Leveraging Graphs for Advanced Analytics in Major Team Sports: A Systematic Mapping Study

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Graph theory, a robust mathematical framework, has emerged as a cornerstone for modeling intricate relationships and patterns inherent in team sports dynamics. This review illustrates the outcomes of a comprehensive Systematic Mapping Study (SMS) conducted to investigate the adoption of graph-based representations, models, and approaches that research groups employ to handle data and information in major team sports analytics. We systematically categorize and map the outlook of diverse graph-based approaches and models, shedding light on their applications, methodologies, and contributions to the ever-evolving field of sports analytics. The results of our study provide a comprehensive overview of the maturation and diversification of methodologies, providing insights into emerging trends. As well we also identify and thoroughly discuss potential research gaps. The present work aims to serve as a valuable reference resource for researchers, practitioners, and enthusiasts seeking to navigate the rich tapestry of graph-based knowledge representation in major team sports analytics. The code to execute the SMS is available at https://github.com/crusso7/systematicmappingstudy

CCS Concepts: • **General and reference → Surveys and overviews**; • **Theory of computation → Graph algorithms analysis**; • **Mathematics of computing → Graph theory**; • **Information systems → Ontologies**; • **Computing methodologies → Knowledge representation and reasoning**.

Additional Key Words and Phrases: Sport Analytics, Graphs, Systematic Mapping Study, Graph Theory, Ontologies, Graph Neural Networks

1 Introduction

Team sports are organized competitive activities involving two or more teams, typically with a standard set of rules, where team members work together to achieve a common objective, i.e. scoring points or goals within a defined time and playing area or field. Such sports, renowned for their strategic intricacies and dynamic nature, have long been a focal point of fascination for enthusiasts worldwide. With the term *major* or *primary* we refer to team sports that are widely played and followed globally or regionally, often identified as a national sport for a specific nation, with professional leagues, large fan bases, and significant cultural or economic impact. Examples include soccer, basketball, baseball, American football, rugby, handball, hockey (ice or field), and cricket. In recent decades, the landscape of primary team sports analysis has witnessed a remarkable evolution, marked

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ACM 1557-7341/2025/10-ART
https://doi.org/10.1145/3773024

by the infusion of cutting-edge technologies [190]. Among these transformative advancements, the application of graph-based approaches has emerged as a pivotal force, reshaping how analysts, coaches, and researchers perceive and interpret the dynamics of team sports [182]. Soccer, often termed the "beautiful game"[89, 92], exemplifies the epitome of team sports global appeal, captivating audiences with its blend of skill, strategy, and athleticism. The advent of graph-based methodologies in the analysis of major team sports, including soccer, has introduced a paradigm shift, offering novel perspectives on player interactions, strategic formations, and the intricate patterns woven into the fabric of the game [43, 182]. While previous reviews [36, 46, 177, 189] have explored facets of sports analytics and technological integration in team sports, a compelling need exists for a dedicated examination of the expansive domain of graph-based approaches. Recognizing the transformative potential and growing significance of such methodologies, this review explores the major team sports landscape comprehensively, elucidating the diverse applications, methodologies, and trends that have materialized at the intersection of graph theory and team sports analytics. In pursuing a more nuanced understanding of the evolving field, it is essential to acknowledge prior reviews contributing to the discourse on sports analytics and technology. While existing reviews may have touched upon broader aspects of sports analytics and technology integration, the depth and breadth of graph-based methodologies in major team sports necessitate a more specialized examination. In fact, as the landscape of sports analytics undergoes continuous transformation, the focus on graph-based approaches in major team sports warrants a dedicated investigation. Petersen et al. [173, 174] have emphasized the importance of systematic mapping studies (SMS) as valuable tools for summarizing research domains and identifying trends. By undertaking a systematic mapping study, this review aims to provide a panoramic view of the existing body of knowledge in the domain, offering insights into emerging trends, potential research gaps, and novel opportunities within graph-based approaches.

The subsequent sections of this work will systematically address key objectives, ranging from identifying prevalent research trends and application areas to examining graph-based techniques and identifying untapped potentials. As major team sports embrace the era of data-driven insights, this review serves as a guiding compass, navigating the intricate web of graph-based methodologies that enrich the analysis and understanding of these captivating athletic endeavors. With this study, we aim to comprehensively explore the multifaceted relationship between graph-based knowledge representations and team sport analysis. Our purpose is to provide a panoramic view of the existing body of knowledge in this domain, shedding light on the diverse applications, methodologies, and trends that have emerged at the intersection of these two domains. In detail, we aim to achieve the following objectives:

- *Identification of Research Trends*: This SMS seeks to discern the predominant research themes and trends that have shaped the subject of our study. By categorizing and classifying existing literature, we aim to uncover the most prominent areas of investigation and innovation.
- *Highlighting Application Areas*: The study endeavors to categorize applications developed in this field, spanning player performance analysis, tactical decision-making, injury prevention, and other pertinent domains.
- *Examination of Artificial Intelligence (AI) Techniques*: The SMS will scrutinize the various AI techniques and algorithms employed in soccer-related research. From machine learning to computer vision, we will explore the methodological toolkit researchers and practitioners employ.
- *Identification of Gaps and Opportunities*: This SMS aims to provide insights into future directions for team sport analysis by identifying gaps and areas where research is limited. We endeavor to guide researchers, coaches, and industry professionals toward uncharted territories with untapped potential.
- *Fostering Collaboration*: our trust is that this study could serve as a catalyst for collaboration among researchers, sports organizations, and technology developers. By presenting an overview of the field, we aim to facilitate interdisciplinary partnerships to drive further innovation.

The paper is structured as follows: Section 2 describes the protocol used to conduct the systematic mapping study, while Section 3 goes into details of the study, providing the answers to our research questions. Section 4 is devoted to discussing results obtained from studying the literature, highlighting gaps and current challenges of the research field. In Section 5 we discern threats to validity of the present study. Lastly, Section 6 draws conclusions by summarizing the main finding of the present study and discusses possible future research directions that deserve to be explored more deeply. A theory background on graph-based representations, details about the protocol for the systematic mapping study, and a more extensive discussion of our results highlighting gaps and current challenges of the research field are provided in the Appendix as supplemental material.

2 Protocol for the systematic mapping study

In defining our research objectives, we articulate the goals and scope of our Systematic Mapping Study (SMS), pinpointing specific aspects of the research domain to explore. First, we create a comprehensive search strategy by specifying databases, search engines, and sources, incorporating search strings and keywords for thorough coverage. Then, we define inclusion and exclusion criteria involving factors like publication date and study type. The study selection process follows multiple stages, including screening titles, abstracts, and full-text articles. Our data extraction plan involves creating a standardized form capturing key study details. We devise a systematic approach for data synthesis, utilizing thematic analysis and categorization to identify trends, patterns, and gaps. Visualizing the literature entails creating charts or tables for an overview. Implementing a validation process involves multiple researchers to enhance reliability with documented biases or limitations. In preparing a comprehensive report, we detail the SMS process, including the research protocol, search strategy, study selection criteria, data extraction methods, and synthesis outcomes. We iteratively refine research questions and criteria based on emerging findings. This researcher-led protocol ensures a systematic, transparent, and reliable overview of the literature in our research domain.

2.1 Research questions

In Section 1 we have mildly outlined the objectives of this work. Here, in pursuing our goal, we define what are the aims of the study in a clearer and more rigorous way by means of specific research questions, stated as follows:

RQ1: What are the primary research trends and areas of exploration in the integration of graph-based representation techniques within major team sports analysis?

