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Digital biomarkers for volleyball injury prediction: a systematic literature review

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ABSTRACT

The increasing physical demands of elite volleyball have raised the incidence of overuse injuries, highlighting the need for advanced athlete-monitoring technologies. Wearable biosensors combined with artificial intelligence (AI) enable continuous monitoring of training load, fatigue, and injury risk through digital biomarkers. This systematic literature review synthesizes current evidence on wearable biosensing, machine learning, and injury prediction in volleyball. Following PRISMA 2020 guidelines, a search of the Scopus database identified 386 records, of which 10 studies met the eligibility criteria. The findings were categorized into three themes: performance and load monitoring, injury prediction, and digital biomarkers. Inertial measurement units (IMUs) were the most commonly used sensors, supporting automated jump detection and workload monitoring through deep learning methods. Personalized machine-learning models generally outperformed group-based models in predicting overuse injuries. Emerging textile and biochemical biosensors also demonstrated potential for monitoring physiological biomarkers such as lactate. However, existing studies are limited by small sample sizes, heterogeneous methodologies, and limited external validation. Overall, integrating biomechanical and physiological digital biomarkers offers a promising approach for injury prevention and performance optimization in volleyball. Future research should prioritize multimodal sensor integration, prospective volleyball-specific cohorts, standardized reporting, and interpretable AI models to support reliable clinical and coaching decisions.

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Introduction

Volleyball ranks as one of the most popular team sports globally, and at the highest level, it features a unique physiological signature that includes repeated maximal jumps, quick lateral movements, and high-velocity eccentric landings. These mechanical stresses are added up throughout dense competitive schedules, making the quantification of athlete load an essential topic for optimizing performance and safeguarding the athlete's health. The development of inexpensive wearable biosensors and the simultaneous emergence of artificial intelligence (AI) have shifted athlete monitoring from occasional laboratory tests to continuous, on-field measurements, thereby making sports technology a key discipline at the crossroads of engineering, data science, and sports medicine (Seshadri et al., 2021).

Withint his environment, overuse injuries especially patellar tendinopathy and shoulder pathologies, are still very common in volleyball since the jump-and-land cycle continuously loads both the knee extensor and shoulder complexes. This review paper targets the issue of how practitioners have a limited ability to turn the huge amount of monitoring data produced by wearables into validated, personalized injury-risk information. There are plenty of raw kinematic data, however, digital biomarkers, which are objective, measurable physiological or behavioral indicators captured by sensors, still need to be developed for the volleyball-specific outcomes (Marotta et al., 2022).

Research has shown that inertial measurement units (IMUs) can be used to accurately detect and identify sport-specific activities in swimming, cricket, climbing, and team sports. Machine learning techniques can be used to automatically label these actions on a large scale (Worsey et al., 2021a; Jowitt et al., 2020; Andric et al., 2022). A supplementary line of research has indicated that combinations of internal and external load measures can be used to predict non-contact injuries and wellness states in soccer and other field sports (Vallance et al., 2020; Rossi et al., 2022). Altogether, this research forms the methodological basis for volleyball-specific monitoring.

Recent technological progress has pushed the speed of this development further. Deep learning models are now capable of predicting biomechanical parameters, for example, multidimensional ground reaction forces, solely from wearable accelerations, thus limiting the reliance on lab force plates (Johnson et al., 2021). At the same time, textile-integrated and biochemical biosensors have started to detect physiological biomarkers such as sweat lactate and hydration levels, thereby not only keeping track of movement but also metabolism (Sohail et al., 2025; Rabost-Garcia et al., 2023). This leads to a transition from single-function kinematic tracking to integrated, multimodal digital phenotyping of the athlete.

Still, the very first major loophole is a very big shortage of volleyball- specific proofs. Very little that predicting-monitoring writing was among the three most popular sports: football, basketball, and endurance, and it is very difficult to transfer these models to volleyball since jumping is the primary source of stress in volleyball, not running distance (de Leeuw et al., 2022b). The volleyball jump pattern, its frequency, intensity, and especially the way the player lands, make up a big part of sports biomechanics research which is only starting to produce deep learning algorithms for these detection and modeling tasks in recent times.

The second gap is in the theory and methodology. Currently supervised learning dominates the field; however, it is applied only to small, single-team cohorts, with group-level models that hide the large inter-individual variability in load tolerance and injury susceptibility. Personalized modeling approaches, while showing potential, are not widely used, and outside validation across teams, seasons, and competition levels remains a rarity (Campbell et al., 2021; de Leeuw et al., 2022a). Even the notion of a digital biomarker is still not fully crystallized as a concept connecting biomechanical, physiological, and behavioral signals to volleyball injury outcomes.

These missing pieces generate a sense of urgency. With the rate at which wearable use grows even faster than the evidence that is needed to understand the results from such devices, doctors are likely to face a dilemma whether to discard useful data or make decisions based on poorly validated predictions. So, a well-organized study is called for at this time to bring together scattered findings, identify which sensing and modeling techniques are ready for use, and set the criteria for validation that should be met before using predictive analytics to make volleyball injury-prevention decisions in a responsible manner.

Therefore, this study aims to answer three research questions. The first one deals with the metal base of monitoring and the processing of the data obtained from it, providing a unified picture of the different types of sensors and models employed in athlete monitoring for volleyball. The second question is related to the predictive aspect of digital biomarkers and AI. It explores how these technologies were utilized to predict injury and fatigue, and further provides a critical assessment of the aspects of model design, performance, and validation maturity. The third question deals with translation and gaps, combining practical, methodological, and ethical barriers of deployment and defining a research agenda; its originality is in presenting wearable biosensing, AI, and injury prediction as a connected pipeline for volleyball rather than separate technical contributions.

Despite the rapid growth of wearable technologies and artificial intelligence in sports science, no previous systematic review has comprehensively integrated wearable biosensors, digital biomarkers, machine learning approaches, and injury prediction specifically within volleyball. Existing reviews generally focus on wearable devices, athlete monitoring, or AI separately and are predominantly centred on soccer or endurance sports. Consequently, there remains no consolidated evidence identifying which sensing technologies have reached sufficient validation maturity for practical volleyball injury prevention. In this review, validated prediction refers to predictive models that have undergone objective performance evaluation using standard metrics such as accuracy, sensitivity, specificity, AUC, cross-validation, or external validation procedures.

