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Bibliometric Analysis of Artificial Intelligence in Team Sports: Research Trends, Collaborations, and Creative Insights

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Abstract: This paper presents a bibliometric analysis of Scopus-indexed publications from 2000 to 2024 to examine the development of deep learning in team sports, particularly in real-time player tracking, performance analytics, and wearable-based monitoring of athletes. The publication trends, collaboration networks, and thematic structures were explored using Bibliometrix (R) and VOSviewer based on the co-occurrence of keywords, co-citation, and clustering. The findings indicate that after 2016, research production has increased significantly, with convolutional neural networks, temporal models, and new transformer architectures emerging as prominent approaches. The analysis identified three predominant research streams: computer vision–based detection and tracking, machine learning–driven performance analytics, and wearable-sensor applications. Object detectors and multi-object tracking frameworks used together to create a computer vision pipeline are now the backbone of real-time sports analytics, and predictive models are increasingly used to support tactical decision-making and workload evaluation. In spite of these developments, there are still issues concerning model interpretability, resiliency to dynamic environments, data privacy, and incorporation into the coaching workflows. It is recommended that future studies focus on multimodal systems combining visual, temporal, and physiological cues, as well as explainable artificial intelligence methods to enhance transparency and trust among practitioners. Further, this paper describes a system-based AI architecture that integrates vision-based analysis, time-based learning, and wearable sensing to support data-driven decision-making. Overall, this bibliometric mapping offers a systematic understanding of the new research areas and sets the stage toward building operational, reliable, and human-centric AI systems in team sports.

Keywords: artificial intelligence in team sports, bibliometric analysis, deep learning, player tracking, VOSviewer

1. Introduction

The speedy digitization of professional sports has resulted in an extraordinary growth in multimodal performance data, including streams of broadcast video, measurements of wearable sensors, and spatiotemporal tracking records [1]. This alteration has increased the adoption of analytics based on deep learning for automated player detection, ball tracking, and tactical analysis in settings for team sports [2–4]. Recent advances in convolutional neural networks (CNNs), recurrence systems, and transformer networks have enabled positional and event-level information to be extracted to facilitate coaching decision-making and performance improvement beyond the traditional statistical models [5–7].

Additionally, systems for computer vision that combine object detectors (like YOLO variants) with multi-object tracking systems, for example, DeepSORT and StrongSORT, are increasingly deployed to accomplish low-latency player and ball tracking in situations involving broadcast and stationary cameras [8, 9]. In terms of physiology, Wearable sensing devices incorporated with machine learning models maintain ongoing workload monitoring, fatigue, and risk of injury, allowing customized training techniques and management of recovery [10, 11]. These developments combined indicate a shift in the analytical descriptive to forecasting and prescriptive uses of artificial intelligence (AI) in the competitive sports landscape.

Although this advancement in technology, many significant obstacles remain insufficiently addressed, including the interpretability of the model, bias in algorithms, data privacy, and the integration of AI outcomes to real-world workflows for coaching [12–14]. Current work on explainable AI in sports further highlights the necessity of transparent and trustworthy models to support practitioner adoption and mitigate bias-related risks [15–17]. Moreover, existing reviews often treat computer vision, performance analytics, and wearable technologies as isolated domains, without examining how deep learning supports real-time tactical decision-making or practical deployment across team sports [18–20].

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From a bibliometric standpoint, earlier research mainly offers comprehensive overviews of trends in publications, patterns of authorship, or co-occurrences of keywords, providing limited understanding into the development of AI models methodologically or their effect on operations regarding pipelines for sports analytics [21, 22]. Accordingly, there isn't enough concentrated quantitative mapping that links productivity of research with the appearance of specific paradigms for deep learning (CNNs, Long Short-Term Memory (LSTM) networks, transformers), systems for tracking in real time, and sensor-based performance monitoring.

To fill in this gap, this research carries out a focused bibliometric analysis of literature indexed by Scopus (2000–2024), organized around the following research question: How has deep learning developed to support real-time player tracking and analytics of team sports performance, and what collaborative patterns and themes describe this change? Using VOSviewer and Bibliometrix, we examine the dynamics of publications, significant contributors, networks for international cooperation, and theme groups, with special consideration to computer vision–based tracking, performance analytics powered by machine learning, and applications for wearable sensors.

This work has four primary contributions. First, we provide a structured mapping of the intellectual landscape that connects deep learning architectures to team sports analytics pipelines. Second, we determine new areas of research and hubs for collaboration, influencing the deployment of AI in real time. Third, we summarize the main organizational and technical issues to direct upcoming computational and practical studies. Fourth, we suggest a functional AI pipeline that incorporates computer vision, temporal modeling, wearable sensing, and decision support.

The remainder of this paper is organized as follows. Section 2 describes the data sources and bibliometric methodology. Section 3 presents the quantitative results. Section 4 discusses technical implications and research challenges, and Section 5 concludes with future perspectives.

2. Methodology

2.1. Data source

To defend the reproducibility and credibility of the research, this bibliometric analysis used Scopus, which is a complete repository of peer-reviewed research. This database was chosen because it has a wide coverage of journals, conference papers, and book chapters in many different disciplines and has strong citation analysis and export capabilities. When compared to other databases, Scopus has superior capabilities for bibliometric analysis, including standardized indexing and higher trustworthiness. Accordingly, the dataset is expected to consist of high-quality and reputable scientific publications, providing a reliable foundation for analyzing research trends in artificial intelligence applied to team sports.

