measures (i.e. rolling values of load) to explain 57% of the variance in session training load, while 33% of the variance was explained by measures of change in load and acute load combined.[11] Other research in professional rugby league reported the most variance in individual training load from field-based skills sessions to be explained by either total distance covered, session-RPE load, or Player Load.[88] Collectively, these studies demonstrate that PCA is an effective approach to data reduction in team sport training load monitoring systems. However, evaluations of player training readiness are also based on a player's individual response to training and matches (i.e. perceptual wellness assessments) and derivative external load measures (i.e. cumulative weekly and monthly internal and external load). Indeed, no research has applied a data reduction method to commonly used player readiness measures to address the issue of data overload for practitioners of professional AF teams.

Separately, to provide useful information to coaches and scientists, monitoring tests should possess measurement characteristics of validity (the ability of a test to measure what it is designed to measure), reliability (the consistency of results from a test) and sensitivity (the extent to which a test can detect changes beyond the typical error in results).[8] Moreover, these tools must be practical and time-efficient to administer regularly without interrupting the training process.[50] Therefore, the inclusion of a variable into a professional athlete monitoring system should be based on measurement characteristics and feasibility (cost and time) in addition to their statistical contribution to a dataset (established via PCA). Consequently, the primary aim of this study was to apply a data reduction technique to athlete monitoring measures in professional AF using PCA. A secondary aim was to provide methods of applying the findings of PCA to inform selection of athlete monitoring measures based on their statistical contribution and practical efficacy.

Methods

Subjects

Data were collected from 45 professional Australian footballers (age: 24.58 ± 4.03 y; height: 1.88 ± 0.07 m; body mass: 86.04 ± 9.07 kg) from one club during the 2018 AFL competition season (week prior to round 1 to round 23, i.e. March to August). Informed consent and institutional ethics approval were obtained (UTS HREC: ETH17-1942).

Perceptual wellness

Players completed a short questionnaire on their smartphone before the main field training session each week, providing a rating from 1 to 5 (1 representing a poor rating and 5 representing a good rating) in relation to their muscle soreness, sleep quality, fatigue level, stress and motivation. While these methods were like those used in previous team sport research,[24,45,46] the questionnaire used in this study was customised for the observation group.

External training load

External training load was measured in training by 10 Hz Global Positioning System (GPS) units (Optimeye S5, Catapult Sports, Victoria, Australia). Each unit was assigned to an individual player and worn in a small pouch in their training or match jerseys. After each session or match, data were downloaded using proprietary software (Openfield 1.20.0, Catapult Sports, Melbourne, Australia). Eight of 22 matches included in the analysis were collected via an alternative system (ClearSky T6, Catapult Sports, Victoria, Australia) due to these matches being played indoors under a roof. All other match data were collected via the same system used for training sessions (Optimeye S5, Catapult Sports, Victoria, Australia). Unpublished data from the technology manufacturer has reported distances covered at low and high speed over 80 m to have differences of <5% between the two systems (Catapult Sports, Melbourne, Victoria, Australia). All data files were then cleaned to ensure only recorded data from time spent on the field and during actual training activities was retained. The training files for each player were then exported and placed into a customised Microsoft Excel spreadsheet (Microsoft, Redmond, USA) for analysis. This provided single figures to represent the total distance covered, total high-speed running (HSR; distance covered between 20 $km{\cdot}h^{-1}$ and 23 $km{\cdot}h^{-1}$) and very high-speed running distance (VHSR; distance covered >23 $km{\cdot}h^{-1}$)[89] covered by each player, their maximum speed (km/h) attained during a training session or match, and a total of inertial movement analysis (IMA) event counts to quantify accelerations, decelerations and changes of direction. Maximum speed attained during the session was then compared to each player's highest maximum speed recorded in a match during the observation season to generate a percentage of maximum. The primary GPS technology used in this study (Optimeye S5) is a valid and reliable method of quantifying movement in team sport activity, however research has reported greater measurement error with higher movement speeds.[90,91]

Internal training load

Internal training load was measured via the session-RPE method within 30 minutes after every training session and competition matches following standardised protocols.[32,92] Session-RPE is a valid and reliable method of quantifying internal training load in professional AF.[92]

Derivative load measures

Training load was classified according to acute and chronic timeframes[87] (Table 6.1). All load measures were inclusive of training and match loads.

__Table 6.1:__ Definitions of acute and chronic training load measures used in PCA.

Training Load Measure	Definition
Acute training load measures	
Daily Load	Distance or arbitrary units completed in one day
Daily Maximum Speed	Highest speed (km/h) reached in each field training session or competition match
Inertial Movement Analysis units	Number of IMA events completed in each field training session or competition match
Chronic training load measures	
Total Weekly Load	Distance or arbitrary units completed in last 7 days (rolling)
Total Month Load	Distance or arbitrary units completed in last 28 days (rolling)
Times >85% last 7 days	Number of instances >85% of maximum speed reached during the last 7 days (rolling)
Times >90% last 7 days	Number of instances >90% of maximum speed reached during the last 7 days (rolling)
Times >85% last 28 days	Number of instances >85% of maximum speed reached during the last 28 days (rolling)
Times >90% last 28 days	Number of instances >90% of maximum speed reached during the last 28 days (rolling)

Statistical Analyses

A total of 84,294 data points was collected from 23 monitoring variables and were collated into a customised Microsoft Excel spreadsheet (Microsoft, Redmond, USA) for analysis. Two PCAs were undertaken on “Daily” measures, i.e. those that were collected daily, and “Chronic” measures, i.e. those that described total load completed over the past 7 or 28 days.[11] Components were named based on the nature of variables identified within each component, for example “Daily External Load” for Component 1 in the “Daily” PCA. Prior to analyses, all data were tested for sampling adequacy using the Kaiser-Meyer-Olkin measure (a threshold of 0.5) and for suitability for component analysis using the Bartlett test of sphericity (significance accepted at $p = \leq 0.05$). For each PCA, orthogonal rotation was used to enhance interpretation of the analysis, while the principal components of each analysis were determined via inspection of a scree plot (Figure 6.1 and 6.2) in addition to eigenvalues of >1. Only variables with a factor loading of >0.70 were reported. These methods correspond with protocols described elsewhere.[11,88,93] Analyses were performed using Jamovi statistical software (Jamovi Project, version 0.9).

Table 6.2: *PCA of "Daily" training load and response measures.*

Component	Factor Loading	Mean	Standard Deviation
Component 1 – Daily External Load (34.4% variance, Eigenvalue: 3.8)			
TD Daily Load (m)	.92	6015.1	4125.6
HSR Daily Load (m)	.90	291.2	267.9
VHSR Daily Load (m)	.88	166.3	178.3
Daily Maximum Velocity (km/h)	.81	26.3	4.1
IMA (AU)	.81	74.7	63.8
Component 2 – Perceived Wellness (27.6% variance, Eigenvalue: 3.0)			
Motivation (1-5)	.84	3.6	.80
Stress (1-5)	.84	3.5	.60
Fatigue (1-5)	.81	3.3	.70
Sleep Quality (1-5)	.73	3.4	.70
Component 3 – Daily Internal Load (9.1% variance, Eigenvalue: 1.0)			
SRPE Daily Load (AU)	.99	211.1	303.3

VHSR: very high-speed running (>23km/h); HSR: high-speed running (>20km/h); TD: total distance; IMA: Inertial Movement Analysis; m: metres; AU: arbitrary units; SRPE: session rate of perceived exertion.

Table 6.3: *PCA of "Chronic" training load and response measures.*

Component	Factor Loading	Mean	Standard Deviation
Component 1 – Chronic Maximum Speed Exposure (33.6% variance, Eigenvalue: 4.0)			
Times >90% last 28 days (instances)	.83	3.3	1.8
Times >85% last 28 days (instances)	.82	6.2	2.1
Times >85% last 7 days (instances)	.79	1.6	.84
Times >90% last 7 days (instances)	.77	.86	.76
Component 2 – 28-day External Load (21.9% variance, Eigenvalue: 2.6)			
TD Total Month Load last 28 days (m)	.89	71045.3	24056.1
HSR Total Month Load last 28 days (m)	.89	3452.5	1388.7
VHSR Total Month Load last 28 days (m)	.84	1976.2	980.3
Component 3 – 7-day External Load (13.7% variance, Eigenvalue: 1.6)			
HSR Total Week Load (m)	.90	998.4	465.6
VHSR Total Week Load (m)	.85	570.9	326.1
TD Total Week Load (m)	.82	494.1	245.1
Component 4 – Chronic Internal Load (8.4% variance, Eigenvalue: 1.0)			
SRPE Total Month Load last 28 days (m)	.91	5687.1	1333.5
SRPE Total Week Load last 7 days (m)	.90	376.8	409.2

VHSR: very high-speed running (>23km/h); HSR: high-speed running (>20km/h); TD: total distance covered; m: metres; AU: arbitrary units; SRPE: session-RPE load.

Results

Three and five components were identified for Daily Measures and Chronic Measures, respectively. The percentage of variance and factor loadings for each component are shown in Table 6.2 and 6.3. Factor loadings denote correlations between each measure and the principal component it belongs to.[88] Kaiser-Meyer-Olkin measures were 0.80 and 0.59 for "Daily", and "Chronic, while both PCAs passed the Bartlett test of sphericity for factor analysis ($p < 0.05$). Of the 23 monitoring measures analysed, one displayed a factor loading below the redundancy threshold of 0.70 (perceived soreness). Three of the remaining 22 measures displayed a factor loading of between 0.70 and 0.80.

