Vol. 7, No. 1, 2026, pp. 1303-1326
DOI: https://doi.org/10.29210/993190

Contents lists available at Elora Center

Lentera Negeri

Journal homepage: https://lentera.eloracenter.org/lentera

Wearable sensors, positioning systems, and computer vision for beach volleyball athlete monitoring: a systematic review

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Article Info

Article history:
Received Aug 02nd, 2026
Revised Aug 24th, 2026
Accepted Aug 26th, 2026

Keyword:
Beach volleyball,
Athlete monitoring,
Wearable sensors,
Electronic performance and bracking systems,
Computer vision

ABSTRACT

Beach volleyball is contested on deformable sand under variable outdoor conditions, creating movement and load demands that differ from indoor volleyball and may challenge the assumptions of athlete-monitoring technologies. This systematic review mapped technology-based monitoring systems used in beach volleyball and synthesised evidence on their validity, reliability, applications, limitations, and research gaps. The review followed PRISMA 2020 and searched Scopus using a structured Boolean strategy. Of 403 records identified, 54 full texts were assessed and 22 peer-reviewed studies published from 2014 to 2026 were included. Six monitoring modalities were identified: satellite/local positioning systems, wearable inertial measurement units, computer vision, machine-learning analytics, video-based mobile applications, and wearable eye-tracking. Validation evidence was heterogeneous and was reported only where individual studies evaluated measurement properties. In official competition, an inertial device achieved 96.29% overall jump-detection sensitivity, while another IMU study reported jump-count precision of 0.975 and recall of 0.836–1.000 depending on jump type. For the My Jump 2 application, reliability ranged from ICC 0.91–0.97 under controlled sand-box conditions but only ICC 0.447–0.594 in open-field sand conditions. Direct comparison of GNSS and ultra-wideband systems also showed significant differences across kinematic outputs, indicating that their values should not be treated as interchangeable. The evidence therefore supports descriptive profiling and role-specific load monitoring, but not yet universal thresholds, cross-device benchmarking, or injury prediction. Future research should prioritise multi-database evidence retrieval, independent multi-reviewer screening, sex- and action-stratified validation, prospective injury surveillance, and multimodal integration.

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Introduction

Monitoring athletes has become one of the defining features of modern high-performance sport. That shift rests on a convergence of miniaturised sensing hardware, satellite and local positioning infrastructures, and analytical pipelines built to handle continuous streams of movement data. Within this landscape, the methodological literature is deepest for team sports played on stable indoor surfaces. Sports contested on deformable outdoor surfaces have advanced far more slowly. Beach volleyball occupies a distinctive place in that hierarchy. It is an Olympic discipline where two athletes cover the entire court, execute every technical action, and keep jumping and changing direction on sand under variable thermal, wind and radiation conditions (Kasprzak & Łopuch, 2022; Racinais et al., 2021). The physiological and mechanical demands these conditions generate differ systematically from those of the indoor game (Figueira et al., 2025; Hank et al., 2024). They also create measurement conditions that strain the assumptions built into most commercial monitoring devices.

The specific problem this review addresses is straightforward. Nearly all of the technological infrastructure now used to quantify beach volleyball performance was developed, calibrated and validated for rigid surfaces and for larger playing areas. Sand attenuates ground reaction forces, changes take-off and landing mechanics, and alters the acceleration signatures that inertial algorithms depend on for event detection (Giatsis et al., 2018; Giatsis et al., 2022; Giatsis et al., 2023). Outdoor play also exposes satellite positioning receivers to signal conditions unlike those of the open-field sports they were designed for. The small court dimensions then compress displacement distances into a range where measurement error becomes proportionally large (Hank et al., 2016; Pino-Ortega et al., 2026). The upshot is that metrics reported in beach volleyball can carry uncertainty that is rarely quantified and almost never propagated into the training prescriptions derived from them.

Historically, research on beach volleyball performance has been dominated by notational and observational match analysis. Systematic reviews within that tradition show a consistent preoccupation with technical-tactical indicators, among them serve, reception, set and attack efficiency, plus the contextual variables that modulate them (Medeiros et al., 2014; Alvarado-Ruano & López-Martínez, 2022). Standardised observational instruments were later designed and validated to make manual coding more reliable (Palao et al., 2015). Descriptive studies have since characterised rally duration, jump frequency and technical distribution in elite competition (Giatsis et al., 2020; Natali et al., 2019). That body of work established the tactical grammar of the sport. Yet it relies on labour-intensive human observation, yields limited kinematic resolution, and cannot supply the continuous individualised load information that contemporary training practice demands.