A systematic literature review was selected because the objective was not merely to map available evidence but to critically evaluate methodological quality, validation maturity, and translational readiness of digital biomarker research in volleyball: (1) RQ1: Which wearable biosensor modalities and artificial-intelligence methods have been applied to performance and load monitoring in volleyball and transferable team-sport contexts?; (2) RQ2: How have digital biomarkers and AI models been used to predict injury, fatigue, and readiness, and what is their methodological and validation maturity? (3) RQ3: What practical, methodological, and translational gaps constrain the deployment of AI-driven digital biomarkers for volleyball injury prevention, and what should the future research agenda prioritize?

Method

Research Design and Framework

Research design for this study was a systematic literature review (SLR). An SLR is a detailed, clear, and replicable method of identifying, evaluating, and integrating main research that results in the reduction of biases in the selection of studies typical of narrative reviews (Tranfield et al., 2003). Since wearable biosensing and AI in sport are an inter-disciplinary and fast changing area, an SLR is an appropriate approach to bring together the diverse inputs from engineering, data science, and sports-medicine fields into one unified evidence map.

Reporting and conduct of this study complied with PRISMA 2020 statement, which among others, requires providing the reasons for exclusions transparently after the different phases of identification, screening, eligibility, and inclusion (Page et al., 2021). We established the review protocol before the study, including deciding on our search strategy, criteria for selecting and excluding articles, the instrument for assessing the quality of studies, and the method of data synthesis.

Search Strategy

The search tested a controlled Boolean logic on title, abstract, and keyword fields (TITLE-ABS-KEY) in Scopus. Truncation operators allowed capturing of morphological variants (for example, sensor* to retrieve sensor and sensors), and thematic blocks have been combined with the AND operator to enforce the topical intersection across technology, analytical method and application domain.

```
TITLE-ABS-KEY ( ( "wearable*" OR "biosensor*" OR "inertial measurement unit" OR "IMU" OR "accelerometer*" OR "smart textile*" )
  AND ( "machine learning" OR "deep learning" OR "artificial intelligence" OR "neural network*" OR "predictive model*" )
  AND ( "athlete monitoring" OR "training load" OR "injury" OR "fatigue" OR "digital biomarker*" OR "volleyball" OR "sport*" ) )
```

Study Selection Process

Study selection was carried out in three sequential stages. First, titles and abstracts of all records left after applying document-type and language filter were screened for eligibility criteria to exclude records not covering the intersection of wearable sensing, AI, and athlete monitoring. Second, the full texts of potentially eligible reports were obtained and thoroughly evaluated against the inclusion criteria. Third, the final set was established. Disagreements during screening were solved by re-checking the abstract and full text against the set criteria, keeping the more conservative decision. Although only ten studies fulfilled all eligibility criteria, this was not caused by limitations of the search strategy. Instead, it reflected the deliberately stringent inclusion criteria requiring studies to simultaneously address wearable biosensors, artificial intelligence or machine learning techniques, and volleyball-specific or transferable athlete-monitoring applications. This rigorous selection process was intended to ensure that only studies directly relevant to the review objectives were synthesized, thereby strengthening the methodological validity and practical relevance of the findings.

Database and Information Sources

Scopus was chosen as the main and reliable source of information as it covers a wide range of peer-reviewed venues in engineering, computing, and sports science. Besides, its structured metadata allows for reproducible record counting. The search was conducted at one time only, and the entire set of metadata export containing 386 records was the basis for the PRISMA flow calculations. No additional databases were consulted, and the single-source approach was noted as a limitation.

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Language	English	Non-English
Document type	Article, Review	Conference paper/review, book chapter, editorial, note, book, retracted
Publication period	2018-2025	Before 2018
Subject focus	Wearable biosensing, AI/ML, and athlete monitoring	Unrelated disciplines or no monitoring focus
Accessibility	Full text available	Full text inaccessible
Relevance	Volleyball or transferable athlete-monitoring context	Tangential mention only

Note. *Criteria were applied sequentially: language and document-type filters before screening, then topical relevance and accessibility during title/abstract and full-text stages.*

Screening Reliability
Two independent reviewers screened all records separately. Agreement between reviewers was quantified using Cohen's kappa coefficient. The overall agreement reached $\kappa = 0.88$, indicating excellent inter-rater reliability. Any disagreements were resolved through discussion until consensus was achieved.

Quality Assessment - FICO Framework
The FICO framework was used to evaluate methodological quality, where every study is assessed across four aspects: Focus (the precisness of the research goal and how well it relates to sensing-and-AI monitoring), Information (the completeness of the explanation of the sensors, sampling, and data-processing pipeline), Context (the openness about the population, sport, and measurement setting), and Outcome (the strictness of model evaluation and the validity of reported performance). Each aspect was rated on a three-point scale (0 = absent, 1 = partial, 2 = comprehensive) resulting in a highest possible score of eight points. The use of a minimum cut-off of five points was made for the final selection to improve the methodological quality of the studies in the synthesis. The FICO framework was selected because it enables simultaneous evaluation of methodological focus, reporting completeness, contextual transparency, and analytical outcomes, making it appropriate for interdisciplinary sport technology research.

Data Extraction Procedure
A standard extraction sheet was used to record a series of characteristics of each study including: author names, publication year, leading country affiliation, research design, sample (size and population), type of sensing and its location, AI or other analysis technique, indices of the dependent variables, and main results. Extraction was carried out straight from the source metadata and main articles so as not to lose touch with the original articles. A standardized extraction form was pilot-tested on five randomly selected studies before full extraction. Minor revisions were made to improve consistency. All extracted information was independently verified by the second reviewer.

