J. Electrical Systems 20-2 (2024): 1897-1910

[1]Yue Ren
[2,*]Shaowei Wang
[3]Xiangyu Wang
[4]Jun Chu

Emerging Trends in Sports and Artificial Intelligence: A Scientometric Analysis in Citespace

Journal of Electrical Systems

Abstract: - This study endeavors to utilize CiteSpace software to construct and examine co-citation networks of references within the domains of sports and artificial intelligence (AI), gathered from the Web of Science. The aim is to delineate the progression of AI applications in sports and to pinpoint current research focal points. Analyzing a corpus of 2,493 papers sourced from the Web of Science via CiteSpace, the findings reveal a year-on-year escalation in the application of AI within sports over the last twelve years (2010 to 2021). Machine learning has found extensive application in sports, notably in the analysis of athlete behavior, prediction of match outcomes, and physiological monitoring, among other areas. The evolution of sports and AI has witnessed two significant fluctuations within the past twelve years, specifically in 2011 and 2014. The modularity shift in 2011 indicated an uptick in the analysis of tasks and the identification of human activities. The year 2014 was marked as a pivotal moment with the advent of visualization utilization in team sports and wearable technologies. The study underscores the presence of numerous unexplored intellectual avenues within the sports and AI domain, which warrant further exploration in future research endeavors. Key milestones spanning from 2010 to 2021 are elucidated through visual analysis.

Keywords: Sports, Artificial Intelligence, AI, Machine Learning, Deep Learning.

I. Introduction

The term 'Artificial Intelligence' (AI) has been delineated to define the capability of machines to perform tasks that typically require human intelligence [1]. According to data from the Web of Science, our study aims to examine the evolution of AI applications within the sports sector and identify the predominant research hotspots. The intersection of sports and AI has become an increasingly interesting area in recent academic efforts. The deployment of advanced technologies, such as wearable sensors and machine learning algorithms, has revolutionized the way sports data is collected and analyzed, enhancing its accuracy and sophistication. These technological advances have opened new possibilities for athletes, coaches, and researchers to improve athletic performance, prevent injuries, and gain a comprehensive understanding of the physiological and biomechanical aspects of sports performance.

Despite the burgeoning interest in the utilization of AI in sports, there is a scarcity of research on the emerging trends within this domain. Consequently, there is a pressing need for an exhaustive analysis of the current research landscape concerning sports and AI. This study seeks to address this void by conducting a scientometric analysis with the aid of CiteSpace. CiteSpace [2, 3] is a software tool developed for the visualization and examination of scientific literature through citation analysis. It facilitates the identification and exploration of emerging trends, patterns, and networks in scientific publications, especially within the realms of science, technology, and medicine. Utilizing advanced algorithms, CiteSpace pinpoints clusters of interconnected research and delineates their progression over time, enabling researchers to discern influential papers, authors, and research collectives. Additionally, it supports the creation of maps depicting co-citation, bibliographic coupling, and co-authorship networks, aiding in the identification of significant research themes, collaborations, and tendencies. Through an analysis of the extant literature on sports and AI, this investigation seeks to uncover the most prominent authors, research institutions, and publications in this arena, alongside the key research themes and trajectories.

The outcomes of this investigation are poised to offer significant insights for researchers, practitioners, and policymakers engaged in the application of AI within the sports domain. By pinpointing the most viable research directions and application areas, this study will furnish insights into the potential of AI to augment athletic performance, enhance training and rehabilitation schemes, and inform sports policy and governance. Moreover, this research will contribute to the wider discourse on AI applications across various sectors, underscoring the transformative potential of AI in tackling complex challenges in today's world.

[1] Capital University of Physical Education and Sports, Beijing 100191, China
[2] College of Physical Education Hebei Normal University, Shijiazhuang 050024, China
[3] Capital University of Physical Education and Sports, Beijing 100191, China
[4] Capital University of Physical Education and Sports, Beijing 100191, China
*Corresponding author: Shaowei Wang

II. MATERIALS AND METHODS

A. Data Collection

The Science Citation Index Expanded (SCI-EXPANDED) and the Emerging Sources Citation Index (ESCI), provided by Thomson Reuters through the Web of Science Core Collection (WOSCC), were utilized to source relevant papers for this study on August 4, 2021, in Philadelphia, PA, USA. This search targeted two specific domains: sports and AI, with the results subsequently merged using the 'and' operator. To refine the search within these expansive fields, we employed specific keywords reflecting the emergent hotspots and trends. Our study identified 13 key areas within AI, encapsulating the primary directions and technologies in AI research, namely: machine learning, knowledge engineering, computer vision, natural language processing, speech recognition, computer graphics, multimedia technology, human-computer interaction, robotics, database technology, visualization, data mining, information retrieval, and recommendation systems. These segments represent the broad spectrum of AI application and development, crucial for exploring the forefront issues in sports AI. Focusing on these pivotal areas allowed for a comprehensive and accurate assessment of AI's research progression and trends within the sports domain [4, 5]. Multiple search terms were applied for each area (Table 1), with the timeframe specified from 2010 to 2021. Only articles written in English were considered. Moreover, document types such as reviews, meeting abstracts, editorial materials, proceedings papers, or letters were not excluded, underlining the emphasis on journal articles due to their comprehensive coverage of research ideas and conclusions. The initial search yielded a total of 2493 articles, all of which were included in the final analysis.

Table 1: Search Terms

Source	Web of Science Core Collection	
Citation	SCI-EXPANDED, ESCI	
Time span	2010 - 2021	
Language	English	
Types	Article	
Search steps	#1	TS=(“machine learn*” OR “machine self-learning” OR “knowledge engineering” OR “KE” OR “knowledge based engineering” OR “knowledge project” OR “computer vision” OR “Machine vision” OR “computer vision system” OR “computer vision technology” OR “computer-visual” OR “computer visual technology” OR “natural language process*” OR “Natura Language Processing” OR “speech recognition” OR “voice recognition” OR “sound recognition” OR “sound identification” OR “voice identification” “acoustics recognition” OR “speech recognization” OR “computer graphics” OR “computer figure” OR “descriptive geometry” OR “real-time computer graphics” OR “real time graphics” OR “multimedia technology” OR “multimedia processing technology” OR “multimedia technique” OR “multi-media technology” OR “computer human inter-action” OR “human computer interaction” OR “man-machine interaction” OR “human-machine interaction” OR “human-computer interaction” OR “humancomputer interaction” OR Robot* OR “electric robot” OR “industrial robot” OR “slave robot” OR robot(Bot) OR “robotic manipulator*” OR manipulator OR “welfare robot” OR “robot feeding” OR “database technology” OR “data base technology” OR “database technique” OR “data base technique*” OR “data technology” OR “Visualization*” OR “visual technology” OR “data visualization” OR “visual display” OR visible OR “visualize" OR “visualization techniques” OR “Data mining” OR “information retrieval” OR “information research” OR “message retrieval” OR “information index” OR “information storage and retrieval” OR “information recommendation” OR “recommendation of web pages” OR “recommendation of information” OR “information recommend” OR “wearable sensing device” OR “wearable device” OR Wearable* OR “artificial intelligence”)
	#2	TS=(“physical culture” OR “physical training” OR sports OR “sports activities” or “athletic sports” or “athletics” or Sport or “sport activities” or “physical culture and sports” or “physical exercise” or “sports activity” or “sports exercise” or “sports movement” or “physical exercise”)
	#3	#2 AND #1

#1: Steps for retrieving AI, #2: Steps for retrieving sports.

