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Sensor-based technologies for motion analysis in sports injuries: a scoping review

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Abstract

Background Insightful motion analysis provides valuable information for athlete health, a crucial aspect of sports medicine. This systematic review presents an analytical overview of the use of various sensors in motion analysis for sports injury assessment.

Methods A comprehensive search of PubMed/MEDLINE, Scopus, and Web of Science was conducted in February 2024 using search terms related to "sport", "athlete", "sensor-based technology", "motion analysis", and "injury." Studies were included based on PCC (Participants, Concept, Context) criteria. Key data, including sensor types, motion data processing methods, injury and sport types, and application areas, were extracted and analyzed.

Results Forty-two studies met the inclusion criteria. Inertial measurement unit (IMU) sensors were the most commonly used for motion data collection. Sensor fusion techniques have gained traction, particularly for rehabilitation assessment. Knee injuries and joint sprains were the most frequently studied injuries, with statistical methods being the predominant approach to data analysis.

Conclusions This review comprehensively explains sensor-based techniques in sports injury motion analysis. Significant research gaps, including the integration of advanced processing techniques, real-world applicability, and the inclusion of underrepresented domains such as adaptive sports, highlight opportunities for innovation. Bridging these gaps can drive the development of more effective, accessible, and personalized solutions in sports health.

Keywords Feedback, Injury, Motion analysis, Rehabilitation, Sensor, Sport

Introduction

Sports-related injuries are a significant concern for athletes at all levels of participation, from amateur enthusiasts to professional competitors. The physical impacts of such injuries can severely hinder an athlete's performance, career longevity, and overall well-being. Understanding the biomechanics of movement associated with injury risk and recovery is crucial for early detection, assessment, and effective rehabilitation strategies [1, 2].

Traditional techniques used in sports medicine to analyze human movement often rely on visual assessment by trained professionals. While these methods provide valuable insights, they are inherently subjective, susceptible to the limitations of the observer's expertise, and often unable to fully capture the intricacies of movement during dynamic athletic activities. Recent advances in sensor-based technologies offer promising alternatives for sports motion analysis, providing objective, quantifiable data on human movement [3]. These compact, wearable sensors

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Table 1 The eligibility criteria of the review

Category	Inclusion criteria	Exclusion criteria
Participants	-Studies involving athletes of all ages and sports backgrounds -Studies investigating a specific sport-related injury type	-Studies solely involving healthy populations -Studies focusing on non-sport-related injuries -Studies involving military personnel
Index test	-Studies utilizing sensor-based technologies for motion analysis -Studies Investigating Diagnosis, assessment, and rehabilitation protocols	-Studies solely reliant on traditional biomechanical analysis methods, such as visual assessment -Studies not reporting specific sensor types used -Studies using sensors solely for physiological monitoring -Studies lacking sufficient detail on motion analysis methodology -Studies using motion analysis to predict or find risk factors
Study design	Any primary research (observational or interventional studies)	-Biomechanical simulations -Hardware design studies (solely focused on developing equipment)
Type of publication and language	Peer-reviewed journal articles in English	1. Gray literature (dissertations and conference proceedings) 2. Review articles, case reports, letters, or editorials 3. Book chapters 4. Guidelines 5. Languages other than English
Time	From inception to the search date (2024/02/22)	-
Settings	Studies conducted in Laboratory environments, real-world sports fields, and clinical settings	

offer several advantages, including portability, affordability, and the ability to capture motion data in real-time and clinical environments [4]. By analyzing the data obtained from the sensors, researchers can gain a valuable understanding of movement patterns and monitor the rehabilitation process associated with sports-related injuries [5, 6].

While several scoping reviews have explored the application of sensors in sports medicine [7–10], none have focused specifically on using sensor technology for motion analysis in the context of sports-related injuries. This gap in the literature highlights the necessity for a comprehensive review of how sensor-based technologies can improve the understanding and management of sports injuries. The main hypothesis guiding the review is that sensor-based motion analysis transforms the management of sports injuries by providing actionable, objective data for diagnosis, assessment, and rehabilitation. By examining the current state of knowledge, the review aims to identify the types of sensor-based technologies currently in use, the range of sports injuries being studied, and how these technologies are implemented in diagnosis, assessment, and rehabilitation protocols. By synthesizing findings from diverse sources, the review will offer insights into future research directions, potential technological advancements, and the practical implications of implementing sensor-based motion analysis in sports.

Methods

In conducting this scoping review, we adhered to the framework proposed by Arksey and O'Malley [11], incorporating the insights provided by Levac et al. [12] to emphasize the focus on iterative stages for scoping reviews, such as defining the research question and identifying relevant studies. We also used the methodological guidance for scoping reviews provided by the Joanna Briggs Institute (JBI) on the use of the Participants, Concept, and Context (PCC) criteria for study inclusion and our approach to systematic mapping and synthesis of data [13]. The overarching structure of the study encompassed the following key stages: (1) formulating the research questions (2), identifying relevant studies (3), conducting study selection (4), charting relevant data, and (5) synthesizing, summarizing, and reporting the results.