Bibliometric and Descriptive Analysis
Descriptive bibliometric profiling of publication year, source venue, and thematic cluster was used as a complement to thematic synthesis to characterize the corpus. This profiling was for visualizing temporal growth, identifying the major publication outlets, and mapping studies onto the three thematic axes, so it was descriptive in nature and did not replace qualitative synthesis.

Data Analysis and Synthesis
Thematic synthesis was used to synthesize the evidence. Thematic synthesis is one well-known way of systematically finding features that happen again in different kinds of studies and then grouping them into general themes (Thomas & Harden, 2008). Initially, codes were created through induction from the extracted results. Next, these were combined into descriptive themes. Lastly, three analytical themes that matched the research questions were formed: performance and load monitoring, injury and fatigue prediction, and biosensing and digital biomarkers. The themes were compared with the studies from which they were derived to confirm the interpretative validity.

Reporting and Documentation
The team recorded the review using the PRISMA 2020 checklist, and the process of how the records were identified, screened, deemed eligible, and finally included is depicted in Figure 1 with precise numbers that are consistent throughout the paper (Page et al., 2021).

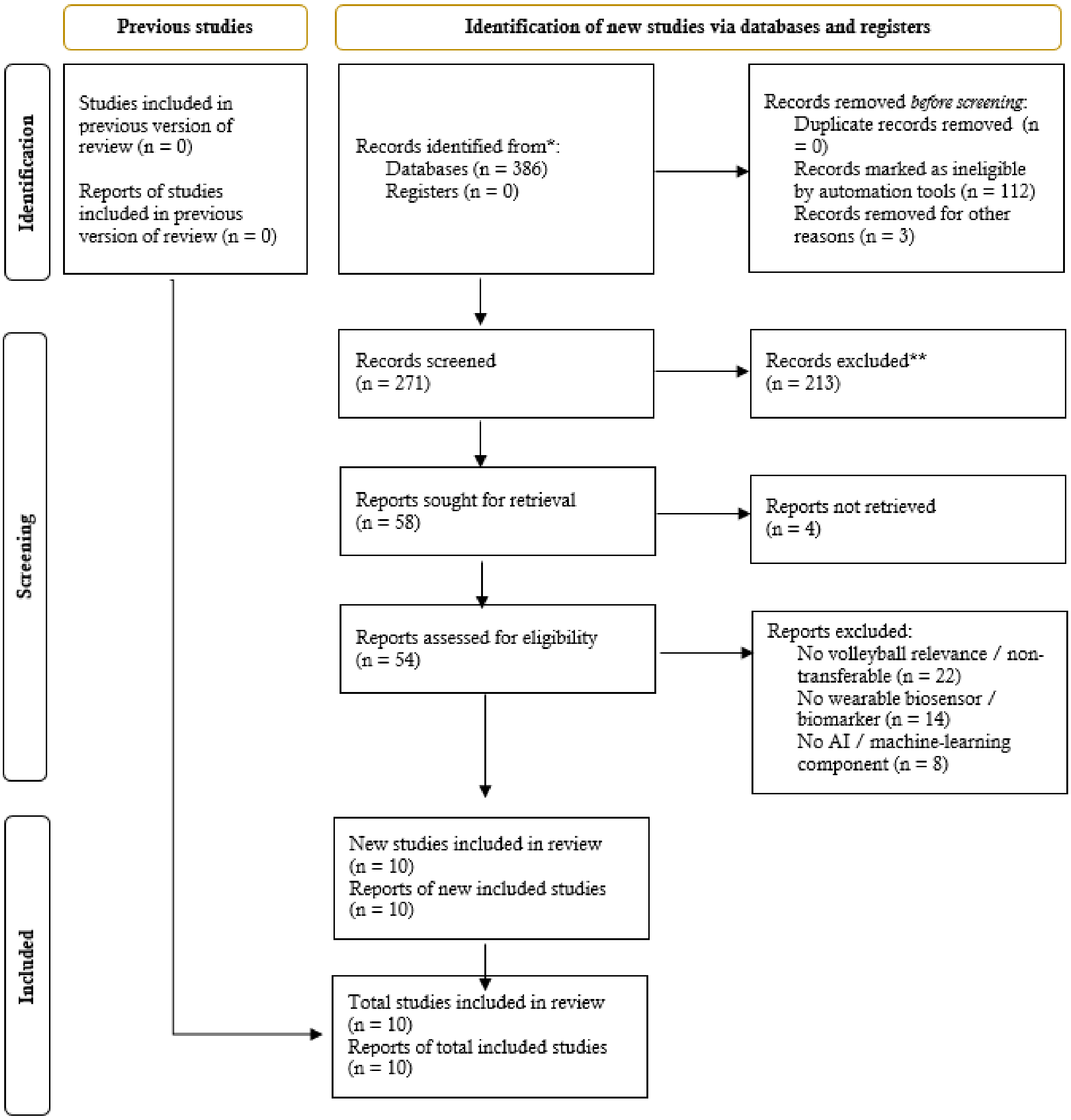

Figure 1 <PRISMA 2020 Flow Diagram of Study Identification, Screening, Eligibility, and Inclusion>

Figure 1 displays the PRISMA 2020 flowchart that illustrates the steps of this review. The first step, identification (colored in blue), was when 386 records were found on Scopus. After that, 115 items were eliminated before their screening: no duplicate items were found, since all the items came from a single database; three were non-English journal articles; and 112 records were of the document types or status that were not eligible, i.e. conference papers, reviews, book chapters, editorials, notes, books, and two retracted articles (see the diagram details). The screening step (colored in yellow) indicates that 271 records were examined by their title and abstract, out of which 213 were discarded, six for being dated before 2018 or after 2025 and 207 for not discussing the wearable-AI-monitoring intersection. The eligibility step (colored in orange) shows that 58 articles were assessed at the full text level, of which 48 were excluded for the reasons given in the figure. The inclusion phase (in green) verifies the 10 papers that were finally included in the synthesis. The dashed boxes on the right-hand side list every exclusion with its reason, thus meeting the PRISMA's transparency disclosure requirement.