RQ2: Which specific application domains within major team sports, such as player performance analysis, tactical decision-making, or injury prevention, have been predominantly influenced by graph-based approaches?

RQ3: What are the prevalent AI techniques and algorithms employed in the implementation of graph-based methodologies in major team sports analysis? How do these techniques contribute to the understanding of team dynamics?

RQ4: In the landscape of graph-based approaches in major team sports, are there identifiable gaps or under-explored areas in current research? What opportunities for further investigation do these gaps present?

RQ5: How can the findings from this SMS inform collaboration and interdisciplinary partnerships among researchers, sports organizations, and technology developers in the context of graph-based approaches in major team sports?

Firstly, *RQ1* will guide us in discerning the predominant research themes and trends, offering a panoramic view of the integration of graph-based methodologies within primary team sports analysis. Simultaneously, *RQ2* will explore the application areas within major team sports, categorizing the specific domains influenced by graph-based approaches. Expanding our focus, *RQ3* delves into the methodological toolkit, examining the AI techniques that underpin graph-based analyses in the context of team sports. *RQ4* aims to identify potential gaps and unexplored avenues within the current research landscape, providing valuable insights for future investigations. Lastly, *RQ5* seeks to foster collaboration and engagement, recognizing the potential for interdisciplinary partnerships that can drive innovation within graph-based approaches in major team sports analysis.

2.2 Search strategies and search strings

Developing a comprehensive search strategy for identifying relevant studies on the use of graph-based approaches in team sports requires thoughtful keyword selection and the use of boolean operators to refine search results. To retrieve a comprehensive list of research studies and to get an exhaustive view of literature, our search strategy combines various keywords and search terms, also considering their synonyms, which have been possibly used as an alternative in certain studies. We follow PICO(C) (Population, Intervention, Comparison, Outcome, and Context) criteria [109] to define the search string systematically. As suggested in [174], the last three dimensions (comparison, outcome, and context) usually act as search filters. Hence, their application may restrict the search too much. Based on this reflection, we mainly focused on population and intervention as they are the most relevant for mapping studies.

- **Population**: We identified “team sports” as the main term of this viewpoint since it is the domain of interest of our study.
- **Intervention**: We identified “graph” as the main term of this viewpoint since our research questions aim at investigating how graph-based structures have been applied to the population.
- **Comparison**: This viewpoint is not applicable in this systematic mapping study since no effect of the intervention on the population is expected.
- **Outcome**: We avoided applying this restriction since we do not want to limit our scope to specific outcomes, which could result in an incomplete mapping.
- **Context**: We identified “analytics” as main term of this view point.

The main term and relative synonyms for each of the PICOC view points are reported in Table 1.

In our study, we considered the following team sports, which are considered the most popular worldwide: soccer (football), basketball, baseball, american football, volleyball, rugby, cricket, hockey, and handball. We did not include other team sports since in our preliminary literature investigation we did not find sufficient cues to consider them relevant to our purposes.

To broaden our search space at the beginning, we tried to use general terms in building the final search string. Moreover, we exploited boolean operators and used parentheses and wildcards to create more complex and comprehensive queries. We also optimized final search queries by avoiding redundant synonym terms.

2.3 Academic Databases

To retrieve a large number of candidate studies that are both consistent and scientifically relevant, we have selected four reputable digital libraries that are well-known in the academic world. These libraries are reported in Table 2.

By leveraging these databases, we aim to gather a diverse and comprehensive set of scholarly articles for our study. In fact, *Web of Science* provides extensive coverage across various disciplines; *IEEE Xplore* is a reputable source for publications related to artificial intelligence and machine learning; *ACM Digital Library* is well-regarded for its collection of articles in the fields of AI and technology; *Scopus*, known for its interdisciplinary approach, was selected to ensure a comprehensive exploration of relevant research across multiple domains.

2.4 Inclusion and exclusion criteria definition

Establishing intelligible criteria for including or excluding studies in a Systematic Mapping Study (SMS) is crucial to support the selection of literature and to ensure its relevance and quality. Table 3 lists the exclusion and

Table 1. PICOC Criteria for team sports analytics and graph structures

View Point	Main Term	Synonyms
Population (P)	team sport	soccer, football, basketball, baseball, volleyball, rugby, cricket, hockey, handball
Intervention (I)	graph	network, graph theory, ontology, semantic network, conceptual graph, hybrid model, knowledge graph, probabilistic graphical model, topic map
Comparison (C)	N.A.	N.A.
Outcome (O)	N.A.	N.A.
Context (C)	analytics	analysis, decision making, business intelligence, forecasting, decision-taking, algorithm, prediction, classification, neural network, gnn, machine learning, pattern recognition, artificial intelligence, AI, machine intelligence, cognitive computing, robotic intelligence, automated reasoning, graph database, geometric deep learning

Table 2. Electronic Databases and Search Engines

Database	Link
ACM Digital Library	http://dl.acm.org/
IEEE Xplore	http://ieeexplore.ieee.org/
Web of Science	https://www.webofscience.com/
Scopus	http://www.scopus.com/

inclusion criteria we have defined for our SMS. For the exclusion criteria, studies were dismissed if they were non-peer-reviewed sources, opinion pieces, or retracted articles (*EC1*); published in languages other than English due to language limitations (*EC2*); not specifically focused on the subject of interest or not relevant publishers (*EC3*); or published more than twenty years ago, to prioritize recent research (*EC4*). Conversely, the inclusion criteria required studies to be peer-reviewed journal articles, conference proceedings, or technical reports (*IC1*); published in English for consistency (*IC2*); directly related to the use of graph-based approaches and models in team sports (*IC3*); and published within the last twenty years, starting from 2004, to ensure the relevance and currency of research findings (*IC4*).

Table 3. Inclusion and Exclusion Criteria for Literature Review

Criteria	Description
Exclusion Criteria	
(EC1) Publication Type	Non-peer-reviewed sources, opinion articles and retracted articles.
(EC2) Language	Non-English publications due to language limitations.
(EC3) Relevance	Studies not relevant or not focused on the subject of our interest.
(EC4) Date Range	Studies published more than twenty years ago to prioritize recent research.
Inclusion Criteria	
(IC1) Publication Type	Peer-reviewed journal articles, conference proceedings, and technical reports.
(IC2) Language	English-language publications for consistency.
(IC3) Relevance	Studies directly related to the use of graph-based approaches and models in team sports.
(IC4) Date Range	Studies published within the last twenty years (starting from year 2004) to ensure the inclusion of recent advancements.

2.5 Quality assessment

In our methodology, the quality assessment stage has been carried out by evaluating the selected primary studies. In particular, we have taken into account the domain covered by this study, that is the use of graph-based structures and their role in the context of a specific study. Given that we already defined *EC3* to discard not relevant works, we decided to avoid imposing stringent criteria on the primary studies, thereby facilitating the acquisition of a broad overview of the topic area [110]. We point out that evaluating the quality of the selected studies was a meticulous process curated by the authors either manually or by using objective quality metrics relating to the editorial placement of the selected studies. This hands-on approach ensured that despite the absence of a formal quality assessment stage, the studies included in our mapping were carefully vetted for relevance and credibility, contributing to the robustness of the overall study. This methodology allows us to encompass diverse perspectives and insights within the field of using graphs and graph-based structures in major team sports analytics. More details about quality assessment in supplementary materials.