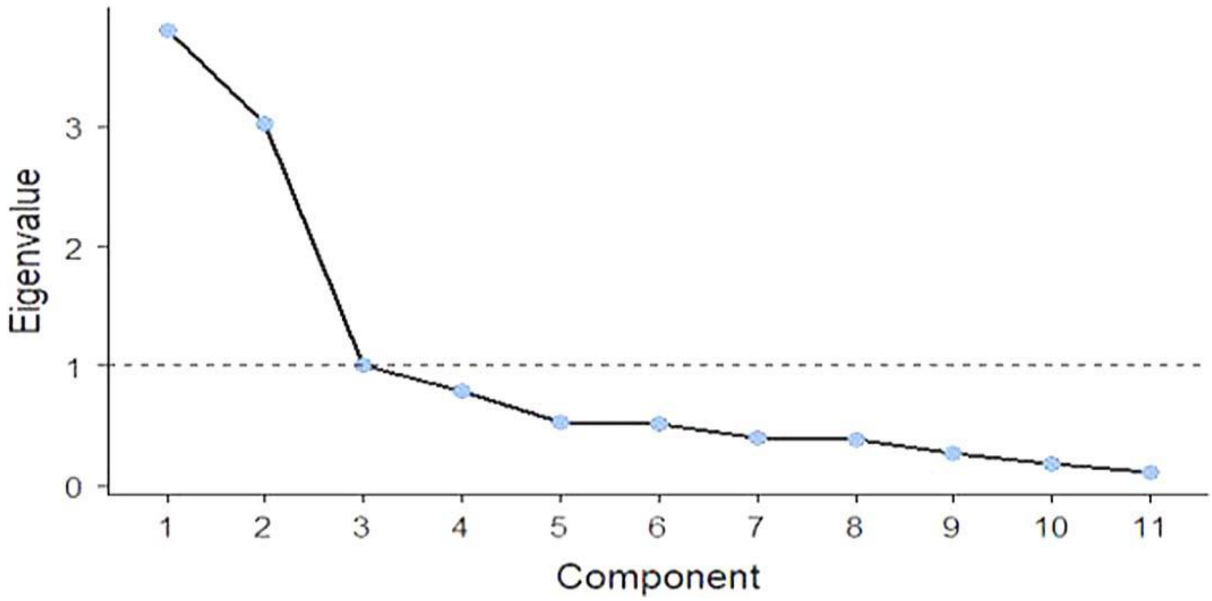

Figure 6.1: *Scree-plot of Daily monitoring measures PCA.*

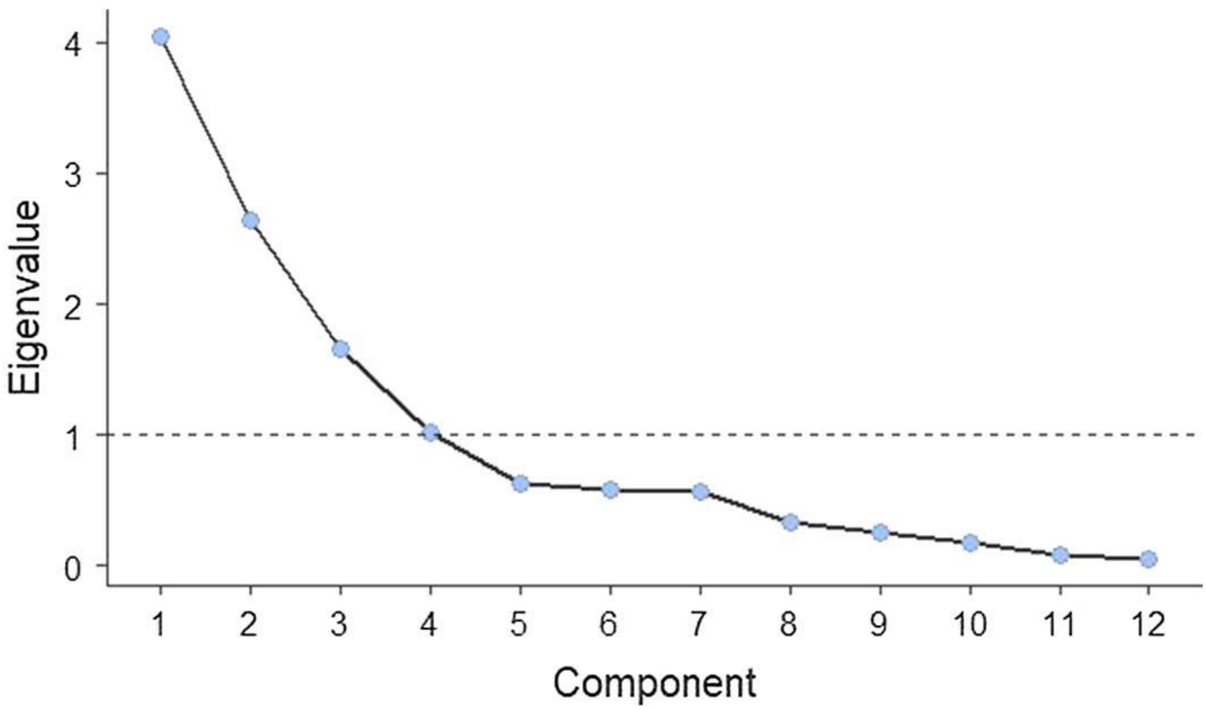

Figure 6.2: *Scree-plot of Chronic monitoring measures PCA.*

Discussion

The aim of this study was to apply a data reduction technique to common athlete monitoring measures in professional AF using PCA. A secondary aim was to apply the findings of the PCA to provide representative athlete monitoring measures based on their statistical contribution and practical efficacy. Of the 23 monitoring measures analysed, one (perceived soreness) displayed a factor loading below the redundancy threshold (0.70). The Daily PCA identified three components to represent daily external load, perceived wellness and daily internal load, respectively. The Chronic PCA identified components to represent four aspects of the dataset; chronic speed exposure, 28-day external load, 7-day external load and chronic internal load.

Daily monitoring measures

The "Daily" PCA highlighted three components to represent daily monitoring measures, with component one contributing 34.4% of variance all daily measures. Variables in this component were external load measures captured via GPS; total distance (TD), high-speed running (HSR) and very high-speed running (VHSR), maximum sprint speed and IMA count (captured via accelerometer within GPS units). Total distance covered and distance covered at high-speed (>14 km/h) captured via GPS have been shown to be practical, valid and reliable measures of movement in team-sport athletes.[27,94] The present findings show that either of these variables can be used to represent daily external load. According to factor loadings of each running distance variable (i.e. TD, HSR and VHSR), TD displayed the strongest correlation with the component, followed by HSR and VHSR, suggesting total distance provides the best representation of daily external load compared to high-speed distances (>20 $km \cdot h^{-1}$). In contrast, previous research in professional AF match-play has reported greater variability in volume of high-speed distances covered compared to total distance and maximum speed,[95] indicating the former is more important when monitoring running output from matches as individual differences are likely derived from high-speed output. However, it is well-established that there is increased measurement error with increased movement speed when quantifying movement in team sport athletes using GPS,[27,94] hence it remains unclear whether variability in higher speed measures during training and matches can be attributed to device error or actual variance in player movement. The difference in findings may be because total distance values (encompassing any locomotive movement) are always greater than high-speed distance values, hence total distance will have a greater loading (correlation) on the component. When selecting variables to represent daily external load, we suggest using total distance as it has the greatest loading on the daily external load component and is collected with less measurement error than high-speed distance measures.

The second component consisted of four perceived wellness elements (motivation, stress, fatigue and sleep quality), contributing 27.6% of the total variance of the dataset. Perceptual wellness questionnaires are commonly used in professional team sports as a practical method of assessing individual player recovery from a match and their readiness to train over acute timeframes.[43] Our findings suggest that perceived motivation, stress, fatigue and sleep represent a similar aspect of the dataset, hence may be used interchangeably when assessing daily perceived wellness of professional AF players. Interestingly, perceived soreness displayed a factor loading below the redundancy threshold of 0.70 within the "Daily PCA" in the present study, indicating a relatively poor correlation with the wellness component identified. This suggests that perceived soreness represents a statistically separate element to the other four wellness measures examined here; fatigue, sleep quality, stress and motivation measure one aspect of a player's perceived wellness while soreness represents an isolated element of a player's psychobiological response to training and match stressors and their readiness to train.

The third component consisted of only one measure, session-RPE daily load, with a factor loading of 0.98. Session-RPE has been established as a valid, reliable and feasible (cost and time-efficient) method of training load quantification[32,92] and is widely used by professional sporting teams. Our findings indicate that session-RPE measures an element of daily load separate to external load measures, in agreement with previous research in rugby league using the same statistical analysis technique.[96] A previous study reported session-RPE to have the highest factor loading among internal and external load measures during conditioning sessions,[96] indicating that a combination of internal and external load measures is required to quantify daily training load among professional team sport athletes. It is also well-established that a combination of external and internal load measures is necessary to comprehensively describe load completed by players, as individual responses to training stimuli ultimately determine training outcomes.[19] Moreover, session-RPE is a practical method of measuring load completed via other training modalities such as cross-training and resistance training.[6]

Chronic monitoring measures

The "Chronic" PCA identified four components to represent monitoring variables collected at rolling time points between 7 and 28 days. The first component consisted of exposures to maximum speed, with 28-day measures displaying stronger correlations to the component compared to 7-day measures. Indeed, players will have more exposures to their maximum speed across 28 days than 7 days, which may explain this observation. However, it is likely that a period of 28 days encompasses different between-match training microcycles (6 or 8 days) compared to 7 days and therefore provides a more representative indication of maximum speed exposure over a chronic period. Interestingly, research in professional AF has suggested that optimal maximum speed exposure (>85% of maximum speed) in reducing injury risk is between 5 and 8 instances over a 28-day period, indicating that monitoring speed exposure over a chronic (28-day) period may be more practical than acute periods relative to injury risk.[87] Taken together, we suggest monitoring maximum speed exposure over a 28-day period in professional AF players based on statistical contribution and practicality (i.e. association with injury risk and variations in between-match training cycle duration).

The second component identified 28-day external load variables (TD, HSR and VHSR distance), with TD and HSR distance displaying the equal-greatest factor loading on the component (0.89). This indicates that both variables contribute the same amount of variance to the dataset and therefore may be exchangeable when evaluating 28-day external load completed by players. However, given the increased measurement error associated with greater movement speed using GPS reported previously,[27,94] we suggest using TD to represent external load over a chronic period of 28 days. In contrast, component 3 identified three measures to represent 7-day external load (TD, HSR and VHSR distance) with HSR displaying the highest factor loading (0.90). This finding contrasts with the Daily PCA, possibly indicating that individual variation in player HSR output is more pronounced over a 7-day period compared to a single training session and is therefore more suitable to represent 7-day external load based on statistical contribution to the component.

Chronic internal load measures were represented by one component of the "Chronic" PCA, with average daily (over the past 28 days) and total weekly session-RPE load displaying strong correlations with the component (factor loadings of >0.90). Interestingly, session-RPE measures showed stronger correlations over longer timeframes (i.e. 28 days) than those over shorter periods (i.e. 7 days), suggesting the former may be a more appropriate period to assess global training load. This is likely due to the fact that any given 7-day period during a competition season may not include a competition match (i.e. eight days between some matches) which represents a substantial portion of a player's in-season load.[20] Therefore, we suggest monitoring internal load over 28 days in contrast to 7 days when evaluating player readiness based on total load completed.

One aim of the present study was to apply a PCA to common monitoring measures to reduce their number based on correlations between variables. However, while several studies have used PCA to reduce correlated athlete monitoring data, no research has proposed ways of using these components to inform selection of athlete monitoring measures on their statistical contribution and practical efficacy. We propose two methods of applying the findings of PCA to enhance efficiency in athlete monitoring; single variable approach and summed variable approach, with examples using the findings of the "Daily" PCA conducted in the present study.

Single variable

The single variable approach requires selecting one variable from each component of the PCA to represent an athlete monitoring measure based on measurement characteristics and practical efficacy. This is advantageous as it reduces a group of similar variables assessing the same aspect of the dataset to one valid, reliable and practical measure. For example, component one of the "Daily" PCA undertaken in the present study produced five external load variables above the redundancy threshold. TD, HSR and VHSR all demonstrated factor loadings of 0.88 – 0.92, hence their statistical contribution to the component is similar. Previous studies have reported GPS to be a valid and reliable method of time-motion analysis,[27,94] however this research also reported increased measurement error with increased speeds. Therefore, if practitioners prefer to select a single measure to represent a construct of daily external training load, we suggest selecting TD to represent daily external load among the variables examined in this study due to lower measurement error than HSR and VHSR distance covered. The benefit of the single variable approach is that it reduces a group of measures that provide similar statistical contribution to a single variable that best represents a monitoring construct and is most practical. However, the reductionist nature of this method can neglect the statistical contribution of other variables within the component that may provide similar contributions but are potentially not as reliable or practical.

Summed variable

The summed variable approach involves taking the values of each variable within a principal component and multiplying it by the factor loading identified via PCA, and then summing these values together to produce an arbitrary figure to represent each construct.[97] An example is shown in Table 6.4 using component one of the "Daily" PCA conducted in the present study. The advantage of this approach is that it provides a single arbitrary figure to represent a monitoring construct while accounting for the contribution of other variables in a component. While this approach is more inclusive than the single variable method, a limitation is that it dilutes the variance in contribution of variables to each component. Moreover, the summed variable produces an arbitrary figure which may be less interpretable that a single variable.

Table 6.4: *Summed variable approach to component one of "Daily" PCA.*

Variable	Equation
TD Daily Load (m)	TD Daily Load (m) x 0.92
HSR Daily Load (m)	(2) HSR Daily Load (m) x 0.90
VHSR Daily Load (m)	(3) VHSR Daily Load (m) x 0.88
Daily Maximum Speed (km/h)	(4) Daily Maximum Speed (km/h) x 0.81
IMA	(5) IMA x 0.81

VHSR: very high-speed running (>23km/h); HSR: high-speed running (>20km/h); TD: total distance covered; m: metres; km/h: kilometres per hour; IMA: inertial movement analysis events.

While this study was the first to apply a data reduction analysis technique to athlete monitoring measures in professional AF, our findings should be interpreted with caution. Firstly, external load during eight of 22 matches included in the analysis were collected using an alternative positioning system due to these matches being played at an indoor stadium, and while both methods are valid measures of player movement in team sport activity,[94,98] no research has established the technical agreement between these two systems. However, unpublished data from the technology manufacturer has reported distances covered at low and high speed over 80 m to have differences of <5% between GPS and LPS system units (Catapult Sports, Melbourne, Victoria, Australia). Secondly, this research did not model changes in any of the 23 variables examined against outcomes measures. Future research may assess the utility of the approaches presented here by establishing associations between a refined collection of monitoring variables and match performance. Lastly, our data were collected from one cohort of professional AF players during one season, hence may reflect the demographics of the group and the periodisation strategies adopted during the observation period. Nonetheless, the single variable and summed variable extensions of PCA may be applied to monitoring data from any cohort of professional athletes.

Conclusion

This study applied a data reduction technique and proposed methods for selecting monitoring measures to represent athlete monitoring measures based on their statistical contribution and practical efficacy. We presented two methods for applying the findings of PCA; a single variable approach and a summed variable approach. While both methods have advantages and disadvantages, we encourage practitioners to consider the exact nature and number of monitoring variables they collect within their training environment to decide the most appropriate approach. Indeed, the inclusion of a variable into an athlete monitoring system should be based on measurement properties and feasibility (cost and time) in addition to statistical contribution. The techniques presented in the current study help achieve efficiency in athlete monitoring, which is an important consideration for practitioners working in professional sport to ensure the best use of human and financial resources.

Practical Applications

- Monitoring player exposure to maximum sprint speed is more appropriate over chronic periods to capture variations in between-match training cycles.
- Subjective ratings of soreness represent an element of a player's perceived readiness to train that is statistically separate from stress, motivation, fatigue and sleep quality.
- Summed variable and single variable approaches are novel methods of athlete monitoring data reduction following principal component analyses.

Chapter Seven | Study Four | Application of a data reduction approach to neuromuscular performance measures in professional Australian football

Abstract

Purpose: To apply a data reduction technique to common measures of neuromuscular performance in professional Australian football.

Design: Prospective, longitudinal.

Methods: Data were collected from 45 professional Australian footballers from one club during the 2018 AFL competition season. Eccentric hamstring force was assessed via maximal Nordic hamstring exercises using a proprietary system. Countermovement jump performance was assessed using a proprietary force plate. Eccentric hamstring force and countermovement jump performance (CMJ) were measured approximately two hours post field training sessions once per week. Adductor strength was assessed via isometric adductor exercises using a proprietary system prior to each field training session per week. A Principal Component Analysis was conducted, with four principal components extracted, respectively. Each component underwent orthogonal rotation with a factor loading redundancy threshold of 0.70. Components were identified via eigenvalue analysis and scree-plot inspection. PCA factor loadings were used in equations to generate an arbitrary figure for each aspect of the dataset identified by the PCA.

