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Cooperative networks in team invasion games: A systematic mapping review

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Abstract
Team invasion games are sports in which individual team members interact and exchange information to coordinate their behaviours and actions in pursuit of the common goal of winning matches. Researchers have used social network analysis to quantify the cooperative behaviours of sports teams (cooperative network analysis), yet this research exists across an array of disciplines and uses various methods. Therefore, accessibility for practitioners and researchers interested in using it to quantify team cooperation in team invasion games may be limited. This systematic mapping review aimed to identify, report and discuss research in this emerging research area. Articles were systematically searched in electronic databases and reference list scans resulting in 112 papers included. Football was the most studied sport (n = 91), and passing was the most observed interaction between players within a sports team (n = 107). This review further revealed a lack of consistency in reporting between the included studies with respect to nomenclature and network measures. A comprehensive map of the current literature on the use of cooperative network analysis in team invasion games is provided which can be used by practitioners and researchers tasked with or interested in analysing team performance.

Keywords
Collective behaviour, football, performance analysis, social network analysis, tactics

Introduction

Team invasion games are those in which the main objectives are to invade an opposition team's territory to score and simultaneously prevent the opposition from doing so. Football/soccer, rugby and hockey, among others, are all popular team invasion games. Team invasion games require cooperative behaviour, which occurs when all players collectively aim to achieve the team's shared goal of defending and attacking together whilst each fulfilling a distinct, independent role.[1, 2] A common method of performance analysis in team invasion games is individual-level notational analysis in which the number, frequency and/or (in)effectiveness of individual or collective actions such as passes, attempts at goal, possessions, kicks and tackles are correlated with match outcomes.[3] Notational analysis provides coaches, athletes and other stakeholders with pertinent information relating to individual and team performance.[3] However, it fails to capture the cooperative nature of invasion games, that is, a group of athletes who can perform effective individual actions such as passing or kicking may not necessarily perform successfully as a team if they lack cooperation. Therefore, methods that can be used to assess cooperative behaviour in sports teams may improve insights into players' relative contributions to the collective aim of the team (i.e. integrative behaviour), as well as how effectively players are working together to achieve their collective goal.[2]

Social network analysis

To investigate how teams and other groups of individuals interact and share information with one another, social network analysis (SNA) has previously been used (e.g. distribution and receipt of emails within a workplace or the

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exchange of messages within a social group or social media website).[4] It refers to the relationship between the individual, at a microscopic level, the structure that they belong to at the macroscopic level and the interaction between these two levels.[5,6] This method of analysis enables the study of how individual components and the system they are a part of interrelate in a bi-directional manner, each influencing the other.[7–9] Network visualisations are often created (i.e. network graphs; see Figure 1 for example) to accompany metrics describing the main features of the network and aiding the interpretation of network features.

Cooperative network analysis in team invasion games

SNA has been applied in sports settings and referred to as cooperative networks as the teams are specifically working towards a common task goal.[1,10,11] For example, in team invasion games, cooperative networks are commonly used to identify cooperation amongst teammates via the distribution and receipt of an object such as a ball (although other observations of cooperation such as spatio-temporal relationships can also be mapped).[12,13] For example, during Australian Football games, external match statistics providers (e.g. Champion Data Pty Ltd, Melbourne, Australia) record every passing interaction between two players (i.e. the name, position and identifying numbers of the passing player and the receiving player), as well as the nature and location of the pass, and even the amount of defensive pressure on the passer, among many other variables. These detailed passing interaction transcripts can then be used to develop cooperative passing network graphs.[13–15] The topography of these passing networks can then be used to derive characteristics/metrics that describe the network. The distribution of the passing network can be examined, for example, by detecting players who are more influential in the passing network than others. Finally, clustering within the passing network can be investigated, whereby distinct groups within the network that work closely together with one another but not with others are identified. Together, these details may yield useful information about a team's strategy or preferred style of play.

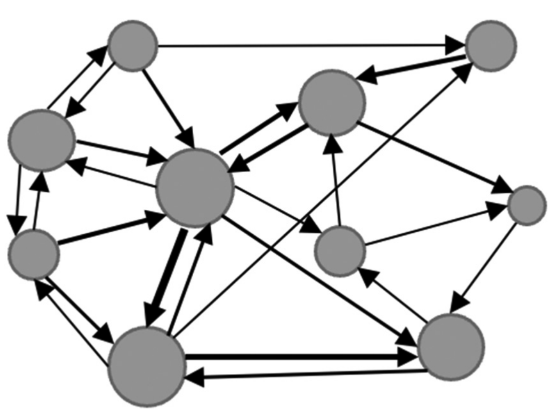

Figure 1. Example of cooperative network visualisation.

