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Using cooperative networks to analyse behaviour in professional Australian Football

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ABSTRACT

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

Practical implications

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

1. Introduction

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

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

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

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

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

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

2. Methods

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

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

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

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

Table 1
Complex network variables.

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

Table 1 (*Continued*)

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

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

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

3. Results

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

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

4. Discussion

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

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

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

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

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

Table 3
Resultant equations from principal components analysis.

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

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

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

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

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

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sports other than Australian Football, following its validation in these other sports.

5. Conclusion

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

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Appendix A. Supplementary data

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

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