Research question formulation

The primary research question guiding this investigation was: *How are sensor-based technologies being used for motion analysis in the context of sports injuries?* The review question was formulated, and subsequently, eligibility criteria were established based on the recommended PCC following the methodological guidance provided by JBI (Table 1). Participants will encompass athletes across various sports. Regarding the concept, the review will explore sensor-based technologies for motion analysis in sports injuries, along with studies using combinations of these technologies. Finally, context refers to the settings relevant to sports injuries, including controlled laboratory environments for data collection, real-world sports fields where injuries occur, and clinical settings for rehabilitation strategies.

We excluded gray literature, review articles, case reports, letters, editorials, book chapters, guidelines, and non-English language studies due to considerations of practical feasibility, the need to maintain methodological transparency and reproducibility, and the focus on synthesizing peer-reviewed original research. Exclusion criteria were defined to ensure a manageable scope and maintain methodological rigor.

Identifying relevant studies

The comprehensiveness of the search strategy according to the research question was achieved by concentrating specifically on the conceptual component of PCC, which consisted of four main parts: sensor-based technologies, motion analysis, sports and athletes, and injuries. Initial search terms for each element were identified and refined through consultation with subject matter experts and review of relevant literature. Synonyms and related keywords were also incorporated to broaden the search and capture potential studies with diverse terminology. Boolean operators ensured that the retrieved studies addressed these key aspects. This iterative query development approach helped provide a comprehensive and targeted search strategy. A thorough search of electronic databases, including PubMed/MEDLINE, Scopus, and Web of Science (WOS), was conducted on February 22, 2024. Database search queries are provided in the Supplemental Digital Content 1.

Study selection

The retrieved documents based on the search queries were imported into Zotero reference management software (Zotero 6.0.4, 2022), where duplicates were identified and removed. After de-duplication, the remaining articles were screened in two stages: title and abstract screening and full-text review. To ensure inter-rater reliability, three reviewers (N.S.H., F.B., and F.B.A.) independently assessed a sample of 100 studies during the title and abstract screening stage. All remaining titles and abstracts were then screened against the pre-defined inclusion and exclusion criteria (Table 1). For the full-text review, two reviewers (N.S.H., F.B.A.) independently reviewed each full-text to assess eligibility. Disagreements at any stage were resolved through discussion or consultation with two researchers (A.A. and SH.A.). The PRISMA flowchart shows the study selection process.

Charting the data

To ensure consistent and comprehensive data extraction, the research team developed a pre-designed form collaboratively. Data extracted from each included study were collected using a predefined form. This form included sport type (individual, team, and adaptive sports designed for people with disabilities), specific injury based on the Orchard Sports Injury and Illness Classification System (OSIICS) [14], sensor technology details including type, placement on the body (mentioned directly or inferred from injury), and sensor type. In addition, the form included motion analysis methods (signal processing, statistical analysis, machine learning), the aim of the application (injury detection, injury or rehabilitation assessment), target users (patients or specialists), study settings (clinic, laboratory, or sports field), and study characteristics (country of responsible author, year of publication). Three independent reviewers (F.B. and F.B.A, A.S.) conducted data extraction and resolved discrepancies by consultation with a third reviewer (A.A.).

Synthesizing, summarizing, and reporting the results

The extracted data was then collated and summarized using a narrative synthesis and descriptive analysis approach to identify key themes and patterns across studies, providing an overall understanding of the current state of research in this area.

Results

The search yielded 4451 documents. After removing duplicates, excluding studies that did not meet the eligibility criteria, and excluding non-English language studies, 2702 documents remained. Subsequent screening of titles and abstracts, followed by full-text review, resulted in 2660 articles being excluded. The process resulted in selecting 42 articles for detailed data extraction and analysis as illustrated in Fig. 1.

Description of the selected articles

The 42 studies reviewed reported six significant themes. The characteristics of the included studies and the areas that have been evaluated more extensively indicate trends and potential research gaps.

The studies were grouped based on their publication year into five-year intervals. The earliest study was published in 2000, and 15 studies have been conducted in recent years (Fig. 2a).

Regarding the type of sport, seven studies focused on team sports, while 19 studies did not specify the sport (Fig. 2b).

The distribution of studies across various categories highlights trends in technological applications (Fig. 2c), injury types (Fig. 2d), analytical methods (Fig. 2e), and practical applications (Fig. 2f). Notably, the percentages for certain variables exceed 100% because some studies encompassed multiple category parameters.