A second stream of research has quantified the physiological and neuromuscular demands of the sport through laboratory and field methods. Physiological work areas, session rating of perceived exertion, salivary hormone concentrations and neuromuscular status have all been measured in beach volleyball populations (Jimenez-Olmedo et al., 2017; Lupo et al., 2020; Costa et al., 2022; Silva et al., 2025). In parallel, biomechanical studies have documented how jump kinetics, postural control and lower-limb function differ on sand (Sebastia-Amat et al., 2020; Giatsis et al., 2022; Buscà et al., 2015). These lines of enquiry converge on a clear conclusion: beach volleyball imposes a specific neuromuscular and metabolic profile. Most of them, however, rely on discrete testing sessions rather than continuous in-competition measurement. The relationship between laboratory-derived capacities and actual match demands therefore remains only partially specified.

Over the past decade, technological advances have begun to close that gap. Electronic performance and tracking systems, which combine global navigation satellite receivers, ultra-wideband local positioning and triaxial inertial units, are now used in beach volleyball training and competition (Marzano-Felisatti et al., 2024; Pino-Ortega et al., 2026). Computer vision pipelines can track players and the ball automatically from broadcast and dedicated camera footage (Gomez et al., 2014; Link, 2014). Supervised learning models have been applied to large positional datasets to classify tactical behaviour (Wenninger et al., 2019; Wenninger et al., 2020). Deep learning architectures have also been used to recognise sport-specific actions directly from wearable sensor signals (Kautz et al., 2017). Artificial neural networks, meanwhile, are increasingly proposed for injury risk modelling across sports (Maghsoomi et al., 2025). So the technical capability exists. What remains unclear is how dependable it actually is in the sand environment.

The first gap this review addresses is the absence of an integrated map of monitoring modalities. Existing syntheses have covered technical-tactical factors (Alvarado-Ruano & López-Martínez, 2022), match-analysis performance indicators (Medeiros et al., 2014), injury patterns (Jimenez-Olmedo & Penichet-Tomas, 2015) and, most recently, physical performance and game demands (Marzano-Felisatti et al., 2025b). None of them has taken the measurement technology itself as the organising unit of analysis. The result is that three bodies of literature, the sensor engineering, computer vision and applied sport science strands, have developed largely in parallel. Cross-citation is limited, and there is no shared account of which constructs each modality can and cannot capture on sand. Practitioners are therefore left without a consolidated reference for selecting instruments suited to a defined monitoring purpose.

The second gap is methodological, and it concerns evidentiary quality. Validation studies in beach volleyball usually run on small convenience samples, often within a single team or a single tournament.

Criterion measures also vary widely across investigations, from force platforms and three-dimensional motion capture to retrospective video annotation (Schmidt et al., 2021; Schleitzer et al., 2022; Medeiros et al., 2024). Agreement statistics are reported inconsistently. Few studies report measurement error in a form that lets practitioners tell genuine change apart from instrument noise. There is a further problem. Because device validation samples are disproportionately male or mixed, the confidence with which manufacturer specifications can be extended to female athletes is restricted, even though documented sex-related differences exist in jump characteristics and court coverage (Marzano-Felisatti et al., 2025a; Hank et al., 2024).

The documented injury and illness burden in the discipline strengthens the urgency of this synthesis. Overuse complaints of the shoulder and spine are common in volleyball populations (Seminati & Minetti, 2013). Injury patterns in beach volleyball differ from those seen indoors (Jiménez-Olmedo et al., 2018; Juhan et al., 2021). Multi-sport surveillance at Olympic and Youth Olympic competitions has further confirmed that beach volleyball athletes face substantial acute and environmental risk (Engebretsen et al., 2013; Steffen et al., 2020; Racinais et al., 2021). Load-based injury prevention frameworks depend on measurement systems whose error characteristics are known. So reviewing the accuracy and applicability of monitoring technologies in beach volleyball is not merely an instrumentation question. It is a prerequisite for evidence-based athlete protection in an environmentally demanding Olympic sport.

With that in mind, this review first asks which technologies have actually been implemented in the sport and what they measure. Mapping the modality landscape shows whether the discipline has built a balanced monitoring ecosystem or has clustered around a narrow set of commercially available products. It also establishes which performance constructs, from external displacement to perceptual-cognitive behaviour, are currently observable.

RQ1: Which technology-based monitoring systems have been implemented in beach volleyball, and which performance and load constructs do they quantify?

Answering it yields a modality-referenced taxonomy, one that lets researchers and practitioners position any individual device within the broader measurement landscape of the sport.

The review then turns to measurement quality and translational value. Knowing what the accumulated validation evidence demonstrates, and where it runs thin, determines how far technology-derived metrics can support individualised decisions. A structured account of methodological limitations, in turn, defines the agenda for the next generation of studies.

RQ2: What evidence exists for the validity and reliability of these monitoring systems when deployed on sand during training and official competition?