B. Statistical Analysis

Data were retrieved from the Web of Science (WOS) in the "Full record and cited references" formats on August 4, 2021. A comprehensive collection of 2493 articles was compiled, meticulously checked for duplicates, then pre-processed and imported into CiteSpace, a sophisticated document data mining and visualization platform designed by Chen's team [2]. CiteSpace employs a blend of social network analysis and cluster analysis techniques, facilitating the exploration of foundational knowledge, research constraints, distinct research characteristics, and evolutionary patterns through article referencing and coupling, scientific research collaboration networks, and thematic contributions [3]. To maintain the integrity and reproducibility of the research, the specific CiteSpace parameters utilized for network reduction/pruning (Pathfinder) are documented. The analysis employed CiteSpace version 5.8 R1, ensuring a consistent and reliable examination of the collected data.

III. RESULTS AND DISCUSSION

A. Distribution of Countries and Institutions in Sports and AI

The United States, the foremost research contributor in the domain of sports and AI as illustrated in Figure 1, achieved a normalized publication count of 0.182 in 2021. Exhibiting a consistent and robust output from 2010 through 2021, the U.S. leverages an extensive research infrastructure, bolstered by a plethora of leading universities and institutions actively pursuing advancements in this arena [6-8]. Concurrently, China witnessed a notable escalation in its normalized publication count over the same period, ascending from 0.002 to 0.257. This surge underscores China's rapid enhancement in sports and AI research, underscored by its commitment to pioneering sophisticated technologies and applications. This growth trajectory is further propelled by substantial governmental investments aimed at establishing China as a global frontrunner in this sector [9, 10].

Australia has also distinguished itself with a considerable output in sports and AI research, particularly between 2013 and 2019, where it exhibited a pronounced growth in its normalized publication count, escalating from 0.303 to 1.267, thereby eclipsing other nations [11, 12]. Similarly, the UK and Italy demonstrated incremental growths in their respective normalized publication counts during this timeframe, signaling their active participation in this research domain. While Germany and Canada maintained relatively stable counts, they too displayed incremental growth. Japan and South Korea, albeit starting from lower baselines, have shown a gradual uptick in interest and contributions to this field, suggesting a burgeoning engagement.

These findings reveal a diverse landscape of research output in sports and AI across different nations. While the U.S. remains a pivotal figure, China, Australia, the UK, and Italy also contribute significantly to the body of research. As the sector continues to expand and mature, it is anticipated that additional countries will emerge as key contributors to this burgeoning field.

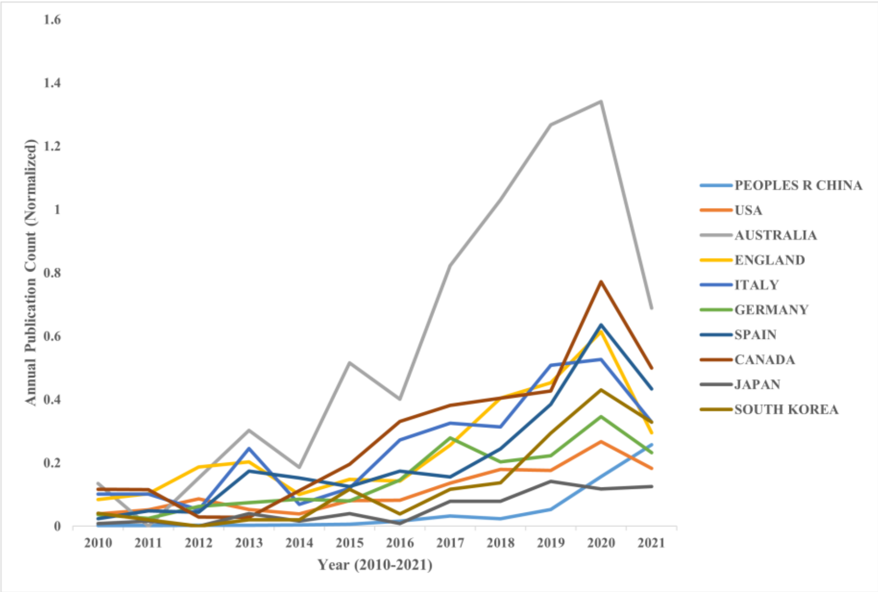

Figure 1: The Cluster of Distribution Countries

B. Disciplines and Topics Involved Sports and AI

1) Disciplines involved in sports and AI

The disciplines involved in sports and AI were analyzed using the CiteSpace tool with specific parameters. The Pathfinder pruning method was applied. The time span for the analysis was from 2010 to 2021, with a slice length of 1. The resulting network had 205 nodes and 319 edges, with a density of 0.0153. The largest connected component consisted of 178 nodes, accounting for 86% of the total network. Only 1.0% of the nodes were labeled. Figure 2 shows a CiteSpace-generated co-occurrence network graph, where the network size was reduced using the pathfinder method. The broadest category, Engineering, was surrounded by a huge circle, while other popular categories included Computer Science and Engineering, Electrical & electronics, and Sport Sciences. Additionally, Materials Science, Physics, Computer Science, Theory & Methods were designated for reference, despite being substantially lesser fields. The findings suggest that techniques developed for one topic may be applied to another, leading to the emergence of new research trends and the initiation of new revolutions.

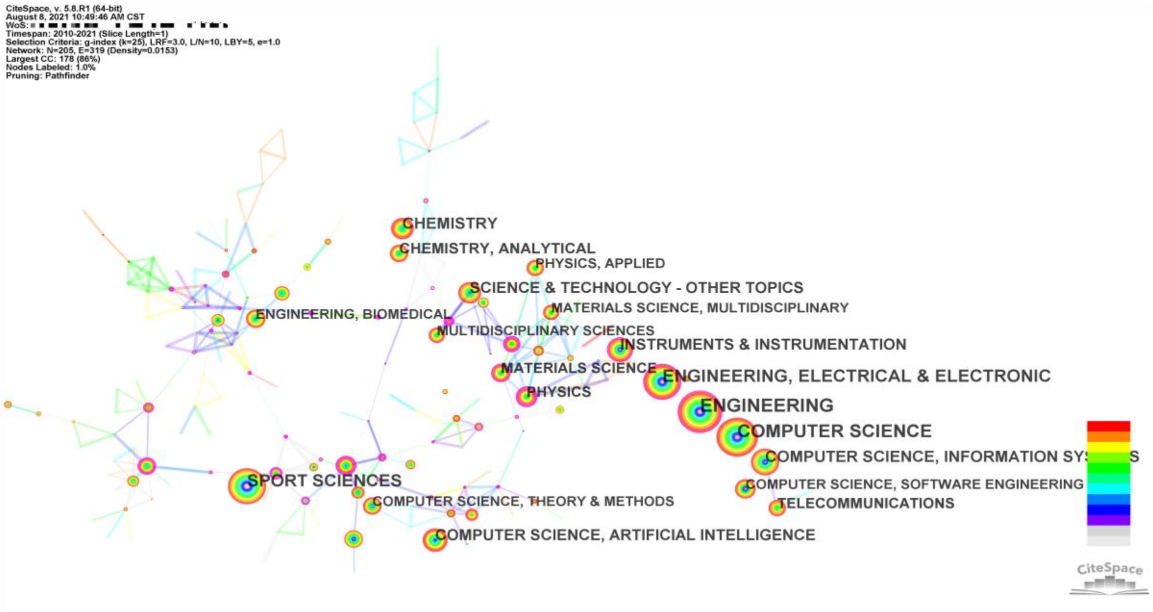

Figure 2: Disciplines Involved in Sports and AI

2) Main Research Areas

Figure 3 shows a co-occurrence network graph, where each node represents a keyword, and the size of the node represents the frequency or importance of the keyword in the literature. The links (or edges) represent the co-occurrence relationship between two keywords, i.e., their frequency of appearing together in the same literature. The Pathfinder pruning method was applied. The keywords used in this study serve as a representation of the primary material related to sports and AI. To distinguish the themes associated with these two fields, we analyzed the keywords given to each article in the dataset. The most popular subjects reflect present study possibilities and potential future growth directions. We noticed that many articles are allocated keywords that are close in proximity, indicating that keywords that are close to each other are often given to the same articles. For instance, the keywords "sports," "sensors," "wearables," and "football" are all near each other. Among the top ten frequent keywords displayed in Table 2, we found that machine learning is the most widely used technology in the field of sports and AI for injury analysis [13-15], injury prevention [16, 17], and reasoning about defensive behavior or other aspects[18]. Additionally, wearable devices are a commonly used technology in this field for data collection about health and exercise. Most of this data is further processed using a machine learning algorithm [19, 20].