3 Systematic Mapping Study Execution

We designed a two-stages semi-automatic selection process, whose entire flow is shown in Figure 1. In detail, for the automatable parts, such as for example the retrieval of articles from academic databases, we have implemented scripts in Python language. Given our base search string, we inspected the academic databases outlined in Section 2.3 to check for the presence of an API and/or a user-friendly web search. Since we want to search for the presence of interesting terms both in the title, abstract and keywords of publications, we built the query for each database prior to perform the search. The date of our last retrieval of works from Digital Libraries is June 09, 2025. We applied the inclusion and exclusion criteria to the search results, directly as filters in web browser search forms or leveraging API methods. To avoid inconsistencies, we manually inspected and filtered results to focus only on relevant items.

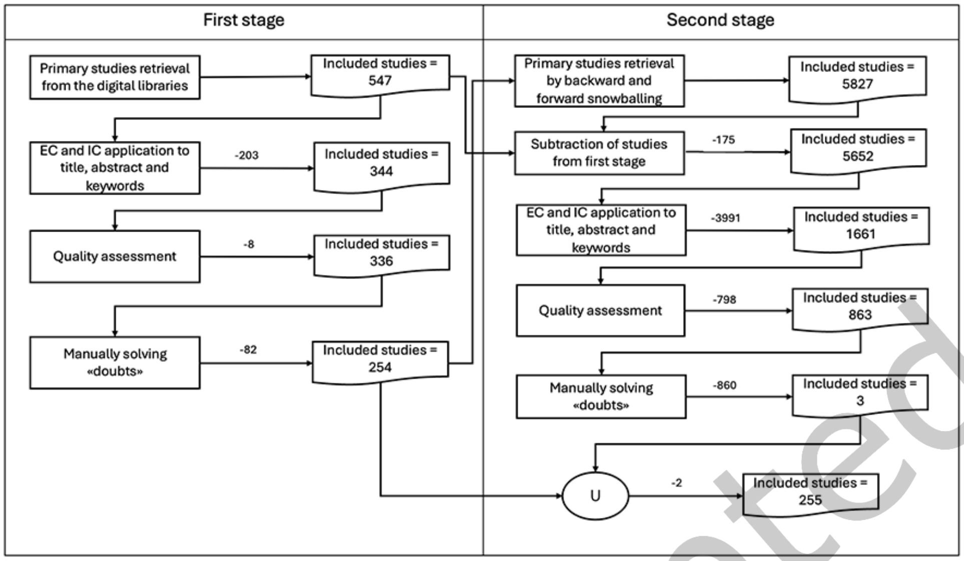

Fig. 1. Diagram of the primary studies selection process execution.

To evaluate our search string, we inspect search results and we check for the presence of selected relevant *control papers* [195, 236, 245, 254]. With this term, we refer to a selection of papers which have been verified in advance as relevant for the subject of the study, i.e. these studies must be present in the results obtained from the digital libraries in response to our engineered search string.

Once we have got the list of research works pertinent to our subject study, we analyze the results to answer the research questions posed in Section 2.1. First, we extract relevant information from the selected studies, key findings and contributions; then we organized and categorized the extracted data to group studies according to relevant features, such as main topics, techniques, or application areas, etc.

Academic Database	Num. Items (raw)	Num. Items (filtered)
Scopus	895	492
Web of Science	389	269
ACM Digital Library	22	22
IEEE Xplore	106	106

Table 4. Number of publications retrieved from academic databases

In Table 4 we report the raw results obtained in term of number of publications found with our search string. As we expected *Scopus* and *Web Of Science* libraries return much more results since their scope is much broader than *ACM Digital Library* and *IEEE Xplore*, which already limit themselves to the computer science subject area. For *Scopus* and *Web of science* we were able to pre-filter results from their websites GUIs, allowing us to reduce the number of works to 492 and 269, respectively. At this stage of the process we have a total of 889 selected works. Starting from this observation, we expect that results from more "focused" libraries are likely to be included in broader libraries, and, in general, it is important to notice that results from individual libraries may overlap each other, hence we need to elide duplicates. Moreover, 95 papers out of 889 retrieved does not present a DOI, which is an essential attribute for a published scientific article. We counted 106 papers with DOI from IEEE, 444 from Scopus, 17 from ACM and 227 from WOS, summing up to a total of 795 papers with DOIs. On this list, we start removing duplicates by converting the list of items into a set. Such operation reduced the total number of works with DOI to 517, while remaining 95 didn't have a DOI, for a total number of works equal to 612. At this point, we make an attempt to retrieve DOIs for the list of 95 papers from their title by using CrossRef API. This operation allowed us to increase the number of works with DOI to 547. Again, if we consider individual sources, hance with possible duplicates, we have 106 from IEEE, 469 from Scopus, 22 from ACM and 254 from WOS.

Figure 2 provides an overview about how results from individual libraries overlap each other.

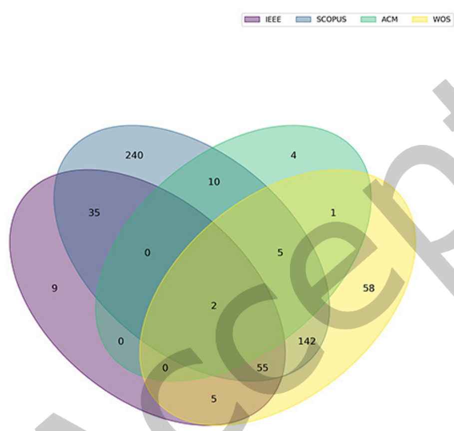

Fig. 2. Search results overlap from the selected digital libraries

3.1 Primary studies

After merging the results from all academic databases, we identified 547 primary studies. Subsequently, we have applied the previously defined inclusion/exclusion criteria. We were able to apply quantitative criteria automatically, while we proceeded manually for qualitative ones. For example, we individually investigated this list of publications to exclude works irrelevant to our scope (*EC3*). After applying the criteria, we could consistently reduce the number of publications to be considered. Such a process allowed us to discard 203 works, reducing the number of papers to 344. Following this, we performed a qualitative assessment to further evaluate the remaining studies. This step involved a more in-depth analysis of each paper's methodological rigor, clarity, completeness, and overall contribution to the field. As a result, 8 papers, despite being topically relevant, were excluded due to insufficient quality or lack of scientific robustness. Then, we manually reviewed each study in the result set in order to resolve any doubts about their relevance. These "doubts" referred to papers that were initially included based on search criteria but, upon closer and deeper inspection of their contents, showed limited or no pertinence to the subject of interest. This manual step enabled a preliminary refinement of the dataset by removing clearly irrelevant works. At the conclusion of this first stage, 254 studies remained in our dataset. In the second stage of the SMS, we have applied the snowballing technique [250]. It is a method used in systematic mapping studies to identify relevant literature by exploring the references and citations of already selected papers. It serves as a complementary approach to traditional database searches, helping researchers uncover studies that might not surface through keyword-based queries alone. There are two primary types of snowballing: *Backward Snowballing* and *Forward Snowballing*. The first involves examining the reference lists of selected papers to find earlier works that are pertinent to the research topic. The second entails identifying newer studies that have cited the selected papers, thereby uncovering more recent research developments. By iteratively applying these methods, researchers can expand their literature base, ensuring a more comprehensive understanding of the subject area. This approach is particularly useful for capturing studies that may use different terminology or are not indexed in major databases. In particular, we performed both backward and forward snowballing to ensure the broadest possible coverage for our search results. Starting from the partial result set of papers from the first stage, we execute snowballing and repeat the same steps as in the first stage. The final number of papers included for the analysis is 255. In Table 5 we have included references to primary studies, grouped by sport, to allow the readers having a quick and easy access to all of them. This table already provides food for thought on the distribution of works. In fact, as we can notice, there is a strong dominant presence of studies related to soccer, followed by basketball and volleyball, which are the sports more spread all over the globe.