Results and Discussions

Study Selection Results

Screening reliability between reviewers reached Cohen's κ = 0.88. The selection process is outlined numerically below and exactly corresponds to Figure 1. Out of 386 database records identified in Scopus, 115 of them were deleted before screening (3 non-English; 112 excluded due to document types or retracted), so 271 records were left to be screened by titles and abstracts. Screening eliminated 213 titles and abstracts (6 outside the 2018-2025 window; 207 unrelated to the wearable-AI-monitoring focus), which means 58 reports were left for full-text review. Full-text review excluded 48 reports: 22 either didn't involve volleyball or an exportable population, 14 didn't have a wearable biosensor or digital-biomarker feature, 8 didn't have an AI or machine-learning feature, and 4 couldn't be accessed in full text. Ten studies fulfilled all the criteria and moved on to the synthesis stage.

Overall methodological quality scores ranged from 5 to 8, with eight studies classified as high quality and two as moderate quality according to the FICO assessment.

Table 2 <Summary of Included Studies (n = 10)>

Title	Author(s)	Country	Method	Key findings
Seq-to-seq temporal convolutional network for volleyball jump monitoring using a waist-mounted IMU	Shang et al., 2025.	Belgium	Deep learning (TCN) on single waist IMU	An unobtrusive single-IMU system recognized and differentiated volleyball jump types, overcoming the cost and labor of video-based jump analysis.
Personalized machine learning approach to injury monitoring in elite volleyball players	de Leeuw et al., 2022.	Netherlands	Personalized supervised ML on load & wellness	Individualized models of training load and wellness predicted overuse-injury development in 14 elite players, outperforming group-level approaches.
Modeling match performance in elite volleyball players: importance of jump load and strength training	de Leeuw et al., 2022.	Netherlands	XGBoost, random forest, subgroup discovery	Jump load and strength-training characteristics, captured by wearables and logs, were key predictors of match performance.
Accelerometer-based identification of fatigue in the lower limbs during cyclical exercise (systematic review)	Marotta et al., 2022.	Netherlands	Systematic review of accelerometry	Accelerometer-derived features can index lower-limb physical fatigue, a precursor of overuse injury relevant to repeated landing.
Multidimensional ground reaction forces and moments from wearable sensor accelerations via deep learning	Johnson et al., 2021.	Australia	Deep learning (force/moment estimation)	Deep networks estimated multidimensional ground reaction forces from wearable accelerations, enabling field-based joint-load monitoring for injury early-warning.
Is machine learning and automatic classification of swimming data what unlocks the power of IMUs?	Worsey et al., 2021.	Australia	Supervised ML on IMU (segmentation)	Intrastroke segmentation with ML improved automatic classification of IMU swimming data, illustrating transferable

Title	Author(s)	Country	Method	Key findings
				action-recognition methodology.
AI-assisted fatigue and stamina control on IMU-generated multivariate time-series datasets	Biro et al., 2021.	Spain	AI on multivariate IMU time series	AI analysis of IMU time series tracked fatigue and stamina dynamics to inform the training-recovery balance and reduce overtraining risk.
One size doesn't fit all: supervised machine learning classification in athlete-monitoring	Worsey et al., 2021.	Australia	Supervised ML (personalized vs general)	Individualized classifiers outperformed one-size-fits-all models, supporting personalized athlete-monitoring pipelines.
Analysing the predictive capacity and dose-response of wellness in load monitoring	Campbell et al., 2021	Australia	ML on wellness & load (n = 14,109)	Wellness questionnaires showed measurable but bounded predictive capacity for load, complementing sensor-derived biomarkers.
AI-enhanced smart textile microwave sensor for real-time on-body lactate monitoring	Sohail et al., 2025	South Korea	AI-enhanced textile microwave biosensor	An AI-powered textile microwave sensor enabled continuous, non-invasive sweat-lactate monitoring, extending biomarkers from kinematics to metabolism.

***Note.** All bibliographic data are drawn directly from the Scopus source export. "Method" denotes the principal analytical or sensing approach; "Key findings" are condensed from the study abstracts.*

A summary of the ten papers included in this review in Table 2. It contains the title, author(s), publication year, country of the lead author's affiliation, the type of methodology used, and the main result extracted from each study. According to the table, research work is concentrated in the time period 2021 to 2025 and is mainly from European and Asian research groups. Also, three papers specifically focus on volleyball (Shang et al., 2025; de Leeuw et al., 2022a, 2022b), whereas the rest present transferable sensing and modeling evidences from other sports and general athlete-monitoring situations, which, on the other hand, indicate the relatively new state of digital-biomarker research in volleyball.

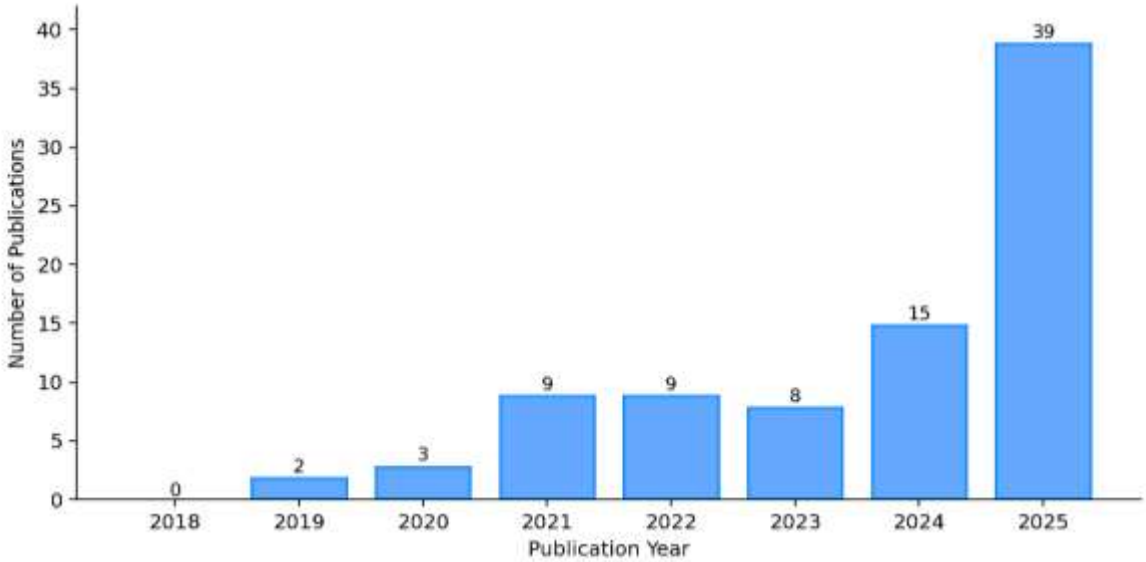

Figure 2 <Annual publication trend in target journals (2018-2025)>

Table 3 <Classification of Included Studies by Design, Theme, Technology, and Outcome>