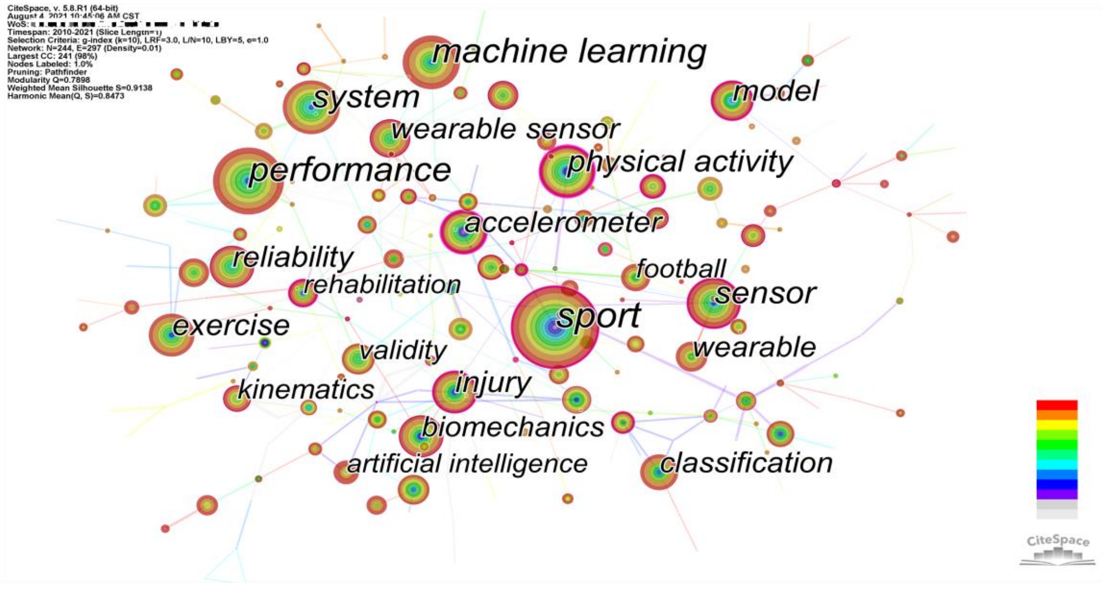

Figure 3: 244 Keywords Network Based on Articles Published between 2010 and 2021

Table 2: The Top Ten Frequent Keywords

Count	Centrality	Year	Keywords
268	0.28	2010	sport
197	0.03	2010	performance
186	0.04	2010	machine learning
142	0.02	2010	system
128	0.2	2012	sensor
106	0.47	2011	physical activity
97	0.08	2011	exercise
92	0.38	2010	injury
91	0.24	2010	model
90	0.43	2010	accelerometer

IV. THE INTELLECTUAL STRUCTURE OF SPORTS AND AI

CiteSpace is a tool that presents the literature as a network of multiple interconnected sub-networks, called 'time slices,' each built using articles published within a year. By stitching these sub-networks together, CiteSpace provides a comprehensive view of how a field of study has evolved. In this study, we constructed each network using the 354 papers that received the most citations between 2010 and 2021 and pruned the network using the Pathfinder algorithm in CiteSpace to reduce noise and improve the clarity of the visualization.

Research papers often include citations to other sources, which can be represented as nodes in a co-citation network. The relationships between these nodes reveal how often the same works are cited together. This two-way relationship between cited references and citing articles generates networks that accurately reflect the research interests of the scientific community [21].

CiteSpace identifies emerging trends and patterns of change in these networks using visual features. Node size corresponds to the number of citations received, and each node is represented by a collection of citation tree rings that symbolize the different time slices. The importance of a node is shown by a purple ring, whose thickness indicates its potential for transformative contributions, especially when it is deemed betweenness central. These nodes tend to span distinct phases of a scientific topic's development. Citation bursts, sudden spikes in the number of citations, are marked by a red ring around each citation and provide insight into the evolution of research concentration.

The co-citation network is divided into several clusters of co-cited references, with the references strongly connected within each cluster and weakly connected across clusters. Table 3 lists the eight principal clusters in order of size, and it is worth noting that clusters with fewer members tend to be less representative because they have fewer cited articles. The homogeneity or consistency of each cluster is demonstrated by the silhouette score, which tends to be close to 1 for homogeneous clusters.

In CiteSpace, LLR, LSI, and MI are three commonly used bibliometric indicators: LLR (Log-Likelihood Ratio): LLR is used to measure the co-occurrence of two keywords A and B in the literature, i.e., the ratio of their frequency of co-occurrence to their individual frequencies. A higher LLR value indicates a stronger co-occurrence relationship between A and B, while a lower value suggests a weaker relationship. LSI (Latent Semantic Indexing): LSI is a method for calculating the similarity between two texts. In CiteSpace, LSI is used to calculate the semantic similarity between two keywords, i.e., the ratio of their frequency of co-occurrence to their individual frequencies. A higher LSI value indicates a higher semantic similarity between two keywords, while a lower value suggests a greater semantic difference. MI (Mutual Information): MI is used to measure the correlation between two keywords in the literature, i.e., the degree of information overlap between them. A higher MI value indicates a stronger correlation between two keywords, while a lower value suggests a weaker correlation.

Table 3: Major Clusters of Co-cited References

Cluster ID	Size	Silhouette	mean (Year)	Lable (LSI)	Lable (LLR)	Lable (MI)
0	30	0.979	2017	deep learning	deep learning	artificial intelligence
2	25	0.966	2016	Human activity recognition	task analysis	distributed databases
3	23	0.883	2017	sports science	Lactate	iot
5	21	0.98	2014	inertial measurement unit	accelerometers	cnts
6	18	0.964	2013	biofeedback	physical activity	impact
7	18	0.932	2014	global positioning system	workload	external load
8	13	1	2015	strain sensor	strain sensor	papermaking
10	12	1	2015	wearable sensors	concussion	head acceleration

Clusters are referred in terms of the labels selected by LLR.

Most of the clusters in Table 3 are homogeneous clusters. Each cluster's contents are identified by using noun phrases from the cited articles' titles [22]. This is mainly due to the lack of information available from primary sources, as Web of Science records may not always include the titles of the cited sources. LLR labels are used in the following discussion. The average year of publication for a cluster indicates how recent it is. For example, in Cluster #6 on physical activity, the median year of publication is 2013. Cluster #0 on deep learning, which was recently formed, has an average year of publication in 2017.

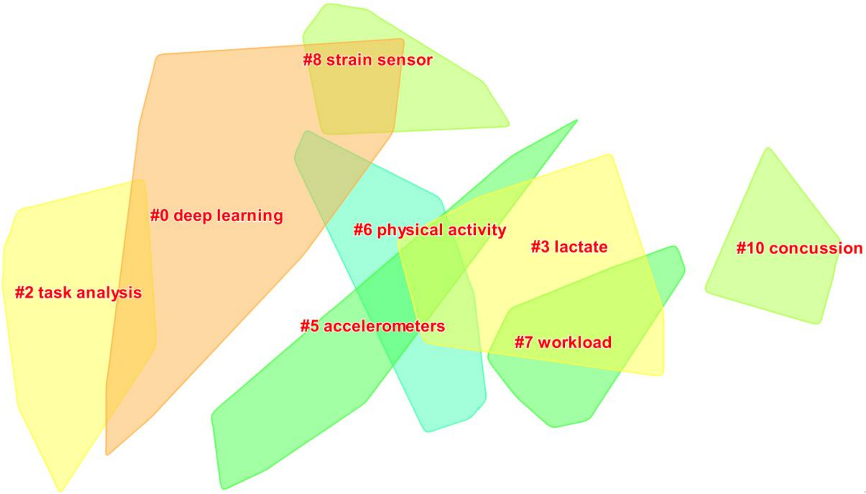

Figure 4: Co-citation Cluster Map of Scholarly Literature in the Fields of Sports and AI.