Whilst other methods of cooperative behaviour analysis are available such as spatiotemporal analysis,[16,17] cooperative network analysis has benefits such as the data generally being widely accessible or can easily be obtained via video encoding. Additionally, along with the capacity to provide pertinent information for the reference team, the availability of appropriate data for SNA often enables the investigation of the cooperative behaviours of opposing teams, subsequently enabling coaches to study their strategies. This is less straightforward for other measures of cooperative behaviour such as the spatiotemporal relationships between players, which are usually derived from Global Navigation Satellite Systems internal to a single team. It is nonetheless important to note that cooperation can consist of many different forms of interaction such as communication or physical contact between players.[10,18,19] Accordingly, the type of network analysed can be related to any of these or other possible interactions.

Construction and features of social networks

To construct social networks, each interaction between teammates is amalgamated into an adjacency matrix, that is, an $n \times n$ table in which the passes from each player are summated in one axis whilst the passes received by each player are summated in the other axis. Metrics and visualisations are then derived from this matrix. Whilst there are numerous ways that a network graph can be presented, visualisations typically involve a set of nodes, often depicted as circles or dots, that are linked by edges, often shown as lines or arrows between nodes. An example of a cooperative network visualisation is presented in Figure 1. Nodes will generally be representative of agents, for example, individuals or players in a sports team, whilst edges represent the interactions between these agents. Edges can be either weighted or unweighted and directed or undirected. Edge weights typically represent the frequency with which interactions occur between the same agents, whilst the edge direction is indicative of the direction of information flow. Additional information can be expressed in these visualisations by using colour coding and/or labelling, among other techniques.[20] For example, in invasion games, a cooperative network could show the passing interactions between players that make up a sporting team, with information about who passes to whom and how often. Subsequent to the development of network graphs, their topography can then be analysed and interpreted further.

In addition to visualisations, network metrics offer a method to quantify cooperative behaviours within teams and can be applied at an individual or team level. At an individual level, the integrative behaviour of a player within the network is analysed. Integrative behaviour is a form of cooperative behaviour that represents individual player behaviour relative to the overall team behaviour.[1] An example of integrative behaviour is an individual player's closeness centrality which indicates how often that player appears on the shortest edge path between players. In other words, it provides a measure of the importance of a player in connecting with their teammates. Cooperative behaviours can also be measured at the team level. For example, network density refers to a ratio of the number of edges present in a network relative to the total possible number of edges, that is, how many potential player interactions have been used by a team.[21] In a 'real world' context, coaches and researchers can study visualisations to identify characteristics of the networks being examined as well as use metrics to assist with interpretation, explore associations with match outcomes, make objective comparisons between teams or monitor performance characteristics immediately or longitudinally. Further to this, the impact of changes to networks, such as adding, removing or substituting players, or the effects of various match circumstances, for example, environmental and task constraints,[22] can also be explored.[14]

The need for a systematic mapping review

Network analysis has multidisciplinary origins, as well as wide-reaching applications, including in sport. Accordingly, a variety of methods, visualisations and interpretations of network topographies have been used to apply cooperative network analysis to team invasion games. Additionally, the broad scope of cooperative network analysis means research exists across a wide spectrum of journals and within many varied topic areas including computer sciences, complexity sciences, psychology, performance analysis, network science, strength and conditioning, and data science. As a result, there is great diversity among the studies on cooperative network analysis in team invasion games in terms of their publication avenue, methodologies, reporting structure, use of technical jargon, and field of focus. This means that whilst much research is available on cooperative network analysis in team invasion games, it has not been collated for researchers and practitioners interested in using it. Therefore, it is the aim of this study to provide a map of these studies in which relevant studies are first identified, before reporting on their findings and what they mean in the context of the study and practical application of cooperative network analysis in team invasion games. It is the intention that this will facilitate the search for and interpretation of relevant literature for researchers and practitioners interested in this topic.

Methods

This systematic mapping review followed a population, exposure, outcome (PEO) format with the population defined as invasion game athletes, the exposure as analysis via cooperative networks and the outcome as the interactions between agents, for example, passing and verbal communication. The PEO approach is used 'to determine the association between particular exposures/risk factors and outcomes'[23] and was chosen in this instance as it captures the broadest range of studies/broader perspective for this mapping review and is not as restrictive as other approaches. This was suitable to the current review as mapping reviews are not hypothesis-driven and can be inclusive of a broader range of studies.

