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Artificial intelligence enabled wearable technologies in beach volleyball: a systematic literature review of current evidence, research gaps, and future directions

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ABSTRACT

The fusion of artificial intelligence (AI) and wearable technology has transformed athlete monitoring, yet evidence in volleyball, particularly beach volleyball, remains fragmented across engineering, computer science, and sports medicine. This systematic literature review (SLR) synthesized peer-reviewed studies on AI-enabled wearable devices for volleyball performance, training load, and injury monitoring, emphasizing the applicability of indoor volleyball findings to beach volleyball. Following PRISMA 2020 guidelines, two independent reviewers conducted study selection and data extraction, achieving excellent inter-rater reliability (Cohen's $\kappa = 0.87$). Methodological quality was assessed using the JBI Critical Appraisal Checklist, and findings were synthesized thematically. A Scopus search identified 102 records; after duplicate removal and screening, 10 studies met the eligibility criteria. Eligible studies were English-language journal articles published between 2018 and 2025 involving wearable sensing and computational or machine-learning applications in volleyball. Four themes emerged: deep learning combined with inertial measurement units accurately recognized volleyball activities and jump types; wearable-derived training load predicted injury risk and performance using personalized algorithms; sensor-based skill assessment was validated mainly indoors; and beach-specific technologies remained limited, except for environmental monitoring. Overall, AI-enabled wearable systems demonstrated high recognition accuracy, but evidence for external validation and beach-specific applications remains scarce. This review provides the first beach-oriented roadmap for future research on wearable AI in volleyball.

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Introduction

Sports have turned into one of the most data-heavy sectors where technology is applied, with wearable gadgets and artificial intelligence being part of the daily schedules of top-level as well as developing athletes. The increase of affordable inertial measurement units (IMUs), the advancement of deep learning, and the need for objective, uninterrupted athlete monitoring have together led to a research field that includes medicine, health professions, engineering, computer science, and decision sciences. In team sports, practitioners are gradually demanding quantitative assessments of movement quality, mechanical load, and physiological strain instead of the subjective impressions that have been the basis of coaching Almeida-Neto et al. (2020). This significant change on a large scale to sensor-driven, algorithmically interpreted performance data sets the context for this review and its focus on how these technologies have been used in volleyball.

Volleyball, in particular beach volleyball, has a unique movement pattern that is characterized by a series of maximal jumps, fast changes of direction, and overhead strikes, all of which require a high mechanical effort. Monitoring the number and intensity of jumps through wearable devices has therefore become the main tool for managing the workload of players in this sport. Beach volleyball intensifies these factors by adding the unstable sand surface, environmental heat, and a two-player format that significantly increase the players' share of court coverage, resulting in their internal and external loads being quite different from the indoor game (Tometz et al., 2022). However, most equipment and modelling studies have been done and tested indoors, so the beach situation is much less studied by comparison. So, to truly understand the specific case of AI-enabled wearable monitoring in volleyball, one should distinguish between what has actually been proven and what has just been assumed as transferable.

Numerous earliest studies have demonstrated the potential to identify sports activities from body-worn sensors. For instance, preliminary machine learning models operating on IMUs placed on the wrist and ankle revealed that convolutional neural networks are capable of classifying diverse sports actions very accurately (Hsu et al., 2019), whereas sensor-fusion and ensemble methods were able to overcome the extreme class imbalance problem inherent in continuously recorded match data (Haider et al., 2020). Similarly, work done in basketball along with other overhead sports has both the wristband form factors and motion-recognition algorithms that have direct relevance to the volleyball striking (Lian et al., 2022). All these studies together laid the methodological basis, signal acquisition, feature extraction, and supervised classification, volleyball-specific applications have been developed since then.

Recent developments in technology and research techniques have sped up the progress of this domain. For instance, piezoelectric sensors powered by the gesture themselves that record the minor spiking movements without the need of external energy have been made (Liu et al., 2022), single-IMU systems mounted on waist combined with temporal convolutional networks are able to identify different jump types during unconstrained training (Shang et al., 2025), and smart Internet-of-Things wristbands allow phase-based dissection of serve biomechanics along with skill-level classification (Chen et al., 2023). On the analytics front, various machine-learning methods such as gradient-boosted trees, random forests, and subgroup-discovery have been employed to establish relations between player load measured by wearables and wellness and match outcomes (Liao & Li, 2022). With the use of Edge deployment and real-time inference, the pipelines mentioned in the reports are able to perform jump detection and height estimation on-device (Magnifouet Zefack & Rocheteau, 2025). All these changes indicate a shift from offline proof-of-concept towards coach-facing tools which are ready for the deployment.

The first one is the lack of reliable data produced in the beach setting. Most of the wearable-AI systems validated so far, have been made for indoor volleyball, where the surface, weather, and gameplay are different from the beach environment (Jia, 2025). Sand changes the way of landing and the features of ground reaction, however, validation studies of devices hardly mention performance in these conditions. When there are data about the beach, they mostly refer to load metrics and not to AI-based recognition (Tometz et al., 2022). Hence, the external validity of activity-recognition and jump-monitoring models for beach volleyball stays almost unknown, and that is something which is hardly noticed in the main papers.

A second gap is theoretical and methodological. For example, several studies use small and homogeneous samples, single-session lab protocols, and internal validation only, which limits generalization and results in overestimated accuracy (Bian, 2025). Besides, model transparency is often lacking, and only a few studies reveal calibration, perform external validation, or provide feature interpretability suitable for high-stakes injury decisions (Almeida-Neto et al., 2020). Besides, different sensor placements, different sampling rates, and different outcome definitions hinder both literature review and comparison across studies (Gielen et al., 2022). Because of these methodological flaws, the field's headline accuracies might not be maintained when put into use in ecological valid, multi-athlete, multi-session settings.