Table 5. Primary studies

Sport	Studies
Basketball	[4, 6, 7, 32, 33, 40, 42, 54, 55, 57, 74, 83, 124, 128, 130, 134, 135, 150, 160, 166, 171, 193, 203, 206, 209, 213, 218, 252, 253, 262, 265, 268, 270, 271]
Baseball	[96, 205, 207, 208, 275, 276]
Soccer	[1, 2, 8, 14, 16, 17, 19–21, 25–29, 34, 37–39, 44, 47–50, 52, 53, 59–61, 63, 66, 68–73, 75–78, 81, 82, 84, 86, 93, 97, 98, 101, 102, 104, 107, 111, 113, 116, 117, 120, 126, 129, 133, 137, 139, 145–148, 151–156, 159, 162–165, 168–170, 172, 176, 178, 180, 181, 183, 187, 200, 204, 210, 214–216, 220–222, 224, 225, 228, 229, 232, 234–237, 240, 242–246, 248, 256, 258–261, 266, 267, 269, 272, 274, 277]
American Football	[9, 41, 51, 62, 85, 90, 95, 103, 106, 118, 175, 184, 198, 199, 212, 217, 254]
Volleyball	[10–12, 24, 30, 65, 87, 91, 99, 100, 112, 114, 121–123, 127, 136, 140, 142–144, 179, 191, 192, 223, 230, 233, 239, 251, 273]
Hockey	[18, 238]
Rugby	[35, 45, 94, 125, 201, 241]
Cricket	[3, 5, 13, 56, 58, 141, 185, 186, 188, 195, 202, 226, 249, 263]
Handball	[22, 31, 157, 247]
General	[15, 64, 67, 79, 80, 88, 105, 115, 131, 132, 149, 167, 194, 211, 219, 227, 231, 255, 257, 264]

Figure 3 shows the distribution of published works over time within the range of years considered, i.e. from 2004 to 2025. Overall, we can notice the absolute number of primary studies published each year is not very high.

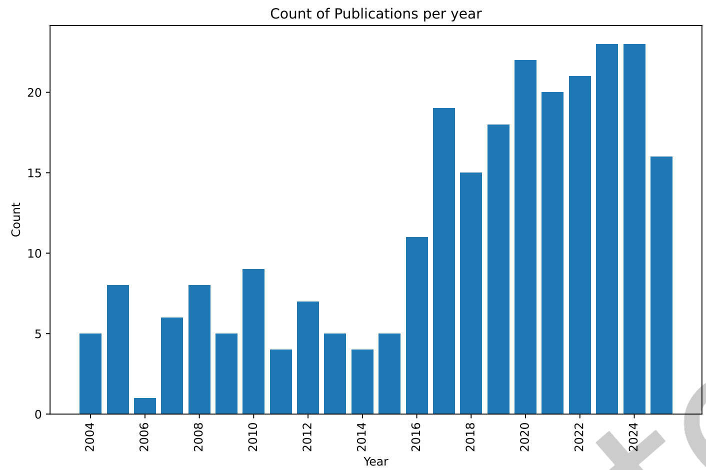

Fig. 3. Distribution of publications per year

However, it is clearly visible from the plot the fact that there is a rising interest of the research community in the field we considered in our study. Starting from 2016 the number of papers per year has increased significantly.

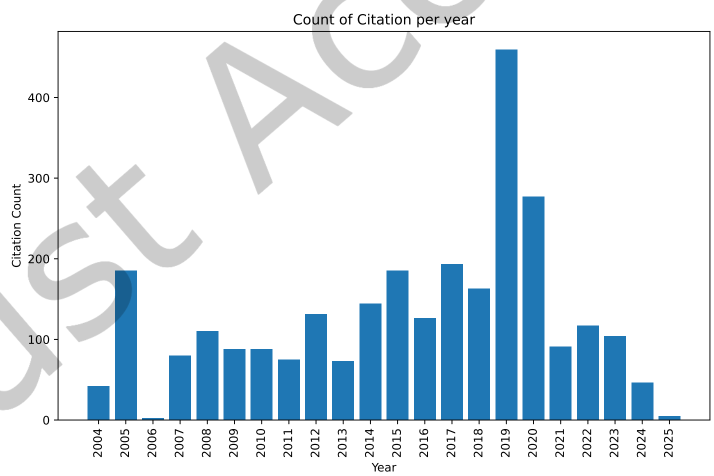

Fig. 4. Citations per year

Figure 4 shows the distribution of citations obtained by relevant works over time within the range of years considered. We point out that here, we refer to the amount of citations, calculated as the sum of citations of all papers published in a year. This is not to be confused with the amount of citations in a year that all papers have gotten.

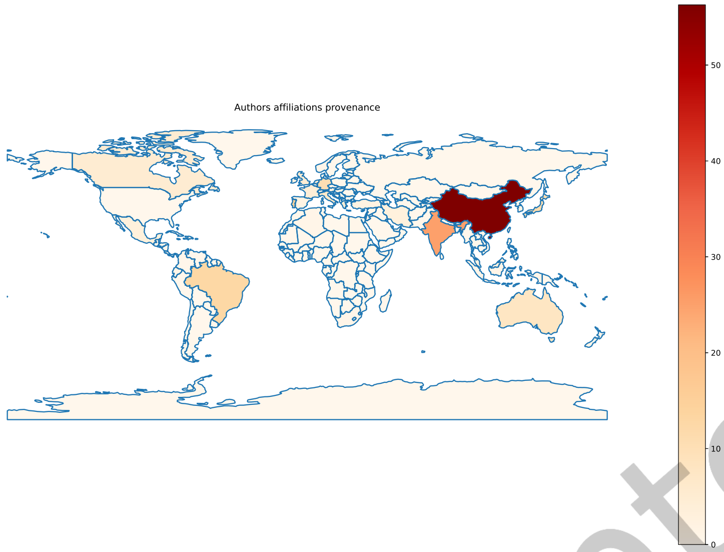

Fig. 5. Provenance of authors' affiliations by country

Figure 5 highlights which countries provided more contributions to the research field. The chart has been obtained by counting authors affiliations in relevant papers normalized by publications. As we can notice from the map, India and China are the countries with more contributions.