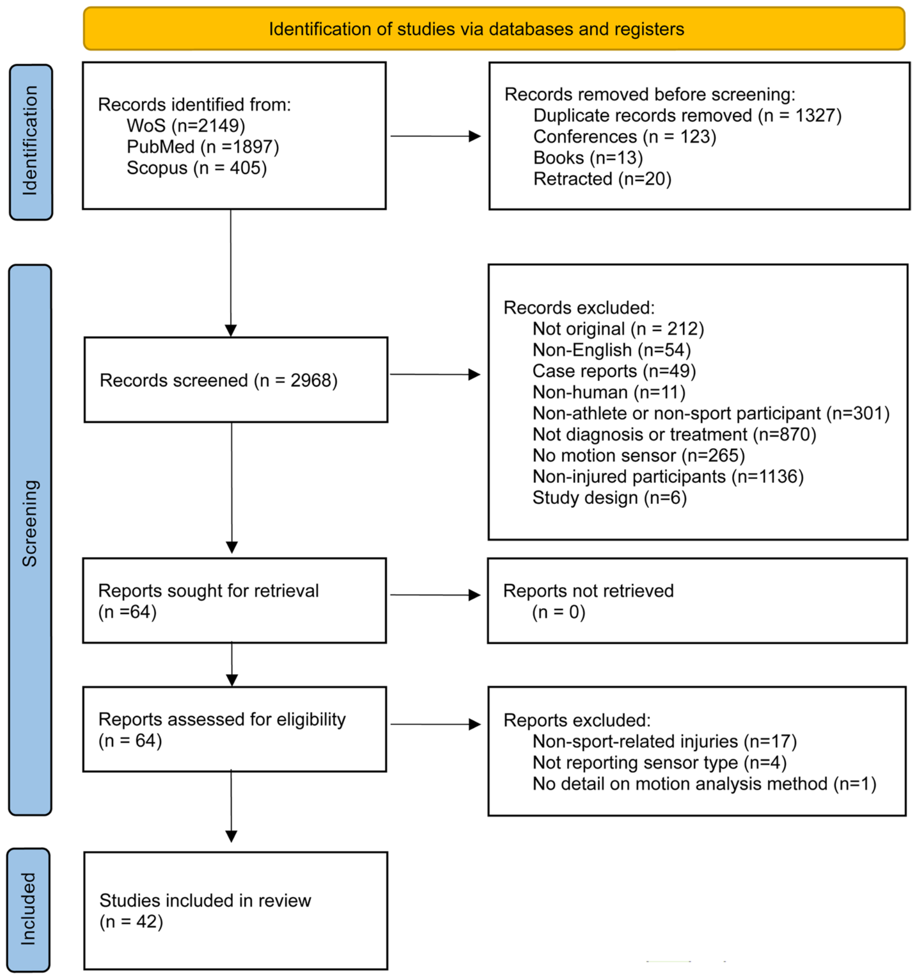

Fig. 1 PRISMA flow diagram for article selection

Sensing approach

As shown in Fig. 3, a total of 26 studies used sensor placement exclusively on the lower limb [15–40]. Nine studies used a combination of trunk and lower extremity sensor placement [17, 41–48]. One study used sensor placement on the head [49], another on the upper limb [50], and two studies used on the trunk only [51, 52]. Three studies used a combination of sensor placement on the trunk and upper limb [53–55].

Among the sensors employed, inertial measurement unit (IMU) sensors offer versatility in terms of configurations. The three internal sensors can be used simultaneously [22, 51, 52], or each can be used independently [15, 24, 29, 40, 55]. Accelerometer was solely used [24, 29, 40], also gyroscopes [15], and magnetometers [55]. In the study, combined electromyography (EMG) data was also used using a magnetometer.

The distribution of co-occurrence among the different sensor types is shown in Table 2. The sensor co-occurrence table shows that the maximum number of sensors used in a single study was three. An arthrometer, as shown in Table 2, was used in combination with a camera and EMG [56], while two studies employed a combination of EMG, camera, and plantar pressure [39, 41]. Dual sensor combinations included camera and plantar pressure in four studies [30, 42, 45, 46], EMG and IMU in two studies [16, 55], camera and EMG in one study [17], and IMU and plantar pressure in one study [18]. Overall, sensor fusion techniques were used in 38% ($n=16$) of studies, with applications in injury detection ($n=\frac{2}{3}$), injury assessment ($n=\frac{8}{18}$), and rehabilitation assessment ($n=\frac{6}{21}$).