Results: Variance explained by components ranged from 11.4% to 30.4%. Of the 12 measures analysed, only reactive strength index (CMJ) did not meet the redundancy threshold of 0.70.

Conclusions: Our findings provide basis for the use of PCA and summed and single variable methods of reducing neuromuscular performance data within monitoring systems of professional AF teams.

Key Words: principal component analysis, athlete monitoring, data reduction

Introduction

Athlete monitoring systems are commonly used in professional team sports to provide an understanding of player training readiness and injury risk.[6] In the case of professional team-sport, the term of athlete readiness is often used by practitioners to describe the athlete's capacity to complete training and competition.[6] Assessments of readiness commonly require input from a variety of sources, such as measures of neuromuscular fatigue,[14] muscular force[59] and muscular strength.[50] Information from these measures help provide ongoing evaluations of a player's neuromuscular performance,[17,99] and this element of the training process is considered by practitioners when making evaluations of individual player readiness to inform acute training load prescription.

Practitioners typically conduct multiple lower limb neuromuscular performance tests with their athletes (i.e. eccentric hamstring force, isometric adductor force, countermovement jump power), and it is likely that data derived from these tests is collinear. This can lead to data overload,[10] whereby data measuring similar constructs is collected and analysed, leading to inefficient use of human and financial resources. The collection of athlete monitoring data requires adequate time and expertise to analyse and present to coaches and practitioners for it to be most actionable.[10] Therefore, it is important to establish methods for enhancing efficiency in collection of monitoring data and address the problem of data overload for coaches and scientists.

One method used to reduce data is Principal Component Analysis (PCA), a data reduction method designed to evaluate the contribution of multiple variables to the variance of an entire dataset of correlated measures.[11,88] A PCA reduces a collection of variables to principal components (PC), with the importance of each component denoted by the amount of variance it contributes to the dataset.[100] Therefore, PCA ranks each variable within a group of measures based on the strength of relationship between the variable and the component it belongs via factor loadings. PCA provides a collection of uncorrelated components to explain aspects of an initial dataset.[11,86,100]

PCA has recently been applied as a data reduction method in athlete monitoring. One study examining the variance explained by 10 derivative measures of internal training load (session-RPE) in professional rugby league players reported cumulative load measures to explain 57% of the variance in session training load, while 33% of the variance was explained by measures of change in load and acute load combined.[11] Other research has applied PCA to common measures of training load and response in professional AF and used the resultant components as part of a single variable and summed variable approach to data reduction (Chapter Six).[101] Collectively, these studies have demonstrated that PCA is an effective method of item reduction in team sport player monitoring systems. However, no research has applied a data reduction method to commonly used neuromuscular performance measures to address the issue of data overload for practitioners of professional AF teams. Moreover, no studies have applied the single variable and summed variable approaches of data reduction to neuromuscular performance measures in professional AF.

Consequently, the primary aim of this study was to apply a data reduction technique to common neuromuscular performance measures in professional AF via PCA. The second aim was to apply the findings of this PCA to provide methods for selecting measures to represent constructs of neuromuscular performance based on their statistical contribution and practical efficacy.

Methods

Subjects

Data were collected from 45 professional Australian footballers (age: 24.58 ± 4.03 y; height: 1.88 ± 0.07 m; body mass: 86.04 ± 9.07 kg) from one club during the 2018 AFL competition season (week prior to round 1 to round 23, i.e. March to August). Informed consent and institutional ethics approval were obtained (UTS HREC: ETH17-1942).

Eccentric hamstring force

Eccentric hamstring force was assessed once per week (72 hours post-match) in the afternoon following the main skills training session of the week (~ two hours post-training following food intake) using a proprietary hamstring strength testing system (Nordbord, Vald Performance, Albion, Australia). The timing of testing aligned with the players' main resistance training session of the week following a match to allow at least 72 hours recovery prior to the next match. Players placed their feet inside two hooks containing two uniaxial strain gauges at the back of the Nordbord (superior to the lateral malleolus of each ankle) at a sample rate of 50 Hz and resolution of 0.25 Newtons and slowly moved their torso forward, with their bodyweight eliciting contraction of the hamstring muscle group. Once in a near-flat prone position, players placed their hands in front of themselves and gently fell toward the floor. Verbal cues were provided to prompt a 50% warm-up repetition (i.e. not maximal effort), followed by three maximum effort repetitions. Test results were analysed by peak eccentric force for both limbs in Newtons (left, right and average). This protocol was based on a previous study using a customised apparatus (Chapter Four),[52] however no research has established specific protocols for the system used in this study.

CMJ performance

CMJ performance was assessed once per week (72 hours post-match) during a strength training session in the afternoon following the main skills session of the week during the competition season (i.e. the same session as eccentric hamstring testing occurred). Players were allowed approximately two hours recovery following the morning training session where fluid and food was provided. Players held a wooden rod (12 x 1200 mm) across their shoulders and were instructed to choose a depth where they felt they could jump as high as possible. Verbal cues were provided to prompt a 50% warm-up repetition, followed by three maximum effort repetitions from the same starting position. This protocol was based on previous research using similar testing systems.[76-78] Peak force and jump height were measured by a proprietary force plate system (ForceDecks, Vald Performance, Albion, Australia) with a sampling rate of 1000 Hz. Vertical force range was 0 to 1000 kg and resolution of the force platform was 15 grams per 15 Newtons. Variables chosen for analysis were based on previous studies in professional AF players[47] and collegiate athletes,[77] including peak jump height (via impulse momentum method), mean concentric force, reactive strength index modified (RSImod), relative peak power (highest power value recorded during one jump) and relative peak force (highest force value recorded during one jump). Calculations of these measures were adapted from previous research.[78]

Isometric adductor force

Adductor strength was assessed using a proprietary testing system (Vald Performance, Albion, Australia) once per week during the competition season. Players lay in a supine position with their knee joint at an angle of 60 degrees. Bar height was customised for each player to ensure they maintained a knee joint angle of 60 degrees while being in the appropriate position beneath the apparatus. Placing the femoral medial condyle of both knees on load cells (sample rate of 50 Hz), players were given a verbal cue to complete a warm-up of one repetition at 80% of their maximum effort. After a short break they were asked to complete a maximum repetition, pushing their femoral medial condyles against the pads as hard as possible for five seconds, providing a measure of force (N) for left and right limbs.

Statistical Analyses

A total of 5,526 data points was collected for 12 monitoring variables and were collated into a customised Microsoft Excel spreadsheet (Microsoft, Redmond, USA) for analysis. A PCA was conducted to identify principal components of correlated variables to explain the contribution of each variable to the initial dataset.[11] Components were named based on the nature of variables identified within each component. Prior to analyses, all data were tested for sampling adequacy using the Kaiser-Meyer-Olkin measure (a threshold of 0.5) and for suitability for component analysis using the Bartlett test of sphericity (significance accepted at $p \leq 0.05$). Orthogonal rotation was used to enhance interpretation of the analysis, while the principal components of each analysis were determined via inspection of a scree plot (Figure 7.1) in addition to eigenvalues of >1. Only variables with a factor loading of >0.70 were reported. These methods correspond with protocols described elsewhere.[11,88,93] Analyses were performed using Jamovi statistical software (Jamovi Project, version 0.9).

Results

Four components were identified from the neuromuscular performance measures PCA. The percentage of variance and factor loadings for each component are shown in Table 7.1. Factor loadings denote correlations between each measure and the principal component it belongs to.[88] Kaiser-Meyer-Olkin measure was 0.65, while the PCA also passed the Bartlett test of sphericity for factor analysis ($p < 0.05$). Of the 12 monitoring measures analysed, one displayed a factor loading below the redundancy threshold of 0.70 (RSImod). One of the remaining 11 measures displayed a factor loading of between 0.70 and 0.80.

***Table 7.1**: PCA of neuromuscular performance measures.*

Component	Factor Loading	Mean	Standard Deviation
Component 1 – Adductor Strength (30.4% variance, Eigenvalue: 3.7)			
Left Adductor Maximum Force (N)	.99	429.3	77.9
Right Adductor Maximum Force (N)	.99	427.6	77.4
Average Adductor Maximum Force (N)	.99	428.7	77.3
Component 2 – Countermovement Jump Height (25.5% variance, Eigenvalue: 3.0)			
CMJ Mean Height (cm)	.97	38.1	4.4
CMJ Maximum Height (cm)	.96	36.7	4.4
CMJ Relative Peak Power (W/kg)	.77	53.7	5.1
Component 3 – Eccentric Hamstring Force (19.8% variance, Eigenvalue: 2.3)			
Left Hamstring Maximum Force (N)	.95	377.4	384.7
Right Hamstring Maximum Force (N)	.93	384.7	71.7
Average Hamstring Maximum Force (N)	.87	380.2	72.1
Component 4 – Countermovement Jump Force (11.4% variance, Eigenvalue: 1.3)			
CMJ Relative Peak Force (N/kg)	.85	1805.9	222.1
CMJ Mean Concentric Force (N)	.82	25.2	2.4

N: Newtons; CMJ: countermovement jump; cm: centimetres; W/kg: Watts per kilogram of bodyweight; N/kg: Newtons per kilogram of bodyweight.

__Table 7.2:__ Summed variable approach to components of neuromuscular performance measures PCA.

Component	**Equation**
(1) Adductor Force	0.99 x left adductor force + 0.99 x right adductor force + 0.99 x average adductor force
(2) Countermovement Jump Height	0.97 x CMJ mean height + 0.96 x CMJ max height + 0.77 x CMJ relative power
(3) Eccentric Hamstring Force	0.95 x left hamstring force + 0.93 x right hamstring force + 0.87 x average hamstring force
(4) Countermovement Jump Force	0.85 x CMJ relative peak force + 0.82 x CMJ mean concentric force

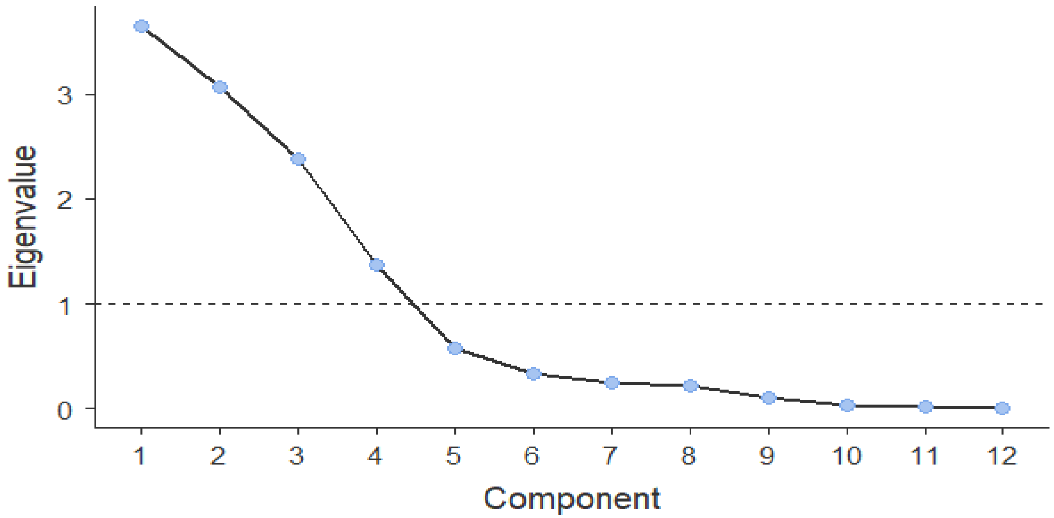

__Figure 7.1:__ Scree-plot of neuromuscular performance measures PCA.

Discussion

The PCA identified four components, with three representing the three neuromuscular performance tests examined; adductor force output, countermovement jump performance and eccentric hamstring force. Adductor force contributed 30.4% of the total variance in neuromuscular performance measures, with left, right and average adductor strength displaying identical factor loadings (0.99), hence near-perfect correlations with the component.[100] These results indicate that left, right and average adductor force may be used interchangeably when assessing these neuromuscular performance measures. Using the single variable approach advocated in previous research (Chapter Six),[101] if practitioners prefer one variable to represent adductor force output, we suggest monitoring average adductor force as it provides an index of left and right limb force. However, a disadvantage of the single variable approach is that it neglects the contribution of other variables within a component, i.e. dilutes possible imbalances between left and right limb adductor force. Therefore, we suggest the summed variable approach (Table 7.2) to reducing adductor force measures for practitioners to monitor.

The second component contained CMJ variables of mean height, maximum height and relative peak power, with both jump height variables displaying near-identical factor loadings (0.97 and 0.96). These measures have established reliability and sensitivity, with previous research in professional AF reporting jump height to display a CV% of <6%.[50] Like component one, we suggest that mean and maximum jump height may be used interchangeably when evaluating CMJ power output. In contrast to adductor force, the single variable approach is appropriate for this component as selecting one of maximum or mean jump height will not dilute the contribution of the alternate variable.[101] We suggest using CMJ mean jump height (across three jumps) to represent the construct of CMJ power as it is easily interpretable and can be used as a point of comparison among a cohort of professional AF players. Interestingly, CMJ force variables were identified in a separate component to power variables, suggesting they measure a statistically distinct element of CMJ performance. These included relative peak force and concentric mean force, with similar factor loadings (0.85 and 0.82). Given the similar factor loadings identified, we suggest a single variable approach[101] to these force measures and recommend using concentric mean force to represent CMJ force output for the same reasons as above for mean jump height (interpretable and comparable).