2.2. Search strategy

To achieve a clear and repeatable process of data collection, a well-defined search strategy was applied within the Scopus database. The query combined thematic keywords related to sports and AI, using Boolean operators to refine the scope:

(sport OR sports OR football OR soccer OR "team sport") AND ("AI" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision") AND (tracking OR detection OR "match analysis" OR event detection)

The main parameters of the search are summarized below:

1) Timespan: 2000–2024
2) Scope: AI in team sports (tracking, detection, performance evaluation)
3) Language: English
4) Document types: journal articles, conference proceedings, and book chapters
5) Final dataset: 1610 documents
6) Publication status: Final.

2.3. Inclusion and exclusion criteria

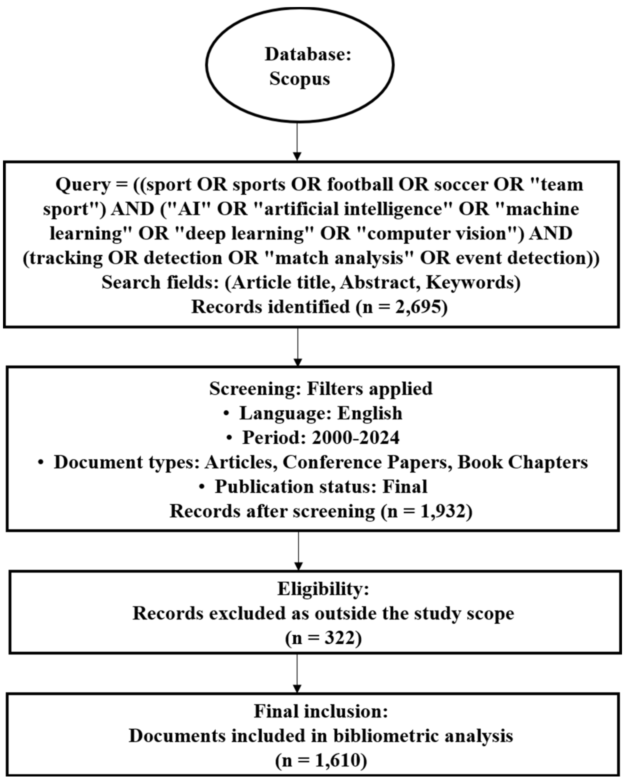
Clear inclusion and exclusion criteria were defined to ensure reproducibility and methodological consistency. Only English-language, Scopus-indexed journal articles, conference papers, and book chapters directly addressing AI applications in team sports were included, covering player and ball tracking, performance analytics, tactical analysis, and wearable-based monitoring.

Following the PRISMA framework (see Figure 1) [23], records underwent duplicate removal, title–abstract screening, and full-text assessment. Studies unrelated to AI, focused on individual sports, editorials, and papers without full-text availability were excluded, resulting in a focused and representative dataset.

2.4. Analytical tools

The dataset exported from Scopus was processed and analyzed using the Bibliometrix R package (via the Biblioshiny interface) for data cleaning, descriptive statistics, and bibliometric

Figure 1
PRISMA flow diagram of the article selection



mapping. VOSviewer was also used to generate and graphically represent co-authorship groups, citation maps, and keyword co-occurrence clusters. Their known ability to handle massive bibliometric datasets, open-source availability, and ability to create consistent and visually appealing results were among the factors in their choice. Understandable outcomes guaranteeing transparency and rigor in the investigation.

2.5. Analytical techniques

The bibliometric approach combined methods for scientific mapping with performance analysis, examining author productivity, citation patterns, and publication growth, while revealing the intellectual structure and cooperation networks within the field. Specific methods comprised:

1) Co-occurrence analysis of keywords to identify thematic clusters (association strength normalization, minimum occurrence threshold = 10).
2) Co-citation and bibliographic pairing to identify influential works and intellectual connections.
3) Analysis of factors and algorithms for clustering based on modularity to group-related research themes and visualize their evolution over time using Bibliometrix and VOSviewer.

2.6. Selected indicators

A variety of bibliometric indicators were utilized to ensure a thorough assessment of the field:

1) Productivity indicators: annual publication trends, most prolific authors, institutions, and countries.
2) Impact indicators: citation counts, average citations per document, and h-index of authors and sources.
3) Collaboration indicators: co-authorship networks, degree of international collaboration, and average co-authors per publication.
4) Thematic indicators: keyword frequency, co-occurrence mapping, and cluster analysis to identify emerging research topics.

These metrics were chosen because they were able to capture the qualitative structure (collaboration and thematic evolution) as well as the quantitative dimension (productivity and impact) of AI applications in team sports analytics. When combined, they offer a strong foundation for assessing the development, impact, and intellectual structure of this field of study.