Operational definitions and inclusion and exclusion criteria were also established prior to searching to reduce the risk of bias. These definitions are identified below:

- *Cooperative networks*. The interaction of various agents (nodes) through various forms of information exchange or actions. In invasion games, this can include players as agents and includes a wide array of possible interpersonal relationships including but not limited to passing of an object such as a ball, verbal communication, non-verbal communication and behaviours. The relationship between these factors and the behaviour of the network as a whole constitutes their cooperative nature.[16]
- *Invasion games*. The primary objective of these games is to invade the opposition's territory in order to score. Often it will include gaining possession of an implement and attempting to score this implement into a goal, target or end zone. Invasion games also require the defending of a team's own goal or target in order to prevent conceding a score. Invasion games are bound by a defined time period (game length).[3]

This review included studies with observations of competitive matches at an open or adult level, where a majority of participants were 18 years of age or older. All study designs were included, all languages were considered and no limits were applied to publication date. Textbooks, conference papers that were peer-reviewed and PhD theses were all included. Studies analysing dyads or triads only (interactions between only two or three players), grey literature that was formulated based on social media posts, magazines, and honours and masters theses were excluded.

The rationale for these decisions was that the analysis aimed to capture all existing peer-reviewed research on cooperative networks for team invasion games in adult competitive populations. Dyads and triads were excluded as they are only a subcomponent of team invasion games and thus are not representative of the collective group in team invasion games which include variable player amounts between 5 and 18. There are various ways in which cooperative networks can be captured; thus, enforcing restrictions on these could omit important and relevant research. Grey literature and magazines were excluded as they were not considered a high level of evidence or having scientific rigour.

The following four electronic bibliographic databases were first searched on 12 May 2020: SPORTDiscus, Web of Science, PubMed, and PsycINFO. Reference lists of included studies were also searched for additional papers. A second search was conducted on 1 February 2022 utilising the same strategy whilst limiting the dates to those between the two searches. The study was registered on the Open Science Framework (OSF): https://osf.io/3yfx5/files/osfstorage.

Search strategy

Search terms included

(network* AND ('continuously learning' OR 'cooperative' OR 'small world' OR 'complex dynamic*' OR 'social' OR 'analysis' OR 'collaborative')) OR 'complex social systems' OR 'systems approach*'

AND

basketball* OR bandy OR hockey OR football* OR 'Australian football' OR 'Australian rules football' OR soccer OR 'Gaelic football' OR gridiron OR rugby OR handball OR hurling OR kabadi OR korfball OR lacrosse OR netball OR 'shinty' OR water polo OR 'team sport*' OR 'ultimate frisbee'

Once systematic searches were complete, titles and abstracts were screened by two reviewers (first search: SP and RT; second search: SP and AN) working independently and using the software 'Covidence' (Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia. Available at www.covidence.org). If there was an agreement between reviewers, then the studies progressed to either the full-text scanning if they met the required criteria or were removed. If there was a disagreement on the progress of studies, they were assessed by a third reviewer (JF) to decide whether inclusion was warranted. Full texts of articles were then assessed for eligibility following the same protocols. If papers were not available, then authors were contacted directly and requests were made to the institution's library for access.

Once the eligible pool of studies was identified (Figure 2), data were extracted for reporting by reading papers and data entry in tabular form. Listed in Table 1 are items aimed to capture information from a broad range of categories evident in the published studies. The items were also designed to encompass different study types and designs and their respective features into a report that captures the uniqueness of studies whilst allowing between-study comparison. This extraction was performed by the lead author and checked where necessary for accuracy by other

Table 1. Data fields included in the extraction process.

Item	Definition
Authors	All authors involved in the paper
Year	The year in which the paper was published
Title	The article title
Study design	The type of study that was undertaken
Single team or multiple teams	The analysis of one or more than one team
Year/years of sample	The year the analysed data was collected in
Invasion game type	The game type that was investigated in the study, for example, football
Sample size (matches/events)	The number of matches, events or similar analysed
Sample size (no. of players)	The number of players, teams or similar were analysed
No. of observations	The number of observations or similar that exist in the dataset
Competition analysed	The competition analysed in the dataset
Type of network analysed	The constituents of the network that was studied and how it was formed
Network measures included	The specific measures that were included in the analysis related to network science
Players excluded from the network	Describes which players, if any, were excluded from the network
Directed versus undirected and weighted versus unweighted	Refers to the characteristics of the network, if the amount and direction of information exchange are considered. Note, in instances in which both occurred, directed supersedes undirected and weighted supersedes unweighted
Visual representation of networks	Visual representations of networks in the paper. Reported on the basis of nodes, edges and formation/layout. Note that, 'weighted' assumes weighted via thickening of edges for count or size of nodes for count and 'directed' assumes interaction of passes. Unless other descriptions are stated. Note, in instances in which both occurred, directed supersedes undirected and weighted supersedes unweighted. If full network visualisation was included, then passing sequence visualisations were not additionally reported
Performance outcome investigated	The performance in the game. Specifically, the match outcome (winning, drawing or losing), score or level of success in the tournament/match
Comparators to network	Other factors that were compared with network measures. Includes statistical analysis and/or in results or discussions

authors. Information was entered into a custom table using the software Google Sheets (Google LLC, Mountain View, California, United States). In instances where information reported in papers was similar to a data item, the associated information was extracted so that the maximum amount of information could be reported.