The reasons for making a systematic review at present are twofold. Firstly, the quantity of relevant publications has dramatically increased, with Scopus data showing a strong increase especially after 2020 and the main periods of activity being in 2022 and 2024, 2025; therefore, a current summary is required to bring together widely scattered results. Secondly, since the field is spread over various disciplines such as engineering, computer science, and sports medicine, no one research community has so far produced a comprehensive integrative account of beach volleyball. A systematic PRISMA-compliant review could identify recognized skills, reveal the indoor-to-beach trail of evidence, and serve as a common reference point for both practitioners and methodologists (Rebelo et al., 2023).

Preliminary database screening identified more than one hundred publications related to AI-enabled wearable technologies in volleyball. However, fewer than 10% specifically investigated beach volleyball settings, whereas the vast majority focused on indoor volleyball. Most available studies evaluated activity recognition, jump monitoring, or workload estimation under controlled indoor conditions, leaving beach-specific validation largely unexplored. This imbalance highlights an important research gap regarding the ecological validity of AI-enabled wearable systems in sandy environments.

Therefore, this systematic literature review aims to systematically synthesize current evidence regarding AI-enabled wearable technologies used in volleyball, critically evaluate their methodological quality, summarize their validity for monitoring performance, training load and injury risk, and identify research gaps related to beach volleyball applications. (1) RQ1: Which wearable technologies enabled by AI and sensing modalities have been actually used in volleyball? Also, what is the reported validity for activity, jump, and skill recognition through these technologies? This query provides a unified list of devices, algorithms, and performance evaluation criteria. The second research question concerns the practical benefits of justifying monitoring investment, namely load, injury, and performance; (2) RQ2: How well do metrics from wearables which are analysed with the aid of machine learning predict training load, injury risk and performance in competition in volleyball? This question results in a critical review of predictive evidence and of the quality of the methods used. The focus of the third research question is the beach context and the trajectory of the field; (3) RQ3: How far can we apply the present evidence in beach volleyball? What are the main characteristics of the field in terms of gaps and future directions? The question brings up a novelty statement: as far as we know, this is the first SLR that will synthesise AI-enabled wearables with a very direct beach-volleyball lead, separating shown from assumed transferability (Lima et al., 2025).

Method

A systematic literature review was chosen as the best method since the research questions are about gathering and critically evaluating scattered, interdisciplinary sources of evidence, rather than primary data. This review relied on the well-developed three-stage method of planning, conducting, and reporting described by Tranfield et al. (2003), as well as the standards defining the rigor and transparency for systematic reviews set out by Liberati et al. (2009). Besides, the presentation of the results was in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 (PRISMA 2020) statement (Page et al., 2021), which is the updated replacement of the original PRISMA statement (Moher et al., 2009) and offers a more up-to-date and widely used framework for reporting identification, screening, eligibility, and inclusion systematically. We opted for the PRISMA 2020 framework rather than earlier ones because its sequence and items are more aligned with database search and the mixed design of studies typical to sports-technology research.

Two independent reviewers conducted the title/abstract screening and full-text eligibility assessment independently. Any disagreements regarding study inclusion were resolved through discussion until consensus was achieved. Inter-rater agreement during the screening process was assessed using Cohen's Kappa coefficient, which reached $\kappa = 0.87$, indicating excellent agreement between reviewers.

There was only one all-inclusive search that was carried out by publicly combining the three concepts artificial intelligence, wearable sensing, and volleyball to a TITLE-ABS-KEY field operator, using Boolean and truncation syntax and this search string was generated as below.

TITLE-ABS-KEY (("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network") AND ("wearable*" OR "inertial measurement unit" OR "IMU" OR "accelerometer*" OR "sensor*") AND ("volleyball" OR "beach volleyball"))*

The asterisk truncation operator was able to represent the different morphological forms of a word (e.g., sensor, sensors, and sensing), whereas quotation marks were used for exact-phrase matching of multiword concepts. Field codes limited matching to titles, abstracts, and indexed keywords, which was a trade-off between recall and precision. Document-type and language limiters were used at the screening stage instead of being incorporated within the query in order to keep an open identification count.

Scopus was selected as the sole database because it provides broad multidisciplinary coverage across sports science, biomechanics, engineering, artificial intelligence, computer science, and wearable technology research. In addition, Scopus offers high-quality bibliographic metadata, standardized indexing, and extensive citation coverage, making it one of the most reliable databases for conducting systematic literature reviews. Although limiting the search to one database may have excluded some relevant studies, the comprehensive scope of Scopus provides sufficient coverage for the objectives of this review.

Eligibility criteria were set fairly strictly and comprehensively to include six different aspects: language, document type, publication period, subject area, accessibility, and topical relevance. Table 0 depicts the concise set of inclusion and exclusion rules applied at the time of screening. Eligibility criteria consisted of six language, document type, publishing year, discipline, accessibility, and topical relevance parameters. Table 1 presents the inclusion and exclusion criteria used during screening.