3.2 Answering the research questions

3.2.1 RQ1. The first research question we aim to answer emphasizes identifying primary research trends in team sports analysis and evaluating the impact of graph-based representation techniques in this field. Selected primary studies have spotlighted several trends. First, we noted that the development of novel graph-based algorithms and methodologies is tailored to analyze complex interactions and relationships within sports data. Second, integrating graph-based representation techniques in team sports analysis involves a multifaceted exploration of trends. This is due to the diverse semantics that graph elements can assume. Based on these observations, it is useful to provide a taxonomy that emphasizes the classification of the existing literature. The goal is to clarify and bring order to the jungle of diverse tasks pursued and, more generally, on the application areas that have been most investigated by the research communities:

- **Motion and Tracking**
- **Social Network Analysis**
- **Event Detection/Classification**
- **Performance Analysis**
- **Action/Activity Recognition**
- **Knowledge Representation**
- **Optimization/Scheduling**

The first drift we identified is *Motion and Tracking*. We include in this category all the works focusing on object/player detection and tracking, movement analysis, trajectory prediction and camera selection. Typically, graph structures are employed to represent the intricate dynamics of players on the field vividly. This facilitates the examination of spatiotemporal patterns, encompassing player trajectories, distances covered, and their interactive behaviors during game-play. Another significant trend revolves around *Social Network Analysis* for team dynamics. In this context, teams are conceptualized as networks, allowing researchers to delve into team communication and coordination nuances. This includes a detailed analysis of passing networks, shedding light on the intricate flow of information within the team and its implications on overall performance. The exploration of advanced network analysis techniques has been widely adopted to uncover hidden patterns, structures, and dynamics in player interactions, team strategies, and game dynamics. Community Detection emerged in particular as the most investigated sub-task. *Event Detection/Classification* has emerged as a significant research trend in sports analytics, revolutionizing the way we analyze and understand sporting events. We considered subtasks such as document summarization, event mining and indexing, video captioning, video understanding, and video mining as they have seen increased application in sports analytics. In this domain, graph structures play a crucial role in modeling and representing the complex interactions and relationships between various elements within a sports event. By representing events, players, and their interactions as nodes and edges in a graph, researchers can capture the dynamic and interconnected nature of sports activities. *Performance Analysis* in sports analytics encompasses a broad range of sub tasks aimed at evaluating and understanding various aspects of player and team performance. This includes match analysis, team ranking, player ranking, lineup prediction, lineup performance prediction, team performance prediction, market prediction, player centrality, tactical pattern analysis. We also included in this category works about human body pose prediction. However, it is important to remark that, in principle, estimating the poses of individuals or objects in images or videos could not be necessarily tied directly to performance evaluation. Graphs serve as a fundamental knowledge representation formalism in this domain, offering a structured framework to model complex relationships and dependencies inherent in sporting data. For instance, in match analysis, graphs can represent player interactions, passing networks, and scoring opportunities, providing valuable insights into team strategies and individual player contributions. Similarly, team ranking and player ranking tasks can benefit from graph-based representations of performance metrics and historical statistics, enabling more accurate assessments and comparisons. Lineup prediction and performance prediction tasks utilize graph structures to model relationships between player attributes, team formations, and match outcomes, aiding in strategic decision-making and performance optimization. Furthermore, tactical pattern analysis leverages graphs to uncover recurring patterns and strategies employed by teams, facilitating adaptive gameplay and opponent scouting. Human body pose prediction tasks utilize graphs to represent skeletal structures and movement trajectories, enabling accurate analysis of player movements and bio-mechanical performance. Another well-established research topic is *Action/Activity Recognition* at both individual and group levels. Group activity recognition, in particular, is widely investigated for volleyball analytics thanks to the presence of the *Volleyball dataset*. A good amount of selected works employs ontologies and knowledge graphs for the purest purpose of *Knowledge Representation*, ontology construction, and knowledge graph query answering. We consider also ontologies as graph-based structures (see Appendix in supplementary materials) since, in principle, an ontology can be always represented as a graph. Finally, we have grouped under the heading *Optimization/Scheduling* all those works whose main topic is about game scheduling and policy learning, such as multi-agent cooperation learning, multi-Agent Reinforcement Learning, and player policy learning. An interesting research trend emerged from our study stands at the intersection between cognitive computing [138], robotics[196, 197] and team sports. In fact, the cross-disciplinary field of robotics is undergoing a transformative phase, and this is particularly evident in the dimension of cooperative learning within team sports. At the forefront of this evolution stands initiatives like the Google Research Football Framework [119] and the RoboCup [108], which serve as driving forces propelling innovation forward. These platforms not only foster competition but also facilitate collaborative research, offering a playground for exploring intricate dynamics of teamwork and strategy in a controlled environment. Through the convergence of robotics, artificial intelligence, and sports science, researchers are pushing the boundaries of what machines can achieve in team-based scenarios. By simulating real-world sporting events and leveraging advanced algorithms, these endeavors not only enhance our understanding of team dynamics but also pave the way for breakthroughs in robotics applications beyond the playing field. To allow the reader to quickly find works pertinent to a particular task, in Table 6 we have grouped the studies by the corresponding task they deal with as well as including a column where we highlight which are the graph representation/techniques mainly used by researchers for individual tasks. Regarding the algorithms and

Table 6. Studies grouped by macro-categories of pursued tasks and graph-based approach employed

Task	Studies	Graph-based Representation/Approach
Action/Activity Recognition	[10–12, 18, 24, 30, 38, 60, 65, 76, 87, 88, 99, 100, 106, 112, 127, 129, 131, 140, 171, 179, 217, 219, 223, 238, 239, 241, 251, 257, 273]	graph neural networks, skeleton graphs, hierarchical graphs
Event Detection/Classification	[13, 15, 25–28, 42, 56, 62, 64, 68, 74, 77, 78, 86, 94, 98, 113, 116, 124, 126, 128, 139, 153, 183, 203, 207, 208, 216, 228, 231, 252, 254, 261, 263]	ontologies, probabilistic graphical models, hybrid models
Knowledge Representation	[3, 20, 37, 39, 52, 57, 72, 81, 101, 130, 160, 180, 204, 206, 215, 227, 235, 260, 262, 267, 275, 276]	knowledge graphs, ontologies
Motion and Tracking	[2, 14, 22, 29, 54, 55, 63, 67, 69, 70, 79, 80, 84, 102, 104, 107, 111, 115, 133–135, 150, 152, 154, 164, 166, 167, 169, 170, 192, 194, 209, 224, 229, 232, 234, 240, 242, 245, 248, 253, 258, 259, 264, 265, 272, 277]	relation graphs, graph neural networks
Optimization/scheduling	[1, 41, 53, 105, 178, 193, 225]	probabilistic graphical models, hybrid models
Performance Analysis	[5–7, 31, 32, 40, 45, 47, 49, 71, 82, 83, 97, 120–122, 136, 141–143, 149, 155, 157, 163, 165, 168, 176, 181, 186, 188, 191, 200, 205, 210, 211, 213, 214, 220–222, 236, 237, 243, 244, 246, 255, 256, 266, 268–271, 274]	player interaction networks, graph neural networks
Social Network Analysis	[4, 8, 9, 16, 17, 21, 33–35, 44, 48, 50, 51, 58, 59, 61, 66, 73, 75, 85, 90, 91, 93, 95, 96, 103, 114, 117, 118, 123, 125, 132, 137, 144–148, 151, 156, 162, 172, 175, 184, 187, 195, 198, 199, 201, 202, 212, 226, 230, 233, 247, 249]	passing networks, community detection algorithms, network centrality metrics

techniques used, we noted a rising interest in integrating machine learning, artificial intelligence, and graph-based models, particularly graph neural networks, which have proven successful in enhancing predictive analytics, game outcomes, tactical decision-making, and player performance evaluation. Integrating heterogeneous data sources such as player statistics, match events, and video footage using graph-based representations is a common approach to uncovering hidden insights and enhancing decision-making capabilities. Implementing graph-based analysis in real-time during live games provides immediate insights for coaches and players. This real-time information aids in dynamic decision-making, such as adjusting tactics based on the evolving game situation. We would like to point out that the definition of a taxonomy is inevitably subjective. In our case, for example, we tried to limit the number of macro-categories. Hence, we sometimes merged tasks that were only partially overlapping from a conceptual point of view.