RQ3: What practical applications, methodological limitations and research gaps emerge from the accumulated evidence base?

Accordingly, this study was designed as a PRISMA 2020-compliant systematic literature review with narrative and thematic synthesis. The review protocol specified the research questions, eligibility criteria, database search strategy, data-extraction fields, quality-appraisal procedure, and synthesis plan before screening. The primary search was conducted in Scopus because the topic spans sport science, sports engineering, biomedical engineering, computer science, and performance analysis. The review treats monitoring technology as the principal unit of analysis and evaluates the evidence according to the construct being measured, the reference or comparator used, the competitive setting, and the reported validity or reliability evidence. Because the included studies were heterogeneous in design, instrument, reference standard, and outcome definition, no pooled meta-analytic estimate was calculated.

Method

Research Design and Framework

The research design chosen was a systematic literature review, because the aim was to aggregate, appraise and synthesise dispersed empirical evidence rather than generate new primary data. Systematic review methodology gives researchers a transparent and reproducible procedure for retrieving and evaluating evidence, and it reduces the selection bias that tends to characterise narrative overviews (Tranfield et al., 2003). Reporting followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 statement (Page et al., 2021), which replaced the earlier PRISMA formulation and its accompanying elaboration for interventional evidence (Liberati et al., 2009). A narrative and thematic synthesis was adopted instead of meta-analysis. The included studies used heterogeneous instruments, criterion measures and outcome metrics, so statistical pooling would only have produced an aggregate estimate without interpretable meaning.

The review protocol was specified a priori. It defined the research questions, the search string, the eligibility criteria, the data extraction template, the quality appraisal instrument and the synthesis strategy. No deviations from the protocol were required while the review was being executed. Because the review analysed previously published aggregate data and involved no human participants, institutional ethical approval was not applicable.

Search Strategy

The search strategy rested on three conceptual blocks joined by the Boolean operator AND. The population block covered beach volleyball, the technology block covered wearable, inertial, positioning, video and artificial intelligence terminology, and the outcome block covered monitoring, load, performance and validity terminology. Within each block, OR combined synonyms and lexical variants. Truncation was applied to pick up morphological variants, and the TITLE-ABS-KEY field code restricted retrieval to title, abstract and keyword fields in order to balance sensitivity against precision.

The following string was executed:

> *TITLE-ABS-KEY (("beach volleyball" OR "beach volley" OR "sand volleyball") AND (wearable* OR "inertial measurement unit" OR imu OR accelerometer* OR gps OR gnss OR "global positioning" OR "local positioning OR "ultra-wideband" OR "electronic performance and tracking system" OR epts OR "computer vision" OR "video analysis" OR "video-based" OR "player tracking" OR "machine learning" OR "deep learning" OR "artificial intelligence" OR "neural network" OR "eye tracking") AND (monitor* OR "external load" OR "internal load" OR workload OR "activity profile" OR "match demands" OR jump* OR performance OR validity OR reliability OR accuracy))*

No language limiter was applied at the database-query stage; language was applied as an eligibility criterion. No subject-area limiter was used because relevant instrumentation studies are distributed across sport science, engineering, computer science, and biomedical journals. The final search date and complete database export should be reported in the submission record. The present review used Scopus as its primary database; expansion to PubMed and Web of Science requires an additional search and an updated PRISMA flow, which is identified as a priority revision rather than inferred from the current dataset.

Database and Information Sources

Scopus was the primary information source because it indexes the interdisciplinary outlets relevant to beach-volleyball monitoring and provides structured bibliographic metadata suitable for reproducible screening. However, a single-database strategy can miss records indexed elsewhere. This limitation is therefore treated as a substantive source of selection bias rather than as evidence that Scopus is exhaustive. To satisfy the reviewer request for broader coverage, the authors should run the same conceptual blocks in PubMed and Web of Science, document the database-specific syntax and search dates, deduplicate the combined exports, and regenerate the PRISMA flow counts before final resubmission.

Reference-list checking was used only as a coherence check and did not contribute additional included records. Consequently, the 403-record flow diagram represents the Scopus identification set only. Any additional records retrieved from PubMed or Web of Science must be incorporated into the revised flow diagram and screening log rather than added retrospectively without updating the counts.

Eligibility Criteria

Eligibility was structured around PICOS, which lays out the population, intervention or exposure, comparator, outcomes and admissible study designs. Table 1 presents the framework, and Table 2 gives the operational inclusion and exclusion criteria that follow from it. The publication window starts in 2013. Wearable inertial and satellite positioning systems only began showing up in beach volleyball research around that time, and anything older predates the instrumentation this review is concerned with.