Table 1 <Inclusion and Exclusion Criteria>

Criterion	Inclusion	Exclusion
Language	English only	Non-English (e.g., Russian, German, Spanish)
Document type	Journal article or review	Conference paper/review, book/chapter, retracted item, editorial
Publication period	2018–2025	Before 2018; in-press 2026 records
Subject area	Medicine, health professions, engineering, computer science, decision sciences	Unrelated disciplines (e.g., pure cardiology, cellular biology)
Accessibility	Full text and sufficient methodological detail available	Abstract-only or insufficient reported data
Relevance	Applies a wearable modality and a computational/AI analysis to a volleyball population	Tangential mention; no wearable or no AI/analytics component

The table operationalises the PRISMA eligibility stage by translating the review scope into screening-ready rules. Language and document-type filters preserve methodological comparability, the 2018–2025 window captures the contemporary surge in AI-wearable research while excluding not-yet-finalised 2026 in-press items, and the relevance criterion enforces the dual requirement that a study contain both a wearable sensing modality and a computational or machine-learning analysis applied to volleyball.

Study selection was done in three stages one after another. During identification, all 102 records from Scopus were exported with full metadata; only one duplicate record (an identically titled IMU shoulder-injury study indexed twice) was removed, resulting in 101 unique records. During screening, titles and abstracts of the 101 records were checked with the help of eligibility criteria, and 70 records that were not about AI-enabled wearables in a volleyball setting were excluded. During eligibility, the 31 full-text articles were the remaining ones and they were checked comprehensively; however, 21 of them were excluded for various reasons that were duly recorded. Screening decisions were made referring to the criteria, and borderline cases were sorted out by re-reading the full text against the relevance criterion, while exclusion was quite strict when the wearable or AI component was missing or just nominal.

The methodological quality of the included studies was assessed using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist appropriate for each study design. The checklist evaluates methodological rigor, risk of bias, participant selection, measurement validity, and statistical analysis. Each article was independently assessed by two reviewers. Studies with lower methodological quality were retained only when they provided important evidence but were interpreted cautiously during the thematic synthesis.

Data from each study was recorded in a well-organized extraction form. Types of data included author(s) and year of publication; country of the corresponding author affiliation; study design; sample characteristics; wearable technology and sensor setup; AI or other analytical method; main outcome variables; and core findings. The data extraction was done mainly based on Scopus metadata and corresponding abstracts. Bibliographic data was copied exactly to maintain data integrity. If any particular descriptor was not available from the source document, its field was left as not reported rather than be assumed. Data extraction was independently performed by the same two reviewers using a standardized extraction form. The extracted information included publication characteristics, study design, participant characteristics, wearable technologies, artificial intelligence methods, measured outcomes, and key findings. Any discrepancies were resolved through discussion until complete agreement was reached.

In addition to qualitative synthesis, a descriptive bibliometric analysis of the entire identified corpus (N = 102) was conducted using the exported metadata. The number of annual publications was counted to describe the temporal development of the field, the countries of first-author affiliations were merged to illustrate the geographic distribution, and the frequencies of author-keywords were analyzed in order to identify thematic clusters. The mapping of keyword co-occurrences was carried out in order to reveal the main conceptual groupings, activity recognition, monitoring jumps and loads, injury prevention, skill assessment, performance modeling, and device design, and to locate the included studies in the context of the broader literature. The analysis was descriptive and was not intended to replace the evaluation of the included studies.

Due to methodological differences among the included studies and lack of a common effect size, thematic synthesis following Thomas and Harden (2008) was chosen over meta-analysis. We initially coded findings from each study in an inductive way to the extracted fields; then codes were grouped into descriptive themes related to sensing modality, analytical method, and applied outcome; later these descriptive themes were aligned with the three research questions to produce analytical themes. Iterative re-reading of the included abstracts was used to validate theme derivation, as was cross-checking each thematic claim against the respective studies supporting it to guarantee that each synthesized statement was fully accountable to the underlying evidence. To improve the credibility of the synthesis, each analytical theme was reviewed independently by both reviewers. The resulting themes were compared and refined until consensus was reached, ensuring consistency between the extracted evidence and the final thematic interpretation.

The review was carried out following the PRISMA 2020 checklist and the process of records through identification, screening, eligibility, and inclusion is reported with numbers in the Results and shown in the PRISMA 2020 flow diagram (Page MJ et al., 2021, BMJ, 372:n71, https://doi.org/10.1136/bmj.n71). All the tabulated record totals across the Abstract, Methods, and Results are in agreement with the flow diagram, and all the included studies are listed in the descriptive tables for the sake of transparency and reproducibility.