2.7. Methodological rationale

Bibliometrix and VOSviewer were selected to provide complementary perspectives on the scientific structure of the field. Bibliometrix supports quantitative performance analysis (productivity, impact, and collaboration), while VOSviewer enables network-based visualization of thematic and intellectual relationships. Association strength normalization was applied to reduce the influence of highly frequent keywords, ensuring balanced cluster formation. Modularity-based clustering was used to identify coherent thematic communities. This combined approach supports both global mapping and focused thematic interpretation, allowing a reliable assessment of methodological evolution in deep learning–driven team sports analytics.

3. Results

3.1. Overview of the dataset

The final dataset comprises 1,610 documents published between 2000 and 2024 across 286 publication sources (see Table 1), which indicates a fast-growing field of research with an annual increase of 20.11%. The average document age (5.07 years) and citation rate (14.6 per document) are relatively small, suggesting a young and rapidly developing field of research due to recent developments in AI. The corpus is dominated by conference papers (1082 records) due to the methodological and prototype-based nature of AI research in team sports and journal articles (504) due to the growing interest in both validation and applied deployment. The mean of 3.68 co-authors per article and 15.28% international collaboration indicates fair global connectedness, which is mainly structured around specialized research groups. These attributes suggest a technologically motivated field that is going through explosive consolidation, in which algorithmic innovation is followed by the translational adoption of large-scale applications.

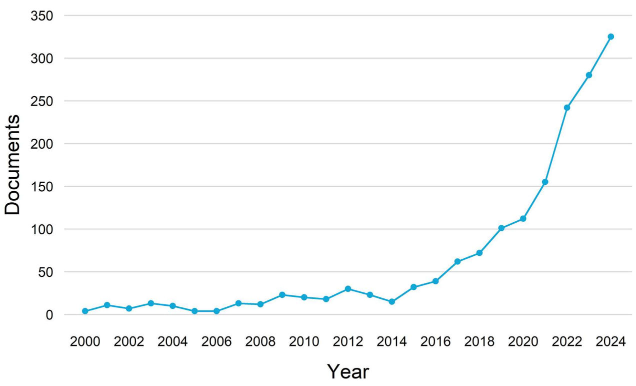
Table 1
Overview of the collected data analyzed with Bibliometrix

Primary information about data	
Period covered total	2000–2024
Number of sources (journals, books, etc.)	286
Total documents	1610
Average document age	5.07
Average citations per document	14.6
Yearly growth rate %	20.11
References	12477
Document contents	
keywords Plus (ID)	8374
Author's Keywords (DE)	9871
Authors	
Authors	5041
Authors of single-authored docs	128
Authors collaboration	
Single-authored docs	133
Co-authors per doc	3.68
International co-authorships %	15.28
Document types	
Articles	504
Book chapters	24
Conference papers	1082

3.2. Annual scientific production and growth trends

Before 2015, the yearly scientific output was comparatively steady and constrained, reflecting the exploratory stage of AI adoption in sports analytics. After 2016, a distinct turning point appears, as shown in Figure 2, following which there was a noticeable acceleration after 2020, with more than 300 publications annually in 2024. Deep learning architectures are being widely used at the same time as this quick expansion, especially CNNs

Figure 2
Annual scientific production trend (2000–2024) based on Scopus data



for player detection and tracking, as well as greater accessibility with extensive sensor and sports video datasets. Beyond a simple increase in volume, this pattern indicates a structural change in the direction of real-time systems for making decisions based on data in professional team sports, showing that AI-based sports analytics has developed into a well-established and rapidly growing field of study.

3.3. Source contribution analysis

3.3.1. Top sources by document count

The examination of source contents based on publication volume reveals a strong methodological orientation of the field toward algorithm development and rapid knowledge dissemination, with Lecture Notes in Computer Science (120 documents) dominating the landscape. This dominance reflects the central role of conference-based outlets in advancing computer vision and deep learning techniques for sports analytics. The prominence of IEEE Access and Sensors indicates a parallel shift toward applied research, particularly in wearable sensing and real-world performance monitoring. Meanwhile, the visibility of CVPR Workshops and SPIE Proceedings highlights the importance of experimental vision pipelines for player tracking and tactical interpretation. Collectively, this distribution suggests a research ecosystem characterized by fast prototyping in conferences and subsequent validation in applied journals, underscoring the translational nature of AI in team sports. Leading publication sources are summarized in Table 2.

3.3.2. Top sources by h-index

The impact analysis of the source using the h-index (Table 3) demonstrates the primary impact of venues focused on computer vision, with CVPR Workshops (h = 19) leading, followed by Lecture Notes in Computer Science and Sensors (h = 17 each). The great exposure of citations of methodological contributions concerning detection, tracking, and deep learning pipelines is shown in this pattern. IEEE Access and CVPR Proceedings (h = 15) further demonstrate the expanding influence of open-access and applicable platforms that facilitate the use of real-world sports analytics. By contrast, specialized journals like IEEE Transactions on Pattern Analysis and Machine Intelligence and Artificial Intelligence Review show reduced h-indices, suggesting a more focused but less frequent contribution to team sports applications. In general, this distribution emphasizes an area of research driven primarily by high-impact computer vision venues, complemented by interdisciplinary outlets bridging algorithmic innovation with practical performance analysis.

