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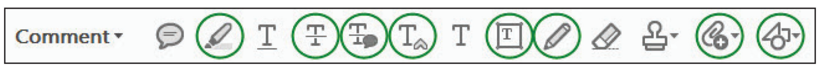

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GQ3
Cooperative passing network features are associated with successful match outcomes in the Australian Football League

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GQ1

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Abstract

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Collective behaviour is an important component of team performance in team sports. This study used a binomial generalised linear mixed effects regression model to investigate the relationship between cooperative passing network characteristics and match outcomes of professional Australian Football League competition games across four seasons between 2016 and 2019. It divided a sample of 1629 observations into a training and testing partition used to develop and assess the validity of the model used in this study, respectively. The results of this study reveal that a team's connectedness is associated with the probability of winning Australian Football League games (Akaike Information Criterion = 1637.3, residual df= 1297, deviance = 1625.3). When most players within a team are involved in the team's passing network bidirectionally (i.e. a well-connected network; odds ratio = 1.053; 95% confidence interval: 4.2–6.5%, $p < 0.001$), teams have a higher probability of winning. The centralisation of a team's passing network was not significantly related to match outcomes. The classification accuracy for the model associating network characteristics with match outcomes was 69%. Collectively, these findings suggest that Australian Football League-specific network features should be incorporated within existing performance analysis methods and can provide a useful, practical tool for coaches to measure collective performance during team practice.

Keywords

Australian Football League, complex system, performance, analysis, social networks

Introduction

The performance and interactions of athletes within the teams can be considered as complex, cooperative systems, consisting of many structurally and functionally heterogeneous components. At the microscopic level, individual athletes may appear to act or move individually, independently and often randomly, while at a macroscopic level, collective team movements or actions reveal large degrees of coordination and cooperation.[1] Since athletes often fulfil match-specific positional roles such as attackers, defenders or midfielders, coordinated and cooperative interdependent behaviour exists at different sublevels within sports teams. These coordination tendencies can be influenced organisationally by the physical proximity of teammates, spatiotemporally through defensive or attacking coordination or informationally via shared information on opponent movements or the movement of the ball.[2] Additionally, these information exchanges often occur nonverbally and are a result of players detecting and responding to shared opportunities for collective action.[3,4] For example, individual players aim to compress and contract their positioning to limit the available space in defence,

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while they expand in attack in order to maximise space when in possession of the ball. Furthermore, these collective actions exhibited by sporting teams attacking or defending are influenced by the movements of the ball, the proximity to the ball and the movements of the opposing team's players. More information of how team sport characterises a complex system is provided elsewhere in detail.[1,5]

Complex collective behaviours such as those observed in team sports have been studied in other research fields, such as in the social sciences. Social network analysis has been used to examine social relationships such as friendships, social interactions and similarities between agents, such as shared attributes or shared place of birth. Furthermore, social networks have also been used to measure how information *flows* through networks.[6] Given their ability to capture these complex, collaborative behaviours, social network analysis has also been proposed as a useful tool to capture collective behaviour of sporting teams.[1,7–10] Given their ability to represent the complexities of social interactions, these networks could be applied to examining passing or shooting interactions to determine which members of a collective (i.e. the team) are connected[11,12] and cooperate. Here, network analysis applied to team sports can be used to reveal collaborative patterns or networks related to successful sequences of play, for example, possession chains[13] or those contributing to successful team performances.[8] As a result, cooperative passing network analyses applied to team sports may provide a useful tool to capture collective performance, and research investigating if cooperative networks analysis augments traditional methods of individual-level or team-level performance analysis is warranted.[14,15]

Cooperative networks have been studied extensively in association football. Results from recent studies that have adopted network analysis in football provide insights into some of the network metrics related to performance. For example, Mendes et al.[16] revealed a positive relationship between the density (i.e. the portion of potential connections in a network that are actual connections) of a passing network and a team's match score and a negative relationship between network density and goals conceded. Furthermore, it was evident that elite teams yielded more dense networks than youth teams. Conversely, Pina et al.[17] reported that successful attacking sequences in the UEFA Champions League were negatively associated with the team's network density. Specifically, the authors argued that a lower network density was related to a greater number of successful attacking sequences. Finally, it has also been revealed that passing networks that are less dependent on a single player (i.e. centrality) are related to successful performance outcomes in adolescent and postadolescent footballers.[18] Therefore, these studies provide an indication that well-connected and decentralised networks may be beneficial to success in team sports such as football.