Table 1. PICOS framework applied to the review

Component	Specification applied in this review
Population (P)	Beach volleyball players of any competitive level (youth, collegiate, national, professional or Olympic) and either sex, participating in training or official competition.
Intervention / Exposure (I)	Application of a technology-based monitoring system, comprising wearable inertial measurement units, satellite or local positioning systems, heart rate telemetry integrated with tracking, computer vision or video-based automated tracking, machine learning analytics applied to performance data, or wearable eye-tracking.
Comparator (C)	A criterion measure (force platform, three-dimensional motion capture, observational video annotation), an alternative device or algorithm, a contrasting playing surface, position, sex or age group, or no comparator in purely descriptive designs.
Outcomes (O)	External load and displacement variables, jump count and jump height, acceleration and deceleration profiles, internal load indicators reported alongside tracking data, automated event or action classification accuracy, perceptual-cognitive behaviour, and validity or reliability indices.
Study design (S)	Peer-reviewed original research articles and systematic reviews employing observational, cross-sectional, longitudinal, experimental, validation or algorithm-development designs.

Table 2. Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Language	Published in English	Published in any other language
Document type	Journal article or review indexed as a peer-reviewed contribution	Conference paper, conference review, book, book chapter, editorial, erratum or note
Publication period	2013 to 2026 inclusive	Published before 2013
Population	Beach volleyball players engaged in training or competition on sand	Indoor volleyball, other sand sports, or non-athlete populations without a beach volleyball sample
Technology	Study deploys an instrumented monitoring system (inertial, positioning, vision-based, machine learning or eye-tracking)	Purely observational notational analysis, questionnaire-only, or laboratory testing without an instrumented monitoring system
Outcome	Reports at least one load, performance, classification accuracy or validity outcome	Reports no quantitative outcome relevant to athlete monitoring
Accessibility	Full text retrievable for assessment	Abstract only or full text not retrievable
Quality	FICO composite score of at least five with no dimension scored zero	FICO composite score below five or any dimension scored zero

Study Selection Process

Study selection was conducted in three stages: de-duplication and automated metadata filtering; title/abstract screening; and full-text eligibility assessment. For a reproducible final submission, two reviewers should independently perform the title/abstract and full-text decisions using the PICOS form, with disagreements resolved by discussion or a third reviewer. The number of independent reviewers and the inter-rater agreement coefficient must be reported from the actual screening log. No Cohen's kappa value is inserted here because the current manuscript does not contain the underlying paired reviewer decisions needed to calculate it.

The screening form retained uncertain records for full-text assessment rather than excluding them at the abstract stage. For data extraction, two reviewers should independently verify the extracted sample characteristics, technology, comparator/reference standard, outcome metrics, and principal findings. Agreement should be reported for both study selection and extraction, with the statistic and its calculation window explicitly stated. If the authors provide the screening/extraction matrix, the kappa coefficients can be calculated and inserted into this paragraph without inventing values.

Quality Assessment: FICO Framework

Methodological quality was originally appraised with the author-developed FICO framework (Focus, Information, Context, Outcome). Each dimension was scored 0–2, yielding a maximum of 8 points; scores of 7–8 were classified as high quality and 5–6 as moderate, with no dimension permitted to score zero. This rubric is useful as a transparent descriptive framework but is not an externally validated quality-assessment instrument. Therefore, the revised manuscript should not present FICO as equivalent to a validated risk-of-bias tool. For measurement-property studies, the preferred substantive revision is to add a design-appropriate appraisal using the COSMIN Risk of Bias tool for reliability, measurement error, and criterion-validity evidence, while using an appropriate design-specific critical-appraisal tool for observational or algorithm-development studies. COSMIN was developed specifically to assess the methodological quality of studies reporting reliability and measurement error, and its use would directly address the reviewer's concern about measurement-property appraisal.

In the current dataset, all 22 included studies met the existing FICO threshold: 21 were rated high quality and one moderate. These FICO scores should be retained only as supplementary descriptive information unless the authors complete the recommended reappraisal. Any new COSMIN or design-specific scores must be recalculated from the full texts and should not be inferred from the existing FICO scores.

Table 3. FICO quality appraisal of the included studies (F = Focus; I = Information; C = Context; O = Outcome)