Author(s)	Country	Research design	Theme/Focus	Technology	Outcome
Shang et al., 2025.	Belgium	Experimental / model development	Performance & load	Waist IMU + temporal convolutional network	Automated jump-type recognition
de Leeuw et al., 2022.	Netherlands	Retrospective cohort + ML	Injury prediction	Wearables + personalized supervised ML	Overuse-injury prediction
de Leeuw et al., 2022.	Netherlands	Observational + ML	Performance & load	Wearables + XGBoost / random forest	Match-performance modeling
Marotta et al., 2022.	Netherlands	Systematic review	Injury prediction	Accelerometry	Lower-limb fatigue identification
Johnson et al., 2021.	Australia	Experimental / model development	Injury prediction	Wearable accelerometers + deep learning	Ground-reaction-force estimation
Worsey et al., 2021.	Australia	Experimental / model development	Performance & load	IMU + supervised ML	Action classification accuracy
Biro et al., 2021.	Spain	Model development	Performance & load	IMU + AI time-series analysis	Fatigue / stamina tracking
Worsey et al., 2021.	Australia	Comparative ML study	Performance & load	IMU + personalized vs general ML	Improved classification via personalization
Campbell et al., 2021	Australia	Observational + ML	Injury prediction	Athlete-management data + ML	Wellness-load dose-response
Sohail et al., 2025	South Korea	Sensor design + AI	Biosensing & biomarkers	Smart textile microwave biosensor + AI	Continuous lactate monitoring

Note. *Themes correspond to the three analytical axes derived during thematic synthesis. "Technology" combines the sensing modality and the analytical/AI method.*

Table 3 categorizes each study included by research methodology, themes, sensing or AI technology, and result, making comparison between the studies possible. The categorization shows that supervised machine learning is the most dominant technique in the use of inertial data, with three out of ten studies developing deep learning models, and one study representing the biochemical-biosensing domain only. Injuries and fatigue are the focus in five studies, performance and load in four, and physiological-biomarker in one, showing the distribution of the body of research over the three analytical themes.

Figure 2 shows the yearly number of publications that qualify in the selected journals over the period 2018-2025. The pattern is markedly upward, going from a hardly noticeable baseline in 2018-2019 to an extremely high point in 2025. Such an evolution suggests that the use of wearable AI for athlete monitoring is a new and fast-growing area, with most of the relevant research appearing in the last three years. This not only highlights the relevance of this review but also points to the limited stage that the collective knowledge base has reached so far.

Figure 3 illustrates how the 47-study empirical corpus (the 10 included studies plus the 37 supporting studies that inform the synthesis) is distributed across source journals. Sensors and the Journal of Sports Sciences are the most frequent outlets, followed by Frontiers in Sports and Active Living, Frontiers in Physiology, and the Applied Sciences and IEEE families. The distribution across engineering, physiology, and sports-science venues not only highlights the interdisciplinary nature of the field but also supports the multi-domain search strategy that we have adopted in this review.