Similar to association football, Australian football is a multidirectional team sport in which comparable cooperative behaviours of systems and subsystems are likely to be present. For example, in the Australian Football League (AFL), the pinnacle of Australian football, games are characterised by their physical demands, involving intermittent high-speed running, collisions and changes in direction[19,20]; high levels of hand and foot skill proficiency for passing, scoring and gaining ball possession[21]; and specific tactical strategies that vary depending on team personnel, coaching philosophies, opposing team and environmental conditions during the match.[21] Within a single team of 22 players (18 on field, 4 interchange), there are generally three main field positions (forwards, midfielders and defenders), within which further positional specialities exist, while regular player rotations and an absence of a rigid positional structures characterise the game. Given the complexity of match play, it is apparent that Australian football performance is *more than the sum of its parts*. Consequently, measuring collective performance within Australian football is undoubtedly difficult. While some studies have attempted to measure Australian football performance using individual players' performance metrics (e.g.[22–24]), these studies' abilities to capture collective performance are undoubtedly limited by their inability to capture the interactions between players alongside the number of actions a player or team performed. Braham and Small[11] illustrated this point by revealing that predictive models of match outcomes using individual skill counts were improved by also including the characteristics of the passing networks that connected these players. Indeed, these researchers concluded that network analysis appears to suit Australian football due to its "free-flowing" nature and relative lack of rigid positional structures and passing rules.

Currently, only a few studies have examined cooperative network structures in Australian football.[10,11,25,26] Sargent and Bedford[25] reported a relationship between team selection, point scoring margin and player network interactions through handballs, marks, kicks and other exchanges of ball possession in one AFL team. They observed that team network structure, particularly eigenvector centrality, a measure of the degree to which players interact with prominent players in the team network, was associated with score margin and that this relationship was mediated by team selection. Braham and Small[11] used network analysis to discover playing styles or strategies for all teams competing in the 2014 AFL season. These authors reported different, better-connected passing networks for teams who finished higher on the league table. Furthermore, several global characteristics of passing networks were positively associated with match outcomes. It was clear that analytical models solely investigating associations with conventional AFL measures such as the number of disposals, kicks, inside 50 s, among others, and match outcomes were markedly improved by including network metrics. In a recent examination of the topic in Australian football, Young et al.[10] recently explored the relationship between several network characteristics and match outcomes and found that teams who win games have denser and less centralised networks (i.e. more mutual interactions between players). These findings collectively emphasise that the inclusion of network characteristics certainly augment current understandings of the quantitative measurement of team performance in Australian football.

While these studies provide interesting insights into the collective behaviour of AFL teams, the interpretation of network analysis in the context of performance in team sports is often complicated.[9] Sheehan et al.[9] approached this problem by using a dimension reduction technique to reduce 14 team network variables to three principal components while maintaining more than 80% of the variance in the original dataset. These authors derived three metrics that can be used to describe passing networks in Australian football: *connectedness*, a team's level of bidirectional interactions through passing; *in-degree variability*, the mutuality of receiving interactions; and *out-degree variability*, the mutuality of distributing interactions. While this method simplifies the use of network analysis to quantify collective behaviour in Australian football, the relationship between these AFL-specific cooperative network features and AFL match outcomes has not yet been explored. Therefore, this study investigated whether the cooperative network structures obtained from all teams across four competitive AFL seasons were related to match outcomes. Based on recent evidence, it was hypothesised that these reduced network variables would yield similar relationships with match outcomes to those revealed in previous studies, where higher levels of connectedness and less centralisation are associated with successful match performance.