Data items and operational definitions were determined prior to registration with OSF. Some slight modifications were made to these data items when undertaking screening to capture the concepts raised in the literature in a more optimal manner. The item 'language published in' was removed as papers were translated to English for extraction using DeepL (DeepL SE, Cologne, Germany) or Google Translate (Google LLC, Mountain View, California, United States). New items added during this process included the year(s) of the sample and the specific invasion game investigated in the study. The competition type was modified to competition analysed as this was clearer for readers. Similarly, the item 'sample size no. of athletes' was changed to 'sample size no. of players' for clarity. Players excluded from the network were originally extracted based on whether all players were eligible for the network; however, this was modified for clarity. Study design was removed as this was a product of the search criteria, that is, only observational studies met the eligibility criteria. *Network analysis was identified and undertaken, statistical analysis used and data presentation* were changed to more simple measures as it was not possible to extract the aforementioned items. The replacements of these items are presented in Table 1 which were added as they were present in many studies and were relevant for sports practitioners and researchers. These are *directed versus undirected and weighted versus unweighted, visual representation of networks, performance outcome investigated, and comparators to network*. Data items *sample size (matches/events), sample size (no. of athletes) and no. of observations* reported what pertinent information was available to capture as much detail as possible.

Results

A total of 112 papers were extracted in the final analysis, all of which used an observational study design. Of these, 91 were in football/soccer, 8 in Australian football, 8 in basketball, 4 in rugby union, 2 in handball, and 1 in water polo. Note that one paper examined three sports, hence explaining how there are more sports investigated than papers. Sample sizes ranged between 1 match observation and 1941 matches. This review includes studies observing 39 unique competitions; the most common was the International Federation of Association Football (FIFA) World Cup, studied on 20 occasions. The earliest publication was a single study in 1979, with the remaining papers published from 2009 onwards. Figure 3 displays the number of studies published per year. Only one study stated that female athletes were specifically investigated.[24]

The primary means of investigating cooperative behaviour was the passing of an object between players, with 107 of the 112 included articles involving this interaction. The five others included verbal communication, turnovers and tackling.[10,11,18,19,25] One hundred three out of 112 studies analysed data in which all members of the team(s) were eligible to be included in the network, that is, the studies did not exclude players who did not play the entire match, substitute players, goalkeepers, or relatively inactive players. The majority of studies (n = 90) reported on both the direction and weighting of the network edges. Two studies reported edge direction only, 16 reported edge weighting only and two reported no edge direction nor weighting, whilst one paper did not specify.

Visualisations were commonly included, with 71 of the 112 studies incorporating a visualisation of the network (i.e. the results) or a demonstrative visualisation to explain the process of creating the network. Visualisations were varied with their specific characteristics in terms of nodes, edges and formation/layout and other notes reported in the supplementary materials spreadsheet (https://osf.io/3yfx5/files/osfstorage). Most commonly, these visualisations included nodes that were unweighted, edges were commonly weighted and directed, and the associated positional formation was the most common layout of nodes. A total of 53 of the 112 studies investigated a performance outcome in relation to cooperative networks. This included associations to network variables of match outcome,[24,26] stage of competition, such as qualification or finals,[27,28] ladder positions,[15,29] win–loss prediction models,[9,30] score margins[15,26] and comparisons of the winning team of the overall competition with others.[2,31]

Almost all papers, 107 out of 112, investigated a comparator to network measures. The most common of which were comparisons such as between players (n = 44),[32–34] teams (n = 51),[35–37] matches (n = 20)[38–40] and positions (n = 39).[41–43] Beyond these, spatial, temporal, predictive, location, goals and goal attempts were explored amongst other comparators.[44–49] Full details can be found in the supplementary file available at https://osf.io/3yfx5/files/osfstorage.

Discussion

This mapping review provides insights into the characteristics of the literature of an emerging area of analysis in team invasion games. The primary themes emerging from the mapping review revealed a range of considerations for interpreting the available literature in particular aspects of study design, nomenclature, diversity of included sports, accessibility, conclusions being drawn and types of interactions. Implications for practice and future research are also discussed.

