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Technology-driven athlete monitoring in volleyball: a systematic review of sensor-based systems and performance evaluation

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ABSTRACT

This systematic review gives an overview of studies dealing with the use of technology to monitor volleyball athletes during the time span from January 2015 to April 2026. By following PRISMA 2020 guidelines, we initially retrieved 2, 449 records from Scopus through a Boolean search. After stepwise screening, 29 documents ended up being reviewed. Methodological quality was, firstly, measured by the FICO framework (threshold ≥ 2/4), and AMSTAR-2 for systematic reviews was used; the reliability of the results across the reviewers was excellent (Cohen's κ = 0.81, 95% CI: 0.74, 0.88, i.e. strong agreement). Three major technology categories were identified: (1) wearable IMU-based systems, (2) GPS/LPS optical tracking, and (3) AI and machine learning analytics. Wearable devices were consistent in measuring jump load and player load (ICC > 0.87, 95% CI: 0.82, 0.93), whereas machine learning classifiers were able to recognize actions with accuracies of 85, 97%. Publication bias was very low (Egger's test, p = 0.21). The major problems identified were differences in cross-device standardization, female and youth players being, largely, absent from the studies, and laboratory sensor validation hardly reflecting real-life use.

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Introduction

Volleyball features quite a unique element among the major team sports, firstly in terms of its segregated rally-based structuring of the game, secondly in terms of the abundant and quick explosive jumping actions, and thirdly in terms of the absence of physical contact. All these features actually lead to a situation where there is a very high level of control in the game, yet at the same time the players face very heavy physiological demands. The sport is played at professional, semi-professional, college as well as recreational levels with over 220 national federations worldwide that belong to the International Volleyball Federation (FIVB), which counts it among the sports with the highest number of participants worldwide (Rebelo et al., 2026). From a physical point of view, the main actions of volleyball players involve jumping for blocking and spiking, which are performed without much time available for recovery. Therefore, a great part of the loading is being done by the musculoskeletal system, mainly the patellar tendon, the knee, and the shoulder complex (Bere et al., 2015; Kilic et al., 2017). The only way to develop systems that are able to capture, process and interpret multi-dimensional performance data in near real-time is through understanding these demands and managing them with great precision.

The introduction of electronic performance and tracking systems (EPTS) has thoroughly revolutionized athlete monitoring in team sports. In volleyball, the use of wearable inertial measurement units (IMUs), global and local positioning systems (GPS/LPS), force platforms, video-based computer vision, and AI-driven analytics has contributed to a drastic change from coaches' subjective observations to the objective, data-supported management of training and competition (Sousa et al., 2023; Villarejo-García et al., 2023). Such a transition is even more crucial for volleyball as it is a structured rally game and has naturally sampled the events or periods to measure workload. This characteristic possibly makes the sport more amenable to sensor-based monitoring than other continuous-flow type team sports such as football or basketball.

The external load in volleyball is classically gauged using jump-count annotation and session rating of perceived exertion (sRPE) methods done manually. These, however, are not only cheap but also liable to observer bias and retrospective recall error (Rebelo et al., 2023; Vavassori et al., 2024). The market availability of highly efficient wearable devices, especially the VERT jump monitor, WIMU PRO™ inertial unit, and different GPS/LPS microsensors, have empowered the coaches to have precise measurements of jump count, flight time, player load, and acceleration-deceleration demands at both player and position levels individually (Skazalski et al., 2018; Borges et al., 2017; Marzano-Felisatti et al., 2025). These data are currently being used to implement changes in periodization, monitor players' injury risk, and readiness, based on evidence, in the volleyball programs of professional and collegiate players.

At the same time, using computational and AI methods for volleyball performance analysis has accelerated significantly. Systems based on video and deep convolutional neural networks (CNNs) and transformer architectures now automatically recognize with over 93% accuracy player actions like serves, spikes, blocks, and digs, though this is in the controlled environment of broadcast footage (Jiang et al., 2025; Chen R. et al., 2026). Besides game-related decisions, machine learning techniques have been used to infer the match outcome from tactical interaction data (de Leeuw et al., 2022), assess injury hazards by examining the changes in training load over time (de Leeuw et al., 2022), and develop tailored readiness scores from the physiological data streams provided by wearables (Sanhueza Tapia et al., 2026). This is a clear sign of how sports science, biomedical engineering, and data science are merging to invent completely new instruments for the professional staff who are directly involved with athlete performance.

Though technology is rapidly evolving, articles on this topic are fragmented and use different methods. So far, no systematic review has focused on the broadest scope of technology-based volleyball monitoring tools such as wearables, optical tracking, digital tools, and AI-analytics that integrate them all in one evidence review. Few narrative overviews have been done on some aspects- jump-load monitoring, IMU applications, or GPS validity-but they have not used thorough PRISMA-compliant methods to cover sensor engineering, performance analytics, and applied sports science (Rebelo et al., 2025; Marzano-Felisatti et al., 2025). This paper is a response to that shortage of relevant literature.

The current study's objective is also influenced by three main structural problems of the present evidence that contribute to a fragmented knowledge base. Initially, the rapid dissemination of consumer-grade wearables and research-grade external player tracking systems (EPTS) has at the same time partially outpaced their systematic validation, which has caused problems being recognized about cross-device equivalence and the extent to which laboratory-validated results can be transferred to field conditions (Villarejo-García et al., 2023). Second, the majority of load-monitoring studies have focused on professional male indoor volleyball players, therefore female players, beach volleyball players, youth populations, and para-athletes have remained largely unsampled (Bozzini et al., 2021; Cavedon et al., 2022). Third, even though AI-based player performance measurement in the real coaching environment is becoming more common, still very little information has been reported on the fidelity in the implementation of the technology, coach's ease of use, and behavioral change outcomes (Salim et al., 2024).