Methods

Sample

A total of 1656 observations (824 losses, 824 wins, and 8 draws) of 18 professional AFL teams over a period of four seasons between 2016 and 2019 were collected. Every season consisted of 23 official rounds with one bye per team and up to four more finals matches.

Methodology

Cooperative network variables were derived from data obtained from ChampionData®, the official data provider to the AFL.[11] ChampionData® annotate all AFL matches for a myriad of skill involvements, and the results of their coding are commonly used in Australian football research.[27–29] A subsample of the statistical indicators used by ChampionData® has been empirically reviewed, including an array of disposal and possession-related statistics that were used in the current study. These investigations reported a high level of reliability (ICC range = 0.980–0.998 RMSE range = 0.0–4.5).[30] The only other reliability information provided about ChampionData® statistics states that 'quantity-based statistics are logged at better than 99% accuracy'.[28] Selected match statistics were used to create a weighted and directed, 22 × 22 adjacency matrix for each game, revealing the number of interactions between all player dyads. An interaction was counted if a handball or kick was successfully received by a teammate. The pass was deemed successful if it was received by a teammate on the full or the pass was to the receiver's advantage, for example, the receiver may not receive the pass on the full, but they are still able to gain possession. This matrix was then used to create a weighted directed graph with the nodes representing individual players and weighted edges signifying the direction and number of passes between each player dyad. The adjacency matrices and graphs were subsequently used to derive the following cooperative network variables using the calculations provided by Sheehan et al.[9]: connectedness, in-degree variability and out-degree variability. These weighted calculations were derived from a principal component analysis, which is a data reduction technique used to reduce the number of metrics related to the cooperative network analysis by grouping network metrics at the team level based on their underlying correlational structure.[9] This technique reduces the dimensionality of the data into a smaller set of unrelated components (i.e. connectedness, in-degree and out-degree variability) whilst maintaining most of the variance in the original dataset. Each team-level principal component score and its composite metrics developed by Sheehan et al.[9] can be found in Table 1. As specified by Sheehan

Table 1. The network measures that make up the Australian football specific cooperative networks scores at a team level (*connectedness, in-degree variability* and *out-degree variability*), including their relative weighting within each component as per the methods of Sheehan et al.[9] (2020).

Variable	Calculation
Connectedness	0.964 × network density + 0.931 × network intensity + 0.935 × in-closeness centrality + 0.939 × out-closeness centrality + 0.949 × team betweenness centrality
In-degree variability	0.925 × in-degree node variability + 0.925 × in-closeness variability + 0.613 × in-degree pass centrality variability + 0.714 × PageRank centrality variability
Out-degree variability	0.895 × out-degree node variability + 0.945 × out-closeness variability + 0.626 × out-degree pass variability + 0.523 × betweenness centrality variability

et al.,[9] superior values of connectedness signify that most players connect bidirectionally and are easily reachable by others. Further, simplified scores were subsequently produced and converted to standardised quotient scores with an average of 100 and a SD of 15 (quotient score = 100 ± z-score×15) as per the methods described by Sheehan et al.[9] Ethical approval was received from the research institution's research ethics committee (approval number: ETH18-3126).