Study	F	I	C	O	Total	Quality rating
Link (2014)	2	2	2	1	7	High
Gomez et al. (2014)	2	2	1	2	7	High
Hank et al. (2016)	2	2	2	2	8	High
Kautz et al. (2017)	2	2	2	2	8	High
Song et al. (2019)	2	1	1	1	5	Moderate
Nunes et al. (2020)	2	2	2	1	7	High
Wenninger et al. (2020)	2	2	2	2	8	High
Schmidt et al. (2021)	2	2	2	2	8	High
Bellinger et al. (2021)	2	2	2	2	8	High
Bozzini et al. (2021)	2	2	2	2	8	High
João et al. (2021)	2	2	2	1	7	High
Tometz et al. (2022)	2	2	2	2	8	High
Schleitzer et al. (2022)	2	2	2	2	8	High
Nicklas et al. (2022)	2	2	1	2	7	High
Medeiros et al. (2023)	2	2	2	1	7	High
Marzano-Felisatti et al. (2024)	2	2	2	2	8	High
Hank et al. (2024)	2	2	2	2	8	High
Medeiros et al. (2024)	2	2	2	2	8	High
Marzano-Felisatti et al. (2025a)	2	2	2	2	8	High
Figueira et al. (2025)	2	2	2	2	8	High
Pino-Ortega et al. (2026)	2	2	2	2	8	High
de Souza et al. (2026)	2	2	2	2	8	High

Data Extraction Procedure

All reports were extracted following one unified template. Besides the bibliographic information, the following features, which characterised the nature of the article itself, were noted: design of the study, sample size, sex, competitive level, setting (laboratory, field training, or official competition), monitoring technology as well as information on the manufacturer and the sampling frequency when provided, the comparator/reference standard, outcome variables, statistical methods used, and the principal findings. In the case of validation studies, the specific form of the extraction was to capture the validity or reliability statistic that was reported by the paper, and so the paper should not report all in one single format or a universal benchmark.

All numerical data were directly extracted from papers. In a case a paper omitted some statistic, that field was noted as not reported rather than estimated. It should be clear that no single ICC, correlation, sensitivity, or error threshold is adequate for every type of technology and construct in this review. Hence, the review is a collection of the measures that each primary study used as well as a commentary on these metrics in view of a particular study's reference standard, outcome definition, and setting.

Bibliometric and Descriptive Analysis

To characterise the structure of the corpus, we ran a set of descriptive bibliometric procedures. A simple yearly count of publications showed how the field has evolved over time. For each study, we coded the monitoring modality using a mutually exclusive classification, which meant the technology acting as the primary measurement instrument decided the category. Author keywords and index terms came from the study metadata, and we grouped them into thematic clusters by semantic proximity. The magnitude of each cluster was simply the number of studies contributing to it. These procedures stayed descriptive throughout. We did not compute network centrality statistics or produce bibliometric mapping outputs, mainly because a corpus this size cannot support stable network estimation.

Data Analysis and Synthesis

We synthesised the evidence with thematic synthesis, following the approach where findings get coded line by line, then grouped into descriptive themes, and finally interpreted as analytical themes that address the review questions (Thomas & Harden, 2008). Coding was inductive and drew on the results and discussion sections of the included reports. Descriptive codes from different studies were compared, merged whenever they referred to the same construct, and arranged into broader themes. Every candidate theme was then checked against the original reports, both to see whether more than one study supported it and to make sure no contradictory evidence had been left out. Finally, the themes were mapped explicitly onto the three research questions. We recorded areas of agreement, disagreement and evidential silence separately, which lets the synthesis tell consistent findings apart from isolated observations.

Reporting and Documentation

Reporting follows PRISMA 2020. Figure 1 documents the current Scopus-only identification and screening pathway, while Tables 1–5 provide the eligibility framework, quality appraisal, study-level extraction, and modality classification. The manuscript reports study-specific validation metrics when available and does not create pooled estimates when the outcome definitions, reference standards, or technologies are not sufficiently comparable. A final multi-database submission must replace the current flow counts with the combined Scopus–PubMed–Web of Science results if those searches are undertaken.

Results and Discussions

Result

Study Selection Results

The Scopus search returned 403 records. Sixteen duplicates were removed and 106 records were excluded by the predefined language, document-type, and publication-window filters, leaving 281 records for title and abstract screening. Of these, 223 were excluded, primarily because they described beach-volleyball performance without an instrumented monitoring system or applied technology to other sports. Fifty-eight reports were sought for retrieval; four could not be retrieved, leaving 54 full texts for eligibility assessment. Thirty-two were excluded at full text: 17 had no deployed technology-based monitoring system, nine did not include beach-volleyball players, and six reported no relevant load, performance, classification, or validity outcome. Twenty-two studies therefore entered the synthesis.

Fifty-eight reports were then sought for retrieval. Four of those could not be obtained in full text and were recorded as not retrieved, leaving 54 reports for a full eligibility assessment against the complete PICOS framework. Thirty-two reports were excluded at this point. In 17 cases no technology-based monitoring system had actually been deployed, even though the abstract used technological terminology. Nine were dropped because the sample did not include beach volleyball players. Six reported no load, performance, classification, or validity outcome. That left twenty-two studies that satisfied every eligibility criterion, and they moved into quality appraisal.