Area of application approach

To use the sensors for motion analysis of subjects who have sustained sports-related injuries, the potential applications of the results of the study were explored in three categories: injury detection, rehabilitation, and injury assessment. Injury detection studies are designed to identify injuries resulting from participation in sports activities. Rehabilitation studies assess the effectiveness of

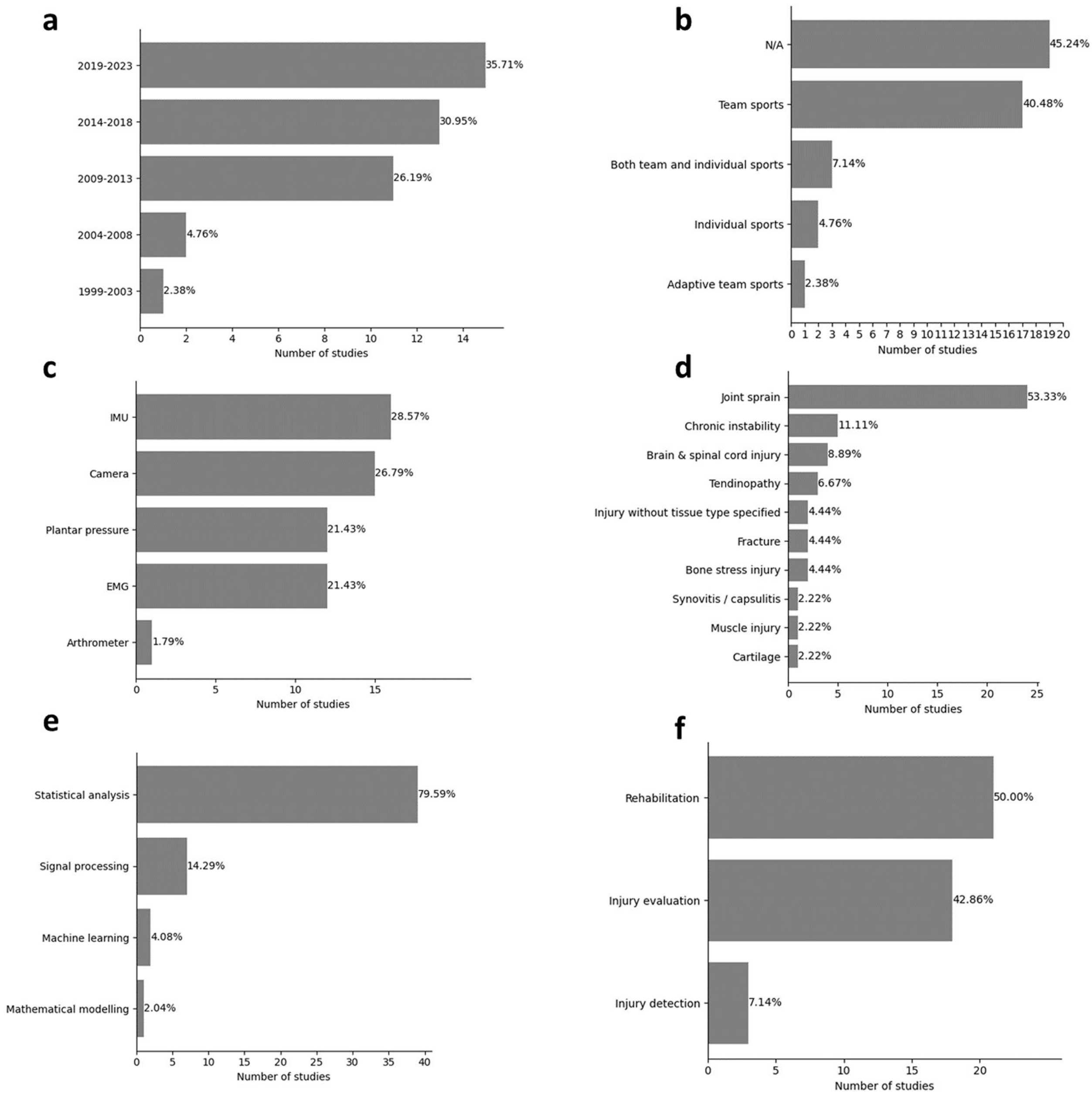

Fig. 2 Characteristics of the included studies. The following variables are shown: **a**) publication year, **b**) sports categories, **c**) sensor type,**d**) injury type, **e**) motion analysis methods, and **f**) aim of the application

rehabilitation protocols, while injury assessment studies quantify and qualify the nature of the injuries sustained.

Injury detection

As illustrated in Table 3, three studies used sensor-based motion analysis to detect knee [41, 42] and ankle [15] joint sprains. Two studies used a combination of sensors to detect knee joint sprains [41, 42], while one study used only IMUs to detect ankle joint sprains [15]. All three studies used statistical methods to analyze the sensor-based motion data. In addition to statistical methods, one study used signal-based methods [41]. Two studies were conducted in clinical settings [15, 42], while one was conducted in a laboratory setting [41].