Statistical analysis

Prior to analysis, the distributions of the explanatory variables in this study were inspected visually, and an outlier labelling rule was used to determine which values could be considered outliers. Values that were outside of AQ9 2.2 × interquartile range (IQR) below or above the 25th and 75th percentile, respectively. This method was adapted from Hoaglin and Iglewicz,[31] who showed that a 1.5 × IQR rule was inaccurate 50% of the time, whilst a 2.2 × IQR rule appeared to be more valid. The upper and lower limits as specified by the outlier labelling rule were 46–154, 45–153 and 45–152 quotient points for connectedness, out-degree and in-degree variability, respectively. Three negative outliers for connectedness, seven positive outliers for out-degree variability and 10 positive outliers for in-degree variability were observed. Resultantly, 19 observations were removed from the data set (one observation reported two outliers). These appeared to be randomly distributed between teams and match outcomes. Subsequently, a total sample of 1629 complete observations across four seasons remained (814 losses, and 815 wins, between 85 and 96 observations per team, and between 405–412 observations per season) after the removal of eight draws from the sample. Before model development, the data were partitioned for cross-validation purposes into training (80% of the data: n = 1303) and testing (20% of the data: n = 326) samples using a random partitioning function in R. Since the aim of this study was to investigate the relationship between team cooperative network characteristics and the probability of winning or losing AFL games and the nature of the data set being hierarchically clustered data, a binomial generalised linear mixed effects regression (GLMER) model with a log link function was used to estimate the effects of connectedness, in-degree and out-degree variability on winning or losing, whilst taking into account the inherent variability that exists in terms of winning or losing between teams in different seasons.[32] As such, whilst all teams competed in all four seasons, a random effect of teams nested within seasons was specified as the sample only included a random subset of the AFL seasons played in by these 18 teams, and the probability of winning or losing for a single team would have varied between seasons. The introduction of this random effect was informed previously by an investigation of the correlation structure of the data. This random intercept model was compared with other random AQ10 intercept models (i.e. with different modes of nesting the data such as nesting network values within games), yet the selected model for this study was the most parsimonious (i.e. it yielded the lowest Akaike Information Criterion (AIC) for the fewest amount of parameters to be estimated). Random slopes models (random slopes for the explanatory variables in the model) and the introduction of interaction effects between the explanatory variables were also considered due to teams potentially having different game styles. However, random slopes models were ultimately not used as they did not improve model fit whilst significantly decreasing model interpretability. Models incorporating the interaction between independent variables yielded high variance inflation factors (VIFs), representing the presence of significant multicollinearity. Hence, these models were not retained.

Following the development of the model on the training sample, the same model was used to evaluate the classification accuracy according to match outcomes in the test sample. Model outputs (odds ratios derived from exponen- AQ11 tiating the model coefficients and their 95% confidence intervals (CIs), conditional and marginal pseudo explained variance using the methods of Nakagawa and Schielzeth,[33] AIC, predicted versus actual outcomes (if the probability of winning a game was $p > 0.5$, the game was classified as a win), and misclassification error percentages were derived from each model and compared for model evaluation. Finally, model diagnostics were performed by checking three assumptions in the model constructed on the training dataset: the linearity of the relationship between the explanatory variables and the dependent variable, the presence of influential data points using Cook's distance and the presence of multicollinearity through the VIFs associated with each independent variable. If any influential data points with a Cook's distance greater than 1 were observed after modelling, they were removed, and the model was rerun. Relaxing the Cook's distance threshold is common practice in relatively large datasets where other threshold methods (e.g. 4/n) are not practically useful. Data analysis was performed using R statistical software using the lme4 package,[32] and significant values were set at $p < 0.05$. The R code used to develop these models AQ12 and a mock data sample of the same structure as the data used in this study can be accessed here:.

Results

The relationship between AFL match outcomes and measures of connectedness, in-degree and out-degree variability demonstrated a linear pattern, with no influential variables in the data that may have skewed the estimations via the using Cook's distance metric, and no multicollinearity was present since VIFs were below 2.0. The binomial

GLMER ($AIC = 1637.3$, residual $df = 1297$, $deviance = 1625.3$) developed on the training partition revealed that in a model with connectedness, out-degree variability and in-degree variability where the intercept is allowed to vary randomly by team within season, connectedness is significantly associated with the probability of winning or losing AFL games at a 95% confidence level (Table 2). As the connectedness of a team increases by one standardised unit, the probability of winning a match increases by 5.3% (95% CI: 4.2–6.5%, $p < 0.001$). No significant association between in-degree variability ($p = 0.496$) or out-degree variability ($p = 0.101$) and the probability of winning or losing was observed. Random variance in the model was associated with the clustering of teams within season, but not with season as a separate random effect (team by season variance $= 0.60 \pm 0.77$, no random variance was associated with the different seasons as a random intercept). A total of 13.8% of the variance in the probability of winning or losing games was explained by the training model's fixed effects (marginal R^2), whilst 27.1% of the variance was explained by a combination of fixed and random effects (conditional R^2).