3.2.2 RQ2. Graph-based methodologies have garnered considerable acceptance within the academic research community as an innovative and successful technique in numerous specialized application domains across major team sports [23, 158, 161, 182]. These applications exploit graph representations to enhance various facets of team sports analysis. From our previous findings, we have noted performance analysis is the most investigated activity. More in detail, one of the most investigated sub-task in sports analytics is the evaluation of players or teams performances by analyzing player interactions, movements, and contributions using graph-based models. Graph-based approaches are widely used to analyze player movements on the field, including trajectories, accelerations, and distances covered. This provides insights into individual player performance and positioning during matches. Graphs can represent player interactions, such as passes, assists, and collaborations. Analyzing these interaction patterns helps assess individual player contributions and team dynamics [23, 182]. Another interesting application domain is that of tactical analysis using graphs, since it has achieved considerable success recently for decision-making by coaches and team managers. Graph-based models contribute to recognizing and analyzing tactical patterns in team strategies. Coaches use these insights to make informed decisions about team formations, playing styles, and strategic adjustments during matches. Representing passing interactions as graphs helps in understanding the flow of information within a team. This information aids coaches in optimizing passing strategies and improving team coordination. Representing opponent teams as graphs enables the identification of weaknesses and strategic planning. Coaches use graph-based insights to formulate game plans that exploit the vulnerabilities of the opposing team. Analyzing historical data of opponents using graph structures assists in predicting and countering opponent tactics. Teams can adjust their strategies based on patterns observed in previous encounters. Utilizing graph-based techniques is possible to optimize team strategies, decision-making processes, and tactical adjustments during matches. Graph-based representations can help analyzing workload distribution, movement patterns, and injury risks to optimize player health and reduce injury occurrence. Graph-based models are employed to model player fatigue and workload, considering factors such as distances covered, sprints, and overall physical exertion. This information is crucial for injury prevention and managing player well-being. Graphs help identify correlations between player interactions (e.g., collisions, physical contacts) and injury risks. This information assists sports scientists and medical staff in implementing preventive measures.

Figure 6 helps to identify which task and which sport are being more studied by research community. For the tasks identified at the beginning of this section we have used some abbreviations in the illustration to keep its visualization more clean. In detail, Act Recog stands for Action/Activity Recognition; Event Det-Cls stands for Event Detection/Classification; KR stands for Knowledge Representation; Mot-Track stands for Motion and Tracking; Optimiz-Sched stands for Optimization/scheduling; Perf. Analysis stands for Performance Analysis; SNA stands for Social Network Analysis.

3.2.3 RQ3. The importance and spread that Artificial Intelligence has in scientific research is undeniable. For this reason, RQ3 was designed for the purpose of observing the technological advances of AI with respect to the object of our study. Investigating selected primary studies, we have identified what are the prevalent AI techniques

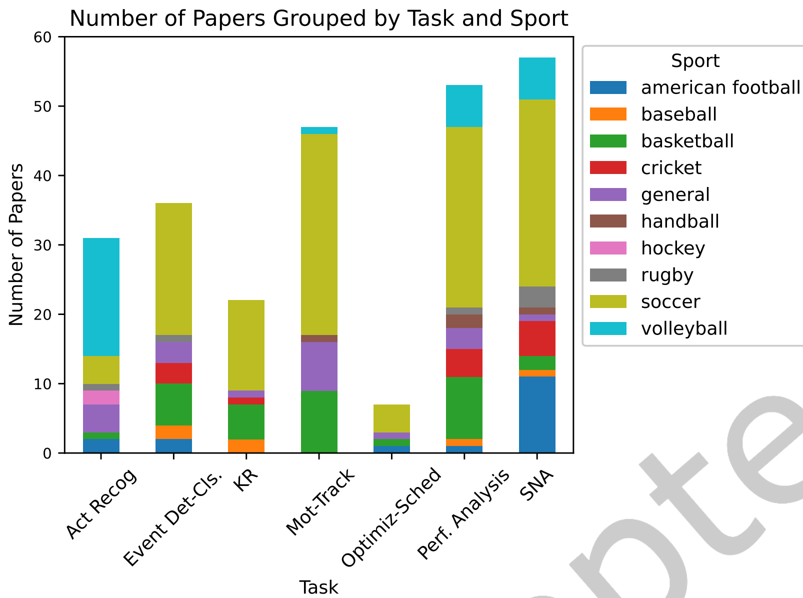

Fig. 6. Distribution of publications by task and sport

and algorithms employed in primary team sports analysis. These techniques contribute to the understanding of team dynamics by extracting meaningful patterns, relationships, and insights from complex interactions. As expected, since our focus is on graph-based methodologies, graph neural networks are dominantly present. GNNs are extensively used in team sports analysis to model the relationships between players, with the team represented as a graph. They are able to capture complex dependencies and interactions within the team, which allows for the analysis of dynamic relationships in player networks, passing patterns, and team coordination. Measures of centrality, such as betweenness centrality and eigenvector centrality, are used to identify key players or positions within a team structure. Understanding the centrality of players provides teams with insights into the influential elements that affect team connectivity, the flow of passing, and the dynamics of overall performance. Reinforcement learning is utilized to model decision-making processes within team sports, taking into account the dynamic nature of the game. Reinforcement learning algorithms can adapt strategies based on the evolving interactions and spatial configurations observed during matches, by incorporating graph-based representations. Techniques for clustering, such as k-means clustering, are used to group players based on similar playing styles, positions, or interaction patterns. Clustering aids in identifying player roles and playing patterns, contributing to a more nuanced understanding of team dynamics and enabling personalized coaching strategies. Algorithms for community detection identify groups of tightly connected players within a team, revealing substructures or subteams. Understanding these player communities helps in assessing team cohesion, communication patterns, and the emergence of player subgroups with distinct roles or functions. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are used to analyze player trajectories and movements. These models contribute to understanding player positioning, movement patterns, and spatial dynamics, enabling coaches to optimize team formations and strategies. Machine learning algorithms, including regression and classification models, are used to predict various aspects of team sports, such as player performance or game outcomes. Predictive models can account for the relational aspects of team dynamics by incorporating graph-based features, offering more accurate predictions. Comparisons based on quantitative metrics have shown superior performances with respect to traditional approaches for several tasks. For example, regarding Activity/Action Recognition, Wu et al. [251] have shown that Graph Convolutional Networks (GCNs) capture appearance/position relations between actors, outperforming CNN/RNN baselines with an accuracy of 91.8% on Volleyball dataset. In the task of player tracking, Figueroa [70] proved that using graphs to model spatiotemporal dependencies between players allows an improvement of +8.2% vs. Kalman filters in terms of *MOTA* (Multi-Object Tracking Accuracy). Shitrit et al. [209] have shown that network flow optimizes global trajectories resulting in an improvement in term of fragmentations, which are reduced by 12% in dense crowds. Pallavi et al. [169] proved that graphs resolve occlusions via relational reasoning with an improvement of precision metric (92.1% (vs. 84.7% for non-graph methods). In Social Network Analysis, quantitative metrics mainly used are the previously mentioned network centrality metrics (e.g., betweenness, eigenvector, etc.), and several works [44, 181, 195, 231] have shown high accuracy in win prediction, showing a correlation between centrality dispersion and win rate, and formation identification. These AI techniques collectively contribute to understanding team dynamics in major team sports by capturing the intricate relationships, patterns, and dependencies present in the complex interactions among players. The analysis of graph-based representations provides coaches, analysts, and researchers with actionable insights for strategic decision-making, player development, and overall team performance optimization.