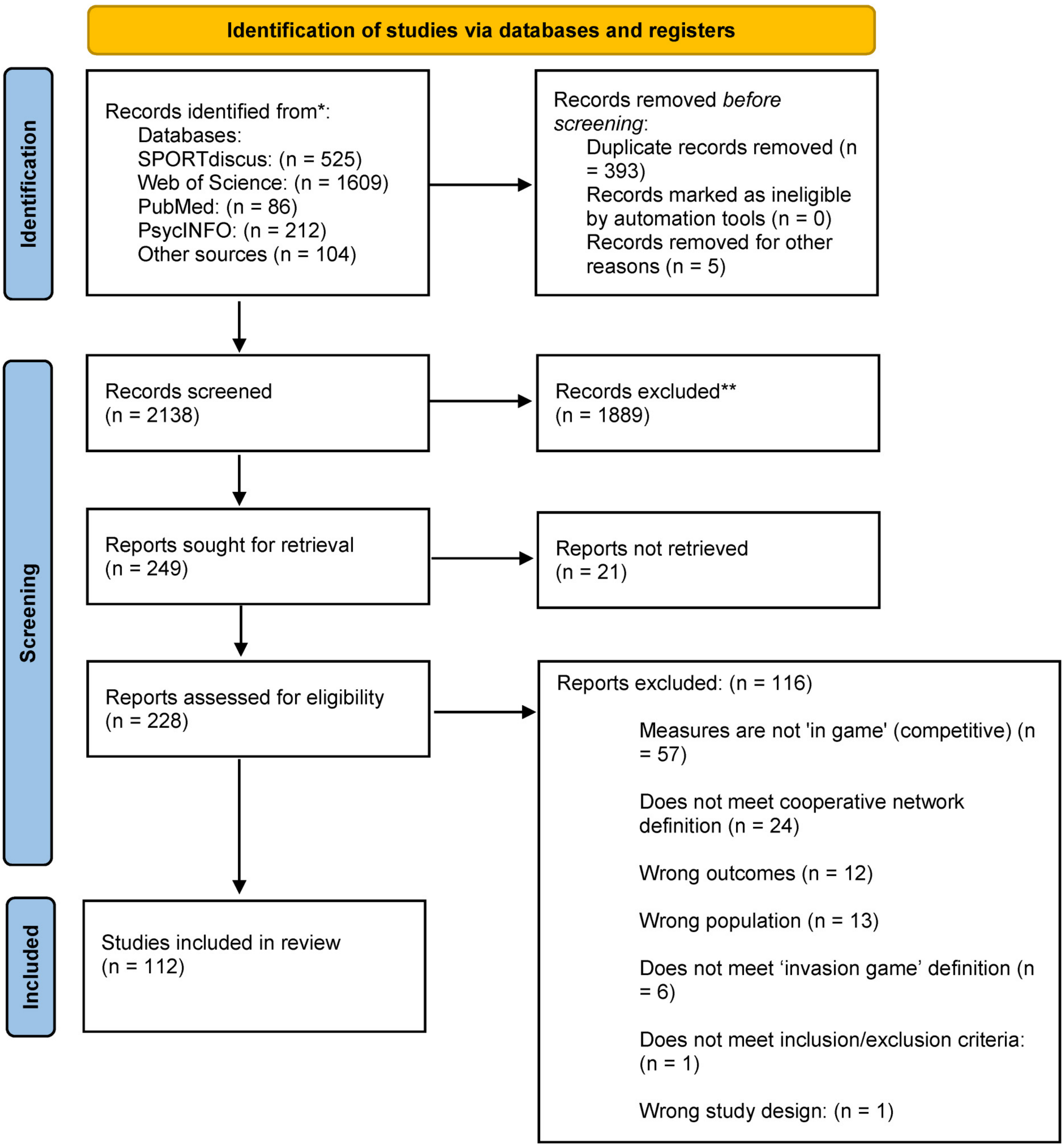

Figure 2. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow chart.

A large majority of studies included in this review examined the passing of an object as the means of interaction measured between agents in the cooperative network. Typically, this was undertaken by using an adjacency matrix based on the movement of the ball/implement amongst players. In all but five of the studied papers, passing was the interaction from which cooperative behaviour was investigated. As passing requires the team to be in possession of the ball, it should be noted that a key finding of this mapping review was almost all studies only observed offensive cooperation and did not address defensive cooperation. The measures used that were not related to passing included communication[10,11,25] and possession turnovers based on tackles.[18,19] Interestingly, in these studies, the investigation of turnovers relates to inter-team interactions, whilst tackling related to intra-team (i.e. cooperative) interactions. The high prevalence of passing analysis can be viewed as both strength and limitation of the topic area as there exists a strong analysis of one element, which can strengthen the development of theoretical frameworks on cooperative passing behaviour within sports teams yet results in a limited representation of