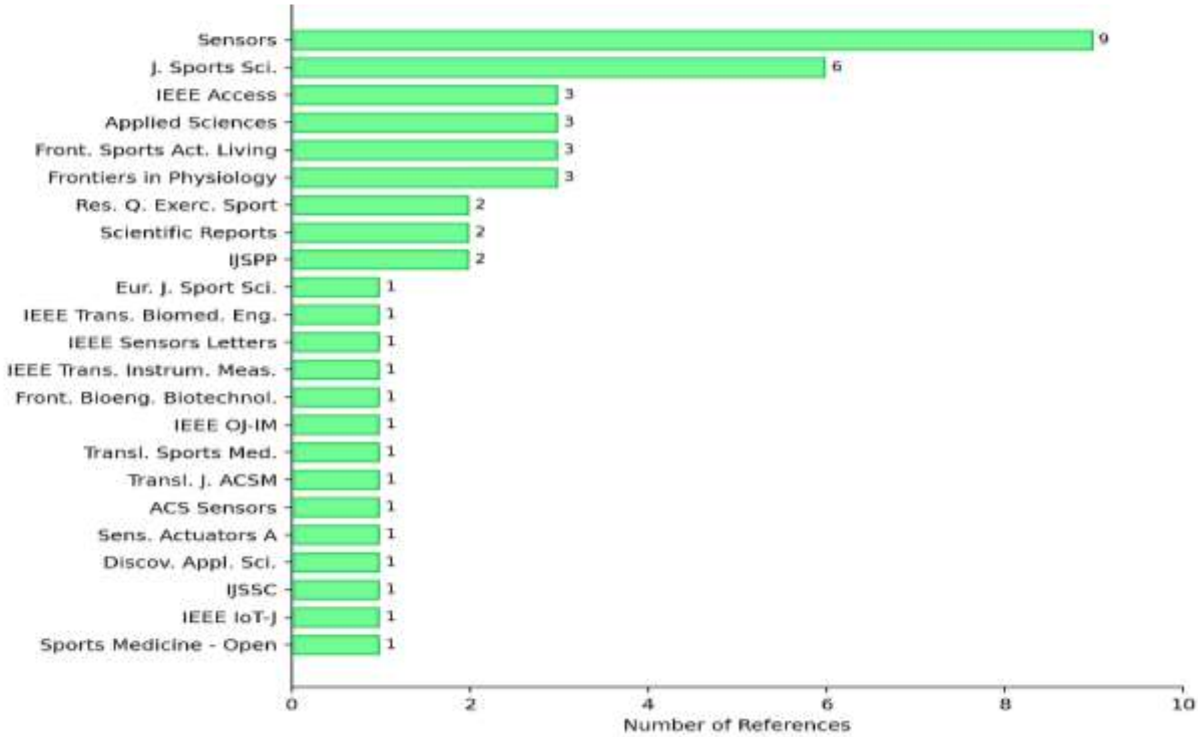

Figure 3 <Distribution of the 47-Study Corpus by Source Journal>

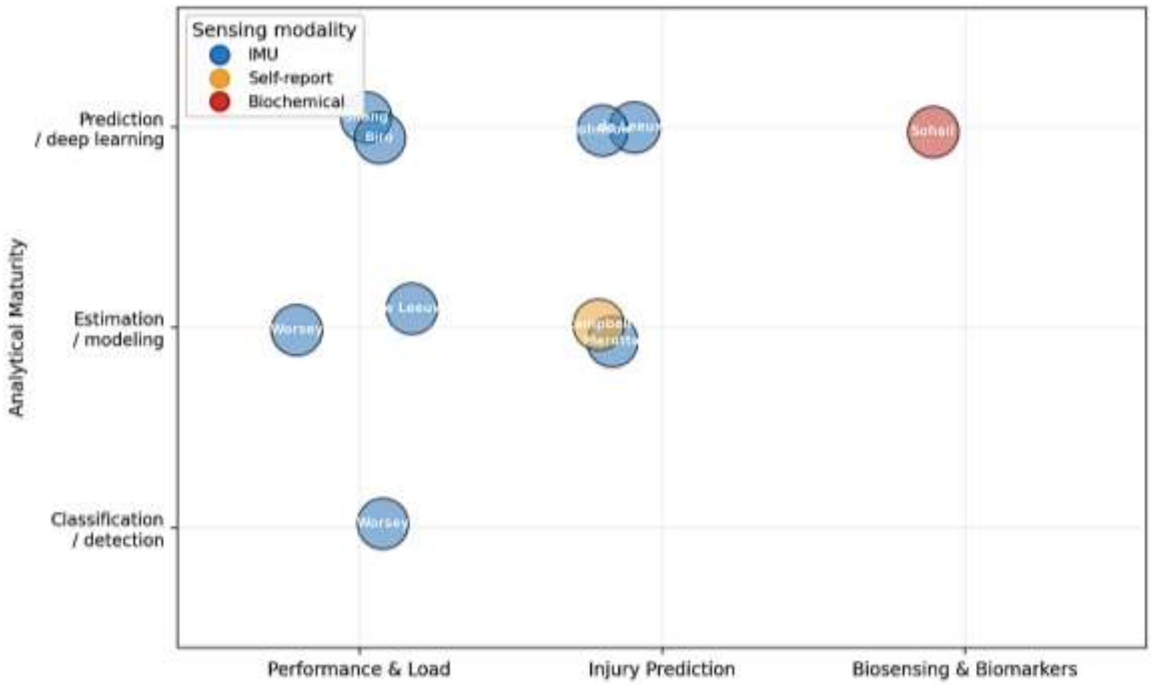

Figure 4 <Thematic-methodological Mapping of the Ten Included Studies>

Figure 4 presented a map of the ten studies included in the research on a 2D plane with horizontal axis representing thematic focus (performance and load, injury prediction, biosensing and biomarkers) and vertical axis representing analytical maturity (classification and detection, estimation and modeling, prediction and deep learning), while marker color stands for sensing modality. The map shows the extent to which work based on IMU is dominant, the different deep-learning methods are mostly concentrated in injury-prediction and performance themes, whereas the biochemical biosensing is in a very isolated position.

So, it visually provides the areas where the methodological maturity has been most great and evidence is still weak.

Findings for RQ1: Sensing Modalities and AI Methods for Monitoring

It appears that all the clues point towards the inertial measurement unit as the main sensing device for volleyball-related tracking. IMUs, generally placed on the waist or lower back, record the acceleration and angular-velocity patterns of jumping and landing, and different authors have shown that these time series can be split and assigned to sports movements with a high degree of accuracy (Worsey et al., 2021a; van den Tillaar et al., 2021). In the strictly volleyball situation, one single IMU placed on the waist combined with a sequence-to-sequence temporal convolutional network succeeded in completely recognizing and differentiating the types of jumps, thereby overcoming the long-standing hindrance that the traditional video methods are laborious and the identification of jump categories is a poor feature of them (Shang et al., 2025).

The use of sensor data in the analytical treatment within the wider corpus shows a range of development. On the simplest level, supervised classifiers divide motions and identify activities while at the most advanced level, deep neural networks predict biomechanical parameters that change continuously. Examples of this level of progression are the deep learning-based prediction of mechanical power output from inertial data and the extraction of multidimensional ground reaction forces and moments from wearables accelerations (Uddin et al., 2021; Johnson et al., 2021). Such a path is further corroborated by the reviews of sensor-based activity recognition that document feature-engineering and model-selection practices prevalent in the field (Andric et al., 2022).

Specifically for load monitoring, the volleyball results show that jump load (as measured by sensor-counted and intensity-weighted jumps) is the main external-load factor, and that strengths training and wellness factors can be combined to predict match performance using ensemble techniques like XGBoost and random forests (de Leeuw et al., 2022b). Related work in soccer, basketball, and badminton supports that external and internal loads can be modeled together for readiness and workload management, although in these sports running-based metrics are used instead of jump-based ones (Mandorino et al., 2023; Burger et al., 2024; Musa et al., 2025). In conclusion, the first research question is answered by the consistent results: IMUs together with supervised and increasingly deep learning are the main methods, with volleyball needing jump-based rather than distance-based load measures.