Rehabilitation assessment

As shown in Tables 4 and 21 studies were conducted to evaluate rehabilitation. In 47% ($n = 10$) of the studies, the

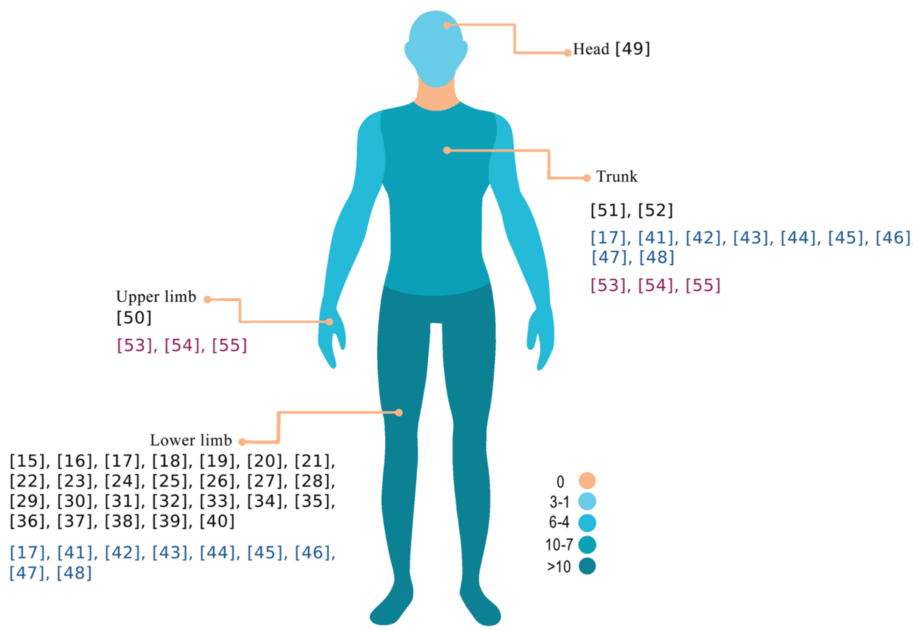

Fig. 3 Placement of sensors on the body for motion analysis in different studies

Table 2 The distribution of simultaneous use of sensors and single use of sensors

	Arthrometer	EMG	Camera	Plantar pressure	IMU
Arthrometer	-	(56)		-	-
EMG		(27,31,38,43,50,53)	(39,41)		(16,55)
Camera		(17)	(20,26,32,34,47,48,54)	(30,42,45,46)	-
Plantar pressure				(21,28,33,35,37)	(18)
IMU					(15,19,22–25,29,36,40,44,49,51,52)

focus was on team sports [17–19, 22–24, 26, 29, 51, 53], while one on individual sports [30], two on a combination of team and individual sports [27, 44], and one on adaptive team sports [50]. A total of 29% ($n=6$) of the studies used sensor fusion to analyze motion related to the rehabilitation process. Joint sprains were investigated in 52% ($n=11$) of the studies. All the studies on joint sprain injury types are related to the knee. 90% ($n=19$) of the studies used statistical analysis to examine rehabilitation. 24% ($n=5$) used signal processing analysis, but signal processing techniques were not used independently. 9.5% ($n=2$) used machine learning, but only one study used machine learning exclusively [22]. A combination of statistical analysis and signal processing was used in 19% ($n=4$) of the studies [17, 19, 23, 49], while one study used a combination of signal processing and machine learning [16]. 43% ($n=9$) of the studies were conducted in a laboratory setting, 33% ($n=7$) in a sports field setting, 14% ($n=3$) in a clinical setting [20, 21, 30], and one in a home setting [25]. Only one study simultaneously examined clinical and sports field settings [23].

Injury assessment

A total of 18 studies were conducted with the objective of injury assessment, as shown in Table 5. Only two studies were published in the last five years [36, 45], conducted in the United Kingdom and Canada, respectively. 33% ($n=6$) of the studies investigated team sports [31–33, 38, 46, 55], one study for individual sports [40], and one for both team and individual sports [54]. Sensor fusion was used to analyze motion related to injury assessment in 44% ($n=8$) of the studies. None of the studies in this category used machine learning methods, and only one used signal processing techniques [38]. 28% ($n=5$) of the studies were conducted in a clinical setting [31, 36, 39, 45, 52], 61% ($n=11$) of the studies were conducted in a laboratory setting [32–35, 37, 38, 40, 47, 48, 55, 56], 5.5% ($n=1$)

Table 3 Specifications of studies related to sports injury detection using sensor-based motion analysis

Aim of application	Injury	Ref.	Body part	Years	Country	Sensor					Analysis			Sport	Place
						IMU	EMG	Camera	Plantar pressure	Arthrometer	Signal processing	Statistical analysis	Machine learning		
Injury detection	Joint sprain	[41]	Knee	2017	USA		*	*	*		*	*		N/A	Laboratory
		[42]		2021	Iran			*	*			*		Team	Clinic
		[15]	Ankle	2021	Hong Kong	*						*		N/A	