3.4. Author contribution analysis

3.4.1. Leading authors by research productivity

It has a concentrated authorship structure, where a few researchers with a high level of productivity make up publication output in AI-based team sports analytics, as illustrated in Figure 3. Halvorsen is the most prolific, closely trailed by Jalal and Midoglu, who have a record of involvement in methodological development and applied research. The fact that there are multiple authors who have published over 10 articles refers to the development of stable research cores, which implies that the production of knowledge in this field is conditioned by a few recurring actors. This trend indicates the establishment of specialized expert communities, which are at the heart of further development of computer vision–based analysis, performance modeling, and data-driven sports applications.

3.4.2. Top authors by h-index

The findings, as illustrated in Table 4, which presents the top 10 authors according to h-index, indicate a small circle of influential researchers who influence the work in the field of AI in team sports. Jalal Ahmad becomes the most influential author, then Ivasic-Kos, and a core of Halvorsen and Midoglu, which can be seen in the visibility of citation and continuity of productivity. This dispersion indicates that scientific power in this field is held by a small group of scholars who merge methodological novelty with practical sports analytics. The fact that some of the

Table 2
Top 10 sources by document count analyzed with Bibliometrix

Source	Document count
Lecture Notes in Computer Science	120
IEEE Access	43
Sensors	42
IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops	36
Proceedings of SPIE—The International Society for Optical Engineering	34
ACM International Conference Proceeding Series	29
Communications in Computer and Information Science	26
Computational Intelligence and Neuroscience	25
Lecture Notes in Networks and Systems	22
Multimedia Tools and Applications	18

Table 3
Leading 10 sources by citation impact analyzed with Bibliometrix

Source	*h*-index
IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops	19
Lecture Notes in Computer Science	17
Sensors	17
IEEE Access	15
Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition	15
Applied Sciences (Switzerland)	9
Multimedia Tools and Applications	8
IEEE Transactions on Pattern Analysis and Machine Intelligence	6
Artificial Intelligence Review	4
Journal of Intelligent and Fuzzy Systems	4

Figure 3
Top 10 authors by number of publications from Scopus

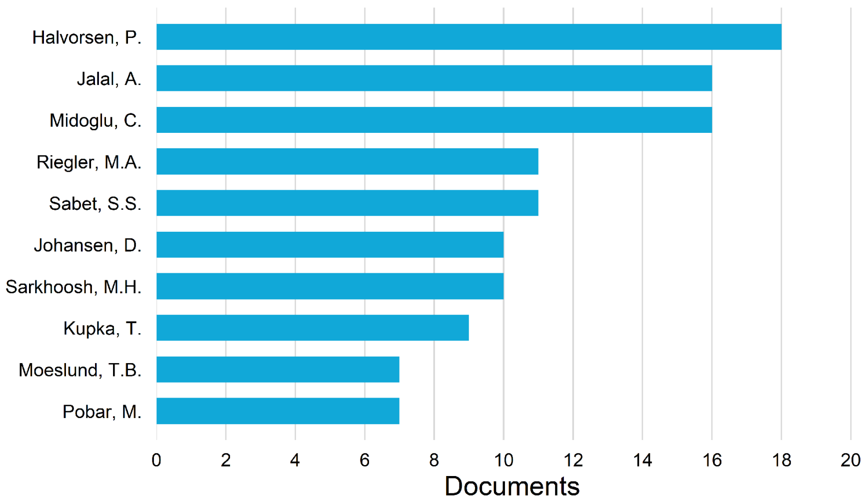


Table 4
Leading 10 authors by citation impact analyzed with Bibliometrix

Author	*h*-index
Jalal Ahmad	9
Ivasic-Kos Marina	8
Halvorsen Pål	7
Midoglu Cise	7
Johansen Dag	6
Kupka Tomas	6
Moeslund Thomas Baltzer	6
Nitti Massimiliano	6
Riegler Michael Alexander	6
Sarkhoosh Mehdi Houshmand	5

authors attain similar values of h-index gives further evidence of a collaborative and moderately balanced impact structure where interconnected research communities can play a significant role in the development of computer vision, performance modeling, and intelligent sports systems.

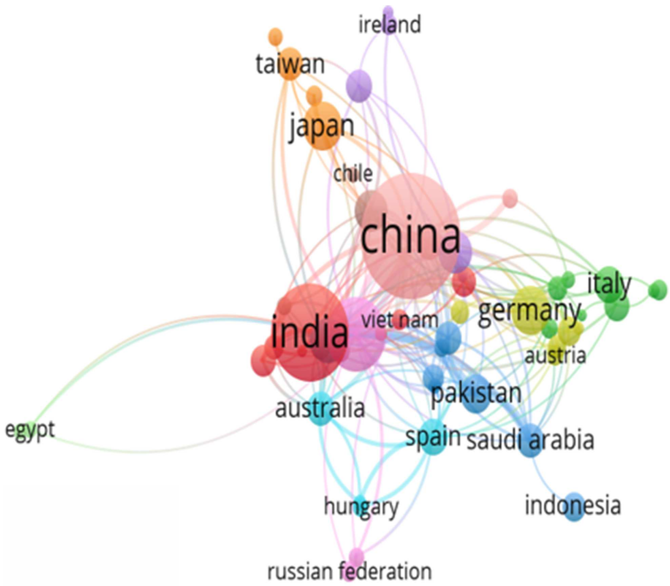
3.5. Country collaboration network

The international co-authorship network, as shown in Figure 4, indicates that there are a few key collaboration centers based in China, India, and Germany, which serve as main bridges between local research communities in Europe, Asia, and the Middle East. The network structure shows that it is a centralized form of cooperation, with a few core countries leading the dissemination of knowledge and diffusion of methodology in AI-based team sports analytics. Peripheral nodes are new actors with less integration, indicating unequal global representation and indicating that there is a possibility of more extensive global collaboration. Clear geographical clusters are noted, especially in East Asia and Europe, suggesting geographically organized patterns of collaboration. Temporal analysis also indicates that the level of collaboration rose significantly since 2020, when sports analytics based on deep learning began to grow worldwide.