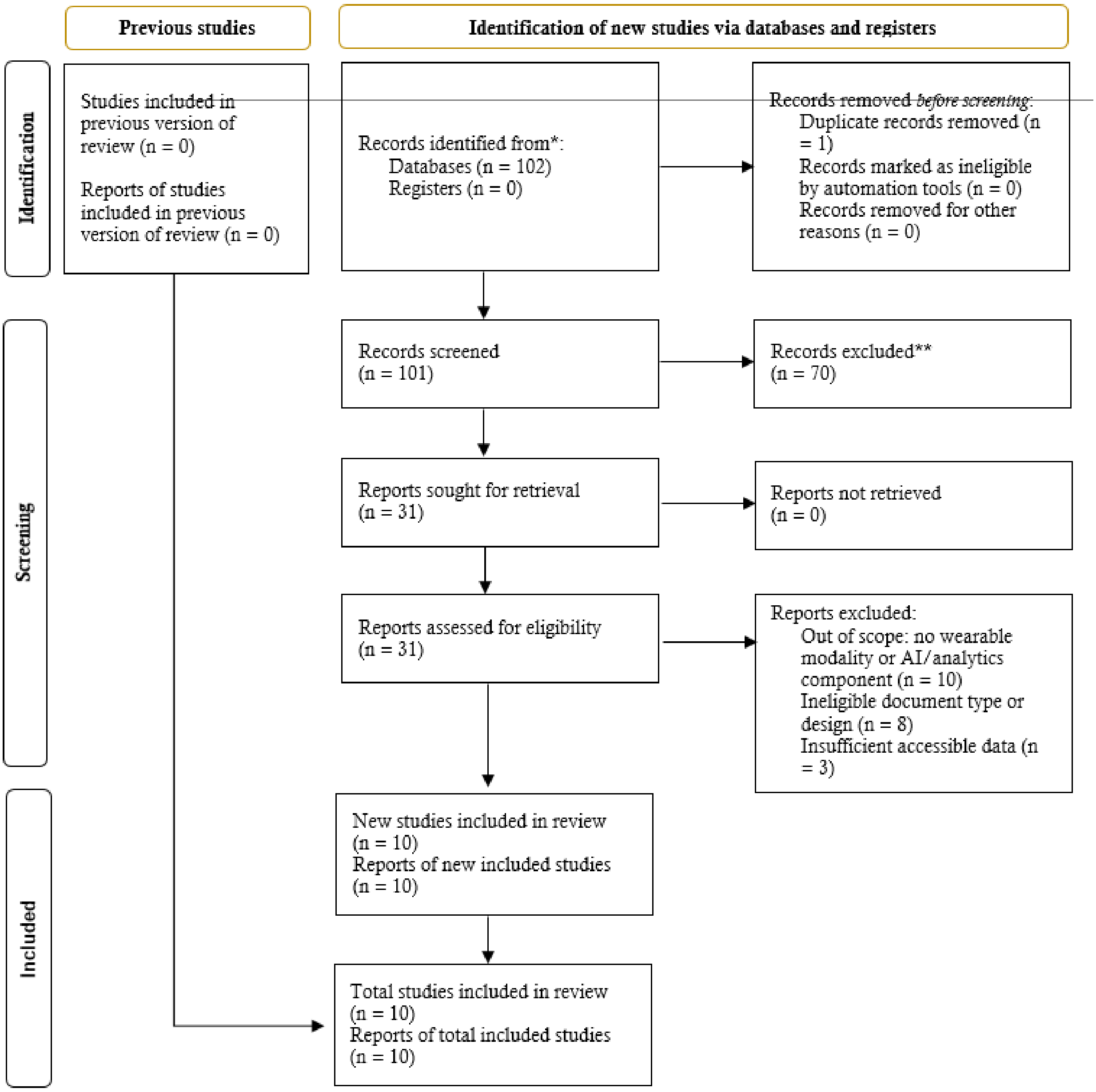

Figure 1 <PRISMA 2020 Flow Diagram of the Study-selection Process>

The diagram traces the four canonical phases of the review. In identification, 102 records were retrieved from Scopus and one duplicate was removed. In screening, 101 records underwent title-and-abstract assessment and 70 were excluded as off-topic or lacking an AI-wearable focus in volleyball. In eligibility, 31 full-text articles were assessed and 21 were excluded (10 out of scope, 8 of an ineligible type or design, and 3 with inaccessible or insufficient data). Ten studies met all criteria and entered the final qualitative synthesis. The exclusion boxes on the right report the count and rationale at each stage, and the numbers are consistent with those reported.

Results and Discussions

The Scopus search found 102 records. One duplicate was removed, so 101 unique records remained for screening. Title-and-abstract screening excluded 70 records because they were about AI-enabled wearable technology in a volleyball setting, for example, clinical cardiology, cellular biomechanics, or non-volleyball people. The 31 articles left were read in their entirety and 21 were excluded: 10 did not have a wearable device or AI/analytics component in their scope, 8 were of document types or designs that were not allowed (conference papers, reviews, book chapters, retracted items, or non-English reports), and 3 had insufficient accessible data. Ten studies met all eligibility criteria and were included in qualitative synthesis. These numbers correspond to those in Figure 1.

These 10 studies/literatures were published between 2019 and 2025 and came from 7 different countries, showing that the field is globally dispersed. Venues of engineering and computer science were the main ones, such as IEEE Access, the IEEE Sensors Journal, the IEEE Internet of Things Journal, Sensors, and Biosensors, besides sports-science journals like the European Journal of Sport Science, the International Journal of Performance Analysis in Sport, and the Journal of Strength and Conditioning Research. Table 2 presents the bibliographic and main features of each paper, while Table 3 groups the papers by design, theme, technology, and outcome.

Table 2 <Summary of the 10 Included Studies>

Title	Author(s)	Method	Key Findings
Wearable Sport Activity Classification Based on Deep CNN	Hsu et al., 2019.	Deep CNN; STFT spectrograms	Wrist+ankle IMUs with a CNN accurately classify multiple sport activities from motion spectrograms.
A super-bagging method for volleyball action recognition using wearable sensors	Haider et al., 2020.	Ensemble (super-bagging); sensor fusion	Balanced-learning ensembles improve action recognition under severe non-action/action class imbalance.
A Self-Powered Wearable Motion Sensor for Monitoring Volleyball Skill	Liu et al., 2022.	Piezoelectric (PVDF) self-powered sensor	Self-powered flexible sensor detects fine spiking gestures and supports big-sports-data pipelines.
Personalized ML approach to injury monitoring in elite volleyball players	de Leeuw et al., 2022.	Subgroup discovery; personalised ML	Individualised load/wellness indicators identify days of elevated overuse-injury risk.
Modeling Match Performance in Elite Volleyball Players	de Leeuw et al., 2022.	XGBoost; random forest; subgroup discovery	Jump load and strength-training characteristics relate to attack and pass performance.
Validation of Internal and External Load Metrics in NCAA D1 Women's Beach Volleyball	Tometz et al., 2022.	GPS, HR, sRPE/TRIMP validation	Beach-specific internal/external load metrics are validated against environmental conditions.
Phase-Based Quantification of Sports Performance Metrics Using a Smart IoT Sensor	Chen et al., 2023.	IoT wristband; phase-based feature selection	Serve motion phases are segmented and skill level classified from a single smart wristband.
A Seq-to-Seq Temporal Convolutional Network for Volleyball Jump Monitoring	Shang et al., 2025.	Multi-stage TCN; seq-to-seq	A single waist IMU differentiates jump types without sliding windows, outperforming baselines.