* Indicates the corresponding analysis or sensor used in the study

Table 4 Specifications of studies related to the assessment of rehabilitation for sports injuries using sensor-based motion analysis

Aim of application	Injury	Ref.	Body part	Years	Country	Sensor					Analysis			Sport	Place
						IMU	EMG	Camera	Plantar pressure	Arthrometer	Signal processing	Statistical analysis	Machine learning		
Rehabilitation	Joint sprain	[43]	Knee	2014	USA		*					*		N/A	Laboratory
		[16]		2015	Brunei	*	*				*		*		
		[17]			Portugal		*	*			*	*		Team	
		[18]		2019	Australia	*			*			*			
		[19]			Spain	*					*	*			Sport field
		[20]			USA			*				*		N/A	Clinic
		[21]			USA				*			*			
		[22]		2020	China	*							*	Team	Sport field
		[23]			USA	*					*	*			Clinic, Sport field
		[24]		2021	Canada	*						*			Sport field
		[25]		2023	Germany	*						*		N/A	Home
	Tendinopathy	[26]		2010	USA			*				*		Team	Laboratory
		[27]		2011	Spain		*					*		Mixed	
	Brain & spinal cord injury	[51]	Head	2018	USA	*						*		Team	Sport field
		[49]		2019		*					*	*		N/A	
		[44]				*						*		Mixed	
	Cartilage	[53]	shoulder	2014			*					*		Team	Laboratory
	Injury without tissue type specified	[50]		2022	Italy		*					*		Adaptive Team	Sport field
	Fracture	[28]	Foot	2008	Switzerland				*			*		N/A	Laboratory
	Chronic Instability	[29]	Ankle	2017	Poland	*						*		Team	
	Bone stress injury	[30]	Lower Leg	2018	USA			*	*			*		Individual	Clinic

* Indicates the corresponding analysis or sensor used in the study

Table 5 Specifications of studies related to assessment of sports injuries using sensor-based motion analysis

Aim of application	Injury	Ref.	Body part	Years	Country	Sensor					Analysis				Sport	Place
						IMU	EMG	Camera	Plantar pressure	Arthrometer	Signal processing	Statistical analysis	Machine learning	Other		
Injury assessment	Joint sprain	[47]	Knee	2005	Greece			*				*		math-ematical modeling	N/A	Laboratory
		[46]		2009	USA			*	*			*			Team	Sport field
		[31]		2011	Croatia		*					*				Clinic
		[32]		2013	Australia			*				*				Laboratory
		[48]			Greece			*				*			N/A	
		[33]			Ireland				*			*			Team	
		[34]		2016	USA			*				*			N/A	
		[45]		2021	UK			*	*			*				Clinic
	Joint sprain, chronic instability	[56]		2000	USA		*	*		*		*				Laboratory
	Fracture	[35]		2015	Canada				*			*				
	Injury without tissue type specified	[36]		2020	Canada	*						*				Clinic
	Chronic instability	[37]	Ankle	2011	Taiwan				*			*				Laboratory
		[38]		2013	France		*				*				Team	
		[39]		2016	Japan		*	*	*			*			-	Clinic
	Synovitis / capsulitis	[55]	shoulder	2011	Taiwan	*	*					*			Team	Laboratory
	Muscle injury	[54]		2012	Australia			*				*			Mixed	Laboratory, Clinic
	Joint sprain	[40]	Ankle	2017	Switzerland	*						*			Individual sports	Laboratory
	Tendinopathy		Lower Leg													
	Bone stress injury															
	Brain & spinal cord injury	[52]	Head	2018	USA	*						*			N/A	Clinic

* Indicates the corresponding analysis or sensor used in the study

of the studies was conducted in a sports field setting [46], and 5.5% ($n=1$) study evaluated in both laboratory and clinical settings [54].

Discussion

Analysis of athlete movement provides valuable biodata in sports medicine. This study uniquely provides an evidence-based overview of using sensor-based motion analysis, specifically in sports injuries, identifying a critical gap in advanced processing applications and real-world implementations. Unlike previous reviews that broadly addressed motion analysis, this study provides a systematic categorization of the use of sensors in injury detection, rehabilitation, and assessment, providing a nuanced understanding of their specific applications and limitations.

The review showed that according to the aim of the study (injury detection, injury, and rehabilitation assessment), the pattern of using sensors and the type of motion analysis in different injuries are different. However, the highest number of studies in general and each aim are referred to the developed countries. The development of the country due to the allocation of more funds, services covered by insurance, and advanced technologies, even in the field of data transmission [57], makes it possible to move towards objective and multimodal analysis [58]. In low-income countries, establishing telemedicine programs usually requires government approval, which requires clear regulations, rules, and funding to facilitate system development and implementation, leading to delays in adopting digital health programs. Developing and maintaining such infrastructure can also be time-consuming and costly for low-income countries [59, 60].