Figure 4 shows that Cluster #0 has the closest color to red and the largest size, indicating a recent uptick in the number of articles on sports-related AI topics, particularly deep learning. The articles in the top four clusters - #0, #2, #3, and #5 - are listed in the following tables, with the top five cited articles and references highlighted for each cluster. Cluster #0 is the most recently formed cluster and includes major cited references related to the use of deep learning in sports and AI, such as Camomilla et al.'s comprehensive review article [23] on SENSORS-BASEL. This article assesses existing data and future possibilities of magneto-inertial sensors in sports performance assessment, with crucial considerations and future trends. The authors concluded that sensor-based performance indicators are reliable. The second most highly cited work is by Aroganam et al. [24], which examines trends and forecasts for wearable technology in the sports industry (excluding professional sports) and highlights which sensors are compatible with one another and how sensor technology can advance for sports applications.

Table 4: Cited References and Citing Articles of Cluster #0 Deep Learning

Cluster #0 deep learning			
Cited References			Citing Articles
Cites	Author (Year) Journal, Volume, Page	Coverage %	Author (Year) Title
26	Camomilla V (2018) SENSORS-BASEL, V18, P0	11	Demrozi, Florenc, 2020, Human Activity Recognition Using Inertial, Physiological and Environmental Sensors: A Comprehensive Survey
13	Aroganam G (2019) SENSORS-BASEL, V19, P0	6	Stoeve, Maike, 2021, From the Laboratory to the Field: IMU-Based Shot and Pass Detection in Football Training and Game Scenarios Using Deep Learning
13	Wang JD (2019) PATTERN RECOGN LETT, V119, P3	6	Golestani, Negar, 2020, Human activity recognition using magnetic induction-based motion signals and deep recurrent neural networks
12	Cust EE (2019) J SPORT SCI, V37, P568	5	Hendry, Danica, 2020, Development of a Human Activity Recognition System for Ballet Tasks
11	van der Kruk E (2018) EUR J SPORT SCI, V18, P806	5	Tuncer, Turker, 2020, Ensemble residual network-based gender and activity recognition method with signals

As can be seen in the Table 4, among the top five most commonly citing articles, all were published after 2020. The article by Demrozi et al. [25] has the greatest citation coverage (11%). The authors found that human action recognition researchers still prefer traditional machine learning (ML) models due to their ability to work with less data and computer resources compared to deep learning models. However, deep learning models have shown greater ability to recognize a wider range of complicated actions. Another cited research compared deep learning models to Support Vector Machine (SVM) and found that deep learning models are more practical for event detection in real-world sports contexts [26].

Cluster #2, focused on task analysis, includes further milestones in physical activity analysis, with wearable sensors and artificial neural networks (ANN) being the most used tools. As can be seen in the Table 5, the 2016 article by Kaiming [27] is the second-most cited article in this cluster. The authors presented a residual learning framework to optimize the training of deep neural networks, which can improve accuracy in image recognition. Mukhopadhyay et al. [28] has 15 citations in Web of Science and used wearable sensors to track human activity, outlining the most recent systems and the obstacles that need to be addressed to overcome them. The first two major citing articles in this cluster are also in Cluster #0, indicating how ANN in conjunction with wearable technology is a typical technique in sports [25, 29].

Table 5: Cited References and Citing Articles of Cluster #2 Task Analysis

Cluster #2 task analysis			
Cited References			Citing Articles
Cites	Author (Year) Journal, Volume, Page	Coverage %	Author (Year) Title
15	Mukhopadhyay SC (2015) IEEE SENS J, V15, P1321	15	Demrozi, Florenc, 2020, Human Activity Recognition Using Inertial, Physiological and Environmental Sensors: A Comprehensive Survey
11	Kaiming He (2016) 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), V0, P770	8	Golestani, Negar, 2020, Human activity recognition using magnetic induction-based motion signals and deep recurrent neural networks
11	Cao Z (2017) PROC CVPR IEEE, V0, P1302	6	Tabrizi, Sahar S, 2020, Comparative Study of Table Tennis Forehand Strokes Classification Using Deep Learning and SVM
11	Ignatov A (2018) APPL SOFT COMPUT, V62, P915	6	Thakur, Dipanwita, 2020, Smartphone based human activity monitoring and recognition using ML and DL: a comprehensive survey
10	Chen YQ (2015) IEEE SYS MAN CYBERN, V0, P1488	5	Wang, Lin, 2020, Convolution Encoders for End-to-End Action Tracking with Space-time Cubic Kernels

Table 6: Cited References and Citing Articles of Cluster #3 Lactate

Cluster #3 Lactate			
Cited References			Citing Articles
Cites	Author (Year) Journal, Volume, Page	Coverage %	Author (Year) Title
37	Gao W (2016) NATURE, V529, P509	8	Zhang, Yi, 2019, Passive sweat collection and colorimetric analysis of biomarkers relevant to kidney disorders using a soft microfluidic system
15	Bariya M (2018) NAT ELECTRON, V1, P160	8	Ray, Tyler, 2019, Soft, skin-interfaced wearable systems for sports science and analytics
12	Li RT (2016) SPORTS HEALTH, V8, P74	5	Parrilla, Marc, 2019, Wearable Potentiometric Ion Patch for On-Body Electrolyte Monitoring in Sweat: Toward a Validation Strategy to Ensure Physiological Relevance
8	Heikenfeld J (2018) LAB CHIP, V18, P217	5	Li, Xinwen, 2021, Embedded system and smart embedded wearable devices promote youth sports health
8	Koh A (2016) SCI TRANSL MED, V8, P0	5	Parrilla, Marc, 2019, A Wearable Paper-Based Sweat Sensor for Human Perspiration Monitoring

Cluster #3's key components represent significant advancements in the field of skin-interfacing wearable technologies. Despite the fact that sweat contains a wealth of physiologically important information, it has traditionally been overlooked for non-invasive health and sports monitoring [30, 31]. As can be seen in the Table 6, The most cited article in this cluster, Gao 2016[30], describes a mechanically flexible and fully integrated sensor array that can simultaneously and selectively measure sweat metabolites (such as glucose and lactate) and electrolytes (such as sodium and potassium ions), as well as skin temperature, all in the same sensor array to calibrate the sensors' responses. This platform can be used for personal diagnostic and physiological monitoring applications. The second most cited reference [31] explores the limitations and prospects of wearable sweat sensors in the development of customized healthcare. The selected citing articles, all published after 2019, are dedicated to the detection of physiological indicators during exercise and the analysis of physiological changes during exercise, unlike Cluster #0 and Cluster #2 [32-36].

Figure 5 demonstrates how the network is separated into various co-citation clusters over time, with each cluster representing a distinct topic or subfield within the broader field of study. Using CiteSpace with the Pathfinder algorithm for pruning, we identified these clusters and their interconnections. As the most recently formed cluster, Cluster #0 has a high concentration of nodes that have been cited in the past few years. Only a few recent high-profile papers can be found for clusters #5 and #6 (Table 7 and Table 8).