All 22 studies met the current FICO threshold, with 21 rated high quality and one moderate. Importantly, the review did not convert these FICO ratings into a universal claim of measurement validity. Validity and reliability were considered only when the primary studies reported an appropriate comparator or reference standard and a corresponding statistic. The resulting evidence is therefore construct-specific rather than based on a single global psychometric threshold.

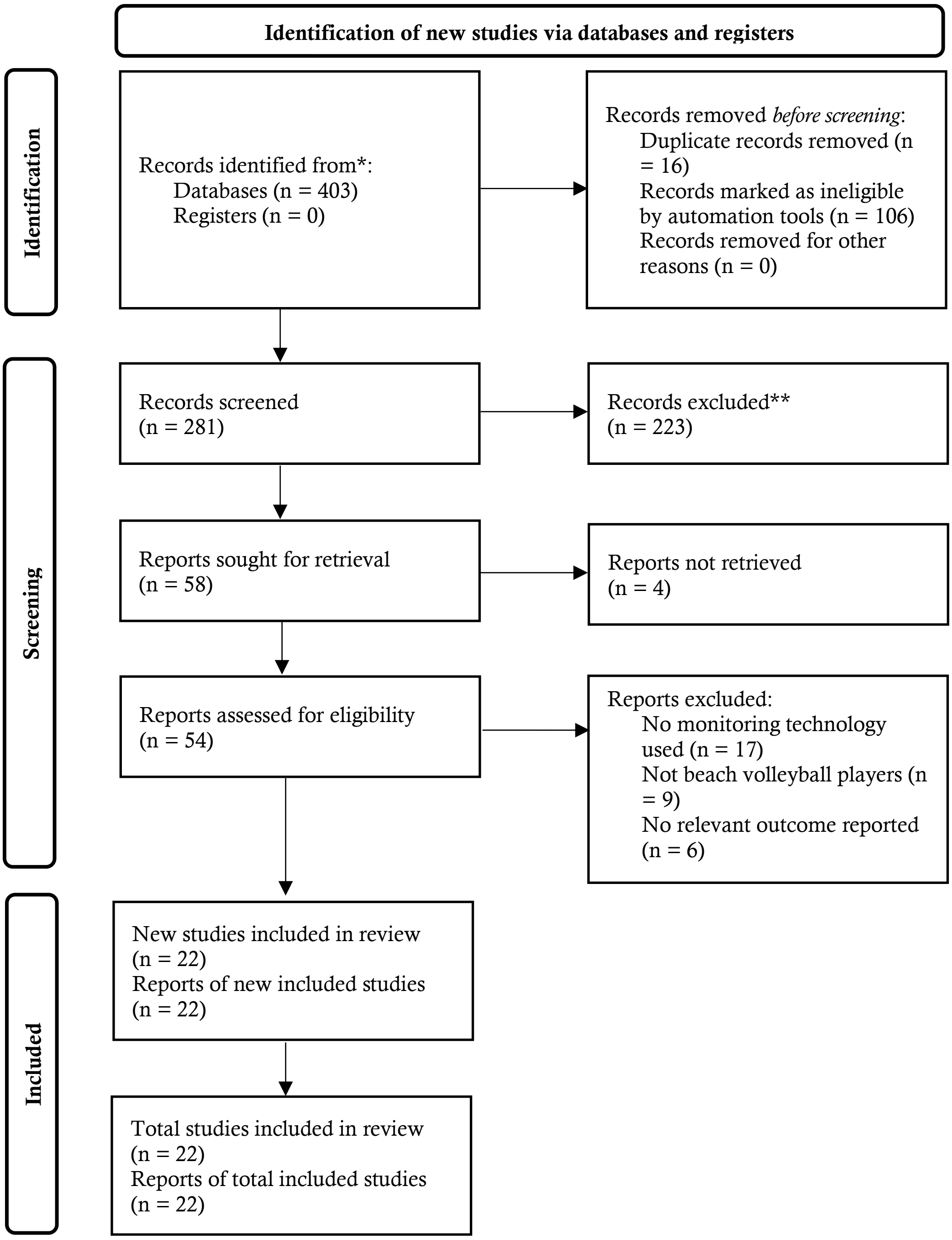

Figure 1. PRISMA 2020 flow diagram of the study identification, screening, eligibility and inclusion process.

Descriptive Characteristics of the Included Studies

The 22 studies that met the inclusion criteria appeared between 2014 and 2026. Look at the annual distribution in Figure 2 and the pattern is unmistakable: a slow build-up from 2014 to 2019, then a sharp climb from 2020 onward. Fifteen of the 22 studies, or 68.2%, were published in 2020 or later, and seven of them (31.8%) came out in 2024 or later. That timing aligns with the commercial availability of integrated electronic performance and tracking systems, and with the maturation of deep learning frameworks for sensor data. The implication is that technology-based monitoring in beach volleyball is a young research area rather than an established tradition.