Title	Author(s)	Method	Key Findings
Influence of wearable biometric sensors on performance indicators of volleyball players	Jia, 2025.	KNN and LDA; multi-IMU network	A wearable-sensor network automates detection of digs and blocks, replacing manual notation.
Associations between internal/external load and match outcomes in men's volleyball	Lima et al., 2025.	Machine-learning association modelling	Internal and external load parameters carry associative value for competitive match success.

The table consolidates each study's bibliographic identity and substantive contribution, drawn directly from the Scopus records. Reading across the rows reveals a field anchored in inertial sensing and supervised learning: five studies centre on recognition tasks (activity, action, skill, jump, dig/block), three on load and its consequences for injury or performance, one on beach-specific load validation, and one on match-outcome association. The chronological spread (2019–2025) and the predominance of engineering venues illustrate that volleyball wearable-AI research has matured most rapidly within the sensing and computing communities.

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

Author(s)	Country	Research Design	Theme/Focus	Technology	Outcome
Hsu et al., 2019.	Taiwan	Experimental (lab)	Activity recognition	Dual IMU + CNN	High multi-class accuracy
Haider et al., 2020.	UK	Experimental (field)	Action recognition	IMU fusion + ensemble	Improved imbalanced recall
Liu et al., 2022.	China	Device development	Skill/technique	Self-powered PVDF sensor	Spike-gesture detection
de Leeuw et al., 2022.	Netherlands	Retrospective cohort	Injury monitoring	Wearable jump load + ML	Risk-day identification
de Leeuw et al., 2022.	Belgium	Observational	Performance modelling	Wearable load + XGBoost	Attack/pass predictors
Tometz et al., 2022.	USA	Validation	Load (beach)	GPS/HR/sRPE	Validated beach load metrics
Chen et al., 2023.	Taiwan	Experimental	Skill assessment	IoT wristband IMU	Skill-level classification
Shang et al., 2025.	Belgium	Experimental (lab+field)	Jump monitoring	Waist IMU + TCN	Jump-type differentiation
Jia, 2025.	China	Experimental	Action recognition	Multi-IMU + KNN/LDA	Automated event detection
Lima et al., 2025.	Portugal	Observational cohort	Load–performance	Load metrics + ML	Match-outcome association

The classification exposes the methodological texture of the corpus. Experimental and observational designs dominate, with only a single explicit validation study and one device-development paper, signalling that the field has prioritised demonstrating feasibility over establishing measurement validity. Thematically, recognition and load applications are well represented, whereas injury monitoring rests on a small number of cohorts. Critically, only one study (No. 6) is set in the beach environment, and it addresses load validation rather than AI-based recognition, visually confirming the indoor-to-beach evidence gap that motivates RQ3.

The chart plots the number of Scopus records per year from 2011 to 2026, with the 2018–2025 review window highlighted. Output is sparse before 2018, rises through 2020–2021, and peaks in 2022 and again across 2024–2025, with a sizeable cluster of 2026 in-press items excluded from synthesis. The trajectory substantiates the review's timeliness: roughly four-fifths of all records appear in or after 2020, indicating that AI-enabled wearable research in volleyball is a recent and rapidly intensifying field.

China and the United States lead by a wide margin, followed by a cluster of European contributors (Italy, Belgium, Portugal, Poland) and emerging activity from Iran, Canada, Brazil, and Taiwan. The concentration of output in engineering-strong economies aligns with the field's sensing-and-computing orientation, while the breadth of contributing nations underscores its global relevance. The distribution also helps explain why beach-specific evidence is scarce: leading contributors are not predominantly beach-volleyball nations.