Table 7: Cited References and Citing Articles of Cluster #5 Accelerometers

Cluster #5 accelerometers			
Cited References			Citing Articles
Cites	Author (Year) Journal, Volume, Page	Coverage %	Author (Year) Title
23	Chambers R (2015) SPORTS MED, V45, P1065	11	Hendry, Danica, 2020, Development of a Human Activity Recognition System for Ballet Tasks
10	Bandodkar AJ (2014) TRENDS BIOTECHNOL, V32, P363	11	Zhang, Yi, 2019, Passive sweat collection and colorimetric analysis of biomarkers relevant to kidney disorders using a soft microfluidic system
7	Boyd LJ (2011) INT J SPORT PHYSIOL, V6, P311	9	Alexander, Jeremy P, 2016, VALIDITY OF A WEARABLE ACCELEROMETER DEVICE TO MEASURE AVERAGE ACCELERATION VALUES DURING HIGH-SPEED RUNNING
7	Stoppa M (2014) SENSORS-BASEL, V14, P11957	7	Benson, Lauren C, 2020, Validation of a commercially available inertial measurement unit for recording jump load in youth basketball players
7	Willy RW (2018) PHYS THER SPORT, V29, P26	7	Parrilla, Marc, 2016, Wearable Potentiometric Sensors Based on Commercial Carbon Fibres for Monitoring Sodium in Sweat

Table 8: Cited References and Citing Articles of Cluster #6 Physical Activity

Cluster #6 physical activity			
Cited References			Citing Articles
Cites	Author (Year) Journal, Volume, Page	Coverage %	Author (Year) Title
12	Cummins C (2013) SPORTS MED, V43, P1025	18	Wundersitz, Daniel W T, 2015, Validity of a Trunk-Mounted Accelerometer to Measure Physical Collisions in Contact Sports
8	Gastin PB (2014) J SPORT SCI, V32, P947	18	Wundersitz, D W T, 2015, Validation of a Trunk-mounted Accelerometer to Measure Peak Impacts during Team Sport Movements
6	Gastin PB (2013) J SCI MED SPORT, V16, P589	14	Wundersitz, Daniel W T, 2015, Classification of team sport activities using a single wearable tracking device
5	Takacs J (2014) J SCI MED SPORT, V17, P496	14	Wundersitz, Daniel W T, 2015, Validity of a trunk-mounted accelerometer to assess peak accelerations during walking
4	Kelly D (2012) SPORTS ENG, V15, P81	12	Pobiruchin, Monika, 2017, Accuracy and Adoption of Wearable Technology Used by Active Citizens: A Marathon Event Field Study

A. Betweenness Centrality Analysis

Betweenness centrality is a measure of a node's relevance in the network, with nodes having high betweenness centrality ratings being particularly significant. Two types of nodes with high betweenness centrality ratings are hubs, which have many connections to other nodes, and nodes that serve as necessary interconnecting connections between groupings of nodes. The second type of nodes is of special importance to us, as they are more likely to provide insights into upcoming patterns than the first type of nodes. Table 9 shows that the synthesized network contains eight references that are structurally critical, meaning that they are essential for linking individual nodes and groups of nodes (such as co-citation clusters) together. Specifically, three clusters in Cluster #0 and two clusters in Cluster #7 rely on these references. These references represent important benchmarks in the field of sports and AI, and their influence can be seen throughout the network.

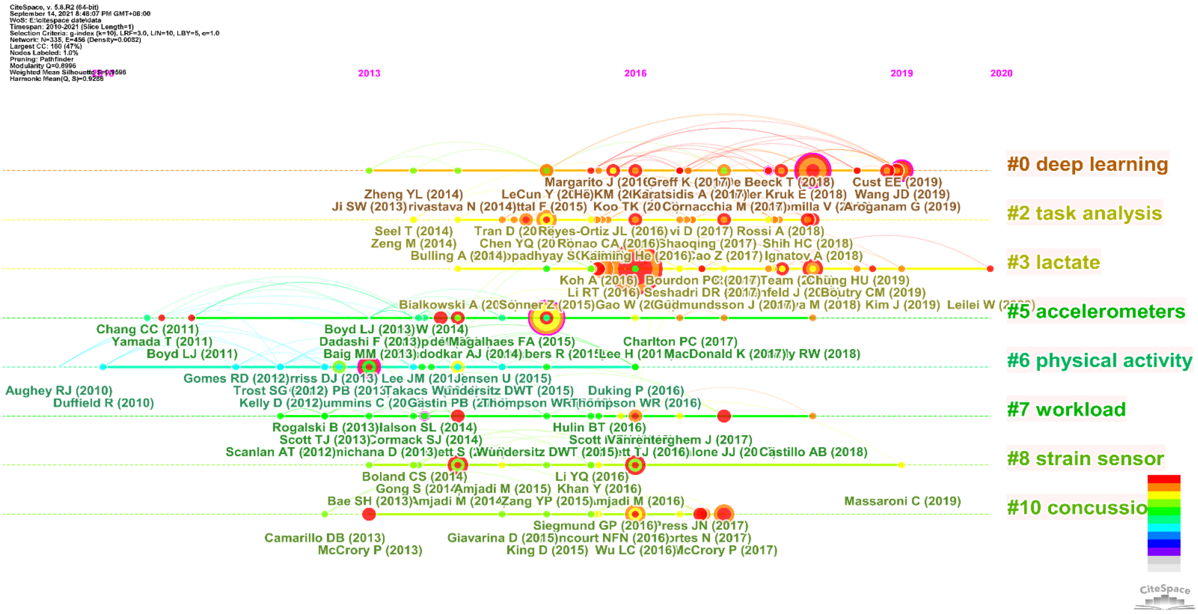

Figure 5: Timelines of Co-citation Clusters

Table 9: Cited Citations with the Highest Betweenness Centrality

Rank	Centrality	References	Cluster #
1	0.19	Cummins C (2013) SPORTS MED, V43, P1025	6
2	0.17	Chambers R (2015) SPORTS MED, V45, P1065	5
3	0.16	Camomilla V (2018) SENSORS-BASEL, V18, P0	0
4	0.16	Aroganam G (2019) SENSORS-BASEL, V19, P0	0
5	0.16	Nweke HF (2018) EXPERT SYST APPL, V105, P233	0
6	0.11	Halson SL (2014) SPORTS MED, V44, P13	7
7	0.09	Gabbett TJ (2016) BRIT J SPORT MED, V50, P273	7
8	0.09	Hassan MM (2018) FUTURE GENER COMP SY, V81, P307	2

There are central in connecting the network's components.

B. *Most Cited Articles*

The impact of an article on society is often reflected in its citation count. Three articles from Cluster #0 are among the top ten most significant ones, with Clusters #3 and #10 each having two members in the list. Table 10 shows that Gao W's article (2016) [30] has 37 citations in our dataset, while Camomilla V's article (2018) [23] has 26 citations. The third article on the list is Chambers R's article (2015) [37], published in the Journal of Sports Medicine. The most recent articles on the list are Gao W's (2016) [30], Amjadi M's (2016) [38], and McCrory P's (2017) [39], which occupy the top three positions on the list.

Table 10: Most Cited References

Citation counts	References	Cluster #
37	Gao W (2016) NATURE, V529, P509	3
26	Camomilla V (2018) SENSORS-BASEL, V18, P0	0
23	Chambers R (2015) SPORTS MED, V45, P1065	5
15	Amjadi M (2016) ADV FUNCT MATER, V26, P1678	8
15	Bariya M (2018) NAT ELECTRON, V1, P160	3
15	McCrory P (2017) BRIT J SPORT MED, V51, P838	10
15	Mukhopadhyay SC (2015) IEEE SENS J, V15, P1321	2
14	Wu LC (2016) ANN BIOMED ENG, V44, P1234	10
13	Aroganam G (2019) SENSORS-BASEL, V19, P0	0
13	Wang JD (2019) PATTERN RECOGN LETT, V119, P3	0

C. *Citation Bursts*

The strength and duration of a citation burst are two important characteristics that reflect a significant increase in the number of citations of a specific literature during a certain period of time. Table 11 presents the references with the strongest citation bursts from 2010 to 2021. The first two articles (Cluster #1 and Cluster #12) come from small clusters, while the third article is edited by Amjadi M (2016) [38]. Interestingly, the fourth and fifth articles are both from Cluster #10 on concussion and written by McCrory P in 2013[40] and 2017[39] respectively, and they were published in the journal of BRIT J SPORT MED.