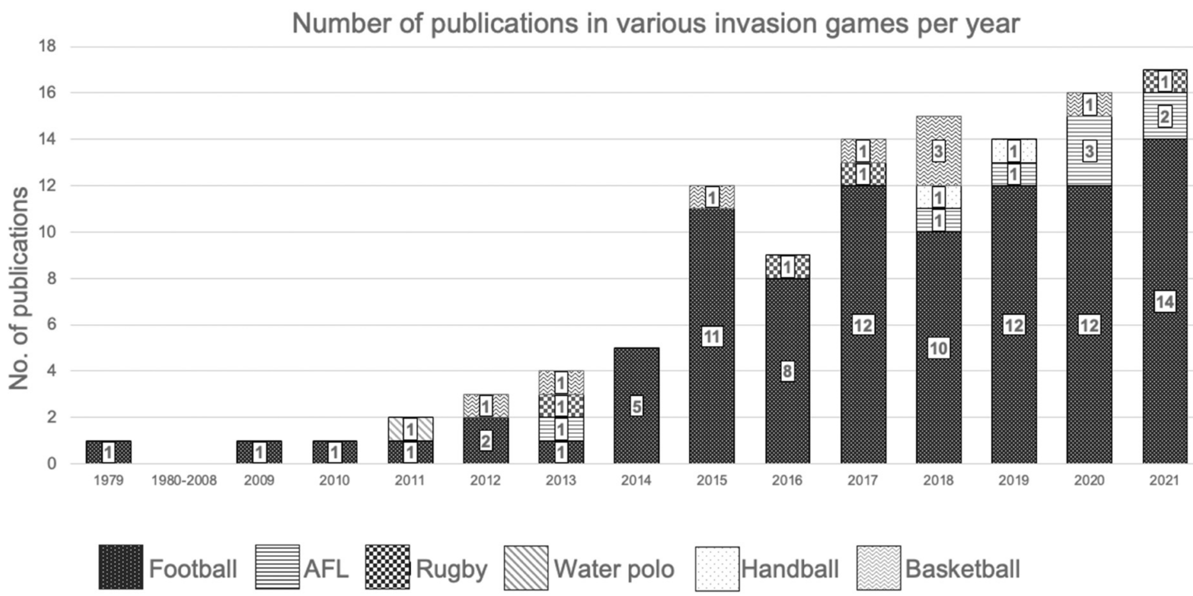

Figure 3. Number of publications per year. *Note 112 publications; however, 114 datasets are presented here as Korte and Lames[102] investigated three unique sports.
AFL: Australian Football League.

other areas. The prevalence of studies examining passing interactions is likely a direct result of the accessibility of these data. This includes observation from live games or broadcasts as well as coding packages from specific third-party providers such as Champion Data (Champion Data Pty Ltd, Melbourne, Australia) and Opta (Stats Perform, London, UK) who also make these available for purchase. Comparatively, verbal communications may not be possible to record in many competitive environments due to privacy issues, the unavailability of recording tools, the risk of damage to players and recording devices or the potential for recordings to reveal key tactics within a team.

This mapping review revealed that only six unique invasion games have been reported using cooperative network analysis. These are Australian football, basketball, football/soccer, handball, rugby union and water polo. The majority of studies included in this review studied cooperative networks in football. As a result, the existing literature studying cooperation in team invasion games using cooperative network analysis may be biased towards applications in football, and there may be a limited transfer of findings to other invasion games, especially given the vastly different constraints that may govern player behaviours in these sports, for example, water polo is played in an entirely different medium (i.e. water) and has no offside rules, and team handball is played indoors on a field which has entirely different field dimensions to football. For example, research in football suggested that 'networks characterised by high intensity (controlling for interaction opportunities) and low centralization are indeed associated with better team performance',[50] Australian football research did not show a similar relationship between centralisation and performance.[1] Accordingly, the associations between cooperative behaviours and team performance in other sports such as handball remain unreported. A further benefit of the wide-ranging investigations in football is that team 'playing styles' can be investigated, that is, the type of play or strategies that a team adopts. Since these datasets and investigations exist, scouting and comparisons with future teams and players are possible. Other studies also included more traditional measures such as global positioning system analysis and notational metrics in combination with network measures.[2,51] Only one study specifically reported on female athletes indicating a large research gap in the current literature.[24] Important elements of networks were variably reported, such as weighting and direction, and whilst it is possible to extract these characteristics, at times they were not clearly identified. The applications of the findings of studies which omit such information are difficult to interpret, and the field would be improved by including such information in all future studies.