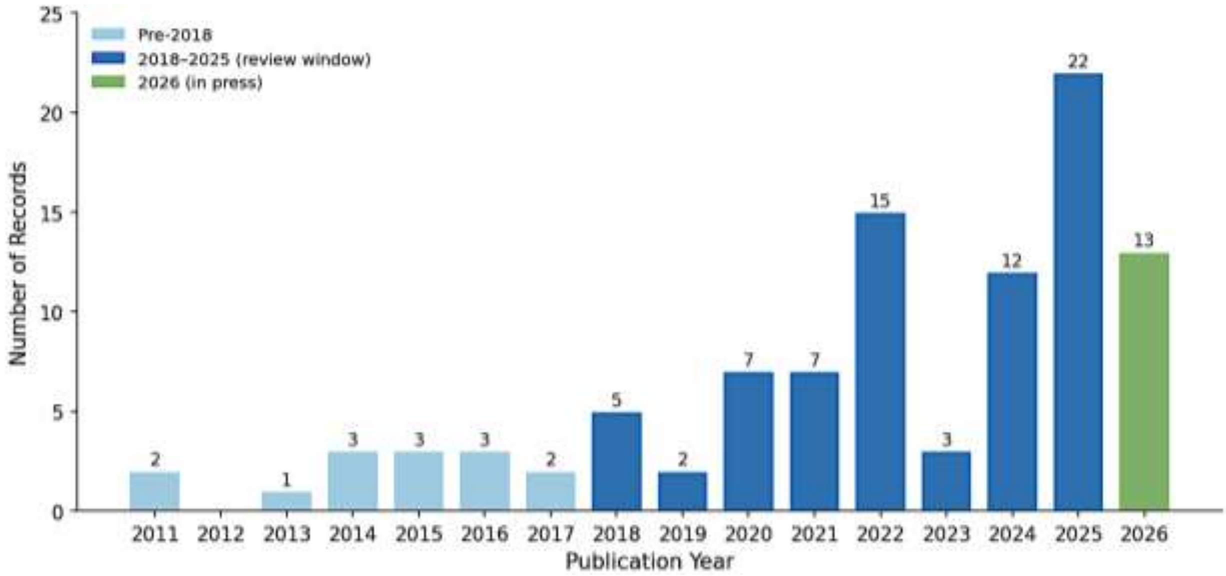

Figure 2 <Annual Publication Trend Across the Full Identified Corpus (N = 102)>

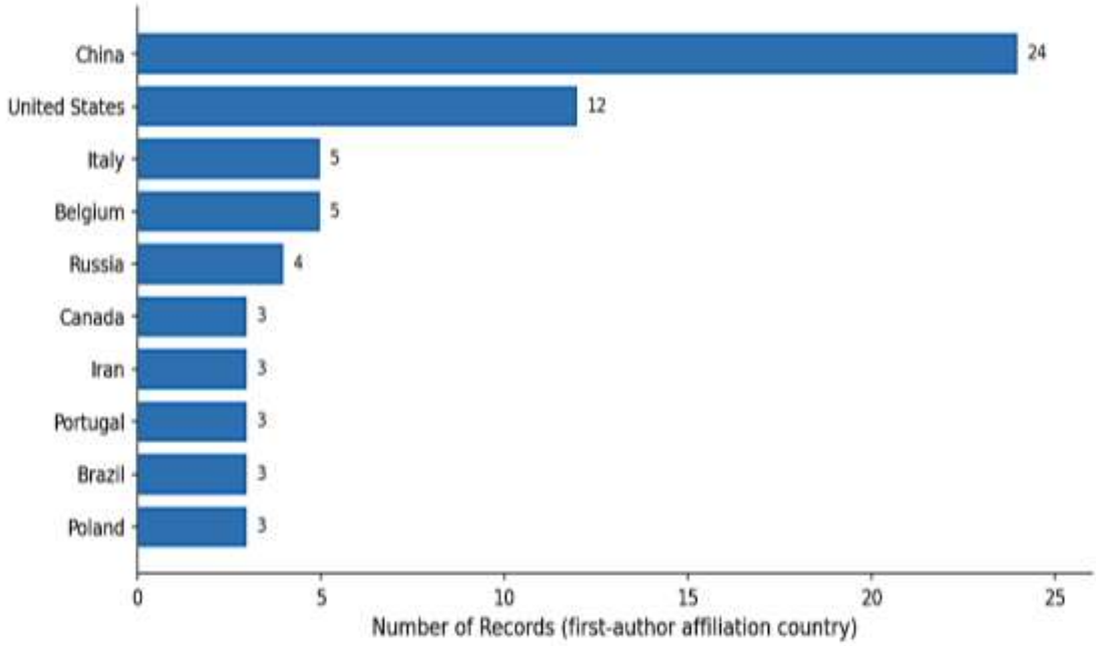

Figure 3 <Geographic Distribution of the Top 10 Contributing Countries (First-Author Affiliation; N = 102)>

China and the United States lead by a wide margin, followed by a cluster of European contributors (Italy, Belgium, Portugal, Poland) and emerging activity from Iran, Canada, Brazil, and Taiwan. The concentration of output in engineering-strong economies aligns with the field's sensing-and-computing orientation, while the breadth of contributing nations underscores its global relevance. The distribution also helps explain why beach-specific evidence is scarce: leading contributors are not predominantly beach-volleyball nations.

The hardware considered in the studies is that most commonly used by the volleyball players for measurement of specific physical activities with the sensors being worn on different body parts of the player such as wrists, waist and limbs and their data being analyzed via supervised learning. Hsu et al. (2019) shows that wrist and ankle-mounted IMU's which when converted into short-time Fourier spectrograms can be classified with the help of convolutional neural network which has proved to be highly accurate in classifying heterogeneous sport activities and thereby provide a template which has been adopted by the volleyball-specific work thereafter. Haider et al. (2020) have contributed further by pointing out the fact that most part of the match footage is made of non-action periods and at the same time, have suggested that ensemble "super-bagging" and sensor fusion can really enhance the recognition of actions even when the dataset is heavily unbalanced. So, both these works together help in answering the first half of RQ1: the modality is inertial, and the analytical engine is deep or ensemble learning.

Recognition validity may be a range from very general activity classes to finely detailed, sport-specific movements. Chen et al. (2023) identified the different stages of a serve and, using data from a smart IoT wristband, were able to judge the player's level of skill, meanwhile, Shang et al. (2025) applied a multi-stage temporal convolutional network to the data from a waist-worn IMU to tell different jump types apart and got rid of the sliding-window based manual heuristics that were causing the degradation of boundary detection. Jia (2025) has even stepped into this area by building a multi-sensor network combined with K-nearest-neighbour and linear-discriminant classifiers to carry out digs and blocks detections automatically thus replacing manual statistical notations. Their going for single- or few-sensor setups with working classifiers that can be deployed to coach-usable, unobtrusive systems is a conscious decision and it is greatly supported by the level of innovation in the devices such as Liu et al. (2022) self-powered piezoelectric spike sensor.