Considering that it is common practice in professional team sports to collect and analyze athlete monitoring data for various purposes, such as assessing performance potential and minimizing the injury risk [61], team sport injuries were also the primary focus of the included studies. However, limited attention has been paid to adaptive sports, such as wheelchair basketball [50], have received limited attention despite their significant impact on the physical and mental health of people with disabilities [62, 63].

The potential of sensor technology for motion analysis has been the subject of extensive investigation [9, 64], particularly in the context of sports injury management. Sensors are the fundamental component of data acquisition in motion analysis [65]. The most common sensor type used in the included studies is the IMU, followed by the video camera. Although single-sensor methods provide a simple and expedient approach to data processing, sensor fusion techniques have been used in several studies [16–18, 30, 39, 41, 42, 45, 46, 55, 56]. Sensor fusion methods play a crucial role in integrating data from multiple sensors to achieve comprehensive insights from motion analysis [66]. IMUs often incorporate a combination of sensors to provide a more accurate representation of motion [67]. This inherent fusion approach within IMUs, coupled with the benefits of combining data from different perspectives, likely explains the widespread use of IMUs. The IMU is the most commonly used sensor alone, which is justified by the nature of this type of sensor [15, 19, 22–25, 29, 36, 40, 44, 49, 51, 52]. Considering the increased use of plantar pressure in combination with other sensors [18, 30, 39, 41, 42, 45, 46], it can be said that combining data from multiple sensors can provide a complete understanding of foot biomechanics [66].

Sensor placement significantly influences user comfort and acceptance, particularly in applications involving prolonged sensor wear or motion analysis during physical activity [68]. The results indicate that most studies used a single-limb approach to sensor placement on a mobile limb (e.g., lower leg) or a relatively immobile body segment (e.g., trunk).

A wide range of injuries were investigated, reflecting the broad range of body parts susceptible to sports injuries. Joint sprains were the most common type of injury studied. In addition, more studies were conducted on knee injuries than on other body parts, which are prevalent in both professional and amateur sports [69, 70]. Many studies on joint sprains, particularly of the knee, have led to different and improved motion capture and analysis methods. For example, all three studies using sensor combination in rehabilitation assessment are related to knee sprains [16–18]. The remarkable parity of attention between injury and rehabilitation assessment for knee injuries highlights the critical role of this joint in sports medicine and the importance of comprehensive assessment and rehabilitation strategies [71]. These findings underlined the broader epidemiology of sports injuries and the need to tailor diagnostic and therapeutic approaches accordingly [72].

Given the diverse data streams generated by sensors, data analysis is a critical step in using sensor technology for motion analysis. However, the results show a limited use of advanced signal processing and machine learning techniques in the reviewed studies. As rehabilitation assessment has become more studied in recent years, more processing methods can be observed [19, 22, 23, 49].

Rehabilitation assessment was the most common application, followed by injury assessment. The importance of assessing rehabilitation effectiveness and monitoring outcomes underscores the importance of objective assessments. Injury assessment has received the least attention and has emerged in recent years. This emphasis on rehabilitation and assessment for diagnosis and treatment planning may overshadow injury detection, with less need for out-of-field motion analysis.

Sensor-based motion analysis has significant potential for remote monitoring applications, offering the convenience of data collection and analysis outside of traditional laboratory or clinical settings [73]. However, the results present limited studies investigating home-based applications [25]. Approximately half of the studies reviewed were conducted in controlled laboratories, emphasizing rigorous experimental methodology and standardized data collection procedures. This focus on laboratory settings likely reflects the need for controlled conditions to minimize confounding factors and ensure the accuracy of motion analysis measurements. While clinical settings accounted for 28.57% of the studies, their inclusion indicates the growing recognition of sensor-based motion analysis as a valuable tool for clinical assessment and rehabilitation. Collecting and analyzing motion data in real-time can provide clinicians with immediate feedback and inform rehabilitation interventions [74]. Interestingly, sports environments were the least common setting for sensor-based motion analysis applications. This observation may be due to the challenges of implementing motion analysis systems in dynamic and unpredictable sports environments, as well as potential concerns regarding athlete privacy and data security. Despite the limited number of home-based studies, the trend toward increased remote monitoring applications is evident [75]. Notably, most studies utilizing sports environments were conducted after 2019, suggesting a growing interest in exploring the feasibility and efficacy of sensor-based motion analysis in real-world sports contexts [19, 22–24, 44, 49, 50].