In this study, the misclassification error ((false positives + false negatives)/total) out-of-sample data was 31.6%. The amount of false-positive and false-negative classifications is presented in Table 3. This confusion matrix is useful to understand the magnitude and nature of the prediction error associated with the model developed in this study, when predicting match outcomes in a sample on which the model was not trained.

Table 2. The OR, exponentiated 95% CIs, Z-statistics and p-value associated with the fixed effects obtained from a generalised linear mixed effects regression investigating the association between team cooperative network characteristics and the probabilities of winning AFL games.

N (training) = 1303	OR	95% CI	Z statistic	p
(Intercept)	0.008	0.001–0.053	–5.044	<0.001
Connectedness	1.053	1.042–1.065	9.480	<0.001
In-degree	1.003	0.994–1.013	0.680	0.496
Out-degree	0.992	0.982–1.002	–1.642	0.101

Note: AFL = Australian Football League; OR = odds ratio; CI = confidence interval.

Table 3. Confusion matrix for the GLMER in the testing sample, and the misclassification error associated with predicting match outcome.

N (testing) = 326	Actual		
Predicted	Loss	Win	Error
Loss	117	60	31.6%
Win	43	106	

Note: GLMER = generalised linear mixed effects regression.

Discussion

The results of this study revealed that the connectedness of a team's cooperative passing networks is related to winning or losing AFL games. A single standardised unit increase in connectedness resulted in a 5.3% increase in the odds of winning an AFL game. Whilst the odds ratio for connectedness reported in this study may appear to be small, the association between connectedness and match outcome probabilities is important when interpreted in light of the variation that can be expected in these cooperative network values across and between teams. Given that connectedness represents a normalised and standardised quotient score,[9] interpreting the coefficients derived from the GLMER in light of a 1 SD change better frames this association. A 1 SD (i.e. 15 quotient points) increase in team connectedness represents a 79.5% increase in the odds of winning. It should be noted, however, that despite the linear relationship between connectedness and the probability of winning, this relationship is likely mediated by the opposition team's performance. Therefore, future studies may want to investigate the extent to which well-connected teams increase win probabilities, relative to the performance of their opponents. This will likely provide coaches and other practitioners with valuable insights into how teams with well-connected passing networks can be strategically countered.

When interpreting the variance in the probabilities of winning or losing a game related to a teams' cooperative network characteristics, one may argue that an explained variance in this model of between 14% and 27% (marginal–conditional R^2) is relatively small. However, given the complexity of human behaviour and performance, and the multitude of factors that may affect winning or losing such as the strength of a team's individual players, contextual factors such as weather or playing home or away or the influence of the officials, the explained variance reported in this study is relevant, and its inclusion as a performance-related characteristic in the AFL is warranted. Braham and Small[11] examined whether the inclusion of network measures alongside conventional AFL measures improved the prediction of match score margins for the 2014 AFL season. They reported that 27% of the variance in match score margin could be explained using passing network measures only, whilst 29% of the variance was explained in a combined model using network and conventional skill metrics. As such, the findings of Braham and Small[11] are similar to those presented in the current study associating network measures and match winning probabilities and hereby demonstrate that the current findings are an extension of those previously reported by Braham and Small.[11] Furthermore, previous studies in team invasion sports (e.g.[34,35]) reported slightly higher levels of conditional explained variance using a linear mixed effects regression aimed at explaining physical (conditional R^2:

21–49%) and technical (conditional R^2: 45–58%) performance of rugby sevens athletes using situational and individual factors. However, these studies reported similar marginal explained variance in physical (7–20%) and technical (19–34%) performance. As a result, the explained variance reported in this study is somewhat in line with other studies investigating multifactorial performance in team invasion sports and far exceeds that commonly reported in other domains (e.g. ecological and evolutionary studies: 2.5–5.4%).[36]