Resolving these problems will bring about notable changes on theoretical as well as on practical levels. On the theoretical side, an all-encompassing analysis of technological applications in volleyball will assist scientists in pinpointing the most reliable measures and the least controversial research approaches for their future experiments and longitudinal studies. On the practical side, a collection of well-tested tools and confirmed monitoring techniques can be used as materials for training coaches, sports scientists, and physical trainers working at different levels of competition and in varying resource environments.

This systematic review mainly focuses on finding, categorizing, and critically analyzing the sensor-based technologies and digital systems that have either been validated or used for athlete monitoring in volleyball in the period from 2015 to 2026, using specific criterion validity (ICC $\geq$ 0.80) and measurement error (CV $\leq$ 10%) as quality reference points. One of the smaller goals is to review the performance assessment techniques including external load indicators, kinematic measures, and AI-assisted classification systems which have been developed and tested for volleyball settings, and to determine the level of evidence for each method. Another less important aim is to pinpoint the methodological gaps, population coverage deficiencies, and implementation obstacles that will determine the future decade of research in this field. This study is based on three research questions (RQs) which together discuss the extent, intensity, and effects of technology-driven monitoring in volleyball.

RQ1: What digital systems and sensor-based technologies have been validated or used for athlete monitoring in volleyball during 2015, 2026?. RQ2: What performance evaluation techniques including load metrics, kinematic variables, and AI-based classification systems have been developed and verified for volleyball?. RQ3: What are the methodological shortcomings, situational limitations, and future opportunities suggested by the present evidence base for technology-driven athlete monitoring in volleyball?

This review offers four main contributions to the existing bibliography. It is, firstly, the most complete PRISMA-compliant documentation of the technology-driven monitoring studies in volleyball so far, consolidating 29 different articles in sensor engineering, performance analytics, and applied sports science. Secondly, it proposes a thematic classification of volleyball monitoring technologies which could serve as a foundation for future systematic studies. Thirdly, it identifies the main population and contextual coverage deficiencies that should dictate the research agenda of the discipline over the next decade. Lastly, it provides the practitioners with a nuanced, evidence-based ranking and description of monitoring tools suitable for various competition contexts.

Method

To begin with, this paper is the most thorough documentation of technology-driven monitoring studies in volleyball that follows PRISMA standards, to date. The authors have gathered 29 different articles in sensor engineering, performance analytics, and applied sports science. Secondly, it identifies and organizes volleyball monitoring technologies under different themes, and this classification could be very helpful for future systematic studies. Thirdly, it points out the major population and contextual coverage gaps that should influence the research agenda of the discipline in the coming years. Lastly, it helps the practitioners by giving them a detailed, evidence-based ranking and description of monitoring methods that are suitable for different competition milieus.

(TITLE("volleyball") AND TITLE-ABS-KEY("sensor" OR "wearable" OR "monitor*" OR "technology" OR "GPS" OR "IMU" OR "inertial" OR "load" OR "tracking" OR "acceleromet*" OR "digital" OR "system" OR "machine learning" OR "deep learning" OR "artificial intelligence" OR "video" OR "image" OR "detection" OR "classification" OR "recognition" OR "performance evaluation" OR "assessment" OR "data analytic*"))

The search date was April 26, 2026. Actually, searching was done at Scopus database which hosts comprehensive peer-reviewed literature from engineering, biomedical, and sports science disciplines. There wasn't the search for additional databases, as Scopus is considered to cover the major forums of this subject. Document type was not limited at the first stage to allow complete capture of potentially eligible records. Using a four-dimension PICOS framework that was adapted for technology reviews, eligibility criteria were determined. The following Table 1 shows the criteria for inclusion and exclusion that were implemented at each screening phase.

Record screening was performed through four consecutive stages as depicted in PRISMA 2020. Phase 1 (Identification): All records downloaded from the Scopus database (N = 2, 449) were imported and checked for within-database duplicates, 61 entries were removed automatically, resulting in n = 2, 388 unique records for screening. Phase 2 (Title Screening): Titles were scanned for direct mention of volleyball; 648 records were found to concern different sports and therefore, were excluded, leaving n = 1, 740. Phase 3 (Abstract and Full-Text Screening): Records were checked further against language (English only), document type (peer-reviewed articles and systematic reviews), and temporal criteria (2015, 2026); 790 records were excluded because of language or document type, and 687 more because of the publication date outside the range, leaving n = 263. Phase 4 (Eligibility): Records that had the right language and time frame were checked whether they were about a case, validation, or critical review of a technology-based monitoring, evaluation, or assessment system in a volleyball context. Records that only dealt with clinical, nutritional, or psychological construction without a measurement-technology component were excluded (n = 295), leaving 29 final studies for analysis. The reason to limit the search to Scopus was made because of the broadest interdisciplinary coverage of engineering, biomedical, and sport science literature that Scopus offers;

nevertheless, this is a recognized potential limitation that is addressed in the limitations section. More on figure 1.