Table 11: References with the Strongest Citation Bursts

Citation bursts	References	Cluster #
6.33	Staudenmayer J (2009) J APPL PHYSIOL, V107, P1300	1
5.56	Perin C (2013) IEEE T VIS COMPUT GR, V19, P2506	12
5.22	Amjadi M (2016) ADV FUNCT MATER, V26, P1678	8
5.19	McCrory P (2017) BRIT J SPORT MED, V51, P838	10
5.05	McCrory P (2013) BRIT J SPORT MED, V47, P250	10

D. Assessing the Contribution of Cited References Using the Sigma Metric

The Sigma metric was used to evaluate the structural centrality and citation burstiness of each cited reference. References that excel in both metrics are more likely to have a higher Sigma value than those that do not (as shown in Table 12). For instance, Cummins C's groundbreaking work (2013) [41] is structurally vital and has a highly impactful citation explosion, earning the highest Sigma value of 2.37. Another highly ranked reference is Camomilla's (2016) [23] publication in SENSORS-BASEL, which discusses GPS and microtechnology sensors in the context of team sports. Magneto-inertial sensors are the most frequently referenced research piece in Cluster #0, which evaluates present evidence and future potential [23]. These results highlight the importance and influence of these highly cited references and their impact on the field of sports and artificial intelligence.

Table 12: Structurally and Temporally Significant References

Sigma	Burst	Centrality	Citations	References	Cluster #
2.37	4.95	0.19	12	Cummins C (2013) SPORTS MED, V43, P1025	6
1.86	4.12	0.16	26	Camomilla V (2018) SENSORS-BASEL, V18, P0	0
1.51	2.62	0.17	23	Chambers R (2015) SPORTS MED, V45, P1065	5
1.49	4.86	0.08	37	Gao W (2016) NATURE, V529, P509	3
1.35	5.22	0.06	15	Amjadi M (2016) ADV FUNCT MATER, V26, P1678	8

V. EMERGING TRENDS

The modularity of a network is the degree to which a network may be partitioned into many groups such that nodes within each group are linked more tightly than nodes between groups. A scientific field's collective intellectual structure may be shown as a network of co-cited references. Networks like this change throughout time. Structure may be significantly altered by newly published papers, or they may have little or no effect at all. Figure 6 depicts the evolution of network modularity over time. Each network is built using a sliding window of two years as a starting point. The number of publications each year has grown significantly in recent years. It is notable that the modularity of the network rose greatly in 2011 and then decreased somewhat in 2014. Based on this fact, it is reasonable to assume that ground-breaking works were produced over these two years. Because of this, we will especially look at any developing trends that may emerge over these two years.

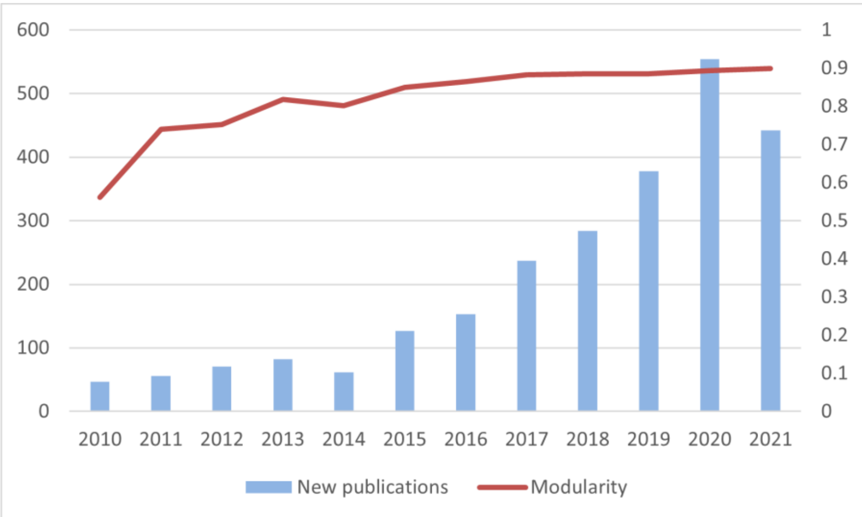

Figure 6: The Modularity of the Network

The release of which articles in 2011 would be most likely to explain the considerable rise in the modularity of the network created on the basis of articles published previous to 2011? If a 2011 publication is followed by a significant increase in citations, we may anticipate that this publication had a critical influence in altering the broader intellectual structure of the field. Three papers from 2011 were discovered to have received a large number of citations in the following months (Table 13). Notably, Boyd et al. [42] was the editor of the first article on the list, which was published in 2011. They investigated the reliability of triaxial accelerometers as a measure of physical activity in team sports and concluded that the MinimaxX accelerometer's reliability is acceptable both within and between devices under controlled laboratory conditions, as well as between devices when field testing was carried out in the field. The second publication on this list is the 2011 paper by Aggarwal et al. [43], which was published in the journal Science. A full summary of several state-of-the-art research publications on human activity recognition was offered by the presenters. Yamada et al. [44] published a paper in which they described a new class of wearable and stretchy gadgets made of thin films of aligned single-walled carbon nanotubes that could be stretched. These findings imply that the shift in modularity that occurred in 2011 is indicative of a new trend in the identification and analysis of human activity and task performance.

Table 13: Articles Published in 2011 with Subsequent Citation Bursts in Descending Order of Local Citation Counts

Ref.	Local citations	Title	Burst	Duration	Range (2010 – 2021)
Boyd 2011 [42]	7	The Reliability of MinimaxX Accelerometers for Measuring Physical Activity in Australian Football	4.23	2015 - 2016	
Aggarwal 2011 [45]	7	Human activity analysis: A review	4.06	2014 - 2016	
Yamada 2011 [44]	5	A stretchable carbon nanotube strain sensor for human-motion detection	2.89	2014 - 2016	

If the change in modularity in 2011 reflects the emergence of a new trend in human activity identification and task analysis, what is the source of the other shift in modularity in 2014? As we can see from the Table 14 there are 6 articles in 2014 with citation bursts. Two of six articles are research articles which are about the utilization of visualization in sports matches analysis. For example, Janetzko et al. [46] demonstrated a system for analyzing high-frequency position-based soccer data at different degrees of detail, enabling the user to explore and study movement aspects and game events in real time, rather than having to wait for results. Polk et al. [47] developed a revolutionary tennis match visualization system known as TenniVis that makes use of readily available datasets and provides two new visualizations that tennis coaches and players may use to acquire a better understanding of how matches are progressing in real time. The next four articles are all about non-invasive wearable technologies and their recent advancements [48-51]. Modularity changed in 2014, according to this evidence, and the advancements of wearables are also a sign of a developing trend in visualization use in sports.