One of the notable features of the available literature is a wide array of research methods. In this regard, some papers have very small samples of as little as one match or team,[52–54] which substantially limits generalisation and application of the findings, whilst others include datasets as large as 1941 matches.[31] Additionally, there is substantial variety in the methods of including players in the formation of networks. For example, some studies chose to exclude goalkeepers[43,55,56] whilst others only included the eight most active players.[50,57] Other examples are evident where substitute players or low-minute players were excluded from the analysis.[51,58] These examples contrast with most papers that do not exclude members of a team, thus limiting the interpretation of a team's overall cooperative behaviours and limiting comparisons of findings between studies. Whilst the purpose of this mapping review was not to formally analyse the quality of reporting, there was limited consistency between studies included in this review, with important information such as the year of the sample, characteristics of participants (such as age), number of interactions and competition analysed being omitted. This heterogeneity in the methods used and the reporting complicates the interpretation of study outcomes and makes replication practically impossible.

A characteristic of the current literature is a lack of consistent nomenclature. Common network measures are often included under a range of different names; for example, the interaction between agents was variably reported as an edge, link, arc or pass.[57,59–61] Another common network measure, centrality, has also been reported in many ways, using different naming conventions. This leads to difficulty in interpretations and mapping the literature, as it is unknown whether the studies were referring to a common measure with different names or an entirely different measure. For example, there are many measures associated with centrality such as betweenness centrality, degree centrality, in-degree centrality, out-degree centrality, density centrality, centrality pass ratio and group closeness centrality with many more examples present in the supplementary extraction spreadsheet.[16,18,19,29,62] Therefore, simply describing the 'centrality' of the network is ambiguous. Whilst the terms are at times identified and defined in individual papers and some of the variability that exists may be developed to identify more specific or varied measures and thus be necessary, interpretability is diminished when specific details of the metrics are not explicitly stated. It is also noteworthy that studies vary greatly regarding which network measures are used in combination; for example, some studies focus more on team-based network measures including network density, clustering coefficient and centralisation[61] with others utilising more individual network measures such as degree centrality, degree prestige and page rank.[63]

Additionally, the distinction between network measures and more traditional notational measures is unclear. For example, in-degree or out-degree measures in the absence of information about the passer or recipient are equal to the traditional notational analysis metrics of total passes completed and received. Network intensity can likewise be reported as a more traditional and interpretable metric of passes per defined time period (e.g. passes per minute). Additionally, if the study simply reports 'out-degree centrality' or 'passes made' without any additional context, it may be unclear whether the metric has been weighted (the total number of passes made by the player) or unweighted (the number of unique teammates that the player passed to) unless it is explicitly mentioned. This heterogeneity in the reporting of network variables may be partly attributable to the broad range of researcher backgrounds and the vastly different research domains from which these studies originate. For example, typical reporting may differ between sport sciences,[21] engineering and physics.[64]

An important consideration for researchers working in cooperative network analysis is the accessibility of their work to its intended audience. Whilst many researchers who have published literature relating to SNA in team invasion games are computer scientists or mathematicians, the practitioners who may use this information may include sports coaches, performance/data analysts, athletes, strength and conditioning coaches, medical practitioners and other researchers or practitioners. Network science is complex by nature and still relatively novel in the performance analysis space. Hence, interpretation by practitioners may be unaided by the array of mathematical formulae that exists within the literature.[31,65] The use of jargon and complex terminology, whilst at times necessary to provide adequate descriptions and to justify the mathematical and conceptual approaches within those contexts, presents a major barrier to uptake in applied settings.[16] There is also an accessibility barrier for researchers and practitioners, with papers existing across an extremely diverse range of journals, in different languages, with different topic names (e.g. SNA, cooperative network analysis and complex systems analysis) and presented in an array of reporting styles.[66,67]

A positive step towards improving interpretability is the use of visualisations, a feature commonly evident in the current literature.[68] This is shown by 71 of the 112 papers including at least one visualisation. These visualisations often provide a more readily understood and contextual understanding of the information, particularly to those with limited exposure to network science. Additionally, they can contain many levels of information such as weighting, direction, centrality, passing accuracy and others.[20] Visualisation characteristics such as qualities of nodes, edges and the formation or layout of these networks are reported in the extraction document.