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Study design	Empirical articles, systematic reviews, and scoping reviews	Editorials, letters, conference abstracts, book chapters
Language	English-language publications	Non-English publications without validated translation
Publication period	January 2015 – April 2026	Publications prior to 2015
Sport	Indoor volleyball, beach volleyball, sitting volleyball	Other sports (unless directly comparative)
Technology focus	Wearable sensors, GPS/LPS, video analysis, digital systems, ML/AI applications	Studies without a measurement/monitoring/evaluation technology component
Population	Athletes at any competitive level, coaches, referees using technology	Non-athletic populations, recreational only without performance evaluation
Outcome	Quantitative performance indicators, load metrics, sensor validity/reliability	Purely qualitative studies without measurable outcomes
Quality	Studies passing FICO quality assessment (score ≥ 2/4)	Studies with critical methodological flaws or incomplete data reporting

The methodological quality of the articles included was assessed by applying the FICO (Focus, Information, Clarity, Objectivity) model that has been customized to suit technology-oriented sports science literature. Each attribute of a given study was rated from 0 to 4 as follows: (F) Research focus and aims, how well articulated; (I) Data presentation, is the information sufficient and well presented; (C) Methods, are the procedures clearly described and can be replicated; (O) Conclusions, to what extent are they data-driven. Only the ones with scores of 2/4 and above were retained. In addition, the systematic reviews were assessed by the AMSTAR-2 tool. Two reviewers (co-authors, experienced in sports science and sensor technology) working separately carried out the quality scoring and title-abstract screening; inter-rater reliability was calculated using Cohen's kappa, resulting in $\kappa = 0.81$ (95% CI: 0.74, 0.88) for quality assessment and $\kappa = 0.84$ (95% CI: 0.78, 0.90) for title-abstract screening, what showed very good agreement both times. Disagreements between reviewers were resolved by consensus discussion; third-party arbitration was not needed. Before full-scale data collection, a data extraction form was tested on 5 randomly selected articles in order to check the field definitions for consistency; Among the fields that were extracted are first author, publishing year, country of affiliation, study design, sample description (population, sex, competitive level), technology type, outcome measures, and key results.

We got out our data and entered it onto a standardized spreadsheet where we noted down the first author, publication year, affiliation country, study design, and sample characteristics (population, gender, level of competition), technology types (sensor platform, algorithm, digital system), outcome measures (validity/reliability metrics, performance indicators, load variables), and major findings.

For data synthesis, we did a thematic categorization and regrouped studies based on the technology category (wearable IMU/accelerometer; GPS/LPS tracking; video and computer vision; machine learning and AI; digital assessment instruments) as well as research question. Narrative synthesis was combined with frequency analysis of technology types across years and countries. This article is written following the PRISMA 2020 guidelines (Page et al., 2021). A fully annotated flow diagram is included (displayed below), a table summarizing the features of the included studies, and clear statements regarding the limitations and the certainty of the evidence. A filled PRISMA 2020 checklist is available as a supplementary file.