Eccentric hamstring force tests have been found to be a valid and reliable method of assessing lower limb force output in professional athletes[50] and general population participants.[52] Eccentric hamstring force variables constituted component three, with left and right force displaying similar factor loadings (0.95 and 0.93) compared to average limb force (0.87). Like component one, to avoid neglecting possible imbalances between left and right limb force, we suggest using the summed variable approach[101] (Table 7.2) when assessing eccentric hamstring force output among professional AF players.

Conclusion

This study applied a data reduction technique and provided a framework for selecting monitoring measures to represent elements of neuromuscular performance based on their statistical contribution and practical efficacy. We presented two methods for applying the findings of PCA; a single variable approach and a summed variable approach. While both methods have advantages and disadvantages, we encourage practitioners to consider the exact nature and number of neuromuscular performance variables they collect within their training environment to decide the most appropriate approach. The methods applied in the current study help achieve efficiency in athlete monitoring, which is an important consideration for practitioners working in professional sport to ensure the best use of human and financial resources.

Practical Applications

- CMJ mean jump height (across three jumps) can be used to represent CMJ power as it is easily interpretable and used as a point of comparison among a cohort of professional AF players.
- A summed variable approach is appropriate to reduce the number of isometric adductor force and eccentric hamstring force variables for practitioners to monitor lower limb neuromuscular output in professional AF players.

Chapter Eight | Study Five | Associations between refined athlete monitoring measures and individual match performance in professional Australian football

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Abstract

The purpose of this study was to assess relationships between measures of training load, training response and neuromuscular performance and changes in individual match performance in professional Australian football. Data were collected from 45 professional Australian footballers from one club during the 2019 competition season. External load was measured by GPS technology. Internal load was measured via session rate of perceived exertion (SRPE). Perceptual wellness was measured via pre-training questionnaires (1-5 Likert scale rating of soreness, sleep, fatigue, stress and motivation). Percentage of maximum speed was calculated relative to individual maximum recorded during preseason testing. Rolling derivative training load measures (7-day and 28-day) were calculated. Principal Component Analysis (PCA) identified eight uncorrelated components. PCA factor loadings were used to calculate summed variable covariates and single variables were chosen from components based on practicality and statistical contribution. Associations between covariates and performance were determined via linear Generalised Estimating Equations. Performance was assessed via Player Ratings from a commercial statistics company. 7-day total distance, IMA event count and SRPE load showed significant positive relationships with performance (18-23% increase in performance z-score). No other covariates displayed significant associations with performance. Individual relative increases in training load within the 7-day period prior to a match may be beneficial for enhancing individual performance.

Key words: training load, training response, neuromuscular performance

Introduction

Athlete monitoring systems are common in professional Australian football (AF). The purpose of such systems is to provide practitioners with information about load completed by players and their response to the stimuli.[6] This information is derived from a variety of sources such as external[11,86] and internal[2] training load measures, neuromuscular performance[50] and perceived wellness assessments.[4] When combined with subjective evaluations of expert practitioners, these objective monitoring measures ultimately inform decisions on the volume, intensity and type of training prescribed to players.[6] This prescription should be a suitable stimulus that allows maintenance of fitness without adding to the resultant fatigue from previous training and matches.[6]

Recently there has been a proliferation of monitoring measures made available to practitioners that has provided an overabundance of information about the training process, and subsequently data overload for coaches and scientists.[101] Specifically, different measures are often used to represent the same fundamental elements of the training process such as load completed and individual responses to load.[101] Collecting and analysing data that measure similar constructs can result in inefficient use of human and financial resources, and reduce the time available to interpret and action the information.[12] Principal Component Analysis (PCA) is a means of reducing datasets by identifying collinear variables and evaluating the contribution of multiple variables to the variance of an entire dataset of correlated measures.[11,88] PCA has been applied to common training load and response measures in professional AF, with this research proposing single and summed variable methods to further reduce monitoring measures to uncorrelated elements of 'acute' and 'chronic' training load and response data.[101] This approach is suggested to be a solution to data overload in athlete monitoring to increase efficiency in data collection and analysis.[101] However, despite these claims, no research has applied this technique and examined relationships between a refined collection of training load, training response and neuromuscular performance measures and changes in individual match performance in professional AF.

Athlete monitoring measures provide information about the training process, however reported relationships between these and match performance measures are inconclusive. One study identified acute increases in total distance covered during training to have a small, positive effect (effect size: 0.13) on subsequent match running performance in professional AF players,[40] while other research has shown that both running distances during training and session-RPE load are associated ($r = 0.76$ and 0.73) with positive changes in relative running distances during matches.[18] Taken together, this research suggests that acute training load may influence subsequent running performance in competition, however running output during competition does not truly reflect individual player performance.[41] The relationship between training load and technical match performance has received some attention, with a study in professional AF reporting standard deviation decrements in a measure of technical match performance (Player Rank, Champion Data, Melbourne, Australia) following increases in weekly external load measures,[102] while other research has reported higher weekly internal load to associate with subsequent match outcome (i.e. team win).[103] Collectively, this research provides conflicting evidence of relationships between training load and improved technical performance. This may be attributed to the difficulty of quantifying individual performance due to the complex technical, tactical and physical requirements of match-play.[41]

Recent research has established a valid measure of individual match performance in an attempt to encompass the technical and tactical output of players.[104] Using previous methods[105] as a basis for the measurement, Player Rating (Champion Data, Melbourne, Australia) assesses the value of player involvement in game phase based on the principle of ‘field equity’, where a player’s involvement is quantified relative to the influence of this involvement on the expected value of their team’s next score.[104] This measure provides greater context of game involvement and potentially a better indication of a player’s influence on the game than alternative statistical indicators.[104] However, to date no research has examined relationships between measures of training load, response and neuromuscular performance and individual changes in Player Rating.

Separately, few studies have examined associations between measures of training response (e.g. perceptual wellness) and individual match performance. Research has reported a small, positive effect of perceived muscle soreness on a statistical indicator of match performance,[40] while another study showed no association between physical match performance and subsequent wellness measures.[46] However, wellness has been poorly defined in previous research and the validity of typical wellness questionnaires used in professional team sport environments is lacking.[6] Additionally, no studies have examined relationships between neuromuscular performance (e.g. adductor force production) and subsequent match performance in professional AF. Collectively, previous research has provided inconclusive evidence of relationships between measures of training response or neuromuscular performance and individual match performance.

Athlete monitoring measures should fit within a conceptual framework, provide useful information and represent an efficient use of time and financial resources.[6] These systems should also assist practitioners to manipulate individual between-match training load to enhance athletes' performance.[6] Therefore, the aim of this study was to assess relationships between a reduced collection of training load, training response and neuromuscular performance measures and changes in individual match performance in professional AF. This information can direct practitioners on the most appropriate monitoring measures to use when assessing player readiness for training and competition.

Methods

Design and subjects

Prospective, longitudinal data were collected from 45 professional Australian footballers (age: 24.95 ± 4.45 y; height: 1.87 ± 0.05 m; body mass: 84.64 ± 9.01 kg) from one club during the 2019 AFL competition season. Informed consent and institutional ethics approval were obtained (UTS HREC: ETH17-1942).

Perceptual wellness

Players completed a short questionnaire on their smartphone before the main field training session each week (1-2 instances depending on length of between-match cycle). Players provided a rating from 1 to 5 (1 representing a poor rating and 5 representing a good rating) in relation to their perception of muscle soreness, sleep quality, fatigue level, stress and motivation. Daily (the session immediately prior to a match), 7-day and 28-day rolling averages of each wellness element were calculated. While these methods were like those used in previous team sport research,[45,46] the questionnaire used in this study was customised for use with the observation group.

External training load

External training load was measured in training by 10 Hz Global Positioning System (GPS) units (Optimeye S5, Catapult Sports, Victoria, Australia). Each unit was assigned to an individual player and worn in a small pouch in their training or match jerseys. After each training session or match, data were downloaded using proprietary software (Openfield 1.20.0, Catapult Sports, Melbourne, Australia). External match loads from eight of 22 matches included in the analysis were collected via an alternative system (ClearSky T6, Catapult Sports, Victoria, Australia) due to these matches being played indoors under a roof. All other match data were collected via the same system used for training sessions (Optimeye S5, Catapult Sports, Victoria, Australia). Unpublished data from the technology manufacturer has reported distances covered at low and high speed over 80 m to have differences of <5% between the two systems (Catapult Sports, Melbourne, Victoria, Australia). All data files were cleaned to ensure only recorded data from time spent on the field and during actual training activities was retained. The training and match files for each player were then exported and placed into a customised spreadsheet (Microsoft, Redmond, USA) for analysis. The selected variables were total distance, total high-speed running (HSR; distance $\geq$20 km$\cdot$h^{-1}) and very high-speed running distance (VHSR; distance covered $\geq$23 km$\cdot$h^{-1})[89] covered by each player, their maximum speed (km/h), and a total of inertial movement (IMA) event counts to quantify accelerations, decelerations and changes of direction. Maximum speed attained during the session or match was then compared to each player's maximum speed recorded during preseason testing to generate a percentage of maximum. The primary GPS technology used in this study (Optimeye S5) is a valid and reliable method of quantifying movement in team sport activity, however research has reported greater measurement error with higher movement speeds.[90,91]

Internal training load

Internal training load was measured via the session-RPE (SRPE) method within 30 minutes following every training session and competition match following standardized protocols.[32,92] Session-RPE is a valid and reliable method of quantifying internal training load in professional AF.[92]

Adductor force production

Adductor force production was assessed using a proprietary system (Vald Performance, Albion, Australia) with players in a supine position with their knee joint at an angle of 60 degrees. Bar height was customised for each player to ensure they maintained a knee joint angle of 60 degrees while positioned beneath the apparatus. Placing the femoral medial condyle of both knees on load cells (sample rate of 50 Hz), players were given a verbal cue to complete a warmup of one repetition at 80% of their maximum effort. After a short break they were asked to complete a maximum repetition, pushing their femoral medial condyles against the pads as hard as possible for five seconds, providing a measure of force (N) for left and right limbs and percentage imbalance between both limbs. Data were captured via the GroinBar iPad application and uploaded to a personalised cloud account and exported into a customised spreadsheet (Microsoft, Redmond, USA) for analysis. These protocols were adapted from previous research.[48]

Derivative load measures

Training load was classified according to acute and chronic timeframes (Table 1).[87,101] All derivative measures were inclusive of training and match loads.

Individual match performance

Individual match performance was quantified using individual Player Ratings for each competition match from rounds 1 to 23 (22 matches in total with one bye week). Player Ratings are produced using a proprietary algorithm from a statistics company (Champion Data, Melbourne, Australia) where a player's involvement in a game phase is measured relative to the influence of this contribution on the expected value of their team's next score.[104] Previous research has shown that Player Ratings are a valid performance measure.[104] Player Ratings for each match were converted to z-scores ($z = (x - \mu) / \sigma$) to account for individual variation in performance across the season.

Statistical Analyses

Principal Component Analyses (PCA)

A total of 17,205 data points was collected from 37 monitoring variables and were collated into a customised spreadsheet (Microsoft, Redmond, USA) for analysis. One PCA was undertaken to identify uncorrelated components to represent aspects of the training process including training load, training response and neuromuscular performance (Table 2). Each component was named according to the nature of the variables within it, for example 'Perceived Wellness'.[101] Prior to analyses, all data were tested for sampling adequacy using the Kaiser-Meyer-Olkin measure (a threshold of 0.5) and for suitability for component analysis using the

Bartlett test of sphericity (significance accepted at $p = \leq 0.05$). Orthogonal rotation was used to enhance interpretation of the analysis, while principal components were determined via eigenvalue analysis (components that were assigned eigenvalues of >1). Only variables with a factor loading of >0.70 were reported. These methods correspond with protocols described elsewhere.[11,88,93] PCA was performed using SPSS (Version 26.0 IBM Company, New York, USA).

The eight components identified by the PCA were then used to obtain summed (component) variable and single variable covariates. The summed component variables were calculated by multiplying the factor loading of each variable within each component (Table 2) by the initial raw value, and then summing each variable figure within each component. This produced an arbitrary figure to represent each of the eight components derived from the PCA.[101] The single variable covariates were calculated by selecting one variable from each of the eight components according to a combination of validity, reliability, sensitivity and practicality at the discretion of the researchers.[101] Justifications for these selections is outlined in Table 3. Each component and single variable covariate were then converted to individual player z-scores ($z = (x - \mu) / \sigma$) to enhance interpretation of Generalised Estimating Equations (GEEs) that were subsequently calculated.[106] These covariate z-scores were then aligned to each individual performance throughout the season.