3.6. Most cited papers

This section identifies the most influential works that influence the analytics of AI-driven team sports. Those that

Figure 4
Global collaboration hubs in AI for team sports



were mostly cited are on the temporal event modeling, spatiotemporal action localization, multi-player tracking, and large sports datasets like SoccerNet and SoccerNet-v2, as shown in Table 5. The fact that the research on complex event detection and tracking seems to be the most prominent highlights the pivotal role of temporal reasoning and computer vision in performance analysis. Also, the contributions to pose estimation, video structure analysis, and out-of-distribution recognition are influential, indicating the growing interest in robust and generalizable learning frameworks. Even though some of these works date back to earlier years, due to the historic importance they hold in the domain, recent research (2020–2025) has pushed the boundaries of these methods with deep learning, transformer-based systems, and real-time sports analytics systems. This development confirms that automated event understanding, player tracking, and dataset development are core but are constantly improved with the latest AI methods.

3.7. Leading contributing countries

According to Figure 5, China, India, and the United States are the top AI-driven team sports research, indicating intensive investments in AI infrastructure. The countries that have already developed computer vision and machine learning ecosystems are central to the development of methodological directions. A second tier is constituted by Germany and the United Kingdom, which frequently serve as a point of contact between Asian and Western scientific circles, and Japan and South Korea emphasize the continuing involvement of East Asia. The international involvement is also growing as Italy, Canada, and Pakistan make their contributions. In general, the area is growing on a global scale, though it is still marked by the lack of research capacity, as it is uneven, which is why a wider international cooperation is necessary.

3.8. Highest-contributing affiliations

A small set of institutions contribute a large percentage of publications, with the top contributors being Air University Islamabad, then OsloMet—Oslo Metropolitan University and Simula Metropolitan Center of digital engineering, as illustrated in Figure 6. This focus indicates the importance of specialized AI and computer vision laboratories in the development of sports analytics. According to major research organizations, such as the Chinese Academy of Sciences and Consiglio Nazionale delle Ricerche, there is a high level of involvement of the public sector. The contributions published by universities all over Asia and Europe not only testify to the international and interdisciplinary character of the field but also indicate a research environment dominated by a few very active academic centers.

3.9. Dominant research terms and conceptual landscape

The most prevalent keywords indicate a powerful methodological focus on computer vision and deep learning, which proves that the area of visual perception and representation learning is the technical heart of AI-based team sports analytics, as shown in Figure 7. The popularity of terms such as object detection, CNNs, and image segmentation suggests that the researchers are concerned with automated player and ball tracking, as well as

Table 5
Top 10 most cited papers in the dataset from Scopus

Ref	Source	Citations
[24]	Learning latent temporal structure for complex event detection	323
[25]	Learning to track for spatiotemporal action localization	248
[26]	Deep 360 pilot: Learning a deep agent for piloting through 360° sports videos	153
[27]	SoccerNet: A scalable dataset for action spotting in soccer videos	145
[28]	Structure analysis of sports video using domain models	137
[29]	Out-of-distribution detection for generalized zero-shot action recognition	131
[30]	Multiple player tracking in sports video: A dual-mode two-way Bayesian inference approach with progressive observation modeling	121
[31]	SoccerNet-v2: A dataset and benchmarks for holistic understanding of broadcast soccer videos	120
[32]	A Comprehensive Review of Computer Vision in Sports: Open Issues, Future Trends, and Research Directions	116
[33]	Multi-person 3D pose estimation and tracking in sports	112