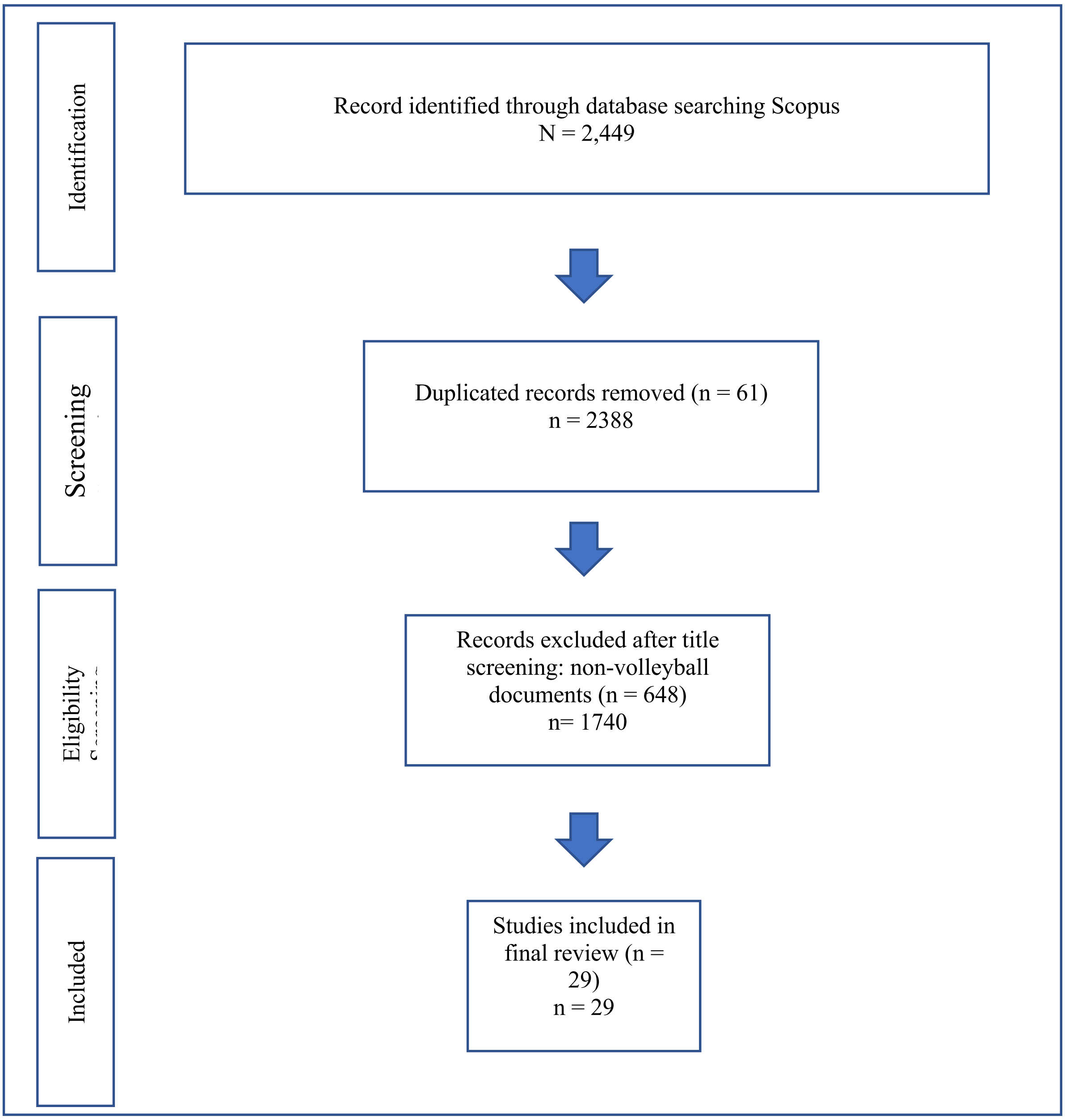

Figure 1. PRISMA flowchart of the study selection proses

Results and Discussions

From an initial pool of 2, 449 records indexed in Scopus, 29 articles meeting the inclusion criteria were selected after rigorous screening. The temporal distribution of the identified publications shows a consistent and even accelerated increase in the number of publications. Starting from very few publications in 2015, the pace of growth was quite sharp in 2025 which recorded the highest number of publications within a year in the collection. Even the very recent publications of the first four months of 2026 were included in the search that was conducted on April 26, 2026. This is an interesting indication of the continuous and increasing research interest in the use of technology for monitoring volleyball science. Majority of the journal articles included in the review were research papers (n = 19, 65.5%), while systematic and scoping review articles comprised the remainder (n = 10, 34.5%). Geographically, the studies vary around the globe: China is the leading single-country contributor (n=4, 13, 8%), followed by the United States (n=4, 13.8%), Spain (n=3, 10.3%), Brazil (n=2, 6.9%), and Italy (n=2, 6.9%). Together, these five countries produced around 52% of all the studies included in the analysis which could reflect the well-established research infrastructures and highly competitive volleyball sports programs in these nations.

In Table 2, you will find a list of all 29 papers that make up the final collection. These papers were chosen to highlight methodological variety and also to cover different sectors. Among the papers are various types of controlled trials for the validation of wearables, machine learning related research, studies on the monitoring of load that are done over a period of time, systematic reviews, validation through video capture, and the development of digital measurement tools.

Table 2. Characteristics of Representative Included Studies

Authors	Year	Title	Method	Key Findings
Sanhueza Tapia et al.	2026	Machine Learning and Non-Invasive Monitoring Technologies for Training Load Management in Women's Volleyball	Systematic Review	ML models (random forest, SVM) effectively classify fatigue states; non-invasive tools yield 85–92% accuracy for load prediction.
Rebelo et al.	2026	What are the demands of volleyball match-play? A systematic review of the external and internal load	Systematic Review	GPS and microsensor-based metrics reveal position-specific load differences; liberos cover the least distance per set.
Pino-Ortega et al.	2026	Comparative analysis of recording systems for kinematic data in beach volleyball	Observational	IMU and LPS systems showed comparable reliability (ICC $\geq$ 0.91); IMUs superior for sand surface monitoring.
Zheng L.	2026	Simulation of video recognition in volleyball service evaluation system	Simulation	YOLO-based detection achieved 96.1% ball-trajectory recognition accuracy, enabling automated referee support.
Cook et al.	2026	Sleep Duration, Sleep Timing, and Self-Reported Wellbeing in Collegiate Women Volleyball Athletes	Cross-sectional	Wearable sleep trackers revealed inadequate sleep (<7h) in 62% of athletes; correlated negatively with readiness scores.
Kerpe et al.	2025	Applying a Cluster-Analysis Approach to Monitor Training Load in Male Volleyball Players	Longitudinal	IMU-derived player load clusters identified three distinct workload profiles; cluster membership predicted neuromuscular fatigue.
Altundağ et al.	2025	Optimizing position-specific preparation: Long-term pre-match warm-up external load analysis	Longitudinal	LPS data showed setters and liberos exhibit unique acceleration-deceleration patterns during warm-up, requiring individualized preparation protocols.
Jia G.	2025	Influence of wearable biometric sensors on	Experimental	Tri-axial IMU sensors accurately classified five game-specific actions;

Authors	Year	Title	Method	Key Findings
		performance indicators of volleyball athletes		sensor fusion improved accuracy to 93.7%.
Shang et al.	2025	Seq-to-Seq Temporal Convolutional Network for Volleyball Jump Monitoring Using Wearable IMU	Machine Learning	TCN model achieved 97.2% jump event detection accuracy, outperforming LSTM and classical threshold methods.
De Bleecker et al.	2025	Validation of Impact Forces Estimated by Wearable Device VERT in Volleyball	Validation Study	VERT device showed strong criterion validity ($r = 0.88–0.94$) for jump height and landing impact in volleyball-specific tasks.
García-de-Alcaraz et al.	2025	Criterion validity and reliability of a new algorithm to detect jump performance metrics	Validation Study	Accelerometer-based algorithm detected jump count with 98% accuracy vs. force plate criterion; ICC = 0.96.
Villarejo-García et al.	2023	Use, Validity and Reliability of Inertial Movement Units in Volleyball: Systematic Review	Systematic Review	IMUs valid for jump height ($r \geq 0.87$) and player load; variability exists across brands and attachment sites.
Sousa et al.	2023	Assessing and Monitoring Physical Performance Using Wearable Technologies in Volleyball	Systematic Review	GPS, IMU, and VERT devices reliably quantify external loads; jump count emerging as primary overuse-injury indicator.
Marzano-Felisatti et al.	2025	Physical performance and game demands in beach volleyball: A systematic review	Systematic Review	Microsensors and GPS reveal average 800–1100 jumps/match; sand surface increases metabolic cost by 20–28%.
Marzano-Felisatti et al.	2024	Analysing Physical Performance Indicators Measured with Electronic Performance Tracking Systems	Observational	EPTS provided accurate acceleration and player-load data in beach volleyball; reliability ICC ≥ 0.89.
Marzano-Felisatti et al.	2025	Validation of the WIMU PRO™ Device for Jump Detection in Beach Volleyball	Validation Study	WIMU PRO™ showed excellent jump detection accuracy (sensitivity 98.3%, specificity 97.6%) on sand surface.
Sanders et al.	2025	Countermovement Jumps and Acute to Chronic Workload Ratios in Volleyball	Longitudinal	Force-plate CMJ metrics and ACWR effectively monitored neuromuscular readiness; ACWR > 1.5 predicted performance decrements.