A common feature of network analysis is the association of network variables with other variables. This is important as understanding the factors associated with cooperative behaviours assessed through cooperative network analysis may aid practitioners in designing interventions that can be used to elicit changes in cooperative behaviour. Examples of these factors include performance-related outcomes such as wins and losses, scores, table positions and progression in tournaments.[28,29,39,69,70] Interestingly, a large majority of papers (107 out of 112) examined a comparator to network variables resulting in the depth of comparisons undertaken being very extensive. This provides a strong base for the literature with many of the potential avenues for investigation having been previously explored. Associations between network characteristics and goals scored, spatial measures and temporal measures between teams, players and even competitions are all examined.[63,71–74] Additionally, studies commonly examined differences in network characteristics between players ($n = 44$), teams ($n = 51$), matches ($n = 20$) and positions ($n = 39$). These comparisons allow both within and between team investigations, which is of interest to practitioners who may be interested in examining behaviours of their own team and as compared to others. Many of the comparators analysed are presented in a context specific to the population studied, for example, investigating a sub-phase such as kick-in possession chains in Australian football and possession outcomes in basketball.[29,75] The reporting network variables related to the specific characteristics of their invasion game provide useful context for practitioners wishing to adopt these methods of analysis. Similarly to other elements of the literature, even in circumstances where a common sport or competition is investigated, a lack of common understanding and terminology often means interpretation of these measures is difficult.

A further key consideration is that on occasion inferences or conclusions have been drawn from papers with limited or no statistical analysis. Examples include inferring a positive style of play or results from a single game sample or implying player importance based on certain network measures such as centrality.[13,28,34] This may result in an over-interpretation of a player's importance based on the amount of possession they received. It is important for researchers to recognise the many constraints that may influence this result. For example, a player may be defended less closely in a football match and thus receive more possession as they are identified as not skilful or threatening by the opposition. Similarly, in basketball, an attacking player may be defended or marked by multiple defending players making them subject to less possession due to the perceived danger they pose to the opposition. In these circumstances, it would be inappropriate to identify these players as unimportant. Overall, it may be advantageous for researchers to collaborate with subject matter experts to assist with making practical interpretations, rather than attempting to infer them only from the data.

Given the complex nature of invasion games, some studies considered the context of network measures, for example, the match situation, time in the match, period of play preceding or score margin when analysing network metrics.[47,55,73,76,77] Additionally, some studies deemed players/teams to be successful 'post hoc'.[76] Whilst this is a useful means of investigation, it is important to be aware of selection or survivorship biases. Researchers should take care when implying the importance and aspects of causality when using network measures, especially in instances where a clear theoretical framework is not discussed and statistical analyses have not been performed. Additionally, analysing networks from a static point of view, that is, at specifically determined time periods, provides limited insights into the dynamics of the network and how changes in cooperative behaviour evolve over time. The importance of considering network dynamics has been identified in other areas of network research outside of sports.[78,79]

Limitations

This systematic mapping review should be interpreted with several limitations in mind. First, it only mapped the literature, and therefore, no in-depth analysis was conducted. Furthermore, an assessment of study quality was not undertaken, and accordingly, the risk of bias is not reported. The search strategy employed and search terms used mean that specific invasion games may not be accounted for. This also means that team sports that utilise network analysis that are not invasion games (e.g. volleyball, cycling, etc.) were excluded. Additionally, as our inclusion criteria only included in-competition analysis, any studies examining training were excluded. The age criteria in the current search strategy also mean that papers investigating those under 18 have not been included. Overall, this review should not be taken as a map of all cooperative network analyses in sport. Having the full-text extraction undertaken by a single author also means that, whilst all precautions were taken, reporting may have been subject to the biases of a single individual. However, the extraction was discussed among all authors on a regular basis. It should be noted that the specific software packages, coding languages and algorithms used to derive network metrics and visualisations were not conducted as part of this review. Anecdotally, some software packages produce somewhat different outputs (e.g. metric values) when compared with others. This may be somewhat attributed to the broad range of nomenclature (i.e. the same terms being used for different calculations) noted in this review, although this should be clarified via further investigation including broader search terms as it may be a problem beyond prior team invasion game research.

Conclusions and future directions

There are many ways in which this research area can be progressed. Firstly, only a small number of invasion games have been reported. Given the accessibility of data (i.e. from video footage or external data providers) on a wide range of team invasion games, this is a limitation that may be readily addressed. Additionally, utilising a more consistent form of reporting when publishing work is a simple way in which researchers can make manuscripts clearer, and the valuable information within them is more accessible to practitioners and researchers both within and external to their specific research field. This includes clearly defining network measures; using consistent nomenclature; reporting on key aspects of datasets such as number of matches, players, year of sample and competition analysed; and identifying important network features such as weighting and direction. Whilst there is a widespread inclusion of visualisations in the cooperative passing network literature in team invasion games, enhancing the clarity in depicting information to these end-users would be advisable. Collaboration with domain experts, such as coaches and players, may help further assist cooperative network research.[80] These experts can assist with interpretation of results as well as provide recommendations about practicalities. Lastly, researchers should consider the dynamic nature of networks and examine temporal components as is being undertaken in other areas of network research.

Data availability

The supplementary extraction sheet is available at https://osf.io/3yfx5/files/osfstorage.

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Supplemental material

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