3.2.4 RQ4. Considering the novelty of the research field, there is much room for improvement in exploring potential areas not yet thoroughly investigated where the use of graph structures could mark a change of pace compared to the techniques currently employed. For example, the role of analytics in player decisions by general managers and coaches could be further investigated. Additionally, the wider adoption and acceptance of data analytics in decision-making within clubs present opportunities for further research. Research into the factors influencing team function and performance across various industries could be applied to high-performance sports support team settings. Key variables such as leadership styles, supportive team behavior, communication, and performance feedback could be further explored in the context of team sports. Also, there is potential for further research in the area of tactical performance analysis in team sports. Investigating the associations between different tactical assessment tools could provide valuable insights into player performance and decision-making. Other gaps include the lack of standardization in data collection and analysis, the need for more sophisticated algorithms to analyze complex data, and the need for more research on the impact of graph-based approaches on decision-making. These gaps present several opportunities for further investigation. For example, researchers could explore the use of machine learning algorithms to improve the accuracy of graph-based approaches or investigate the impact of graph-based approaches on team performance and decision-making. These research gaps present opportunities for further exploration and innovation to enhance our understanding of team dynamics, player performance, and decision-making in team sports. They could also lead to the development of more effective strategies and tools for teams and coaches.

3.2.5 RQ5. The findings from this study can significantly inform collaboration and interdisciplinary partnerships among researchers, sports organizations, industry and technology developers in the context of major team sports. By answering previous research questions, we have highlighted areas where further research is needed, or existing methodologies can be improved. Identifying research gaps informs researchers about specific challenges and opportunities, motivating collaborative efforts to address these gaps through joint projects and initiatives. A major gap emerged from the SMS regarding data availability and the challenges related to data standardization and sharing in graph-based sports analytics. Collaborative efforts can be initiated to develop common data standards, protocols, and sharing mechanisms that benefit the entire sports analytics community. From our inquiry into the field, the representation of information by means of graphs has shown great potential; however, their use is still limited. Shared knowledge from the SMS can help build a community of practice around graph-based sports analytics. This community could facilitate ongoing knowledge exchange, mentorship, and collaboration, further advancing the field. By highlighting the interdisciplinary nature of graph-based sports analytics, we showcased the need for collaboration between data scientists, sports scientists, coaches, and technology experts. This knowledge encourages the formation of interdisciplinary research teams that bring diverse expertise to the table, resulting in more holistic and practical solutions. Researchers can use the SMS findings to disseminate knowledge about the current state of graph-based approaches in sports analytics. Sharing these insights with sports organizations and technology developers provides a comprehensive landscape overview, fostering a shared understanding among stakeholders. Sports organizations can benefit from understanding the practical applications of graph-based approaches revealed in the SMS. This knowledge can inform collaborations with researchers to develop tailored solutions that address specific needs within the organization, such as player performance optimization, injury prevention, or strategic decision-making. Technology developers can gain insights into the current trends and preferences in graph-based sports analytics. This information is valuable for refining existing tools or developing new technologies that align with the needs and preferences of sports organizations. Collaborating with researchers ensures that technological advancements are grounded in robust scientific principles. Sports organizations and technology developers can use the SMS findings to benchmark their current practices against industry standards and emerging trends. This knowledge can inspire collaborations to improve performance analytics methods and stay ahead of the curve in the rapidly evolving field of sports technology. Sharing the SMS findings can contribute to educational initiatives, helping train the next generation of sports analytics professionals. Collaborations between academic institutions, sports organizations, and technology developers can result in joint training programs, workshops, and courses that bridge the gap between theory and practice. By leveraging the insights gained from the SMS, collaboration among researchers, sports organizations, and technology developers can be more targeted, effective, and aligned with the current state of graph-based approaches in major team sports analytics. This collaborative approach drives innovation, advances research, and delivers practical solutions that enhance team performance and sports analysis.

4 Discussion

In this section, we provide additional considerations on the results of our study. We discuss about current limitations and look into the possible causes. A first reflection concerns the meaning of the entities in the graphs, that is, what nodes and arcs represent. In fact, according to the specific application and research goal, graph components may assume different meaning. Hence, the centrality role and relevancy of a graph in the context of sports analytics may be strongly affected by this aspect. Often, players are viewed as network nodes, connected through relevant information variables such as a ball-passing action. This forms complex patterns of interaction between teammates, often referred to as a ball-passing network. One of the key benefits of this approach is that it highlights the interactional processes established by team players within and between teams as a major focus of performance analysis. While the use of graph-based structures in sports analytics has shown promise, it is not without its limitations and challenges. One of the main issues is the lack of adequate datasets. This makes it difficult to apply graph-based structures consistently and accurately across different sports or even within the same sport. Surprisingly, another aspect that catches the eye when analyzing the selected primary studies concerns the limited conception of graph structures as spatio-temporal graphs, only being addressed by recent literature. Another braking element to the evolution of the field is the dominance of industries over academics. It can be attributed to several factors, and the scarcity of public datasets is indeed a significant constraint that hampers academic research in this area. Another reason for the industry's dominance is the access to proprietary data. Another challenge, as we already briefly mentioned, is the computational complexity associated with graph-based structures. The analysis of complex networks requires sophisticated algorithms and significant computational resources. This can be a barrier for sports organizations with limited technical capabilities or resources. Additionally, the interpretation of results from graph-based analyses can be complex and require a deep understanding of both the sport and the analytical methods used. While our mapping study outlines a wide range of graph-based methodologies applied to team sports analytics, a closer inspection of the technical intricacies underlying these methods reveals important considerations related to computational complexity, scalability, and real-time applicability. Many recent approaches employ graph neural networks (GNNs), especially graph convolutional networks (GCNs), to model complex spatial-temporal relationships among players. For instance, Wu et al. [251] introduced Actor Relation Graphs (ARGs) for group activity recognition, using sparsified graphs to limit computational overhead. While their model achieves high accuracy, its inference time of approximately 0.2 seconds per video clip underscores the trade-off between model expressiveness and runtime performance—particularly relevant for applications requiring near-real-time responsiveness. Similarly, works like [254] in sports outcome prediction show how permutation-invariant GNN architectures can scale flexibly across sports with varying team sizes. These models effectively capture relational dynamics but are generally trained and evaluated in offline settings, with little emphasis on deployment constraints such as latency, throughput, or memory efficiency. Optimization strategies such as pruning, quantization, or architectural simplification are rarely detailed in the surveyed literature. Graph-based approaches for analyzing multi-agent spatiotemporal data in team sports offer a powerful paradigm for capturing the complex dynamics and interactions inherent in such environments. In Raabe et al. [182], Tactical Graph Networks (TGNets) are introduced as an efficient and lightweight method for encoding contextual relationships among players by translating trajectory data into graph structures. The approach shows state-of-the-art accuracy with significantly reduced computational overhead compared to deep neural alternatives, highlighting high efficiency and moderate scalability especially for tasks like ball recovery prediction in football. Meanwhile, Jiang et al. [100] present a Local–Global Context-Aware Graph Reasoning model (LG-CAGR) for group activity recognition by modeling actor–scene interactions using multi-graphs and attention mechanisms. This model enables scalable reasoning across varying group sizes and scene contexts through localized feature extraction and global scene awareness. However, the added complexity of managing both scene and actor-level reasoning increases computational demand. Both works underscore that while graph-based models offer superior interpretability and flexibility, their scalability is tightly linked to graph construction strategies and the efficiency of reasoning modules, especially when scaling to larger datasets or real-time systems in high-speed sports like basketball or football. Moreover, real-time applicability remains an open challenge. Although several models demonstrate strong predictive performance in retrospective analyses, few report on system-level benchmarks that would be required for live match analysis or in-game decision support. The absence of standardized evaluation protocols for runtime efficiency, graph construction overhead, and end-to-end system performance hinders a complete understanding of the practical feasibility of these methods.