Table 8.1: *Definitions of derivative training load measures used in PCA.*

Training Load Measure	Definition
Daily Load	Distance covered or arbitrary units completed in one day
Daily Maximum Speed	Highest speed (km/h) reached in each field training session or competition match
Inertial Movement Analysis units (IMA)	IMA event count in each field training session or competition match
7-day Load	Distance covered, event count or arbitrary units completed in last 7 days (rolling)
28-day Load	Distance covered, event count or arbitrary units completed in last 28 days (rolling)
Times >85% last 7 days	Number of instances >85% of maximum speed reached during the last 7 days (rolling)
Times >90% last 7 days	Number of instances >90% of maximum speed reached during the last 7 days (rolling)
Times >85% last 28 days	Number of instances >85% of maximum speed reached during the last 28 days (rolling)
Times >90% last 28 days	Number of instances >90% of maximum speed reached during the last 28 days (rolling)

Table 8.2: *PCA of athlete monitoring measures.*

Component	Factor Loading
Component 1 – Perceived Wellness (31.0% variance, Eigenvalue: 12.7)	
Average Wellness Last 7d	0.938
Average Wellness Last 28d	0.928
Wellness Total	0.927
Average Stress Last 28d	0.923
Average Sleep Quality Last 28d	0.912
Average Stress Last 7d	0.886
Average Sleep Quality Last 7d	0.856
Stress	0.853
Average Motivation Last 28d	0.849
Average Motivation Last 7d	0.844
Average Fatigue Last 28d	0.834
Sleep Quality	0.793
Motivation	0.759
Average Fatigue Last 7d	0.755
Fatigue	0.746
Component 2 – Adductor Force (13.7% variance, Eigenvalue: 5.6)	
Average Left Force Last 7d	0.962
Average Right Force Last 7d	0.953
Average Left Force Last 28d	0.951
Average Right Force Last 28d	0.942
Left Adductor Force	0.920
Right Adductor Force	0.905
Component 3 – Maximum Speed Exposure (11.8% variance, Eigenvalue: 4.8)	
Acc Days >90% Max Speed (28 d)	0.815
Acc Days >90% Max Speed (7 d)	0.787
Acc Days >85% Max Speed (7 d)	0.745
Acc Days >85% Max Speed (28 d)	0.730
Component 4 – Perceived Soreness (7.0% variance, Eigenvalue: 2.9)	
Average Soreness Last 7d	0.800
Muscle Soreness	0.779
Average Soreness Last 28d	0.757
Component 5 – Acute Training Load (5.7% variance, Eigenvalue: 2.3)	
TD Last 7d	0.867
SRPE Load Last 7d	0.812
IMA Last 7d	0.803
Component 6 – Adductor Force Imbalance (4.9% variance, Eigenvalue: 2.0)	
Average Adductor Imbalance Last 7d	0.937
Average Adductor Imbalance Last 28d	0.902
Adductor Imbalance	0.834
Component 7 – Chronic External Load (3.6% variance, Eigenvalue: 1.5)	
TD Last 28d	0.847
IMA Last 28d	0.842
Component 8 – Chronic HSR (3.1% variance, Eigenvalue: 1.3)	
HSR Last 28d	0.786

HSR: high-speed running (>20km/h); TD: total distance; m: metres; d: days; SRPE: session-RPE load; IMA: inertial movement analysis count.

Table 8.3: Justification for selection of single variable covariates.

Component	Variable Chosen	Rationale
1 (Perceived Wellness)	Average Stress Last 28d	Stress demonstrates greater sensitivity and reliability.[50] 28d variable had highest factor loading of stress measures.
2 (Adductor Force)	Combined Adductor Force Last 7d	Left and right adductor force demonstrate reliability and sensitivity.[48] 7d variable had highest factor loading of adductor measures.
3 (Maximum Speed Exposure)	Acc Days >90% Max Speed Last 28d	Chronic measure reportedly more appropriate to encompass between-match training cycles and injury risk.[87]
4 (Perceived Soreness)	Average Soreness Last 7d	Highest factor loading of soreness measures.
5 (Acute Training Load)	SRPE Load Last 7d	Highest factor loading in component and encompasses load completed across all modalities.[2]
6 (Adductor Force Imbalance)	Average Adductor Imbalance Last 28d	Similar factor loading to other imbalance variables but 28d measure encompasses between-match training cycles.
7 (Chronic External Load)	TD Last 28d	Both variables within component have identical factor loadings but TD is valid and reliable[27] in contrast to IMA for which measurement properties have not been established.
8 (Chronic HSR)	HSR Last 28d	Only one variable in component.

Generalised Estimating Equations (GEE)

Linear GEEs were constructed to quantify changes in individual match performance based on changes in component and single variable monitoring covariates.[107] GEEs were used as they account for repeated measures on the same individuals, as is the case for longitudinal, observational investigations in professional team sport research. Player performances were excluded from analyses if the player competed in only one game during the competition season, as a z-score could not be derived. A total of 16 models were constructed to assess the influence of PCA-derived components on performance change, and single variables on performance change.[106] Collinearity between covariates was avoided via PCA prior to GEE construction, therefore an independent correlation structure existed between all covariates, and a model-based covariance estimator was used.[101] The effect of individual player was included in all GEEs to account for data pseudoreplication.[108] Models were constructed using a step-up approach used in previous research[106] where the addition of a covariate to the model was determined by both the significance of the Wald chi square value ($P < 0.05$) and if the quasi-likelihood independence model criterion (QIC) decreased (i.e. the model fit was improved).[109] Beta values were converted to exponent values (Exp(β)) to enhance practical interpretation of results. A beta exponent value indicates an odds ratio, with a Exp(β) of >1 demonstrating an increased percentage probability of an outcome and an Exp(β) of <1 indicating a reduced probability of an outcome with every unit increase in the significant covariate.[110] 95% confidence intervals (CI) were calculated to assess the precision of(Exp(β) values. GEE models are shown in Table 4 and Table 6. Assessment of model fit improvements with the addition of all other covariates to significant covariates were assessed and are shown in Table 5 and Table 7. All GEE models were constructed using SPSS (Version 26.0 IBM Company, New York, USA).

Results

A total of 465 individual performances by 37 players (average 13 ± 7 matches) were analysed. The Acute Training Load component (consisting of the sum of total SRPE load, total distance covered and total IMA events in the last 7 days) displayed a positive effect on performance (Exp(β) = 1.23), while total SRPE load in the last 7 days (single variable) also demonstrated a positive effect on performance (Exp(β) = 1.18). No other covariates displayed significant associations with individual performance or improved model fit when added to significant GEE models.

Table 8.4: *Generalised Estimating Equation model effects for summed variable component z-score vs. individual match performance z-score.*

Model	Intercept	Athlete	Component	β	SE	Exp(β)	95% CI
Null Model							
Wald P Value	0.89						
QIC	431.01						
Model 1 ('Perceived Wellness' Component)							
Wald P value	0.46	1.00	0.23				
QIC	416.18						
Model 2 ('Adductor Force' Component)							
Wald P value	0.101	1.00	0.12				
QIC	313.24						
Model 3 ('Maximum Speed Exposure' Component)							
Wald P value	0.97	1.00	0.59				
QIC	428.01						
Model 4 ('Perceived Soreness' Component)							
Wald P value	0.70	1.00	0.63				
QIC	415.74						
Model 5 ('Acute Training Load' Component)							
Wald P value	**0.97**	**1.00**	**0.00***	**0.21**	**0.04**	**1.23**	**1.12, 1.35**
QIC	**412.31**						
Model 6 ('Adductor Force Imbalance' Component)							
Wald P value	0.55	1.00	0.85				
QIC	371.49						
Model 7 ('Chronic External Load' Component)							
Wald P value	0.97	1.00	0.06				
QIC	429.85						
Model 8 ('Chronic HSR' Component)							
Wald P value	0.97	1.00	0.60				
QIC	432.45						

Wald: Wald chi square; P: alpha value ($p = \leq 0.05$); β: beta coefficient; SE: standard error; Exp(β): exponent of beta; CI: confidence interval, QIC: quasi likelihood independence model criterion; HSR: high-speed running.
*denotes significance ($p = \leq 0.05$).

Table 8.5: *Model fit with addition of covariates to significant model (Model 5) for summed variable component z-score vs. individual match performance z-score.*

Model	Intercept	Athlete	'Acute Training Load'	Added Covariate
Model 5 ('Acute Training Load' Component)				
Wald P value	**0.27**	**1.00**	**0.00***	
QIC	**412.31**			
Added 'Perceived Wellness' Component				
Wald P value	0.48	1.00	**0.00***	0.24
QIC	402.78			
Added 'Adductor Force' Component				
Wald P value	0.12	1.00	**0.00***	0.15
QIC	307.45			
Added 'Maximum Speed Exposure' Component				
Wald P value	0.97	1.00	**0.00***	0.21
QIC	412.36			
Added 'Perceived Soreness' Component				
Wald P value	0.70	1.00	**0.00***	0.78
QIC	400.16			
Added 'Adductor Force Imbalance' Component				
Wald P value	0.55	1.00	**0.00***	0.66
QIC	308.53			
Added ''Chronic External Load' Component				
Wald P value	0.97	1.00	**0.00***	0.09
QIC	412.53			
Added 'Chronic HSR' Component				
Wald P value	0.97	1.00	**0.00***	0.47
QIC	414.05			

Wald: Wald chi square; P: alpha value ($p = \leq 0.05$); QIC: quasi likelihood independence model criterion; HSR: high-speed running.
*denotes significance ($p = \leq 0.05$).

Table 8.6: *Generalised Estimating Equation model effects for single variable z-score vs. individual match performance z-score.*

Model	Intercept	Athlete	Component	β	SE	Exp(β)	95% CI
Null Model							
Wald P Value	0.89						
QIC	431.01						
Model 1 (‘Perceived Wellness’ Component)							
Wald P value	0.84	1.00	0.99				
QIC	417.74						
Model 2 (Combined Adductor Force Last 7d)							
Wald P value	0.55	1.00	0.15				
QIC	313.47						
Model 3 (Acc Days >90% Max Speed Last 7d)							
Wald P value	0.97	1.00	0.76				
QIC	429.91						
Model 4 (Average Soreness Last 7d)							
Wald P value	0.78	1.00	0.51				
QIC	395.55						
Model 5 (SRPE Load Last 7d)							
Wald P value	**0.97**	**1.00**	**0.00***	**0.17**	**0.04**	**1.18**	**1.08, 1.30**
QIC	**419.57**						
Model 6 (Average Adductor Imbalance Last 28d)							
Wald P value	0.55	1.00	0.25				
QIC	313.69						
Model 7 (TD Last 28d)							
Wald P value	0.97	1.00	0.06				
QIC	429.94						
Model 8 (HSR Last 28d)							
Wald P value	0.97	1.00	0.60				
QIC	432.45						

Wald: Wald chi square; P: alpha value ($p=\leq 0.05$); β: beta coefficient; SE: standard error; Exp(β): exponent of beta; CI: confidence interval, QIC: quasi likelihood independence model criterion; HSR: high-speed running; SRPE: session rate of perceived exertion; TD: total distance.
*denotes significance ($p=\leq 0.05$).

Table 8.7: *Model fit with addition of covariates to significant model (Model 5) for single variable z-score vs. individual match performance z-score.*

Model	Intercept	Athlete	'SRPE Load Last 7d'	Added Covariate
Model 5 (SRPE Load Last 7d)				
Wald P value	**0.97**	**1.00**	**0.00***	
QIC	**419.57**			
Added 'Average Stress Last 28d'				
Wald P value	0.85	1.00	**0.00***	0.82
QIC	406.54			
Added 'Combined Adductor Force Last 7d'				
Wald P value	0.54	1.00	**0.00***	0.13
QIC	311.84			
Added 'Acc Days >90% Max Speed Last 7d'				
Wald P value	0.97	1.00	**0.00***	0.87
QIC	419.18			
Added 'Average Soreness Last 7d'				
Wald P value	0.80	1.00	**0.00***	0.67
QIC	384.44			
Added 'Average Adductor Imbalance Last 28d'				
Wald P value	0.54	1.00	**0.00***	0.23
QIC	312.14			
Added 'TD Last 28d'				
Wald P value	0.97	1.00	**0.00***	0.07
QIC	418.09			
Added 'HSR Last 28d'				
Wald P value	0.97	1.00	**0.00***	0.59
QIC	421.51			

Wald: Wald chi square; P: alpha value (p=≤0.05); QIC: quasi likelihood independence model criterion; HSR: high-speed running; SRPE: session rate of perceived exertion; TD: total distance.
*denotes significance (p=≤0.05).

Discussion

The aim of the present study was to assess relationships between a reduced collection of training load, training response and neuromuscular performance measures and individual match performance in professional AF. We found that measures of acute training load in the 7 days prior to a match show a significant positive relationship with individual performance. Other common measures of training load, training response and neuromuscular performance displayed no associations with individual performance. These findings suggest that more training than individual average (z-score increase) in the 7 days prior to a match can have a positive influence on subsequent individual match performance.