Figure 3 shows how the primary monitoring modality broke down. Satellite and local positioning systems were the most frequently deployed, appearing in 7 studies (n = 7; 31.8%). Wearable inertial measurement units came next, with 5 studies (n = 5; 22.7%). Computer vision and video-based tracking accounted for 4 studies (n = 4; 18.2%), machine learning and data-mining analytics for 3 (n = 3; 13.6%), video-based mobile applications for jump assessment for 2 (n = 2; 9.1%), and wearable eye-tracking for 1 (n = 1; 4.5%). The corpus is heavily concentrated on quantifying displacement and jump activity, while perceptual, cognitive, and interpersonal constructs receive comparatively little attention.

Sample sizes were consistently small across the board. Six studies analysed fewer than 13 participants, and three were explicit single-team case studies covering one defender and one blocker. The largest human samples consisted of 32 young male players and 26 male players respectively. The biggest datasets, by contrast, were archival, spanning 1, 356 games, 2, 336 movement trajectories, and 469 rallies. Ten studies included female or mixed-sex samples, five were male-only, and the remaining seven analysed video or archival data where participant sex was not the analytical unit. Settings ranged from official competition to field training and controlled laboratory environments, and several validation studies combined laboratory and field phases within a single protocol.

Table 4 provides the complete study-level extraction for all 22 included reports, including sample characteristics, monitoring technology, and principal findings. Where a study evaluated validity or reliability, the table reports the metric actually used by that study (for example, precision, recall, sensitivity, or ICC). For descriptive, observational, or machine-learning studies that did not test measurement properties against a reference standard, a psychometric coefficient is not applicable and is therefore not imputed. Table 5 classifies the studies by design, monitoring modality, thematic cluster, and outcome domain.

Table 4. Summary of the 22 included studies

Author (Year)	Full title of the included study	Sample and setting	Monitoring technology	Key findings
Link (2014)	A toolset for beach volleyball game analysis based on object tracking	German national beach volleyball teams; applied software development study	Computer vision object tracking integrated with touch-screen live coding and positional analysis modules	Three integrated tools were developed for live data capture, automatic player and ball tracking, and quantitative-qualitative analysis; five design principles for game analysis software were derived, including separation of collection from analysis and use of computer vision to reduce manual input load.
Gomez et al. (2014)	Tracking of Ball and players in beach volleyball videos	Beach volleyball match video sequences	Particle filter and rigid grid integral histogram player trackers; background-subtraction ball detection	The rigid grid integral histogram tracker outperformed the classical particle filter, correctly tracking 82.6% versus 74.6% of frames for front players, with faster processing and fewer player confusions; occlusion and camera perspective remained the principal sources of tracking error.
Hank et al. (2016)	Evaluation of the horizontal movement distance of elite female beach volleyball players during an official match	Eight elite female players from four teams; 106 rallies and 368 movement distances during	Three-dimensional kinematic video analysis	Mean rally duration was 7.27 s, with 83.7% of rallies lasting under 10 s; mean horizontal displacement was 9.39 m per rally and 287.5 m per set, and 85.3% of movements were shorter than 15 m; playing

Author (Year)	Full title of the included study	Sample and setting	Monitoring technology	Key findings
		official match play		position did not affect distance covered.
Kautz et al. (2017)	Activity recognition in beach volleyball using a Deep Convolutional Neural Network: Leveraging the potential of Deep Learning in sports	Beach volleyball players instrumented during play; sensor-based activity dataset	Wearable inertial sensors with a deep convolutional neural network compared against five conventional classifiers	The deep convolutional network outperformed all conventional classification algorithms for sport-specific activity recognition, demonstrating that unobtrusive automatic monitoring can replace time-consuming video examination and enable systematic investigation of overuse injury risk factors.
Song et al. (2019)	Design and Implementation of Beach Sports Big Data Analysis System Based on Computer Technology	Beach volleyball match datasets processed within a purpose-built analysis platform	Data mining architecture using sorting prediction and Markov-based algorithms	A functioning big data analysis system was implemented that predicted cooperation success rate and identified key action transfer processes within matches; experimental testing verified algorithm effectiveness and supported evidence-based training and tactical planning.
Nunes et al. (2020)	Match analysis and heart rate of top-level female beach volleyball players during international and national competitions	One blocker and one defender from a top-level female team; 66 international and 33 national championship matches	Global positioning satellite tracking combined with percentage of maximum heart rate zone analysis	Activity and heart rate zone distribution differed markedly between the blocker and the defender and between national and international competition, indicating that positional role and competition level jointly determine internal and external match demands in elite female beach volleyball.
Wenninger et al. (2020)	Performance of machine learning models in application to beach volleyball data	Dataset of 1,356 top-level beach volleyball games	Multi-layer perceptron, convolutional network, recurrent network and gradient boosted tree classifiers	Classification accuracy for tactical behaviour differed significantly between models, with significant interaction effects between model, input feature set and target behaviour; performance approached that of previously published approaches, confirming the feasibility of automated tactical classification from positional data.
Schmidt et al. (2021)	Quantifying jump-specific loads in beach volleyball by an inertial measurement device	Match-play jump counting (439 jumps) with laboratory validation against three-dimensional motion analysis	Commercially available wearable inertial measurement device	Jump counting during match play achieved excellent precision (0.975) with recall between 0.836 and 1.000 depending on jump type, whereas jump height estimation showed larger typical error against three-dimensional motion analysis, indicating that count-based rather than height-based metrics are currently defensible for load monitoring.
Bellinger et al. (2021)	Quantifying the activity profile of female beach volleyball tournament match-play	Ten adult and ten under-23 female players across 60	10 Hz global positioning system units	External output was quantified across competition levels and score contexts using linear mixed models; adult and under-23