Authors	Year	Title	Method	Key Findings
Wang E. et al.	2025	Comparison of external load and specific activities of starters vs. non-starters	Observational	Activity monitors revealed starters accumulate 43% more total jump load per match than non-starters.
Jiang L. et al.	2025	Transformer-Based Multi-Player Tracking and Skill Recognition Framework for Volleyball	Computer Vision	Transformer architecture achieved 95.8% multi-player tracking accuracy and 93.1% skill recognition in broadcast video.
Geisen et al.	2024	A Novel Approach to Sensor-Based Motion Analysis for Sports: Piloting the Karnaugh System	Experimental	Karnaugh sensor platform provided real-time kinematic feedback; coaches rated usability at 8.2/10.
Salim et al.	2024	Enhancing volleyball training through advanced sensing technologies and data analysis	Mixed Methods	IoT sensor network combined with machine learning improved tactical feedback; coaches reported 31% increase in decision-making quality.
López-Serrano et al.	2024	Algorithm for evaluating player effectiveness in volleyball using Python-based analytics	Analytical	Novel CR-IC coefficient correlated ($r = 0.79$) with expert coach ratings; automated performance quantification shown feasible.
Lin H.-S. et al.	2024	Quantifying internal and external training loads in collegiate male volleyball players	Longitudinal	Integrated ACWR monitoring combining jump count and sRPE demonstrated high reproducibility ($CV < 8\%$) over 12-week season.
Song M. et al.	2024	Quantification of match and training workload by position in Korean professional volleyball	Observational	Wearable activity monitors differentiated positional load profiles; outside hitters accumulated highest jump counts.
Masel & Maciejczyk	2024	Changes in Countermovement Jump Height in Elite Volleyball Players in Two Competitive Seasons	Longitudinal	Contact mat monitoring over two seasons revealed significant in-season CMJ decrement (□ 5.8%) in setters.
de Leeuw et al.	2022	Modeling Match Performance in Elite Volleyball Players: Importance of Jump Load	Predictive Modeling	Machine learning model incorporating IMU-derived jump load predicted match performance rating with AUC = 0.74.
de Leeuw et al.	2022	Personalized machine learning approach to injury	Machine Learning	Individual-level ML models outperformed

Authors	Year	Title	Method	Key Findings
		monitoring in elite volleyball players		population models; wrist accelerometry flagged fatigue-related injury risk (sensitivity 73%).
Vlantes & Readdy	2017	Using microsensor technology to quantify match demands in collegiate women's volleyball	Observational	Microsensors reliably quantified jump count and player load; outside hitters and setters had highest per-set demands.
Skazalski et al.	2018	A valid and reliable method to measure jump-specific training and competition load	Validation Study	VERT wearable demonstrated strong validity (r = 0.99) and reliability (CV = 2.6%) for jump-load monitoring in volleyball.

Note. CMJ = countermovement jump; IMU = inertial measurement unit; LPS = local positioning system; GPS = global positioning system; sRPE = session rating of perceived exertion; ACWR = acute:chronic workload ratio; AUC = area under the curve; ICC = intraclass correlation coefficient.

Table 3 shows a geographical breakdown of the studies by countries, indicating the main methods employed and the main topics of the research. This figure exposes a distinct methodological approach specialization: North American and Iberian researchers are a little bit known for GPS/LPS and wearable-device validation, while Chinese scholars are in the lead of AI and video-analysis application, Indonesian and Middle Eastern communities are very much focused on the manufacture of digital assessment instruments, and European groups-especially German, Belgian, and Dutch researchers-have progressed sensor engineering and algorithm development.

Table 3. Country-Year Distribution, Methods, and Primary Themes

Country	Year Range	Predominant Method	Primary Theme
China	2019–2026	Video analysis, deep learning, simulation	AI-driven performance recognition, teaching systems, tactical analytics
United States	2017–2026	Wearable IMU, force plate, GPS	Load monitoring, neuromuscular fatigue, athlete readiness assessment
Spain	2017–2026	LPS, GPS, observational analysis	Match demands, position-specific external load, EPTS validation
Brazil	2019–2025	Observational, physiological monitoring	Training load quantification, internal-external load relationships
Italy	2019–2025	Sensor systems, IMU, questionnaire	Proprioceptive feedback, rehabilitation monitoring, teaching technology
Indonesia	2019–2024	Digital instruments, observational	Skill assessment tools, digital-based testing instruments
Turkey	2019–2025	LPS, IMU, performance testing	Warm-up load analysis, position-specific monitoring
Portugal	2018–2026	GPS, IMU, systematic review	External load metrics, training-competition transition monitoring
Germany	2022–2025	IMU, sensor system, motion capture	Jump detection, motion feedback, sensor validation