Table 14: Articles Published in 2014 with Citation Bursts

Ref.	Local citations	Title	Burst	Duration	Range (2010 – 2021)
Janetzko 2014 [46]	8	Feature-driven visual analytics of soccer data	4.04	2017 – 2018	
Stoppa 2014 [48]	7	Wearable Electronics and Smart Textiles: A Critical Review	4.01	2016 – 2017	
Amjadi 2014 [49]	13	Highly Stretchable and Sensitive Strain Sensor Based on Silver Nanowire–Elastomer Nanocomposite	3.98	2016 – 2019	
Polk 2014 [47]	7	TenniVis: Visualization for Tennis Match Analysis	3.53	2017 – 2018	
Barrett 2014 [50]	7	PlayerLoad™: Reliability, Convergent Validity, and Influence of Unit Position during Treadmill Running	3.53	2017 – 2018	
Bandodkar 2014 [51]	10	Non-invasive wearable electrochemical sensors: a review	3.05	2016 - 2019	

Several papers citing Janetzko et al. [46] have been found by an examination of the co-citation network. The citing publications indicated in Table 15 may help us determine if Janetzko et al. is the start of a new growing trend. It is Gudmundsson 2017[52] that has received the most citations, as there are 74 references to it. Gudmundsson 2017 examined visualization in team sports in a similar way to Janetzko et al. Spatiotemporal data from team sports were used as input, and non-trivial computing was included, in their study, which examined current research efforts. They organized the efforts into a cohesive framework and highlighted several outstanding research topics. Two publications by Stein et al. [53, 54] showed how to visualize team sports data for analysis.

Table 15: Articles that Cite Janetzko et al.'s 2014 Article.

Article	Citations	Title
Gudmundsson 2017 [52]	74	Spatio-Temporal Analysis of Team Sports
Stein 2018 [53]	43	Bring it to the Pitch: Combining Video and Movement Data to Enhance Team Sport Analysis
Stein 2017 [54]	28	How to Make Sense of Team Sport Data: From Acquisition to Data Modeling and Research Aspects
Wu 2018 [55]	25	iTTVis: Interactive Visualization of Table Tennis Data
Perin 2018 [56]	21	State of the Art of Sports Data Visualization
Machado 2017 [57]	7	Visual Soccer Match Analysis Using Spatiotemporal Positions of Players
Ryoo 2018 [58]	5	Visual analysis of soccer players and a team
Metulini 2017 [59]	2	Spatio-Temporal Movements in Team Sports: A Visualization approach using Motion Charts.

In summary, the area of Sports and AI has had two significant variations in the previous 12 years of growth, which may be separated into two distinct periods: 2011 and 2014. The shift in modularity that occurred in 2011 suggested the emergence of a new trend in the identification and analysis of human activity and task. The year 2014 saw the introduction of visualization into team sports. But wait, there's more. This year has also seen substantial progress in the field of wearable technology.

VI. CONCLUSIONS

In conclusion, this study has mapped the evolution of collective knowledge in Sports and AI over the last twelve years, identifying areas for future research. Employing CiteSpace, we identified emerging trends and patterns, highlighting the dynamic integration of AI in sports as a rapidly evolving field. This analysis, based on domain experts' publications, demonstrates the utility of computational techniques in uncovering trends across cited references and co-cited clusters. Our findings contribute valuable insights into the state of Sports and AI research and suggest potential directions for future exploration. Key insights are based on scientometric patterns from CiteSpace, revealing two major trends: the advancement in human activity detection since 2011 and the expansion of visualization techniques in team sports from 2014 onwards, alongside progress in wearable technology. This work shows the significant role of deep learning and the growing body of review publications, indicating rapid knowledge expansion in Sports and AI. The findings underscore AI's increasing applicability in sports, poised to revolutionize both the field and societal practices. The fusion of sports and AI promises exciting developments ahead.

REFERENCES

[1] BINI S A. Artificial intelligence, machine learning, deep learning, and cognitive computing: what do these terms mean and how will they impact health care? . The Journal of arthroplasty, 2018, 33(8): 2358-61.

[2] CHEN C M. CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature. Journal of the American Society for Information Science and Technology, 2006, 57(3): 359-77.

[3] CHEN C M, HU Z G, LIU S B, TSENG H. Emerging trends in regenerative medicine: a scientometric analysis in CiteSpace. Expert Opinion on Biological Therapy, 2012, 12(5): 593-608.

[4] DENG J Q, CHEN X F. Research on Artificial Intelligence Interaction in Computer-Aided Arts and Crafts. Mobile Information Systems, 2021, 2021.

[5] GAO J, HUANG X P, ZHANG L L. Comparative Analysis between International Research Hotspots and National-Level Policy Keywords on Artificial Intelligence in China from 2009 to 2018. Sustainability, 2019, 11(23).

[6] BAILES J E, PETRAGLIA A L, OMALU B I, et al. Role of subconcussion in repetitive mild traumatic brain injury A review. Journal of Neurosurgery, 2013, 119(5): 1235-45.

[7] BOURDON P C, CARDINALE M, MURRAY A, et al. Monitoring Athlete Training Loads: Consensus Statement. International Journal of Sports Physiology and Performance, 2017, 12: 161-70.

[8] SESHADRI D R, LI R T, VOOS J E, et al. Wearable sensors for monitoring the physiological and biochemical profile of the athlete. Npj Digital Medicine, 2019, 2.

[9] BAI H M, GONG Z Q, SUN G Q, LI L. Data-Driven Artificial Intelligence Model of Meteorological Elements Influence on Vegetation Coverage in North China. Remote Sensing, 2022, 14(6).

[10] SAVELIEV A, ZHURENKOV D. Artificial intelligence and social responsibility: the case of the artificial intelligence strategies in the United States, Russia, and China. Kybernetes, 2021, 50(3): 656-75.

[11] PEAKE J M, KERR G, SULLIVAN J P. A Critical Review of Consumer Wearables, Mobile Applications, and Equipment for Providing Biofeedback, Monitoring Stress, and Sleep in Physically Active Populations. Frontiers in Physiology, 2018, 9.

[12] SEYEDIN S, UZUN S, LEVITT A, et al. MXene Composite and Coaxial Fibers with High Stretchability and Conductivity for Wearable Strain Sensing Textiles. Advanced Functional Materials, 2020, 30(12).

[13] BAILON C, DAMAS M, POMARES H, BANOS O. SPIRA: an automatic system to support lower limb injury assessment. Journal of Ambient Intelligence and Humanized Computing, 2019, 10(6): 2111-23.

[14] BARCHEK A R, DLUGONSKI D, BAEZ S E, et al. The relationship between injury-related fear and physical activity in people with a history of anterior cruciate ligament reconstruction. Physical Therapy in Sport, 2021, 50: 201-5.

[15] BRUNNER M, HEMSLEY B, DANN S, et al. Hashtag #TBI: A content and network data analysis of tweets about Traumatic Brain Injury. Brain Injury, 2018, 32(1): 49-63.

[16] DI PAOLO S, ZAFFAGNINI S, PIZZA N, et al. Poor Motor Coordination Elicits Altered Lower Limb Biomechanics in Young Football (Soccer) Players: Implications for Injury Prevention through Wearable Sensors. Sensors, 2021, 21(13).

[17] RAWASHDEH S A, RAFELDT D A, UHL T L. Wearable IMU for Shoulder Injury Prevention in Overhead Sports. Sensors, 2016, 16(11).

[18] HAEBERLE H S, RAMKUMAR P N, KARNUTA J M, et al. Predicting the Risk of Subsequent Hip Surgery Before Primary Hip Arthroscopy for Femoroacetabular Impingement Syndrome A Machine Learning Analysis of Preoperative Risk Factors in Hip Preservation. American Journal of Sports Medicine, 2021, 49(10): 2668-76.

[19] ALHARTHI A S, CASSON A J, OZANYAN K B. Spatiotemporal Analysis by Deep Learning of Gait Signatures From Floor Sensors. Ieee Sensors Journal, 2021, 21(15): 16904-14.

[20] FENG Q K, LIU Y Y, WANG L J. Wearable Device-Based Smart Football Athlete Health Prediction Algorithm Based on Recurrent Neural Networks. Journal of Healthcare Engineering, 2021, 2021.

[21] CHEN C M. Predictive Effects of Structural Variation on Citation Counts. Journal of the American Society for Information Science and Technology, 2012, 63(3): 431-49.

[22] CHEN C, IBEKWE ‐ SANJUAN F, HOU J. The structure and dynamics of cocitation clusters: A multiple ‐ perspective cocitation analysis. Journal of the American Society for information Science and Technology, 2010, 61(7): 1386-409.