Our results showed a significant relationship between the sum of 7-day total SRPE load, total distance covered and IMA event counts (component variable), and 7-day SRPE load (single variable) and individual match performance. Specifically, a one unit z-score increase in these acute load measures associated with an increase in performance z-score by 18 to 23%. This result is supported by other research in professional AF that reported higher weekly training load prior to a match to associate with positive match outcome at a team level.[103]. The combination of these findings suggests that higher than normal individual load in the 7 days prior to a match associates with improved individual and team performance. However, the exact mechanisms of this relationship are unclear. The associations identified by the present study may reflect a likely benefits of training continuity (i.e. cohesiveness amongst teammates and knowledge of team tactics) provided by completing more training than normal prior to a match, rather than any physiological gain. Future research that examines the effect of training completion on performance may provide practitioners with more information on the benefits of acute training load prior to a match.

Our finding is in contrast to previous research that found higher weekly loads prior to a match were associated with decrements in individual performance,[102] while another study of simulated team-sport activity found a reduction in running performance following four days of increased internal training load.[39] One possible explanation for difference in findings is that the results of the present study may be an artefact of the playing schedule of the team investigated. Indeed, there were 18 occurrences of ≥7day between-match recovery cycles in the present investigation. Longer between match periods may provide greater opportunity to schedule more sessions and complete more load, i.e. several on-field skills and resistance training sessions. Certainly, a 6 day between-match period limits manipulation of the training program and by extension individual acute training loads as players are unlikely to recover adequately until 96 hours following a match,[75] allowing only two days prior to the next match. High acute training loads may have a detrimental effect on performance as it can exacerbate fatigue and interfere with player recovery, however this was not explored by the present study. The confounding effect of competition schedule on training load has been explored previously[111] where greater training loads are completed during longer between-match training cycles. Further, despite the association between 7-day load and positive performance change identified here, it is likely that acute training load that there is a certain amount of acute training load that relates to performance decrements (i.e. short-term fatigue) rather than improvement. However, this practical ceiling was not examined in the present investigation. These factors highlight the difficulty in prescribing between-match training load to players to allow appropriate recovery but with a training stimulus that avoids acute fatigue and a reduction in performance. These difficulties are exacerbated by different between-match periods throughout a competition season which are beyond the control of practitioners.

We found no significant relationships between a range of common monitoring measures and individual player match performance, including 28-day load (external and internal), perceptual wellness and adductor force variables. Our finding complements previous research in professional AF that reported trivial or unclear effects of 2-, 3- and 4-week rolling accumulations of external training load on individual match performance.[102] While chronic measures of training load (i.e. load completed over two to four weeks) have historically demonstrated no observable effect on team sport performance,[40,102,112] in practice changes in these measures can be used to inform the delivery of individual training load leading into a competition match. Indeed, acute training load appears to be a result of the process of between-match training cycle periodisation at an individual player level that occurs repeatedly throughout a competition season.[6]

Our analyses showed that the sum of several acute training load measures display a significant relationship with performance change; 7-day total distance covered, total IMA event count and total SRPE load. Total SRPE load also showed a significant positive relationship with performance in isolation. The present findings suggest that these acute training load measures represent a similar dimension of a player's completed training load prior to a match. Therefore, practitioners may wish to interpret changes in these measures in combination or refine them to enhance monitoring system efficiency.

Some limitations should be considered when interpreting the findings of the present study. Data were collected from one club during one competition season, therefore monitoring measures may reflect the physical and tactical design and delivery of training from coaches and performance staff of the observation group. Additionally, external load from 8 of 22 competition matches were collected via an alternative system (ClearSky for indoor matches) to the system used in training and the remaining 14 matches. Given the differences in measurement error in quantifying locomotion in team sport activity between the two systems reported previously,[98] match loads contributing to derivative acute and chronic measures analysed in this study may be slightly different depending on which system was used in a given match. However, high-speed distance is typically quantified with more measurement error than low-speed distance,[90,91] and no derivative high-speed distance measures demonstrated significant effects on performance in the present study. Nonetheless, practitioners should consider this limitation when interpreting our results.

Practical Applications

- Individual relative increases in training load within the 7-day period prior to a match may be beneficial for enhancing individual performance.
- Practitioners may select one of 7-day total distance covered, IMA count and SRPE load to represent acute load completed to reduce data collected and enhance efficiency in athlete monitoring

Conclusion

This study assessed relationships between a reduced collection of training load and response measures and changes in individual match performance in professional AF. Our results show that higher acute training load prior to a match relates to a positive change in match performance. Many commonly-used monitoring variables examined in the present study demonstrated no observable effect on performance; however, in practice these measures inform the prescription of acute training load, which demonstrated an association with performance in the present study. We cannot infer causality between monitoring measures and individual performance based on our results, and discourage focusing on single variables assessments of individual player readiness. Despite the collection and analysis of high-quality data with suitable measurement properties, monitoring systems only indicate a portion of a player's overall preparation for competition. Therefore, we suggest that assessments of player readiness to inform training prescription result from a combination of objective monitoring data and knowledge from experts in medical, physical and coaching domains.

Chapter Nine | General Discussion

The importance of high-level competition performance and maximum player availability for matches necessitates significant financial and human resource investment by professional AF teams in the physical, psychological, technical and tactical preparation of their players. Part of this investment is directed to athlete monitoring systems which are designed to control the training process[16] and balance the 'fitness and fatigue' of players to enhance performance and minimise their risk of injury and illness.[6] In practice, these aims are achieved through the combination of technical and tactical goals from coaches, expertise from medical and conditioning staff, and objective assessments of player readiness via athlete monitoring tests.[6] These information sources ultimately determine the manipulation of individual training volume and content, which is designed to deliver an acute training stimulus that allows optimal performance in the subsequent match.[6]

Practitioners require athlete monitoring tests to be submaximal and non-fatiguing in nature, easily administered and with a capacity to identify changes in training load, response and neuromuscular output regularly throughout training and competition periods. This allows minimal interruption or inconvenience to athletes and the training process. Further, these tests should be valid (the ability of a test to measure what it is designed to measure), reliable (the consistency of results from a test) and sensitive (the extent to which a test can detect changes beyond the typical error in results).[8,9] The information derived from valid, reliable and sensitive monitoring tools allows practitioners to confidently interpret changes in test results to inform individual acute training load prescription on a between-match basis.

A further important consideration for practitioners working in professional sport is to ensure the best use of human and financial resources. This requires maximising the efficiency of monitoring systems to ensure adequate time and resources are available to analyse, interpret and action information derived from monitoring data. Moreover, it is important that data obtained from monitoring tests display relationships with competition performance, as a key aim of athlete monitoring is to manage the training process to ultimately allow high-level competition performance.[16] Therefore, prudent selection of monitoring tests by practitioners should be based on their validity, reliability, sensitivity, practicality and relationships with outcome measures such as training availability and performance.

However, information on the reliability and sensitivity of commonly used monitoring tools in professional AF is limited. Secondly, despite the issue of data overload in athlete monitoring acknowledged elsewhere,[11,12] no research has provided a practical method of refining athlete monitoring data to collect, analyse and action information about elements of the training process efficiently. Lastly, no studies have examined the effect of a refined collection of training load, training response and neuromuscular output on subsequent changes in individual match performance in professional AF. Therefore, this thesis contained a series of studies that examined measurement properties of commonly-used monitoring tests, established methods for reducing the amount of data collected and analysed by practitioners, and assessed the relationships between a refined collection of monitoring measures and changes in individual competition performance in professional AF.

Measurement characteristics of athlete monitoring tools

It is impractical for professional team sport athletes to complete maximal physical capacity tests during the season to determine changes in fitness and fatigue due to environmental constraints and risk of injury.[7] Therefore, practitioners rely on monitoring tools that are submaximal, easily administered and can identify changes in elements of training load, training response and neuromuscular output regularly throughout training and competition to assess the readiness of their players. To provide useful information to coaches and scientists, these tools should display measurement characteristics of validity, reliability and sensitivity.[8,9] Such measurement properties allow confident and accurate interpretation of test result changes to inform evaluations of training and match readiness of players and subsequent acute training load prescription.[6]

Study One and *Study Two* of the thesis examined the reliability and sensitivity of a submaximal fitness test (heart rate recovery test), training response measure (perceptual wellness questionnaire) and three neuromuscular performance tests (adductor strength test, countermovement jump test and eccentric hamstring force test). Reliability was evaluated via a test-retest method, where measurements were collected from the same players under identical test conditions separated by a standardised rest period. This produces a typical error measure, expressed as a coefficient of variation percentage (CV%) that indicates the level of error (noise) to be accounted for when interpreting changes in that test.[61] Unless a test result exceeds this level of error, practitioners cannot be certain that the result represents a meaningful change. We found the adductor force test, eccentric hamstring force test, heart rate recovery test and countermovement jump test to display CVs of between 1.2% and 7.0%, while the typical error (Likert scale unit) of the perceptual wellness questionnaire examined ranged from 0.07 to 0.71 across five elements (stress, mood, sleep quality, soreness and motivation). In isolation, these values provide a minimum threshold for interpreting meaningful change in these measures for practitioners. However, their level of acceptability cannot be assessed without combining typical test error with sensitivity measurement, i.e. weekly variation in test results.

Sensitivity was assessed using signal-to-noise analysis,[48] which involves combining the test CV established via reliability testing with the weekly variation in test results across an athlete cohort. In the case of team sport athlete testing, the weekly variation can be considered the "signal", while "noise" can be represented by the typical error in the measurement (from test-retest reliability analysis). These elements can be combined to produce a signal-to-noise ratio (SNR), providing practitioners with an index of responsiveness in a measure relative to the typical error in the test. The higher the SNR, the more confident practitioners may be that a test result will consistently exceed the test error (noise) and therefore identify meaningful changes in results. Sensitivity of the five monitoring tests examined in *Study One and Study Two* were considered at least "acceptable",[66,81] with SNRs ranging from 1.3 to 11.1. While a rating of SNR was adapted from previous research,[66,81] ultimately this form of analysis should be viewed as a dichotomy, where monitoring tests that have a SNR of >1 are considered sensitive (i.e. results consistently exceed the test error and can be interpreted as meaningful), while tests with SNR of <1 are not considered sensitive, as test results do not consistently exceed the measurement noise.

Study Two was the first investigation to date that established the reliability and sensitivity of perceptual wellness questionnaires in professional AF. Notably, perceived stress and perceived soreness were the only two elements to display SNRs of >2.0 at any time point, suggesting that these were the most responsive to training and life stressors among the five wellness elements examined. Interestingly, perceived stress displayed the equal-lowest SNR at 96 hours post-match, suggesting that factors affecting player stress levels were most influential at 48 and 72 hours post-match, possibly related to the previous week's match. Collectively, SNRs for all wellness elements were lower at 96 hours post-match than at earlier time-points, with perceived soreness the only element to display a SNR of >1.5, indicating that players had stable perceptions of stress, motivation, sleep quality and fatigue within 96 hours post-match. This is in agreement with previous research in professional rugby league that reported perceived fatigue, general wellbeing and soreness to return to pre-game values within four days post-match.[75] Other research in professional AF also reported perceived fatigue, stiffness, sleep quality, stress and general wellbeing to improve as gameday approached (i.e. as hours following the previous match increased).[45] Collectively, this suggests that the previous match has a greater influence on perceptual wellness than an upcoming match. Nonetheless, a limitation of the present study was the use of a customised wellness questionnaire for the observation group. While such a modification is common in professional team sport monitoring systems, the questionnaire used here had not undergone accepted psychometric validation procedures and hence it is unclear whether the prompts contained within the questionnaire are obtaining valid perceptions of an athlete's wellness.

In examining measurement characteristics of the submaximal heart rate test, *Study Two* reported the typical test error in HRex and HRR to be considerably higher than those reported in previous research using similar protocols.[49] This disparity was possibly due to subtle differences in test protocols, the smaller sample of players and the different manufacturer of the heart rate monitors used in the present study. Nonetheless, HRex and HRR displayed acceptable SNRs, indicating that the test can identify changes that exceed the typical error. Notably, HRex displayed greater sensitivity than HRR (5.3 compared to 1.4), therefore we suggest using heart rate *during* submaximal exercise in preference to heart rate *recovery* as a monitoring measure in professional AF.

Two of the neuromuscular performance measures examined in *Study One* and *Study Two* (eccentric hamstring force test and isometric adductor force test) demonstrated lower typical error than previous research.[7,52,68,72] This was likely due to the standardisation of protocols using relatively novel measurement equipment (NordBord and GroinBar), where both systems are consistently customised for the athlete being tested which reduces possible interrater and intrarater error. However, CMJ performance variables (relative peak power, relative peak force and relative mean force) displayed a higher typical test error than those reported previously,[77] potentially explained by the design of *Study Two*, whereby testing was conducted following on-field skills sessions on contrast to previous studies in a more controlled laboratory environment. While the timing of testing was not preferable, the nature of applied, observational research means that data collection is often dictated by training and competition scheduling beyond the control of the researchers. Notwithstanding, an important application of *Study One* and *Study Two* was the proposal of methods to assess reliability and sensitivity within a professional AF training environment. It is vital that practitioners establish these measurement characteristics within their specific training environments using custom protocols to obtain the most relevant information and maximise the accuracy of test result interpretation.