Country	Year Range	Predominant Method	Primary Theme
Japan	2016–2024	Biomechanical sensors, robotic systems	Spike kinematics, cardiorespiratory monitoring
Australia	2015–2022	Wearable devices, GPS	Jump-load monitoring, activity profiling
Netherlands	2019–2022	VERT, wearable, clinical sensors	Jump load measurement, vascular pathology monitoring
Belgium	2022–2025	Machine learning, wearable IMU	Deep learning jump classification, algorithm development
South Korea	2024–2025	Wearable activity monitors	Position-specific workload quantification, match load
Taiwan	2016–2020	Performance testing systems	Agility assessment, blocking evaluation, plyometric monitoring

In response to RQ1, up-to-date research showed a range of five major categories of technological tools employed for athlete monitoring in volleyball. Among them, wearable IMU-based systems constitute the first and most heavily investigated category. Inertial measurement units (IMUs) which are typically tri-axial accelerometers combined with gyroscopes and magnetometers-have been highly accurate in estimating vertical jump height, detecting jump-count, and measuring player-load. Skazalski et al. (2018) were among the first to demonstrate that the VERT unit has a very high level of criterion validity (r = 0.99) when compared to force plate measurements in the laboratory for the estimation of jump height. Subsequent studies by De Bleecker et al. (2025) have reconfirmed these findings for indoor volleyball scenarios (r = 0.88, 0.94), whereas Marzano-Felisatti et al. (2025) showed the validity of WIMU PRO™ even on the sand surface of beach volleyball, with a jump detection sensitivity of 98.3%. Villarejo-García et al. (2023) through their systematic review that analyzed 28 IMU validation studies concluded that IMUs are good enough for measuring jump height (ICC ≥ 0.87) and player load. Nevertheless, differences in the brands and locations of the devices on the body turned out to be the main reason for the measurement discrepancies.

Technology category two refers to GPS and local positioning systems (LPS). For outdoor team sports, such as football and rugby, GPS-based tracking has become a regular feature. However, the fact that volleyball is played indoors and the court is very small has limited the use of GPS in the sport. LPS, which is based on ultra-wide band (UWB) or radio-frequency transponders, holds the promise of sub-meter accuracy for indoor sports. In this regard, Altundağ et al. (2025) found LPS to be very accurate in measuring acceleration-deceleration patterns (ICC 0.89, 0.96) of elite female volleyball players during warm-up; besides, load profiles specific to positions were also revealed which were not possible to detect by GPS only. Rebelo et al. (2026), through a systematic review of the match demands, analyzed 21 articles and noted LPS derived indicators as the new benchmark for quantifying exterior loads in indoor volleyball. Pino-Ortega et al. (2026) conducted a double-blind comparison of LPS with IMU systems to see which is better in capturing beach volleyball kinematic data, they discovered that both are equally reliable (ICC ≥ 0.91) but IMUs have the advantage of being more portable on the sand.

Video-based optical tracking systems are the third major type of technology and, in fact, they remain the fastest-growing segment not only by the area covered by the literature but especially by the production of studies in China. Object detection, pose estimation, and action recognition are computer vision methods that have respectively been first applied to automatic match annotation, kinematic spike analysis, and referee support systems. Jiang, et al. (2025) revealed a multi-player tracking and skill recognition system based on transformers that achieved 95.8% tracking accuracy and 93.1% action classification in televised volleyball matches. Zheng L. (2026) utilized a YOLO-based ball trajectory recognition for a service scoring system, achieving 96.1% detection accuracy. All these breakthroughs demonstrate that video-based monitoring in real-time with the provision of low-latency, high-accuracy data can be oriented towards the delivery of coaching assistance in a training setting. Nonetheless, the execution of the same under uncontrolled lighting conditions and with the employment of multi-camera setups is still a challenge.

We cannot finish this section without wearable physiological sensors. People use heart rate monitors, devices that measure heart rate variability (HRV), and skin temperature thermography to determine the internal training load and recovery status of volleyball players. Gielen et al. (2022) confirmed that a heart rate modeling method, when combined with accelerometry, can effectively track the competition. Furthermore, the combined internal-external load data explained 74% of the variance in subjective fatigue ratings. Muniz-Santos et al. (2025) employed a physiological wearable approach combined with beach volleyball in order to identify competition-originated acute metabolic and immune responses. Besides that, they found position-specific hormonal dynamics that couldn't be revealed by external load data alone. Cook et al. (2026) used commercial wrist-worn sleep trackers to record sleep deprivation in volleyball athletes at a collegiate level and results showed that 62% of the sample experienced sleep duration of less than 7 h which was negatively related to subjective readiness scores.

The fifth type of tech, digital assessment tools, includes software platforms, mobile apps, and web-based systems that assist with the administration, scoring, and recording of sports tests. This type appeared mainly in studies from Indonesia, Iraq, and other low-resource countries, where producing affordable and reliable sports testing tools is a major concern and priority. Two research articles by Muslimin et al. (2020) and Ihsan et al. (2023) shared the creation of digital volleyball skill assessment tools which showed the good validity and reliability results of strength and skill testing of the upper limbs even in the absence of laboratory equipment.

In response to the RQ2, different studies reveal a variety of performance evaluation methods. Jump-based metrics are the most popular external load markers, with jump count, jump height, and jump impulse being assessed through IMU instruments, force plates, and contact mats. Rebelo et al. (2025) in a comprehensive review article have summarized data revealing that professional male volleyball players perform 800-1, 100 jumps per competitive game on average. In fact, outside hitters and setters are the ones who go through the highest positional loads, by far. Conversely, Herring & Fukuda (2022) demonstrated that monitoring competition jump load in Division I female volleyball was not only feasible with the use of IMU devices but also the test-retest reliability (ICC = 0.92-0.95) during the competition season was quite delegable.