Reported validity is generally high but unevenly substantiated. Many studies put forth strong in-sample knowledge accuracy only to be based on small, single-session protocols, a pattern also seen in related edge-deployment research on real-time jump recognition (Magnifouet Zefack & Rocheteau, 2025), wearable-inertial detection of sport-specific jumps (Panni et al., 2025), and on-device height estimation (Xu et al., 2025). Machine-learning movement classification with linear discriminant analysis has also been shown operating in near-real time (Kotteda et al., 2025), and neural-network models have been used in biomechanics (Alawadi & ALjamaly, 2024). Hence, the solution to RQ1 is a bit complicated: a well-developed set of IMU-plus-learning systems identify volleyball activities, jumps, and skills with high reported accuracy, but external validation across athletes, sessions, and surfaces is such a rare case that it is hardly the rule (Sun et al., 2021; Dai & Li, 2021).

Various types of wearable-based load measurements, most importantly jump count and intensity, constitute the major supporting structure for inspiring a-ha moments. To begin with, Skazalski et al. (2018) came up with a well-validated and fairly durable method to measure jump-specific training and competition load in elite-level volleyball, thus setting the main metric on which subsequent modelings rely. Referring to such load information, de Leeuw et al. (2022a) carried out a personally tailored subgroup-discovery technique that located, for each athlete, the load and wellness factors leading to a high risk of overuse injury, proving that individualisation really does go beyond simply generic thresholds. Personalized perspective in this way completely answer a long-standing challenge to that population-level load rules disregard between-athlete heterogeneity.

According to the above research programme, it was found that wearable load affects the competitive output of athletes. de Leeuw et al. (2022b) used gradient boosting, random forests, and subgroup discovery techniques to understand match performance, and they identified lower-body strength-training features and jump-load patterns to be associated with attack and pass quality. Moreover, Lima et al. (2025) found both internal and external load factors, when analysed via machine learning, are indicators of match success in men's volleyball. Besides that, Gielen et al. (2022) investigated the correlations between continuously measured internal and external loads during competition. All these findings point to the fact that wearable load is not only used as a safety measure but also a performance indicator, thus the answer to both RQ2 for injury and performance domains lies in affirmative, however, the studies were carried out with small sample sizes.

However, a critical appraisal puts a fence around these conclusions. Most of the predictive studies use retrospective or single-team cohorts, report only internal validation, and hardly ever quantify calibration or external transportability, which restrains their readiness for deployment in injury-critical situations (Rebelo et al., 2023). Beach-specific load is quite different from indoor load, since Tometz et al. (2022) demonstrate that the environment significantly determines the internal and external metrics of NCAA Division I women's beach volleyball. Complementary instrumentation such as countermovement-jump force metrics (Sanders et al., 2025), semi-automated three-dimensional load reconstruction (Hostyn et al., 2024), and pre-season wearable prediction of season performance (Ozolcer et al., 2025) add to the tools but still do not address the generalisability issue. In answer to RQ2, wearable-AI load models are highly potential and internally trustworthy, but the demonstration of their predictive validity for injury and performance through multi-cohort, externally validated studies is still to come.

The results highlight a strong imbalance between the evidence for indoor and beach settings. Out of the total number of studies, only Tometz et al. (2022) who validated the load measurement for beach-specific use in the sand environment is actually a sand study, and it purposely deals with measurement validity rather than AI-based recognition. All recognition and modelling studies (activity classification, jump monitoring, skill assessment, and injury prediction) were developed indoors, where the hard surface, controlled climate, and the six-player tactical structure are different from the beach. Since sand changes landing mechanics and groundreaction force patterns, the external validity of indoor-trained models for beach volleyball should not be taken for granted, and the current evidence does not support it.

Several lines of work next to each other offer possible transfer paths while also highlighting the gap. Lower-limb biomechanical determinants of jump performance (Deng et al., 2025), the kinetics of the jump serve (Liu et al., 2025), and groundreaction determinants of spike-jump height (Dong et al., 2024) are all very sensitive to the surface and would need beach-specific recalibration, as would center-of-pressure and landing analyses developed on stable surfaces (Darvishi et al., 2025). Two-dimensional video and musculoskeletal-modelling approaches to knee-valgus and anterior-shear estimation (Erdman et al., 2024), and pose- and stability-based inference from exercise video (Alves et al., 2025), provide different, marker-light ways that might be validated on the sand. The range of volleyball-technology activity lately, from AI teaching assistants (Liu & Hang, 2024) and video-description systems (Zhang, 2021) to glove-based prototypes (Ferrara et al., 2018) and even going to innovation surveys at large (Nagorna et al., 2024), is a sign of continuing excitement but not on-the-beach validation.

The next set of research objectives, therefore, naturally stems from the data. The main focus should be on obtaining data specific to beach volleyball and using it for the model recalibration, on the multimodal sensor fusion which combines inertial, positional, and physiological data streams, and on the modelling that is transparent, externally validated, and has calibration and feature interpretability being reported. Considering the ecological factors that coordinate with the beach load such as fatigue dynamics (Pawlik & Mroczek, 2022), heart-rate-variability responses (Liao & Li, 2022), recovery interventions (Bian, 2025), sensorimotor and perceptual-cognitive determinants (Gorelik et al., 2018; Shlonska et al., 2025; Zwierko et al., 2022; Kanatschnig et al., 2025), postural balance and sway modelling (Bendo & Brovina, 2024), eligibility- and competition-related response profiles (Edmonds et al., 2021), physical-training system design (Shang et al., 2024), maturation and morphology (Almeida-Neto et al., 2020; Koźlenia et al., 2024), and protective, rehabilitative, or footwear interventions (Lam et al., 2018; George et al., 2025; Parsa et al., 2025), would help to position wearable AI in a complete athlete model. So, the response to RQ3 is that the transfer to beach volleyball is not yet confirmed, and the process of closing that gap constitutes the most important next step of the field.