Collectively, *Study One* and *Study Two* established important measurement characteristics of a commonly used selection of tests to measure neuromuscular performance, training response and aerobic fitness and found that all possess acceptable levels of reliability and sensitivity. Specifically, these studies identified thresholds (test CV%) for identifying meaningful change in common monitoring tests to allow confident interpretation of results and found that these tests consistently produce results that exceed the typical test error and hence are meaningful changes. Moreover, test-retest analysis and SNR were shown to be simple and unobtrusive methods of establishing these measurement characteristics in any professional team sport environment.

Data reduction approaches to athlete monitoring

A challenge faced by coaches and scientists is synthesising and communicating information from a broad range of data sources to support decision-making regarding a player's preparation for training and competition. Indeed, monitoring professional AF players is a complex process with inferences of player readiness derived from many data sources.[6] While extensive access to monitoring data allows practitioners to capture important information about the training process, this can lead to data overload, where data representing similar constructs (i.e. training load, training response and neuromuscular performance) are analysed and reported.[11] This likely results in data collinearity, which can cause exaggeration of relationships between monitoring variables and outcome measures when conducting observational analysis of athlete preparation data.[12] Collinearity also represents inefficient use of valuable time and resources in collecting and analysing data that measure similar elements of the training process.[101]

One approach to address the issue of data overload in athlete monitoring is to systematically reduce the number of variables that are collected and analysed to improve the efficiency of analysis without losing the veracity of the information provided by these data. One such method is Principal Component Analysis (PCA), a data reduction technique designed to evaluate the contribution of multiple variables to the variance of an entire dataset of correlated measures.[11,88] PCA has been shown to be an effective approach to data reduction in team sport training load monitoring systems.[11,12] However, evaluations of player readiness are also based on a player's individual response to training and matches (i.e. perceptual wellness assessments), neuromuscular performance and derivative external load measures (i.e. cumulative weekly and monthly load).

Therefore, *Study Three* and *Study Four* of the thesis applied PCA to measures of training load, training response and neuromuscular performance in professional AF, and extended this analysis to propose two practical methods of using findings of PCA to enhance efficiency in team sport monitoring systems. Among 35 measures analysed, *Study Three* demonstrated that external load, internal load and perceived wellness represent statistically separate constructs of the training process, across both acute (7-day) and chronic (28-day) timeframes. *Study Four* also identified constructs to represent isometric adductor force, eccentric hamstring force and countermovement jump power. These findings indicate that many individual measures that are commonly collected and analysed in professional team sport monitoring systems assess similar elements of the training process, with comparable contributions of variance (i.e. factor loadings of a PCA). For example, when quantifying daily external load, the results of *Study Three* reported total distance (m), high-speed running distance (m) and very high-speed running distance (m) to contribute approximately the same amount of variance to a monitoring dataset. Therefore, practitioners could select one or two of these measures to collect and analyse to save time and resources.

An important finding of *Study Three* was that perceived soreness displayed a factor loading below the redundancy threshold of 0.70 within the “Daily PCA”, indicating a relatively poor correlation with the wellness component identified. This suggests that perceived soreness represents a statistically separate construct to the other four wellness elements examined in our research. Indeed, it appears that fatigue, sleep quality, stress and motivation measure one aspect of acute perception of readiness while soreness represents an isolated element of a player's perception of wellness. However, as mentioned previously, a limitation of the present study was the use of a customised wellness questionnaire for the observation group and hence may lack psychometric validity.

Separately, we found maximum sprint speed exposure to represent one component, with 'chronic' (28-day) speed exposure having a higher factor loading than 'acute' (7-day) exposure. It is likely that a period of 28 days encompasses different between-match training microcycles (6 or 8 days) compared to 7 days and therefore provides a more representative indication of maximum speed exposure over a chronic period. This complements previous research in professional AF that suggested optimal maximum speed exposure (>85% of maximum speed) in reducing injury risk is between 5 and 8 instances over a 28-day period, indicating that monitoring speed exposure over a chronic (28-day) period may be more practical than acute periods relative to injury risk.[87]

Study Three also proposed two methods of selecting monitoring measures based on PCA factor loadings, in addition to practicality, reliability and sensitivity (established partly in *Study One* and *Study Two*). A single variable method involves selection of one variable among a group of measures in a component with similar factor loadings based on practicality and measurement characteristics. For example, *Study Three* demonstrated that when quantifying daily external load, total distance (m), high-speed running distance (m) and very high-speed running distance (m) display factor loadings of 0.92-0.88 (i.e. minimal difference in variance, or correlation to the component). In this instance, we would suggest using total distance based on previous research that has reported greater measurement error with increased speed when using GPS technology to quantify locomotive movement.[27,94] Further, a summed variable approach may be used to reduce monitoring variables that measure the same construct by multiplying the variable (e.g. 1500 metres of total distance) by its factor loading established by the PCA (e.g. 0.81) for each variable within each principal component, then summing these values together to produce a total value (arbitrary figure) for the component. While both the single and summed variable approaches may increase efficiency by reducing the number of variables to be collected and analysed, they each have advantages and disadvantages. The single variable approach is more reductionist and therefore may neglect the contribution of other variables with similar factor loadings in a component because they are slightly less practical. In contrast, the summed variable approach accounts for all variables and their individual variance, however it produces an arbitrary figure that may be less interpretable than a single variable.

Taken together, the findings of *Study Three* and *Study Four* provide basis for using PCA to reduce athlete monitoring data in professional AF, and present two applications of PCA results to further increase efficiency in monitoring training load, training response and neuromuscular performance of professional AF players. Indeed, these methods can be applied to any athlete monitoring or performance dataset where the aim is to reduce the number of collinear variables. Like the establishment of measurement characteristics in *Study One* and *Study Two*, we suggest practitioners undertake PCA with their own athlete monitoring data to identify factor loadings of the specific measures they collect and analyse to reflect periodisation strategies and demographics of their playing cohort.

Associations between refined athlete monitoring measures and performance

The process of athletic training has historically been based upon quantifying fitness (training load completed over chronic timeframes) and fatigue (physical impairment or performance reduction due to residual fatigue from an acute training dose).[17] Subsequently, practitioners of professional AF teams have adapted this model to be congruent with typical training schedules of ~7 days, as most team sports have a match scheduled every 6-8 days during their competition phase.[6] Indeed, the theoretical aim of athlete monitoring is to optimise physical performance and reduce the risk of injury and illness to maximise player availability for training and competition.[38] However, elements of the generic framework proposed by Banister et al[17] widely used in professional team sport have not displayed consistent descriptions or predictions of subsequent performance or injury risk to date.[6] Therefore, the use of the 'fitness' and 'fatigue' framework is questionable in achieving the aims of athlete monitoring in team sports. Indeed, in practice, the volume, nature and intensity of individual training is manipulated at an acute level (typically ~7 days prior to a match) based on information derived from measures of training load, training response and neuromuscular performance.[6] The exact nature of most of this training is usually determined by coaches to address strategic and technical requirements for the upcoming competition opponent.[6] Given the scarce evidence to support the application of Banister's model[17] in team sport, *Study Five* of the thesis examined relationships between a refined collection of acute and chronic monitoring measures (established by *Study Three and Study Four*) that possess acceptable reliability and sensitivity (established by *Study One* and *Study Two*).

Study Five analysed the effect of 37 original and derivative measures of training load, training response and neuromuscular output on competition performance change (assessed via Player Rating score). These variables consisted of acute measures (rolling accumulations and averages of the 7 days prior to a competition match) and chronic measures (rolling accumulations and averages of the 28 days prior to a competition match) to represent the generic theoretical framework of athlete monitoring proposed previously.[17] The findings of this analysis showed that only acute training load (either total SRPE load or a summed variable of total distance, total SRPE and IMA event count) in the 7 days leading into a match displayed significant relationships with performance change. Specifically, z-score increases in individual acute training load associated with an 18-23% increase in performance z-score, complementing previous research in professional AF that reported higher weekly training load prior to a match to associate with positive match outcome at a team level.[103] However, our finding is in contrast to previous research that found higher weekly loads prior to a match were associated with decrements in individual performance,[102] while another study of simulated team-sport activity found a reduction in running performance following four days of increased internal training load.[39]

One possible explanation for difference in findings is that the results of the present study may be an artefact of competition fixturing. Indeed, there were 18 occurrences of 7-day (or more) between-match training cycles in our investigation. These relatively long between-match cycles provide practitioners with greater flexibility to schedule training sessions following adequate recovery.[75] For example, longer between match periods provides greater opportunity to schedule more sessions and complete more load, i.e. several on-field skills and resistance training sessions. Indeed, a 6 day between match period may limit the flexibility of acute training load prescription as players are unlikely to recover adequately until 96 hours following a match,[75] allowing only two days prior to the next match for acute load completion. This potential confounding effect of competition schedule on acute training load completion is an important extension of the findings of *Study Five*. Such an effect has been explored previously where higher training loads are completed during longer between-match training cycles, which has implications for injury risk and subsequent performance.[111] High acute training loads before players have recovered adequately or too close to a subsequent match may have a detrimental effect on performance, however this has not been explored to date. In addition, a practical ceiling likely exists regarding acute training load completion prior to a competition match. Despite the association between 7-day load and positive performance change identified here, it is likely that a certain amount of acute training load relates to decrements in performance (i.e. too much load prior to a match), however this plateau was not examined in the present investigation. Certainly, these factors highlight the difficulty in delivering suitable training load to players in between competition matches to ensure appropriate recovery but with an adequate training stimulus that avoids acute fatigue and a decrement in performance. These complexities are exacerbated by different between-match training cycle lengths throughout a competition season which are beyond the control of practitioners.

Another important finding of *Study Five* was the lack of significant relationships displayed between a range of commonly collected monitoring variables on performance change, including chronic training load measures (external and internal), maximum speed exposure, perceived wellness and adductor force output. Our results complement previous research in professional AF that reported trivial or unclear effects of a range of chronic derivative training load measures on performance (2-, 3- and 4-week rolling accumulations of external load) on subsequent individual match performance.[102] Indeed, while chronic measures of training load (i.e. load completed over two to four weeks) have historically demonstrated no direct, observable relationships with team sport performance,[40,102,112] in practice changes in these measures inform practitioners on cumulative load completion, which can be used to inform the prescription of individual training load between matches. It is possible that these chronic measures of elements of the training process may influence other mediating factors that relate to competition performance, such as training completion or subsequent acute training load completion. For example, a change in chronic training load may not display a relationship with performance immediately, but potentially in subsequent matches, however this was not explored in the present research. Nonetheless, measures of chronic training load, response and neuromuscular output measures should continue to be used to inform acute training load prescription between competition matches.

Collectively, *Review One, Review Two, Study One, Study Two, Study Three, Study Four* and *Study Five* contribute to the conceptual model of acute training load prescription in professional AF (Figure 9.1).