Figure 5
Top 10 countries by scientific contribution from Scopus

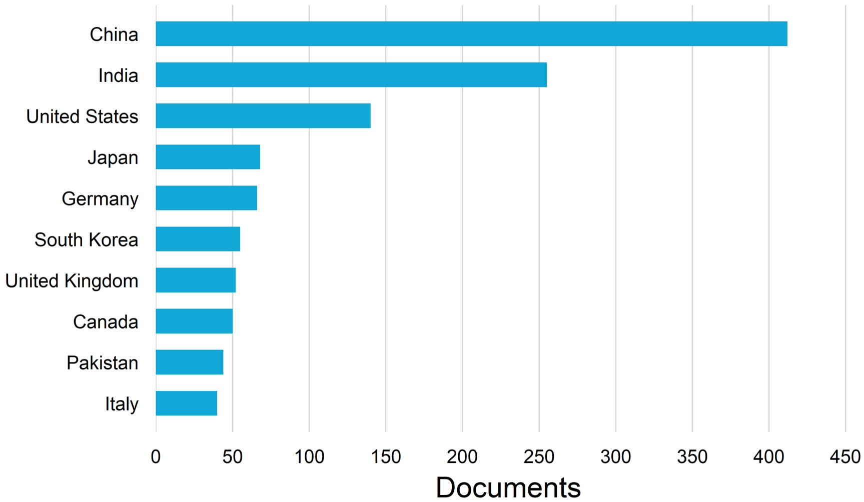


Figure 6
Top 10 affiliations by number of documents published from Scopus

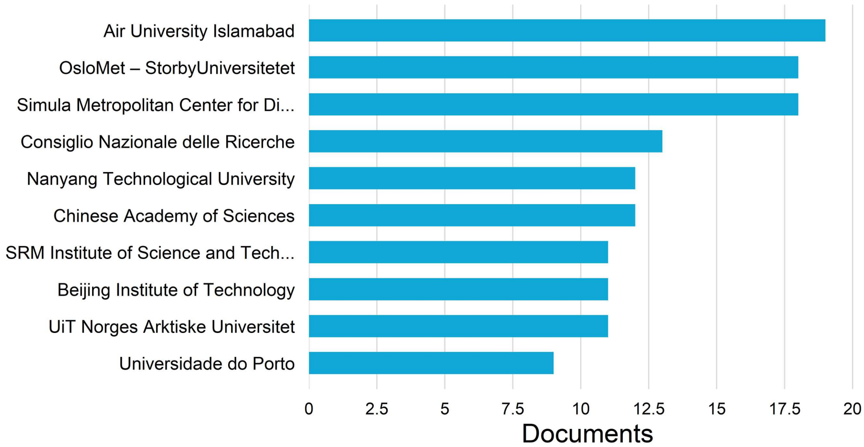
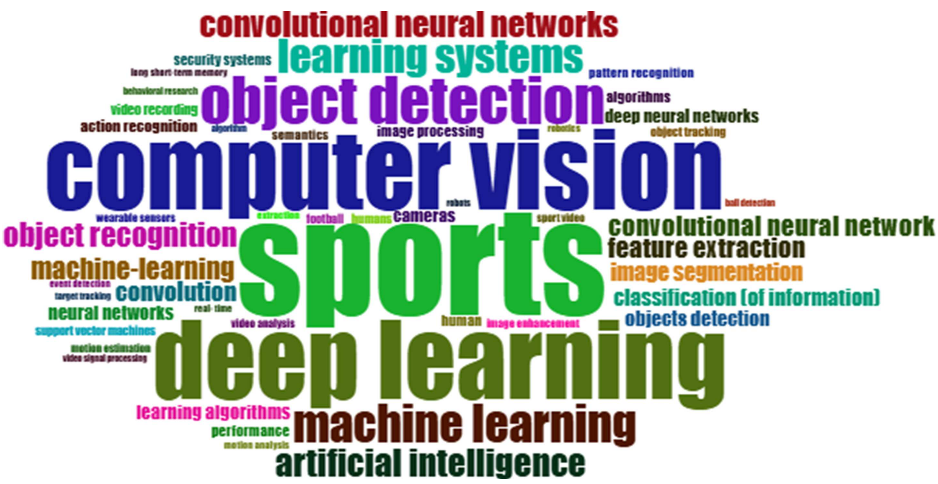


Figure 7
Most frequent research terms visualized as a word cloud using Bibliometrix



fine-grained event understanding. Simultaneously, repeated allusions to machine learning and feature extraction indicate the persistence of data-driven modeling to measure performance. All these trends point to the fact that there is a shift in the descriptive analysis of videos to real-time, learning-based decision support systems, which highlights the growing technical complexity and interdisciplinary combination of the current sports analytics studies.

3.10. Keyword Co-occurrence network and thematic cluster mapping

The keyword co-occurrence network identifies three dominant and interconnected research streams, reflecting the technical evolution of AI in team sports analytics, as shown in Figure 8.

1) Cluster 1: computer vision and object detection in sports

The most common terms in this cluster are object detection, player tracking, ball detection, and image enhancement, which shows that computer vision pipelines play the key role in real-time sports analytics. The major studies are based on CNNs and deep visual representations that are used to automate the localization of the athlete, event recognition, and analysis of broadcast video. The popularity of this cluster indicates the transition to perception-driven systems that facilitate tactical analysis, officiating support, and automated annotation.

2) Cluster 2: machine learning and performance analytics

This cluster focuses on the areas of classification, neural networks, predictive modeling, and learning algorithms as the implementation of deep learning structures in performance assessment and tactical decision support has increased. In addition to the descriptive statistics, this stream is starting to absorb temporal modeling and representation learning to forecast match results, measure player performance, and aid in strategic decision-making, pointing to a methodological shift toward decision-making that is data-driven.