Comparing methodological approaches across the corpus reveals a clear dominant paradigm-body-worn inertial sensing analysed with supervised machine learning-and several underused alternatives. Deep architectures (convolutional and temporal convolutional networks) and tree ensembles (XGBoost, random forests) appear frequently in recognition and prediction tasks, whereas probabilistic, Bayesian, and explicitly interpretable models are relatively scarce. Validation designs are similarly imbalanced: experimental feasibility studies are the most common, formal measurement-validation studies are the least common, and external or multi-site validation is almost non-existent. Over time, the field has been moving from offline activity classification to real-time, edge-deployed inference and from population thresholds to personalised modelling, reflecting general trends in wearable analytics. The methodological evolution is real, but the way it has gone has, in fact, favoured showing something new over the slower work of validation and reproducibility, a tension that is repeated in engineering-led sports-technology literatures (Hostyn et al., 2024; Erdman et al., 2024).

The synthesis suggests that AI-powered wearable devices have the ability to identify the specific actions of volleyball players, measure their physical exertion, and connect these to the risk of injury and performance in the game. However, most of these things were done in indoor locations and on small groups, which is an area of weakness. Hence, the findings imply that the recognition and association problems have been basically resolved by the field, but the validation and transfer problems still remain largely unaddressed.

Theoretically, these findings can also be seen as extending athlete-monitoring frameworks by recognizing the wearable signal not only as a performance variable, but also concurrently as a safety variable, thus disputing the traditional division of load monitoring from performance analysis (de Leeuw et al., 2022b; Lima et al., 2025). Furthermore, they emphasise individualisation, which in turn supports a move away from population norms towards personalised, athlete-specific models (de Leeuw et al., 2022a).

Practitioners and coaches can use the synthesis as a practical checklist: confirmed jump-load quantification is a basis for continuous load control (Skazalski et al., 2018; Gielen et al., 2022), single-IMU devices allow monitoring of jumping and actions without heavy instrumentation (Shang et al., 2025; Jia, 2025), and there are load indices for the beach but they have to be used with the awareness of environmental factors (Tometz et al., 2022).

Compared to previous scoping studies on wearables and biomechanics for injury prevention in sports in general (Rebelo et al., 2023), this review is more focused on sport but much deeper in its beach volleyball perspective, and it highlights the indoor-to-beach transfer issue that broader reviews tend to overlook.

Apparent contradictions, i.e., high accuracies reported together with warnings about generalisability, can be best explained by the difference in validation rigour and not by opposing effects. Studies that only validate internally report a much higher performance level than those that simulate external conditions (Magnifouet Zefack & Rocheteau, 2025; Xu et al., 2025).

At least three gaps are clearly visible: (1) there is hardly any beach-specific AI validation; (2) small, single-session, internally validated datasets that are incomparable to each other are used; and (3) only very few models are transparent and calibrated in a way that they can be used for injury-critical situations.

This review is limited because it relied on a single database (Scopus only, without backward-citation searching), was restricted to English-language journal articles which may exclude relevant conference and non-English papers, and depended on abstract-level extraction for some descriptors, thus limiting the detail of the quality appraisal.

Here are three detailed recommendations: first, carry out prospective beach-volleyball studies involving multiple teams with on-sand inertial and positional data collection; second, develop and publish externally validated, calibrated models with interpretable features which are suitable for injury decisions; third, by using multimodal sensor fusion combining inertial, positional, and physiological signals, create a single athlete-monitoring model.

In summary, In response to RQ1, a mature IMU-plus-learning toolkit with high but unevenly validated recognition accuracy is presented; RQ2 is met by promising, internally credible but externally unconfirmed load-based injury and performance models; and RQ3 is answered by the fact that transfer to beach volleyball is still unproven, and so beach-specific validation should be the priority of the field.

Conclusions.

By analysing and synthesising the findings of ten primary research studies on AI-enabled wearable technologies in volleyball, the authors aim to identify which aspects have been proven and which are still only speculated. To answer the first research question, it was found that deep and ensemble learning that analyse the data from inertial measurement units can distinguish volleyball activities, jumps, and skills with very high reported accuracy, often using only one single sensor that is not inconvenient for the player and which can therefore be more easily used in practice. To answer the second research question, by using wearable-derived load e.g. jump load one can forecast the overuse-injury risk and that is also related to the player's performance in the match when one uses the personalized and gradient-boosted machine learning algorithms, but the very limited number of subjects supporting such claim have mostly been validated internally. To answer the third question, the findings apply to beach volleyball rather weakly: practically all of the recognition and modelling are performed indoors, and the only beach-specific contribution is the one that validates the load metrics as opposed to AI recognition, thus the model performance on sand remains untested. This review's main result is the first beach-oriented ecosystem of this interdisciplinary field, splitting demonstrated capability from assumed transferability. In practical terms, it equips coaches with a well-organized summary of confirmed monitoring options and the delineation of their limits, thereby facilitating data-driven adoption rather than mere uncritical excitement. The review is limited by a single-database, English-language, journal-only design and abstract-level extraction. Nevertheless, this synthesis reveals that the decisive next step is a rigorous, prospective, externally validated study in the beach setting, preferably using multimodal sensor fusion, so that the potential of intelligent wearables can be realised in the place where the sand, the climate, and the two-player game differ the most from the indoor court.

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