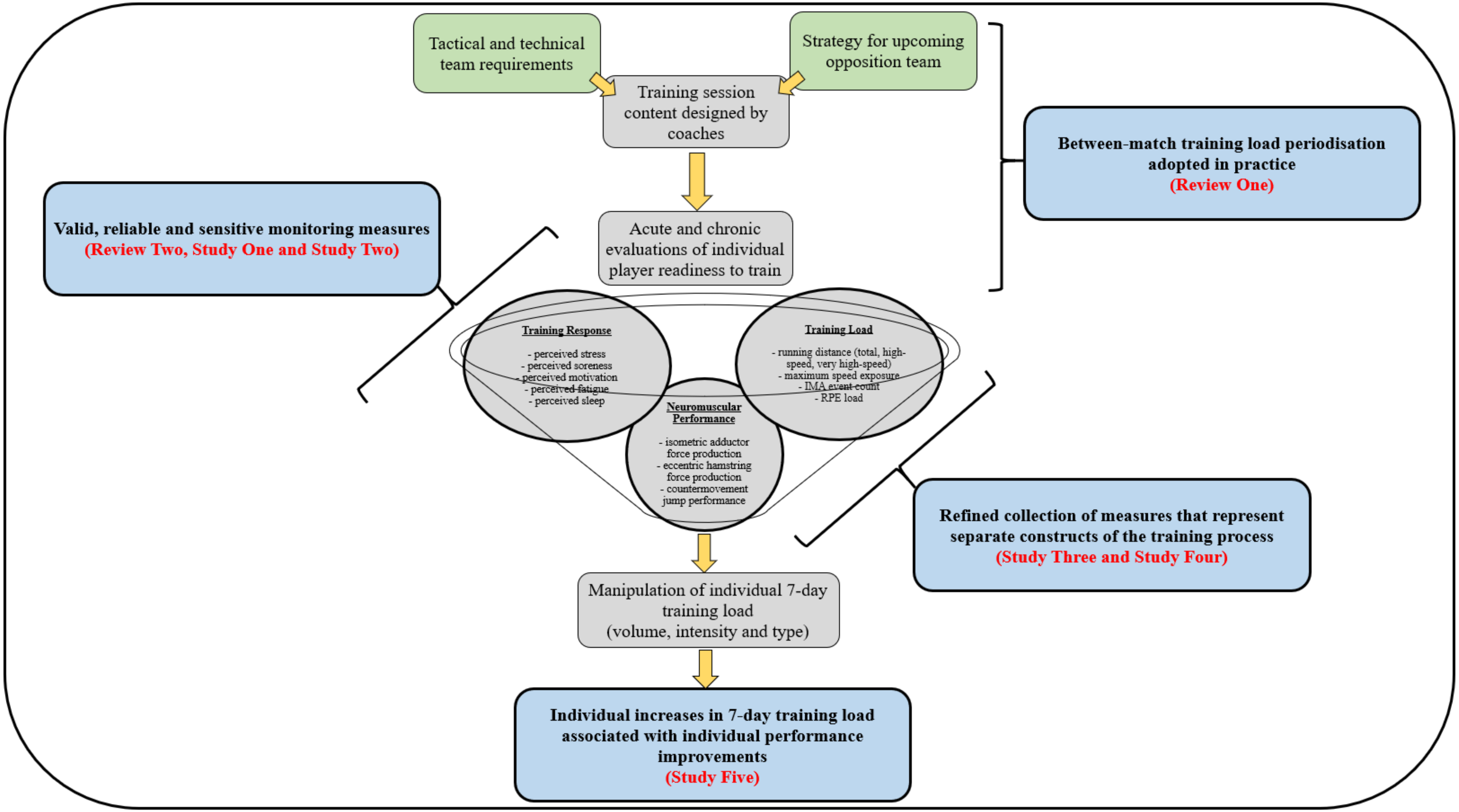

Figure 9.1: *Conceptual model of the PhD.*

Limitations

The nature of observational research common in professional team sport poses several limitations that should be considered when interpreting the results and applying findings of the studies within this thesis. Data collected and analysed for *Study One, Study Two, Study Three, Study Four and Study Five* were collected from the same club across a three year period (2017 to 2019), with each study examining data from one season. Therefore, raw data and subsequent results of analyses may reflect the demographics, physical characteristics and competition performance of players and the periodisation and tactical strategies employed by coaches and high performance staff during these periods. Nonetheless, the methods of analysis reported in all studies are suitable for any cohort of professional team sport athletes. Indeed, the authors advocate the need for practitioners of other teams and other sports to conduct their own analysis on their athletes within their specific training and competition environments to produce the most population-specific results. Future researchers may wish to collaborate with other clubs within their professional competition and combine datasets to enhance the practical application of findings derived from the analysis methods presented in this thesis.

GPS technology is a common method of quantifying locomotive movement in professional team sports.[90,91] However, research has also reported greater measurement error with higher movement speeds[90,91] which should be considered when interpreting changes in locomotive load completed at high-speed. Moreover, external match GPS data from 8 of 22 competition matches (in season 2018 for *Study Four* and season 2019 for *Study Five)* were collected via an alternative system (ClearSky, Catapult Sports, Melbourne) for indoor matches to the system used in training and the remaining 15 outdoor matches in each season. While unpublished manufacturer data has reported <5% error between systems, unfortunately this has not been established by independent researchers. Therefore, we suggest caution when combining or comparing external loads measured by the two different systems. Additionally, IMA (a novel proxy measure of mechanical load that counts each acceleration, deceleration and change of direction movement) was examined in *Study Four* and *Study Five*. Unfortunately, this measure has not been validated nor has the typical measurement error been established, hence IMA should be interpreted as purely a count of physical activity during training and matches. Future research may establish the validity of this measure by comparing IMA counts to training and competition vision of collisions and instances of acceleration, deceleration and change of direction to assess the precision and usefulness of this measure in quantifying mechanical load.

Contribution of Thesis

This thesis proposed a contemporary conceptual model of acute training load prescription in professional AF. While the approach highlighted in the model is evident in practice, no research had presented this approach as a way of monitoring player preparation for competition.

Specifically, the thesis examined measurement characteristics of common athlete monitoring tests used as part of a contemporary approach to training load prescription in professional AF. In doing so, this research proposed simple, unobtrusive methods of establishing reliability and sensitivity within professional team sport training environment. Reliability information provides practitioners with an interpretable threshold for changes in test results to ensure meaningful fluctuations can be acted upon when determining acute training load prescription. Additionally, quantification of measurement sensitivity provides practitioners with an index of test responsiveness to determine whether it is yielding useful information (i.e. detecting changes that exceed the typical measurement error).

Further, this thesis addressed the issue of athlete monitoring data overload for professional AF practitioners by applying a previously established data reduction technique (PCA) to measures of training load, training response and neuromuscular performance. The research also proposed two practical methods of further reducing collinear variables to a fewer number of monitoring measures using the results of PCA, thus enhancing efficiency and reducing the number of variables necessarily examined by practitioners when planning the prescription of acute training load to individual players.

This research also examined a refined collection of training load, training response and neuromuscular output measures using the combined findings of earlier studies in the thesis (*Study One, Two, Three and Four*) and their relationships with individual performance changes in professional AF. *Study Five* highlighted the difficulty faced by practitioners in manipulating training loads in between competition matches to ensure adequate recovery while allowing for high-level performance in the following match, particularly with different between-match training cycle lengths throughout the season. It is speculated that there is a confounding effect of team competition schedule on acute training load completion which may affect subsequent match performance, however this was not explored in the present investigation. Additionally, no relationships between a range of commonly collected monitoring variables including chronic training load measures (external and internal), maximum speed exposure, perceived wellness and adductor force production were identified.

Collectively, the findings of these studies support the contemporary method of acute training load prescription proposed initially in the thesis whereby training load is prescribed and monitored on a between-match basis (i.e. over acute timeframes of ~6 to 8 days). This is in contrast with previous theoretical models that prescribed training based on the combination of acute and chronic load completed. Indeed, information regarding both acute and chronic measures of training load, training response and neuromuscular performance are considered when planning and delivering acute training load to professional AF players, with 7-day acute training load an artefact of this process in displaying a positive effect on performance change. The acute and chronic measures of training load, training response and neuromuscular output used in the between-match prescription of between-match training load must possess appropriate reliability and sensitivity, and be as refined as possible to maximise the use of human and financial resources within professional AF clubs.

Practical Applications

- Practitioners should establish monitoring test reliability (via test-retest method) and sensitivity (via SNR) within normal training environments using protocols specific to their team for the most useful measurement characteristic assessment.
- Monitoring test CV should be used as a threshold for individual changes in test results. If a test result does not exceed the test CV (i.e. it does not exceed the measurement noise in the test), it should not be interpreted as meaningful.
- Monitoring test SNR should be >1 to provide useful information to practitioners. If results from a monitoring test do not consistently exceed the test CV, changes in test results cannot be interpreted as meaningful.
- The inclusion of monitoring tests in an athlete monitoring system should be based on their fit within a suitable conceptual framework. This includes their measurement characteristics (i.e. the value of information they provide), their practicality, feasibility, resource requirements, and their relationship with enhanced competition performance.

- PCA is an effective method for reducing collinear athlete monitoring data (measures of training load, training response and neuromuscular performance) to enhance efficiency of team-sport athlete monitoring systems. Practitioners should conduct PCA on specific athlete monitoring data collected within their club environment to reflect the exact nature of their monitoring systems.
- Summed variable and single variable methods are useful extensions of PCA to further enhance efficiency in athlete monitoring by either combining collinear variables into one arbitrary figure or selecting one of a number of collinear variables to represent an element of the training process.
- Total distance covered, total IMA count and total SRPE load measure similar dimensions of a player's acute preparation for a match and should be interpreted in combination as they display similar associations with subsequent performance.
- Practitioners are encouraged to maximise conditions for heightened acute load prescription between matches via training and recovery scheduling.
- The observable relationships between monitoring variables and performance reported in this thesis do not indicate causality, therefore practitioners are discouraged to focus on single variables to guide assessments of individual player readiness to enhance performance.

Chapter Ten | Summary and future directions

Summary

The thesis established a contemporary framework (Figure 9.1) of acute training load prescription that while evident in practice had previously not been presented empirically. Based on the findings of the thesis, practitioners are encouraged to select athlete monitoring measures by the value of the information they provide, the volume and nature of resources required to use them effectively, and their relationships with competition performance. Moreover, practitioners are advised not to focus on any single monitoring measure when preparing their athletes for competition. Despite the collection and analysis of high-quality data (i.e. with suitable measurement properties) and suitable actioning of this information, no monitoring system can completely account for an individual player's preparation for competition.

Future Directions

The thesis has elucidated several avenues for future research that while beyond the scope of this thesis would provide valuable contributions to literature and practice.

1. A key finding of the thesis was that individual increases in acute 7-day training load was positively related to subsequent performance. However, a potential confounding effect of competition schedule on the amount of load completed between matches and subsequently the effect on performance remains unclear. Future research may examine how acute training load is distributed across the week (i.e. when the load is delivered and in what form) to inform optimal training scheduling during between-match cycles of different lengths.

2. Individual match performance in professional AF is difficult to quantify as it requires a complex interplay of physical, psychological, technical and tactical proficiencies, in addition

to involvement from teammates and coaches. Therefore, while the Player Rating metric used to quantify individual performance in this thesis is a valid measure of performance, it does not completely quantify a player's output during a match. Indeed, only coaches are cognisant of individual roles and competencies (i.e. adherence to team tactics and other strategies) expected by players, which change on a weekly basis during competition periods. Therefore, coaches are best qualified to assess individual and team match performance. Future research should conduct qualitative examinations of the elements of competition that coaches consider when they evaluate individual and team performance. This would provide a global account of performance that has not been established previously.

3. The inherent nature of observational team-sport research is that it is often conducted on a single cohort of athletes from one competition season or training period. Therefore, the results and applications of these studies are reflective of cohort demographics, playing style, tactics, individual and team form, philosophies of coaches, strength and conditioning and medical staff and injuries. An important outcome of this thesis is the proposal of several methods of data collection and analysis (i.e. PCA, SNR and GEEs) that can be applied to any athletic cohort regardless of the above factors. However, specific results and findings of the thesis would be more generalisable if they included analysis of data from multiple cohorts of athletes (i.e. different teams) during several competition seasons. This would reduce the above limitations and enhance the practical application of findings.

4. Perceptual wellness questionnaires are common-place within team-sport athlete monitoring systems due to their simplicity and unobtrusiveness. Indeed, many questionnaires are modified to reflect the preferences of coaches, athletes and high performance staff within

individual clubs and therefore have not undergone validity assessment. They are also vulnerable to significant response bias when used as a tool to influence player training availability, where players may manipulate their responses to enhance chances of team selection. This thesis established the reliability and sensitivity of a customised perceptual wellness questionnaire in team-sport athletes, however practitioners would benefit from future research that examined the construct validity of these instruments and a universal definition of common perceptual wellness elements.

Chapter Eleven | References

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Chapter Twelve | Appendices

Appendix A: University Ethics Approval

Dear Applicant

Thank you for your response to the Committee's comments for your project titled, "Preparing for high performance: the efficacy of monitoring systems in preparing players for optimal performance professional Australian football.". Your response satisfactorily addresses the concerns and questions raised by the Committee who agreed that the application now meets the requirements of the NHMRC National Statement on Ethical Conduct in Human Research (2007). I am pleased to inform you that ethics approval is now granted.

Your approval number is UTS HREC REF NO. ETH17-1261.

Approval will be for a period of five (5) years from the date of this correspondence subject to the provision of annual reports.

Your approval number must be included in all participant material and advertisements. Any advertisements on the UTS Staff Connect without an approval number will be removed.

Please note that the ethical conduct of research is an on-going process. The National Statement on Ethical Conduct in Research Involving Humans requires us to obtain a report about the progress of the research, and in particular about any changes to the research which may have ethical implications. This report form must be completed at least annually from the date of approval, and at the end of the project (if it takes more than a year). The Ethics Secretariat will contact you when it is time to complete your first report.

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.

You should consider this your official letter of approval. If you require a hardcopy please contact Research.Ethics@uts.edu.au.

If you have any queries about your ethics approval, or require any amendments to your research in the future, please do not hesitate to contact Research.Ethics@uts.edu.au.

Yours sincerely,

Associate Professor Beata Bajorek
Chairperson
UTS Human Research Ethics Committee
C/- Research & Innovation Office
University of Technology, Sydney
E: Research.Ethics@uts.edu.au

Appendix B: University Ethics Amendment Approval

Dear Applicant

UTS HREC REF NO. ETH17-1942

The UTS Human Research Ethics Expedited Review Committee reviewed your amendment application for your project titled, "Preparing for high performance: the efficacy of monitoring systems in preparing players for optimal performance professional Australian football", and agreed that the amendments meet the requirements of the NHMRC National Statement on Ethical Conduct In Human Research (2007). I am pleased to inform you that the Committee has approved your request to amend the protocol as follows:

"We wish to incorporate the use of medical imaging technique known as dual energy x-ray absorptiometry (DEXA) to examine precise changes in the body mass, fat mass, lean body mass and bone density of the research participants."

You should consider this your official letter of approval. If you require a hardcopy please contact the Research Ethics Officer (Research.Ethics@uts.edu.au).

If you wish to make any further changes to your research, please contact the Research Ethics Officer in the Research and Innovation Office on 02 9514 2478.

In the meantime I take this opportunity to wish you well with the remainder of your research.

Yours sincerely,

Associate Professor Beata Bajorek
Chairperson
UTS Human Research Ethics Committee
C/- Research & Innovation Office
University of Technology, Sydney
E: Research.Ethics@uts.edu.au