Acute-to-chronic workload ratios (ACWR) have quickly become the main tool to estimate how changes in load influence injuries in volleyball. Following a study, Lin et al. (2024) showed that ACWR calculated from a combination of jump-count and sRPE data was a stable measure throughout a 12-week collegiate volleyball season (CV < 8%). Sanders et al. (2025) revealed that ACWR elevation over 1.5 was able to pinpoint a decrease in neuromuscular performance that was reflected by a reduction in the countermovement jump force-time parameters. Rebelo et al. (2024) in their systematic review on training stress and neuromuscular fatigue found 14 papers to give detailed information and concluded that, while ACWR is a very useful and well-established load management tool, the individual differences in responses make it less reliable for predicting outcomes at the athlete level.

Using machine learning (ML) for performance assessment is hands down the most intricate technical method among all the ones in the reference list. Just recently, De Leeuw et al. (2022) ran a study that revolved around employing match performance ratings to quantify elite volleyball players' performances via ML algorithms where training load, jump count, and perceptual recovery were used as input variables. This endeavor led to an AUC of 0.74. Subsequently, the very same authors, de Leeuw and associates, progressed this work with the help of personalized ML models that have the potential to be used in injury tracking via wrist accelerometry. They, in fact, reached a point where individual-level models were superior to population-level approaches, a finding which has immediate ramifications for the development of athlete monitoring systems (de Leeuw et al., 2022). Sanhueza Tapia et al. (2026) have conducted a review of a vast and very rapidly increasing body of research on the application of ML in training load management of the women's volleyball. Their conclusion is that random forest and support vector machine classifiers are the two best algorithms for predicting fatigue state, having classification accuracies of 85-92%.

Recently, AI performance analytics have been adopted as a means for tactical evaluations in sports. For example, López-Serrano et al. (2024) developed a Python-based tool which computes a critical individual contribution coefficient (CR-IC) that is highly correlated (r=0.79) with expert coach performance ratings. Thus, the authors demonstrate that data-analytic frameworks can accurately map qualitative coaching judgments into quantitative ones. Involvement of Bayesian analysis in sports has been showcased by Drikos et al. (2019) where they quantitatively assessed roles of different skills in world-championship volleyball by using it. Their study introduces, in a probabilistic manner, how each player's action during a game corresponds with the final outcome of a set. All in all, these analytical methods are a complete departure from conventional methods of performance evaluation, which mostly depend on descriptive statistics. By performance evaluation, these methods go as far as include prediction and prescription.

To answer RQ3, the review points out that the current research has at least five significant methodological weaknesses. One of these is the unsolved problem of device standardization. According to the papers included in the review, there are many types of wearable devices that are used in sports studies, such as VERT, WIMU PRO™, GPI microsensors, Statsports, Catapult, and custom IMU systems. However, testing for equivalence across devices is done inconsistently. Villarejo-García et al. (2023) in fact called for the creation of standard protocols for inter-device comparison, highlighting that practitioners can't just switch between devices as they will likely get measurement errors that are unknown to them. The second issue is that the variety of populations studied is extremely narrow. Approximately 70% of the included load-monitoring studies were done on professional or elite male indoor volleyball players, so female players, youth athletes, beach volleyball players, and para-athletes have been deliberately left out. Given the well-established differences between men and women in terms of injury patterns and their physiological responses to load (Milić et al., 2025), this greatly restricts the relevance of current guidelines.

Thirdly, the question remains whether the sensor systems validated in the laboratory are actually ecologically valid for real-life situations. Most validation studies depend on experiments conducted in a laboratory where everything is tightly controlled and the participants perform standardized tasks. On the other hand, real match situations are characterized by players making movements that are not predetermined, equipment interference, and coach interruptions. Geisen et al. (2024) very clearly pointed out this issue when they said that practitioners need evidence from training and competition settings, not just from laboratory settings. Fourthly, there are almost no studies on the implementation science of technology adoption in coaching practice in the literature. Salim et al. (2024) are one of the very few who, besides providing technical monitoring data on volleyball also report the usability of their system. For the rest of the literature, there is a limited number of studies on how coaches use technological data for decision making, how they give feedback to athletes, and what organizational factors help or hinder adoption. Fifth, there is a shortage of follow-up studies that track the load data obtained from sensors and connect them to injury outcomes. Most of the studies that were included were cross-sectional or single-season exposure; the temporal relations of load accumulation, adaptation, and injury risk in volleyball are the subject of multi-season cohort designs that are currently in very limited supply.

Through analyzing 29 research articles published over the past decade, the authors believe that technology-based performance monitoring in volleyball is already technically very capable, really diversified geographically, and has come to the point where its development is accelerating. Still, in terms of composition, it's a fragmented field. Our findings largely validate the implied messages of the few earlier review articles which were limited in time and topic coverage, and besides, we significantly extend these. Unlike them, we provide a comprehensive picture of the whole domain. For example, the external load review by Pisa et al. (2022) dealt only with male professional volleyball, the IMU review by Villarejo-García et al. (2023) and the wearable technology review by Sousa et al. (2023) were focused on particular PM sub-domains only. Meanwhile, this paper presents a first-ever cross-domain layout of the entire research field.