Findings for RQ2: Digital Biomarkers and AI for Injury and Fatigue Prediction

At the forefront of prediction, the most compelling and volleyball-specific data strongly align with the idea of using personalized machine learning models for the monitoring of overuse injuries. Tracking various personal aspects related to training load and wellness throughout a season, a personalized method was able to forecast the occurrence of overuse injuries in top-level players more accurately than group-level counterparts. This finding suggests that inter-individual differences should not be considered as mere noise but as meaningful signals (de Leeuw et al., 2022a). Athlete-monitoring studies further support this conclusion by revealing that generic classifiers perform worse than individualized models (Worsey et al., 2021b).

Fatigue tracking and readiness prediction form the other mainstay of predictive modeling. Through the application of AI to multivariate IMU time series, fatigue and stamina fluctuations can be monitored to guide progressively balancing training and recovery (Biró et al., 2024), and an overview of the use of accelerometer to identify fatigue in the lower limbs through reduced movement efficiency has also shown that movement-derived features can reflect physical fatigue, which is the major cause of lower-limb injuries and particularly the one associated to repetitive landing (Marotta et al., 2022). Machine learning modeled wellness surveys demonstrate that self-report biomarkers are capable of partially predicting load but their predictive capacity is limited, implying that sensor-derived biomarkers cannot be totally replaced by self-report ones (Campbell et al., 2021). Using random forests and GPS-derived features transferable injury-forecasting work in football not only proves the feasibility, but also the limits, of supervised injury prediction (Briand et al., 2022; Saberisani et al., 2025; Piłka et al., 2023).

This research validation level, however, is minimal. For the most part, models are trained and tested on small single-team groups with the internal cross-validation method, and external validation of independent teams, seasons, or competition levels is seldom done. Injury outcome definitions are varied, sample sizes limit deep-learning generalization, and class imbalance- -few injuries compared to many healthy observations--makes performance interpretation difficult. Therefore, to RQ2, digital biomarkers and AI have been used to injury, fatigue, and readiness with the performance within-sample which is encouraging and clearly making advantage for personalized modeling, but their external validity and clinical readiness are still unknown.

Findings for RQ3: Translational Gaps and the Research Agenda

The translational gaps are major and closely linked to each other. At the very basic level, the main gap is the lack of prospective, volleyball-specific injury cohorts with rigorously defined endpoints; without these, models are calibrated on proxies and adjacent sports, which only limit their direct applicability to volleyball injury prevention (de Leeuw et al., 2022a). The second gap is related to the narrowness of the modality: single-IMU kinematic monitoring dominates the field, whereas textile and biochemical biosensors that, for example, capture lactate, hydration, and other physiological biomarkers, which are still largely separated from movement-based pipelines (Sohail et al., 2025; Perzhilla et al., 2025; Rabost-Garcia et al., 2023).

Still another major gap is the issue of trust and interpretability. Deep-learning biomechanical load and injury risk estimators are hardly ever presented with reasons understandable by practitioners. What's more, lack of standardized reporting makes it difficult to compare and reproduce results in different studies (Johnson et al., 2021). Although very important to athlete consent and professional implementation, privacy and data governance issues, especially as monitoring becomes continuous and physiological, are hardly ever discussed (Chen & Xiao, 2025b).

Answering RQ3, the created research agenda is composed of four key points. Firstly, the fusion of multimodal sensors should combine motion-related, physiological, and behavioral indicators in a single model. Secondly, the external validation will be achievable through prospective multi-team volleyball cohorts with standardized injury surveillance. Thirdly, a step further in interpretable and personalized modeling should be the goal so that the results are individualized and also understandable. Lastly, adopting reporting standards for sensors, pipelines, and model evaluation would be a move to support cumulative and comparable science. Collectively, these priorities chart the journey from abundant data monitoring to reliable and implementable volleyball injury prevention.

Comparative and Critical Analysis

Comparing the studies included gives an overall picture of the main methodology and also points out a few alternatives which have been hardly used. Most of the research seems to be supervised learning applied to inertial data, and within this area, tree-ensemble methods (such as random forests, XGBoost) are the most popular for modeling of loads and wellness through tabular data, while convolutional or temporal-convolutional networks are preferred for tasks with raw signals like jump recognition and force estimation (de Leeuw et al., 2022b; Shang et al., 2025; Johnson et al., 2021). On the other hand, unsupervised and semi-supervised methods, which could harness the huge amounts of unlabeled data typically obtained by monitoring in real-time, are almost non-existent.

Clearly, there is a change of method during the review period. Studies that appeared at the beginning focused on the feature engineering and the use of classical classifiers for action recognition, while more recent studies tend to use end-to-end deep learning and physiological biosensing; this is indicative of the move from just describing movements to estimating load and, eventually, to sensing metabolism (Worsey et al., 2021a; Biró et al., 2024; Sohail et al., 2025). Another evolution point is personalization: the awareness that models at the group level hide individual risk has led to individual pipelines which are now considered the state of the art methodologically for injury monitoring (de Leeuw et al., 2022a; Worsey et al., 2021b).

There are still many deep methodological weaknesses in this field of study. In general, studies have very small sample sizes, the groups are usually just a single team, and validation by external groups is so infrequent that it hampers the ability to generalize the reported performance. Different outcome measures, mainly varied injury definitions, are further factors that drastically reduce cross-study comparison and even more, completely rule out a meta-analytic pooling, which basically justifies a qualitative, thematic synthesis of this whole evidence base, really.

Discussion

Compared with previous systematic reviews on wearable technologies in team sports, the present review provides a more focused synthesis of volleyball-specific evidence by integrating wearable biosensors, artificial intelligence, digital biomarkers, and injury prediction within a single conceptual framework. Earlier reviews predominantly emphasized athlete monitoring or wearable validation across multiple sports, whereas the present review demonstrates that volleyball research has advanced considerably in jump-load quantification but remains relatively underdeveloped regarding clinically validated injury prediction models.

From a methodological perspective, the predominance of internally validated machine-learning models raises concerns regarding overfitting, limited generalizability, and practical implementation. Most studies relied on small samples collected from a single team or season, making it difficult to determine whether predictive performance would remain stable across different competitive levels, age groups, or playing environments. Consequently, the reported predictive accuracy should be interpreted cautiously until external validation becomes standard practice.