Despite these threats, we believe the potential benefits of graph-based structures in sports analytics are significant, especially when considering the potential insights from other domains. In fact, graphs serve as a powerful and versatile representation formalism across a wide range of domains, enabling the modeling of complex relationships, dynamic interactions, and structured dependencies among entities. Fields such as finance, bioinformatics, autonomous systems, and traffic management have long tackled problems involving dynamic graphs, temporal evolution, and heterogeneous data integration—challenges that are now becoming central in sports contexts. By drawing from these domains, sports analytics can evolve from descriptive and retrospective analyses to more predictive and prescriptive systems or vice-versa. Continued advancements in data collection technologies, machine learning algorithms, and computational resources are likely to mitigate some of these limitations in the future. As the field continues to evolve, it will be important for researchers and practitioners to collaborate closely to ensure that the methods used are both scientifically rigorous and practically relevant. We refer the reader to the “Further Considerations” section (see Appendix in supplementary material), where we discuss in more depth the different concepts covered in this section.

5 Threats to validity

The validity of this Systematic Mapping Study (SMS) is subject to several potential threats, which must be acknowledged and considered to ensure the integrity of our findings. These threats pertain to the comprehensiveness of the search, the selection of studies, and the data extraction process. The following threats are taken into account:

- **Publication Bias:** A significant threat to validity in any systematic study is publication bias, where positive or statistically significant results are more likely to be published. In this SMS, we have attempted to mitigate this threat by including conference proceedings, technical reports, and non-peer-reviewed sources to capture a broader spectrum of research outcomes.
- **Language Bias:** Limiting our search to English-language publications may introduce language bias. Studies published in other languages may have been excluded, potentially leading to the omission of valuable insights. We acknowledge this limitation and recommend further research to address language-diverse sources.
- **Database Coverage:** The comprehensiveness of our search depends on the coverage and indexing of the selected databases. It is possible that some relevant studies were not indexed or available in the chosen sources, potentially affecting the completeness of our findings.
- **Search Strategy:** Despite our efforts to create an inclusive search strategy, the selection of keywords and search terms may introduce bias. We have attempted to mitigate this by consulting experts and conducting pilot searches to refine our strategy.
- **Study Selection:** The inclusion and exclusion criteria set for study selection may introduce subjective judgment, potentially leading to the exclusion of studies that could be considered relevant by others. To address this, we employed a clear and predefined set of criteria and conducted inter-rater reliability checks during the selection process.
- **Data Extraction:** The accuracy and completeness of data extraction rely on the information provided in the selected studies. Inaccurate or incomplete reporting in the source material may introduce bias or affect the categorization of studies. We have taken measures to ensure consistent and objective data extraction, and any uncertainties or ambiguities were discussed and resolved through consensus among the research team.
- **Timeframe Limitation:** The choice of a publication date range may introduce temporal bias, potentially excluding older studies that could provide valuable historical context. This limitation is addressed by focusing on the most recent and relevant research within the defined timeframe.

While these potential threats to validity are acknowledged, we have strived to minimize their impact through careful methodology design and transparency in reporting. The findings of this SMS should be interpreted in light of these considerations, and future research in this field should aim to address these limitations for a more comprehensive understanding of the investigated domain.

6 Conclusions

The goal of our mapping study was to systematically understand how graph-based approaches and representations of knowledge have been applied to support team sports analysis. As a result, we were able to uncover the interplay between the two domains and to reveal trends and possible future research directions. To achieve this goal, we defined five RQs and conducted a systematic mapping study. We designed a strict research protocol and followed a systematic and peer-reviewed process to: (1) select our sources of information, (2) extract evidence from them, and (3) analyze the extracted data to answer our RQs. Starting from an initial set of 307 primary studies retrieved from four major computer science digital libraries, the selection process led us to 126 relevant high-quality primary studies. By analyzing the publication space we were able to devise the following: (1) the distribution of the selected primary studies over the publication years allowed us to observe an interesting fact, namely that the last three years have seen a sharp increase in the number of publications. This is an indication that the field of research we have been investigating is young and is attracting increasing interest in the scientific community; (2) the filter applied on publishers and the quality of journal and conference venues significantly reduced the number of papers selected based on the search string we defined. In addition, only a small proportion were published in top-ranked journals or conferences. Together with the observation made above, this allows us to infer that the field still offers vast potential in terms of explorability of research areas, but also that the limitations and challenges (see discussion in Appendix section of supplementary materials), are a major obstacle to the development of the field; and (3) most of the authors' affiliations are located in Asia (India, China) and America (Brazil, USA). The analysis of the data extracted from the selected studies let us answer our (research space) RQs and derive the following main conclusions: (1) several graph-based approaches are being used to represent knowledge in diverse tasks, each with different meaning, with networks of players being the most popular one; (2) social network analysis and community detection algorithms constitute a well-established research trend in the field and stand out from other techniques. This is mainly due to the presence of a "standard" dataset, frequently used for benchmark activities, which collects information of American college football games, as a network. While this can not be neglected, we believe it is of less interest for the intended aim of our study, that is the exploitation of graphs for advanced prediction tasks in sports analytics; (3) the majority of selected primary studies for volleyball investigated the group activity recognition task. As for the previous point, the presence of the "Volleyball dataset" is the driving force of this research branch; (4) the advent of Graph Neural Networks has significantly shoved the research in team sports analytics by means of graphs. Modeling and representing input data as graphs, allow researchers to provide more insights and capture more complex interactions.

Future research in graph-based sports analytics must prioritize three interconnected challenges: enhancing computational scalability, enabling real-time inference, and refining domain-specific models to translate theoretical promise into practical impact. A critical gap persists in the systematic benchmarking of latency and scalability metrics, particularly for latency-sensitive applications like live tactical decision support and broadcast augmentation. To establish methodological credibility, short-term efforts should emphasize experimental rigor—incorporating robust baselines, thorough statistical validation, and fully reproducible pipelines. Applying established Graph Neural Network (GNN) architectures to core tasks (e.g., player positioning, ball trajectory forecasting, and pass outcome prediction) offers a pragmatic pathway to evaluate their operational utility in sporting contexts. Concurrently, developing curated public datasets and open-source tooling is paramount to foster reproducibility and accelerate community-driven innovation. Longer-term advancements hinge on designing GNNs that explicitly encode the intrinsic spatiotemporal and multi-agent dynamics of team sports. Integrating multimodal data streams will be essential to capture the holistic complexity of athlete and team behaviors. Such integration could catalyze the development of real-time decision support systems, transforming in-game analytics. Sustained interdisciplinary collaboration with domain experts is also vital to ensure graph-derived insights yield tangible improvements in training methodologies, athlete health, and strategic periodization. To the best of our knowledge, this research is the first secondary study investigating how graph-based approaches are exploited to advance the field of team sports analytics. As a result of this research, we obtained a fine-grained mapping that describes the current interplay between graphs and team sport analysis. Researchers can leverage this mapping to identify opportunities for future research on new primary studies to be conducted or new applications of graphs for teams sports analytics to be developed. Practitioners can also use the mapping to take an informed decision on which AI technology to possibly adopt in support of their processes.

Acknowledgments

We acknowledge financial support from the PNRR MUR project PE0000013-FAIR.

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Received 15 April 2024; revised 13 October 2025; accepted 17 October 2025