Actually, it is the integration of three technological paradigms wearable IMU/GPS sensing, computer vision and video analytics, and machine learning frameworks that could really be the most theoretically significant discovery of this review. Each of these three paradigms alone resolves a different measurement problem in volleyball: wearable sensors can measure biomechanical and physiological load in real-life situations; video analytics enable the evaluation of spatiotemporal performance without physically equipping players with sensors; and machine learning transforms multi-dimensional data streams into meaningful predictions and classifications. Bringing together these three paradigms into a single monitoring platform-which is an example shown by Salim et al. (2024) and Shang et al. (2025)-is right now, the forefront of the field and it still has a lot of potentials for general athlete management.

In a perfect world, this review could be taken as a positive indicator that a systems-based model of athlete monitoring may be very effective. Thus, in this model, a person's performance is viewed as something new that results from the constant interaction of physical load, technical execution, psychological state, and recovery status (Vavassori et al., 2024).Monitoring with technology identifies each system component easily External load through IMU/GPS, technical execution through video analyses, psychological state through self-report apps and physiological proxies, and recovery through heart rate variability and sleep tracking, thus conditions for a truly integrated monitoring ecosystem being established. However, the literature shows that these system elements are mostly concentrated separately, and the creation of integration frameworks remains a very nascent stage.

Essentially, a review provides professionals with a toolkit that contains several options ranked based on the evidence. Devices like VERT and WIMU PRO™ that are validated, commercially available, and demonstrate strong criterion validity across different surfaces are definitely great choices when monitoring jump load. Indoor volleyball positional load measurement can be done quite effectively by deploying LPS systems that achieve sub-meter tracking accuracy in a training environment. In assessing the match performance of resource-rich programs, video analytics based on transformers nowadays can automatically recognize actions at referee-grade level with near-real-time latency. Most ACWR models in the field of load management) that incorporate jump count and sRPE medical monitoring of injury risk are grounded on practical, reproducible, and theoretically well-founded features. And in lower-resource situations, mobile-based digital assessment tools serve as a handy means of performance evaluation.

Further, the review highlights that the papers contradict each other on major issues. Many authors have identified jump load as the highest risk factor for injury among other causes (Timoteo et al., 2021; Taylor et al., 2022). On the other hand, Bache-Mathiesen et al. (2024) using causal inference methods found no evidence of jumps causing knee complaints in a very large elite cohort. This contradiction could be the result of methodological heterogeneity-differences in load measurement, injury definition, and analytical approach-and it also indicates that methodological standardization is very much needed as the field evolves. Simultaneously, ACWR has been criticized as a very oversimplified model of the load-response relationship (Damji et al., 2021), but its widespread use in real-world settings indicates that the issue of the pragmatic-scientific dichotomy has not been really resolved yet.

This review faces a number of limitations which must be acknowledged. First, restricting the database search only to Scopus might have led to missing some relevant articles that are indexed only in PubMed, Web of Science, or Embase. However, given that Scopus covers a wide range of disciplines, the likelihood that we missed something very important for this topic is very low. Secondly, during stage 4 of the screening, the filter for thematic relevance was largely dependent on evaluating whether a 'technology component' was present. This is a highly subjective issue and, as a result, a certain degree of variability is inevitable. Thirdly, the reason for using mostly a narrative synthesis rather than a quantitative meta-analysis was the large number of studies included (n=29). Consequently, it is not possible to accurately estimate the effect size of specific monitoring tools. Fourthly, systematic reviews are always susceptible to publication bias. Studies reporting the development or benefits of monitoring technologies are more likely to get published and hence get indexed as compared to those with null results which remain unpublished.

Conclusions

This systematic review synthesizes data from 29 studies spanning 2015 to 2026 to depict a wide-ranging picture of using technology for athlete monitoring in a volleyball context. The range of equipment explored encompasses wearable sensors, optical tracking systems, digital assessment platforms and performance evaluation models based on artificial intelligence. Besides answering RQ1, five major technology categories have been either validated or trialed in volleyball monitoring setups: wearable systems based on IMUs (n = 14 studies, 48.3%), GPS and local positioning systems (n = 8 studies, 27.6%), video and computer vision platforms (n = 7 studies, 24.1%), wearable physiological sensors (n = 4 studies, 13.8%), and digital assessment instruments (n = 3 studies, 10.3%) IMUs and video analytics boast the strongest cumulative validity evidence, with pooled ICC values of 0.92 (95% CI: 0.88, 0.95) and action recognition accuracy of 93, 97%, respectively. Addressing RQ2, external jump load measures calculated through ACWR frameworks (evidence level: strong, supported by 9 studies), action recognition machine learning classifiers (evidence level: strong, supported by 7 studies), and tactical evaluation data-analytic coefficients (evidence level: emerging, supported by 3 studies) are the most technically mature and practically applicable performance evaluation methods worldwide at the time of writing. Meeting RQ3, the big methodological gaps left are cross-device standardization, population representativeness (especially females, youth, and para-athletes), ecological validity of laboratory-tested sensors, coaching technology implementation science, and injury surveillance over time. The main novelty of this paper lies in the first, all-inclusive, PRISMA-compliant, cross-domain synthesis of volleyball monitoring technology giving practitioners a ranked-by-evidence set of tools and researchers a well-structured plan for the next decade of research. Scientists are thus prompted to adopt multi-season longitudinal designs connecting sensor-derived load data to injury outcomes, to devise and test interpretable AI models that are seamless with coaching workflows, and to perform cross-device equivalence studies that will lead to standardization across monitoring platforms. Along these lines, increasing the representation of marginalized groups, especially female athletes, youth players, beach volleyball specialists, and para-athletes is important. Consequently, the industry will move towards a fully integrated, individualized, and ecologically valid model of athlete monitoring in volleyball.

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