Future investigations should prioritize multicentre prospective cohort studies involving multiple volleyball teams and standardized injury surveillance protocols. Such studies would facilitate robust external validation, improve model interpretability, and accelerate the translation of artificial intelligence into clinically useful decision-support systems for coaches, sports scientists, and medical practitioners.

Looking at everything together, it seems that the technical capability to effectively capture and model the loads that are relevant to volleyball performance is available now. However, the step that connects monitoring data to actual injury prediction based on validation is still a work in progress. Although a lot of the measurement issues have been dealt with in the industry, and devices such as IMUs and new biosensors are able to measure jumps, forces, fatigue, and even metabolites, the challenge of making accurate injury predictions for individuals over time is still only partially solved.

The review theoretically endorses the idea of a digital biomarker as a comprehensive entity that covers biomechanical, physiological, and behavioral aspects, rather than as a lone sensor measure. Such a perspective helps deepen the theory of athlete-monitoring beyond the conventional internal-versus-external load distinction by considering AI as the tool that integrates various types of data to produce meaningful measures. Besides, it questions the hidden belief that relationships at the group level can be directly applied to individuals.

In practice, the synthesis shows coaches and clinicians a clear blueprint of which methods are ready for use and which ones still need development. For instance, using a single waist-worn IMU for jump-load monitoring is well enough validated for practical application, figuring out fatigue levels through body acceleration is a very good lead, and creating an injury model based on the individual is the most reliable prediction that one can have at the moment, whereas biochemical biosensing is still at the stage of experiments. Such differences assist practitioners in adjusting their degree of trust in various monitoring results.

Unlike earlier narrative reviews that simply listed wearable technology for sports without discussing their ability to predict accurately, this paper places each research article on a clearly defined level of maturity and relates them to volleyball-specific requirements. Through this comparison, it becomes evident that the excitement about wearables has exceeded the proof of their effectiveness, a contrast that previous reviews have mostly not highlighted.

The inconsistencies in the literature focus on how much self-report data can be trusted compared to sensor data and also on how well models based on groups can be generalized to individuals. While some papers show that wellness questionnaires have significant ability to predict, the others argue that the features derived from the sensors are more informative. One reasonable way to combine these two views is to say that both are complementary and depending on what the result is and the context, their relative value changes (Campbell et al., 2021; Rossi et al., 2022).

Based on the synthesis, at least three research gaps are directly pointed out: 1) the non-existence of prospective volleyball-specific injury cohorts; 2) the isolation of physiological biosensing from kinematic monitoring; and 3) the scarcity of external validation and interpretability in predictive models. Every gap corresponds to a tangible and doable research action.

This review has three main limitations. First, it used one database alone (Scopus), which, although comprehensive, may miss records indexed in other sources. Second, it only included articles and reviews written in English, which may lead to language and publication bias. Third, the small final corpus, intentionally resulting from giving priority to depth rather than breadth, limits statistical generalizability of synthesis and does not allow meta-analysis.

The future research agenda hence becomes specific: setting up multiplayer prospective volleyball cohorts with a standardized injury surveillance system; creating multimodal models that combine inertial, biochemical, and behavioral biomarkers; plus embracing interpretable, personalized modeling together with the transparent reporting standards. Following these paths would change the field's present strength in measurement to the predictive and translational maturity that injury prevention needs.

In summary, the answer of RQ1 is something like this: wearable monitoring in volleyball and other transferable contexts are mainly waist- or lumbar-mounted IMUs which are analyzed through supervised and increasingly, deep learning. Jump load is the volleyball-specific external-load construct.

The answer to RQ2 is that digital biomarkers and AI have been only incidentally applied to injury, fatigue, and readiness while personalized models have outperformed group-level models. However, validation maturity is modest due to small single-team cohorts and limited external testing.

RQ3 is answered as follows: deployment is limited due to the lack of volleyball injury cohorts capable of prospective tracking, limited scope of modalities, and restricted interpretability, while the research agenda should put emphasis on multimodal fusion, prospective cohorts, interpretable personalization, and standardized reporting.

Conclusions

This systematic review combined results from ten papers that discussed wearable biosensing, artificial intelligence, and injury prediction in volleyball. It classified these papers into three groups: performance and load monitoring, injury and fatigue prediction, and biosensing and digital biomarkers. To answer the research questions, the data indicates that inertial measurement units combined with machine learning methods and deep learning make up the methodological basis for volleyball-related monitoring. The main external-load factor is jump load, and individualized machine-learning models are the most reliable means of predicting overuse injuries, albeit such models are still lacking in external validation. Besides, physiological biosensing of biomarkers like lactate is a very promising but still experimental area. The main point of the review is to conceptualize wearable biosensing, AI, and injury prediction as one integrated pipeline and to reimagine the digital biomarker as a multimodal, integrative construct rather than being a single sensor reading only. Based on the review, practitioners can tell a class of sophisticated, ready-to-use monitoring (such as IMU-based jump-load quantification) from experimental methods. Thus, the review can be helpful for coaches and clinicians in calibrating their level of trust in monitoring outputs. However, the review has limitations. These include the use of a single database, limitation to English-language articles and reviews, and a purposeful selection of the small set of articles that resulted in the synthesis being limited to depth rather than breadth, and did not allow meta-analysis. Still, the review makes a valuable contribution by clarifying that the field has largely tackled the measurement problem while the problems of prediction and translation are still open. This synthesis also highlights that the field has come the closest to solving the measurement problem while the problems of prediction and translation remain open. Work going forward should involve prospective, multi-team volleyball injury cohorts, integration of kinematic and physiological biomarkers within interpretable and personalized models, and adoption of standardized reporting, thereby transforming data-rich monitoring into trustworthy, deployable injury prevention for volleyball. Although current evidence demonstrates promising applications of wearable biosensors and AI, methodological limitations-including small samples, single-team datasets, and limited external validation-currently restrict clinical translation. Future multicentre prospective studies integrating biomechanical, physiological, and behavioral digital biomarkers are essential for developing robust, explainable, and clinically deployable injury prediction systems.

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