3) Cluster 3: wearable sensors and human-centered applications

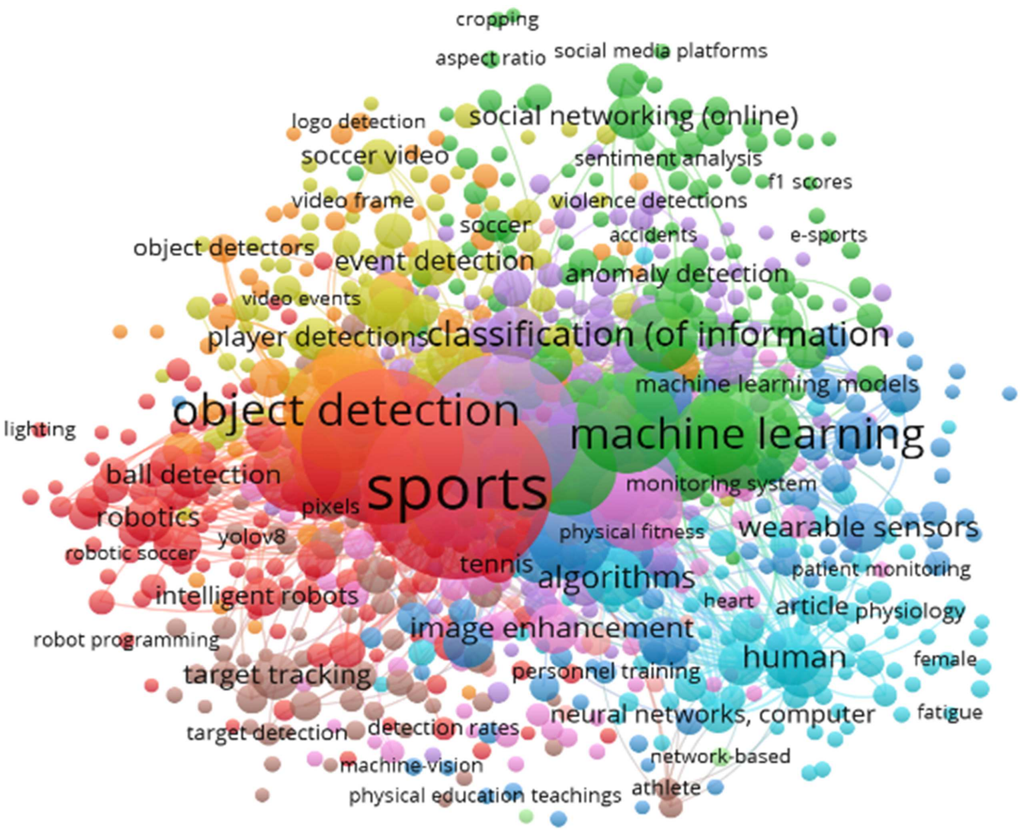
Keywords related to wearable sensors, physiological monitoring, fatigue, and injury prevention characterize this cluster, illustrating the integration of multimodal sensing with AI for personalized training and health management. While enabling continuous athlete monitoring, this stream also exposes practical challenges related to sensor reliability, data heterogeneity, and deployment in dynamic environments.

Collectively, these clusters indicate a shift toward combined AI ecosystems consisting of perception, prediction, and physiological monitoring, having been initially isolated as vision-based applications. The evolution highlights the new trends in real-time decision support and human-in-the-loop systems, as well as underscores the unsolved issues with model interpretability, robustness, and ethical data management in the context of professional sports.

4. Discussion

This bibliometric study offers quantitative proof of a systemic change in analytics for team sports, mostly fueled by developments in deep learning and the accessibility of vast amounts of data. Beyond the expansion of publications. The findings show a methodological shift from handcrafted feature extraction and rule-based video analysis in the direction of comprehensive learning frameworks. Preliminary studies mostly relied

Figure 8
Keyword co-occurrence map generated with VOSviewer



on domain-specific descriptors. Conversely, CNNs are being used more and more in recent studies. For spatial perception, temporal models for action understanding, and transformer-based architectures for comprehensive match representation, enabling real-time player tracking and automated event detection [34, 35].

The co-occurrence and clustering analyses also demonstrate that there is an overlap between computer vision, machine learning, and wearable-sensor research streams. The contemporary uses are dominated by vision-based pipelines, which are used to localize players and track the ball, and performance analytics are starting to use predictive modeling to perform a tactical evaluation. Meanwhile, wearable sensing can provide physiological information to monitor workload and predict injury risk. Recent research has corroborated that multimodal visual and sensor fusion are indeed highly effective in motion recognition and performance analysis, as well as the shift toward combined AI pipelines [36–38].

Figure 9 presents a conceptual operational AI pipeline based on the identified bibliometric clusters. Multimodal data fusion combines video streams and wearable sensors to assist computer vision–based player detection and ball tracking and temporal modeling for action recognition and event detection. These deliverables drive performance analytics to monitor workload, predict its occurrence, and assess the likelihood of an injury, and feed a decision support system to provide coaching feedback and development of strategy. A mechanism of refinement of a closed-loop model resets decision outputs into multimodal fusion and allows the system to adapt continuously. Even with these advances, the existing implementations are still disjointed, and it is important to have coherent multimodal architectures and deployment-oriented tests.

Although these advances have occurred, there are a number of issues that still do not allow real-world implementation. Computer vision models are also vulnerable to occlusions and camera variability, whereas wearable platforms have to contend with signal noise and synchronization challenges. Furthermore, deep learning systems can be quite opaque, limiting interpretability to users and introducing issues of algorithmic bias and data management. The recent increase in the number of studies on explainable AI in sport shows the importance of transparent models to enhance trust and usage in coaching contexts [39, 40].