[23] CAMOMILLA V, BERGAMINI E, FANTOZZI S, VANNOZZI G. Trends Supporting the In-Field Use of Wearable Inertial Sensors for Sport Performance Evaluation: A Systematic Review. Sensors, 2018, 18(3).

[24] AROGANAM G, MANIVANNAN N, HARRISON D. Review on Wearable Technology Sensors Used in Consumer Sport Applications. Sensors, 2019, 19(9).

[25] DEMROZI F, PRAVADELLI G, BIHORAC A, RASHIDI P. Human Activity Recognition Using Inertial, Physiological and Environmental Sensors: A Comprehensive Survey. Ieee Access, 2020, 8: 210816-36.

[26] STOEVE M, SCHULDHAUS D, GAMP A, et al. From the Laboratory to the Field: IMU-Based Shot and Pass Detection in Football Training and Game Scenarios Using Deep Learning. Sensors, 2021, 21(9).

[27] HE K M, ZHANG X Y, REN S Q, et al. Deep Residual Learning for Image Recognition; proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, F Jun 27-30, 2016. Ieee: NEW YORK, 2016.

[28] MUKHOPADHYAY S C. Wearable Sensors for Human Activity Monitoring: A Review. Ieee Sensors Journal, 2015, 15(3): 1321-30.

[29] GOLESTANI N, MOGHADDAM M. Human activity recognition using magnetic induction-based motion signals and deep recurrent neural networks. Nature Communications, 2020, 11(1).

[30] GAO W, EMAMINEJAD S, NYEIN H Y Y, et al. Fully integrated wearable sensor arrays for multiplexed in situ perspiration analysis. Nature, 2016, 529(7587): 509-14.

[31] WILSON E K. Wearable Sweat Sensors. Engineering, 2019, 5(3): 359-60.

[32] LI X W, SUN L, ROCHESTER C A. Embedded system and smart embedded wearable devices promote youth sports health. Microprocessors and Microsystems, 2021, 83.

[33] PARRILLA M, GUINOVART T, FERRE J, et al. A Wearable Paper-Based Sweat Sensor for Human Perspiration Monitoring . Advanced Healthcare Materials, 2019, 8(16).

[34] PARRILLA M, ORTIZ-GOMEZ I, CANOVAS R, et al. Wearable Potentiometric Ion Patch for On-Body Electrolyte Monitoring in Sweat: Toward a Validation Strategy to Ensure Physiological Relevance. Analytical Chemistry, 2019, 91(13): 8644-51.

[35] RAY T, CHOI J, REEDER J, et al. Soft, skin-interfaced wearable systems for sports science and analytics. Current Opinion in Biomedical Engineering, 2019, 9: 47-56.

[36] ZHANG Y, GUO H X, KIM S B, et al. Passive sweat collection and colorimetric analysis of biomarkers relevant to kidney disorders using a soft microfluidic system. Lab on a Chip, 2019, 19(9): 1545-55.

[37] CHAMBERS R, GABBETT T J, COLE M H, BEARD A. The Use of Wearable Microsensors to Quantify Sport-Specific Movements. Sports Medicine, 2015, 45(7): 1065-81.

[38] AMJADI M, KYUNG K-U, PARK I, SITTI M. Stretchable, Skin-Mountable, and Wearable Strain Sensors and Their Potential Applications: A Review. Advanced Functional Materials, 2016, 26(11): 1678-98.

[39] MCCRORY P, MEEUWISSE W, DVORAK J, et al. Consensus statement on concussion in sport-the 5th international conference on concussion in sport held in Berlin, October 2016. British Journal of Sports Medicine, 2017, 51(11): 838-47.

[40] MCCRORY P, MEEUWISSE W H, AUBRY M, et al. Consensus statement on concussion in sport: the 4th International Conference on Concussion in Sport held in Zurich, November 2012. British Journal of Sports Medicine, 2013, 47(5): 250-8.

[41] CUMMINS C, ORR R, O'CONNOR H, WEST C. Global Positioning Systems (GPS) and Microtechnology Sensors in Team Sports: A Systematic Review. Sports Medicine, 2013, 43(10): 1025-42.

[42] BOYD L J, BALL K, AUGHEY R J. The Reliability of MinimaxX Accelerometers for Measuring Physical Activity in Australian Football. International Journal of Sports Physiology and Performance, 2011, 6(3): 311-21.

[43] ARORA S, AGGARWAL R, SEVDALIS N, et al. Development and validation of mental practice as a training strategy for laparoscopic surgery. Surgical Endoscopy and Other Interventional Techniques, 2010, 24(1): 179-87.

[44] YAMADA T, HAYAMIZU Y, YAMAMOTO Y, et al. A stretchable carbon nanotube strain sensor for human-motion detection. Nature Nanotechnology, 2011, 6(5): 296-301.

[45] AGGARWAL J K, RYOO M S. Human Activity Analysis: A Review. Acm Computing Surveys, 2011, 43(3): 43.

[46] JANETZKO H, SACHA D, STEIN M, et al. Feature-Driven Visual Analytics of Soccer Data; proceedings of the Proceedings of the 2014 IEEE Symposium on Visual Analytics Science and Technology (VAST '14), F, 2014.

[47] POLK T, YANG J, HU Y Q, ZHAO Y. TenniVis: Visualization for Tennis Match Analysis. IEEE Transactions on Visualization and Computer Graphics, 2014, 20(12): 2339-48.

[48] STOPPA M, CHIOLERIO A. Wearable Electronics and Smart Textiles: A Critical Review. Sensors, 2014, 14(7): 11957-92.

[49] AMJADI M, PICHITPAJONGKIT A, LEE S, et al. Highly Stretchable and Sensitive Strain Sensor Based on Silver Nanowire-Elastomer Nanocomposite. Acs Nano, 2014, 8(5): 5154-63.

[50] BARRETT S, MIDGLEY A, LOVELL R. PlayerLoad™: Reliability, Convergent Validity, and Influence of Unit Position During Treadmill Running. International Journal of Sports Physiology and Performance, 2014, 9(6): 945-52.

[51] BANDODKAR A J, WANG J. Non-invasive wearable electrochemical sensors: a review. Trends in Biotechnology, 2014, 32(7): 363-71.

[52] GUDMUNDSSON J, HORTON M. Spatio-Temporal Analysis of Team Sports. Acm Computing Surveys, 2017, 50(2).

[53] STEIN M, JANETZKO H, LAMPRECHT A, et al. Bring it to the Pitch: Combining Video and Movement Data to Enhance Team Sport Analysis. IEEE Transactions on Visualization and Computer Graphics, 2018, 24(1): 13-22.

[54] STEIN M, JANETZKO H, SEEBACHER D, et al. How to Make Sense of Team Sport Data: From Acquisition to Data Modeling and Research Aspects. Data, 2017, 2(1).

[55] WU Y, LAN J, SHU X H, et al. iTTVis: Interactive Visualization of Table Tennis Data. Ieee Transactions on Visualization and Computer Graphics, 2018, 24(1): 709-18.

[56] PERIN C, VUILLEMOT R, STOLPER C D, et al. State of the Art of Sports Data Visualization. Computer Graphics Forum, 2018, 37(3): 663-86.

[57] MACHADO V, LEITE R, MOURA F, et al. Visual soccer match analysis using spatiotemporal positions of players. Computers & Graphics-Uk, 2017, 68: 84-95.

[58] RYOO M, KIM N, PARK K. Visual analysis of soccer players and a team. Multimedia Tools and Applications, 2018, 77(12): 15603-23.

[59] METULINI R. Spatio-temporal movements in team sports: a visualization approach using motion charts. Electronic Journal of Applied Statistical Analysis, 2017, 10(3): 809-31.