The ability to form a well-connected network is associated with positive outcomes in Australian football[11] and soccer,[37] among other team invasion games. Well-connected networks foster decentralisation, where receiving and distributing ball possession has relatively equal contributions among players. As a result, well-connected teams can readily adapt their passing networks to meet the evolving strategic goals as they emerge during the game. For example, teams with well-connected networks may be able to temporarily adapt their passing network to escape opposition pressure by reaching players away from contests and subsequently adapt back to rapid play through key midfielders when the opposition pressure eases. This ultimately provides these teams with greater flexibility and fosters system degeneracy (i.e. the ability for teams to produce similar outcomes in a variety of ways). Grund[37] highlighted that the connectedness of a team's network is the greatest contributor of match outcomes compared with measures of the centralisation of the distribution or receiving networks. This is corroborated by the findings in the current study, in which connectedness was associated with the probability of winning an AFL match, whilst measures of centralisation were not (in-degree and out-degree variability).

Whilst likely less important than network connectedness, decreased centralisation of the passing network distribution (distributing ball possession is shared across a larger number of players rather than across few key players) has previously been found to be associated with performance. For example, professional soccer network analyses have revealed that minimal reliance on key players (i.e. decentralisation) is a characteristic commonly associated with successful team performance.[18,37] It is hypothesised that decentralised teams foster greater interdependence whereby teams do not solely rely on a few key players. This encourages coordination and cooperation, which in turn encourages strategies and tactics that are perhaps less easily predictable. This is ultimately beneficial to a team's likelihood of winning competitive matches.[37] The GLMER used in this study was not able to corroborate the findings from previous studies in other team invasion
AQ13 games. This likely indicates that while a decentralisation of the incoming and outgoing passing networks, while not associated to the probabilities of winning AFL games, may need to be investigated further.

The results of this study revealed a classification accuracy of approximately 69% when using an out-of-sample validation. These findings are to some extent comparable with those of other studies investigating the classification accuracies of performance models in the AFL. For example, Fahey-Gilmour et al.[38] reported a 73.3% accuracy classification rate when using a predictive machine learning approach incorporating 33 fixture and team characteristics. Young et al.[26] developed a much more accurate predictive model using decisions trees and a generalised linear model that successfully predicted match outcomes using 45 match statistics deemed important in the 2009–2016 seasons with 89–93% accuracy. The classification accuracy observed in the current study (69%) – while similar to the accuracy reported by the prematch prediction by Fahey-Gilmour et al.[38] – is significantly lower than the accuracy reported by Young et al.[26] However, the current study's method only used only three independent variables. This prediction accuracy versus model input is a significant practical consideration, as limiting the information that needs to be collected and inserted in performance models may greatly improve its uptake by relevant practitioners. Despite the use of classification accuracy as a diagnostic tool to validate the model developed in this study, it should be noted that this model should primarily be viewed as an explanatory model. Therefore, the association between network features and performance in AFL should be viewed as its main finding.

The classification accuracy of the model in the current study is substantial (i.e. two-third games are correctly classified according to their match outcome). However, the relatively large classification error undoubtedly further reveals the complexity of team performance. Performance in AFL matches is complex and multifactorial, and models like the current one that observe one aspect of performance only (i.e. cooperative network features) are therefore likely to lack explanatory power. Consequently, the network characteristics observed in this study should be used alongside additional technical and tactical analyses in order to better capture the association between collective team behaviours and the probability of winning AFL matches. Perhaps, researchers can build on the current study's findings and explore methods such as structural equation modelling or path analysis that allow the analysis of both the direct and indirect effects of network measures as part of larger, holistic performance models that include measures of physical, technical and tactical performance of AFL teams.