A key research gap identified in this study concerns the limited development of unified, explainable, and multimodal AI systems capable of combining perception, prediction, and physiological monitoring in real time. While individual components are actively studied, few works address their joint optimization within operational workflows. Future research should therefore prioritize multimodal fusion architectures, explainable AI techniques, and deployment-oriented evaluations that translate model outputs into actionable tactical insights (see Table 6).

In computational engineering terms, it is shifting to operational intelligence platforms as opposed to experimental

Figure 9
Operational AI pipeline for team sports analytics

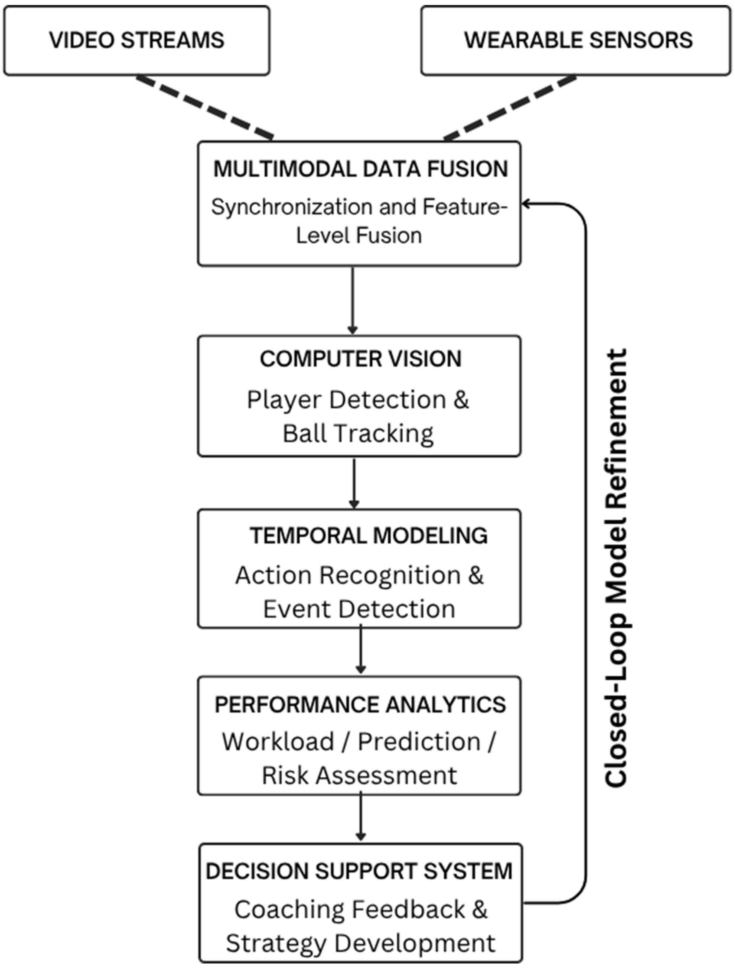


Table 6
Key research gaps and future directions

Area	Current focus	Identified gap	Future direction
Computer vision	Player/ball tracking	Occlusion sensitivity	Multimodal fusion
Temporal modeling	Action recognition	Limited temporal	Transformers
Performance analytics	Workload prediction	Low interpretability	Explainable AI
Wearables	Physiological monitoring	Noisy signals	Sensor-aware models
System integration	Separate modules	Fragmented pipelines	Unified closed-loop systems

prototypes. Extensive recent surveys also show new opportunities for advanced hardware acceleration and full AI ecosystems of sports analytics. The continued development will be based not only on the development of model architectures but also on robustness at the system level, human–AI interaction, and ethical governance, which will be necessary to make AI a trustworthy part of real-time decision-making in team sports.

5. Conclusion

This paper has examined 1610 publications indexed by Scopus to examine the history of AI in team sports, focusing on deep learning–based player tracking, performance analytics, and wearable sensing. The findings indicate that there is a clear shift in handcrafted feature extraction to end-to-end learning systems that are mostly CNNs, temporal, and novel transformer. It was found that there are three key streams of research: computer-vision-based detection and tracking, machine learning–driven performance evaluation, and sensor-based athlete monitoring. The current computer vision pipelines based on object detectors and multi-object tracking systems are the foundation of real-time sports analytics, with predictive models progressively aiding in tactical decision-making and workload evaluation.

The analysis also points out some of the enduring issues that are associated with the interpretability of models, their strength in unstable settings, privacy of data, and their use in the coaching process. Future studies must concentrate on unified multimodal architectures based on visual, temporal, and physiological cues and explainable AI methods to enhance transparency and practitioner trust. Models involving transformers, real-time multimodal fusion approaches, and deployment-based assessments are some of the encouraging new prospects in the development of intelligent sports systems. Generalizing the datasets to a wide range of real-life match conditions and using generative AI to achieve data augmentation can provide an even better generalization of the model. Comprehensively, this bibliometric mapping offers an organized basis upon which to construct coherent, reliable, and working AI systems that can convert computational intelligence into performance insights that can be applied in team sports.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Doha Lefhal: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration, Funding acquisition. **Ali Ouacha:** Validation, Supervision. **Abdeslam El Harraj:** Resources. **Soumia Ziti:** Supervision.

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