Despite the extensive research in sensor-based motion analysis, several challenges and gaps remain. The diversity of sensors and technologies used in motion analysis provides opportunities for data fusion at multiple levels (data, feature, and decision) to improve analysis and interpretation [76]. However, developing and validating robust and generalizable fusion methods across different sensor types and modalities remains a challenge. The effectiveness of sensor fusion techniques is highly dependent on the specific application and the underlying motion analysis task. The potential of machine learning and signal processing tools to extract deeper insights from complex motion patterns remains largely unexplored. The lack of sufficient studies investigating signal processing and machine learning methods hinders the comparative evaluation and identification of optimal approaches. Given the wide range of injuries and the lack of research in most injury types, it is evident that there is a lack of research and development in some injury areas. Many studies did not report complete information on the type of exercise and analysis conditions, making generalizability and method development for these studies challenging.

Several directions for future research are suggested: Further research is needed to develop application-specific fusion strategies that effectively integrate data from different sensor sources and provide meaningful insights for the intended application. Further research is needed to investigate the impact of processing methods on the feasibility of non-laboratory applications, such as remote healthcare. Considering the hardware characteristics and data types collected by IMU and EMG sensors, these technologies are well-suited for use in everyday environments [77–79]. In contrast, camera-based sensors typically require more controlled settings to function effectively [80]. Addressing the limitation of the predominance of studies conducted in controlled laboratory environments and adapting these sensors for real-world use could significantly expand future research opportunities.

Furthermore, while injury evaluation and detection applications can often be achieved in single-session formats, injury rehabilitation requires multiple sessions. In this context, developing and implementing home-based and real-world techniques could advance the field and enhance accessibility and patient outcomes. This includes evaluating the effectiveness of different processing techniques in extracting meaningful insights from sensor data in real-world settings. Future research should focus on developing and applying advanced machine learning algorithms to sensor data to identify hidden patterns, predict movement outcomes, and personalize interventions. The lack of sufficient studies investigating signal processing and machine learning methods hinders comparative evaluation and identification of optimal approaches. Future research should prioritize rigorous comparative studies to evaluate the performance of different processing techniques in different motion analysis tasks and applications.

Limitations

This review has several limitations that may introduce bias. Exclusion of gray literature, non-peer-reviewed studies, and non-English publications may have omitted relevant findings. We excluded non-English language studies due to practical constraints on time and resources for translation and interpretation. In addition, exclusion criteria such as non-sport-related injuries and military populations may have excluded studies with findings indirectly applicable to sports injuries. Also, the predominance of studies conducted in controlled laboratory settings may not fully reflect real-world sports environments, reducing the applicability of findings to practical, on-field scenarios. Variability in study quality, including inconsistent reporting on data collection methods, sensor placement, and analysis techniques, further introduces heterogeneity and affects the reliability of comparative insights. Future reviews may benefit from broader inclusion criteria, multilingual searches, and standardized protocols to enhance the comprehensiveness and generalizability of findings.

Conclusion

This review highlights how sensor-based motion analysis revolutionizes sports injury management by offering objective and actionable data. It also systematically shows how sensor-based motion analysis in sports injury is developing. Unlike previous reviews, it fills significant gaps by offering a focused overview of sensor types, data processing methods, and their specific applications in sports injuries. By identifying underexplored areas - such as the limited use of advanced machine learning techniques - and emphasizing the implementation of appropriate processing techniques, the need for a combination of carefully selected sensors with optimal placement, and the potential for real-world applications in adaptive sports and home rehabilitation, this study sets the stage for future innovation.

By addressing issues that can improve the applicability, analysis, and objective assessment of complex motion patterns, this area of research holds considerable and promising potential not only to advance our understanding of human motion, but also to provide innovative technological solutions for sports health. The findings emphasize the value of sensor-based technology in providing real-time insights and tailored tools for athletes and clinicians. This work is significant in informing research and practice, advancing personalized sports injury management, and improving outcomes for athletes worldwide. It paves the way for future research that can lead to innovative solutions in sensor-based technologies for motion analysis in sports injuries.

Abbreviations

WOS	Web of Science
PCC	Participants, Concept, Context
IMU	Inertial Measurement Unit
JBI	Joanna Briggs Institute
OSIICS	Orchard Sports Injury and Illness Classification System
EMG	Electromyography

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13102-025-01063-z.

Supplementary Material 1.

Supplementary Material 2.

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Authors' contributions
S.A., A.R.K., A.A. contributed to the study conception and design. The search procedure (screening the paper, full text assessment and item extraction) was conducted by A.A., S.N.S., F.B.A., F.B.B., and A.S.H. . S.A., A.A. and S.N.S. drafted the manuscript. All authors read and approved the manuscript.

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Data availability
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This study was approved by the Ethics Committee of Mashhad University of Medical Sciences and Medical School (Ethical code: IR.MUMS.MEDICAL.REC.1403.145).

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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