The use of network measures in performance analysis is not yet widespread, likely due to the complexities involved in interpreting methods traditionally developed to study social interactions to collaborative passing networks.[9] Braham and Small[11] already demonstrated that certain network metrics, alongside traditional key performance indicators in AFL, were significantly associated with match outcomes. This finding was further corroborated by Young et al.[26] who demonstrated superior classification accuracies when network measures were used alongside more traditional match statistics to explain the variance in performance outcome probabilities. Collectively, these studies strengthen the rationale for incorporating collaborative passing network features in traditional performance analysis methods used in team invasion sports. However, the vast number of network features used in these studies, as well as the complexities involved in their interpretations in light of passing network features in AFL teams, may limit their practical use by performance analysts, coaches and skill acquisition specialists. However, the fact that this study used dimensionally reduced network features specifically developed to understand collective behaviour in AFL teams,[9] rather than individual network characteristics, is novel and may facilitate the adoption of network characteristics along with more traditional measures used in performance analysis in sporting teams (e.g. skill involvements, physical demands, etc.). Furthermore, this study revealed that while some random variance was attributed to repeated observations within teams nested in seasons, no substantial random variance was related directly to seasonal variation. This may indicate that the relationship between network measures and match outcomes in AFL is relatively stable across seasons. While this somewhat contrasts the findings by Young et al.,[10] who found inconsistencies in team network measures across eight seasons, this finding further strengthens the value of incorporating network characteristics in the measurement of collective performance of AFL teams, especially when used across limited time periods (i.e. four seasons).

This study derived its network characteristics from match statistics obtained from an external provider. However, this does not mean that network characteristics can only be used to assess collective performance during competitive games. The characteristics of passing networks can also be investigated in practice by manually coding the interactions between players of the same team. Consequently, coaches and other support staff can analyse and develop training scenarios that promote favourable network behaviours such as improving a team's connectedness. While network characteristics during practice have not yet been examined in Australian football, 5v5 small-sided games in soccer have been found to be useful tools in promoting favourable passing networks. For example, constraining the defending team to a conservative defensive pattern, such as zonal defence, has yielded increases in the number of passes between field zones and higher levels of reciprocal passing between different areas.[39] Similar approaches may be adopted by Australian football coaches and should be explored in future studies.

The current study's strengths lie in the representative sample of AFL matches, the use of simplified cooperative network metrics developed specifically for Australian football and the use of an out-of-sample validation of the models developed in this study. Nonetheless, this study's results should be viewed in light of its limitations. The findings in this study are specific to the AFL and not directly generalisable to other samples (i.e. other performance levels in competitive Australian football or other team invasion games such as soccer and rugby). Hence, while this study's methodology could be transferred to lower levels of competition or indeed other invasion games, the current findings can only be used to interpret the association between passing network measures and match outcomes in the AFL. Further, the current study only investigated how total network scores derived from an entire game were related to match outcomes and provided no insights into how the dynamic nature of these networks was related to performance. It is possible that two teams' network metrics are equal, yet the temporal dynamics differ throughout the game. As a result, future studies may be useful to investigate the relationship between temporal network dynamics and match outcomes in the AFL. Regardless, this study's findings have wide-ranging applications for practitioners.

Practical implications

The findings of the current study are relevant to both performance analysts and coaches in Australian football, yet the methodology would certainly be worthy of investigation in other team sports. Given the relationship between simplified network features and performance in the AFL, it appears that performance analysts should include cooperative network analysis alongside traditional quantifications of performance during competition and training. This study's findings indicate that dimensionally reduced network characteristics yield similar practical value than the inclusion of more granular network characteristics, which subsequently improves their translation to the end user (i.e. performance analysts, coaches and skill acquisition specialists). Additionally, this study's findings indicate that coaching staff should aim to develop their team's connectedness by designing training interventions to improve players' interdependence.

Conclusion

This study investigated the relationship between three network measures developed to capture the topography of cooperative passing networks in Australian football and winning probabilities in the AFL. The findings suggest that during individual matches, teams with highly connected networks have a greater probability of a successful match outcome.

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