Author (Year)	Full title of the included study	Sample and setting	Monitoring technology	Key findings
		tournament matches		players differed in activity profile, and external output varied with competition level, score differential and phase of the match, providing reference values for conditioning prescription.
Bozzini et al. (2021)	Evaluation of performance characteristics and internal and external training loads in female collegiate beach volleyball players	Twenty NCAA Division I female players monitored across a six-week competitive season	Integrated global positioning system and heart rate monitoring individualised from preseason testing	Internal and external workload metrics were quantified across the competitive season and compared between travelling and non-travelling squad members, establishing the first season-long load reference profile for collegiate women's beach volleyball and revealing differing exposure between squad subgroups.
João et al. (2021)	Global position analysis during official elite female beach volleyball competition: A pilot study	Twelve professional female players across 30 official matches and 50 sets	10 Hz global positioning system devices (Minimax S4)	Peak player load, distance covered at different intensities, and acceleration and deceleration profiles differed between defenders and blockers; within-match variation was more pronounced for defenders, whose acceleration intensity increased while displacement velocity and jump height declined across sets.
Tometz et al. (2022)	Validation of Internal and External Load Metrics in NCAA D1 Women's Beach Volleyball	Thirteen NCAA Division I female players; 578 data points from 51 team sessions across a 15-week preseason	Training impulse, session rating of perceived exertion and distance covered with environmental condition recording	Internal load metrics (training impulse and session rating of perceived exertion load) and external distance covered were quantified across practice, competition and conditioning, and environmental variables were incorporated, supporting the concurrent use of internal and external metrics for load validation in outdoor sand training.
Schleitzer et al. (2022)	Development and evaluation of an inertial measurement unit (IMU) system for jump detection and jump height estimation in beach volleyball	Twenty participants in a laboratory sandbox mounted on force plates and five beach volleyball athletes in field conditions	Purpose-built two-unit inertial measurement system with automatic jump detection	A sand-specific inertial system was developed and validated for automatic jump detection and jump height estimation, addressing the absence of wearable equipment designed for deformable surfaces; detection performance supported field deployment while height estimation remained the weaker component.
Nicklas et al. (2022)	Gaze behavior in social interactions between beach volleyball players—An exploratory approach	Eighteen expert beach volleyball players under high and low game performance pressure	Wearable mobile eye-tracking system	Higher performance pressure produced more frequent and longer fixations on teammates' faces, interpreted as an increased need for unambiguous communication, demonstrating that wearable gaze technology

Author (Year)	Full title of the included study	Sample and setting	Monitoring technology	Key findings
				can capture socially mediated performance behaviour that positional systems cannot detect.
Medeiros et al. (2023)	Activity profile of training and matches activities of women's beach volleyball players: A case study of a world top-level team	One defender and one blocker from the Brazilian national women's team; 57 training sessions and 33 matches over five months	Wearable tracking with player load, jump count, distance and change-of-direction outputs	Physical demands differed systematically between formal matches, match warm-up, physical training and technical-tactical training, showing that training sessions did not consistently replicate the jump and change-of-direction demands of competition in a world top-level team.
Marzano-Felisatti et al. (2024)	Analysing Physical Performance Indicators Measured with Electronic Performance Tracking Systems in Men's Beach Volleyball Formative Stages	Thirty-two young male players (U15 and U19; beach and indoor specialists) across 40 matches	Electronic performance and tracking system (WIMU PRO)	U19 players and beach volleyball specialists covered greater total and relative distance and performed more accelerations and decelerations than younger and indoor-specialised counterparts, establishing age- and specialisation-dependent reference values for the formative stages of the discipline.
Hank et al. (2024)	Differences in external load among indoor and beach volleyball players during elite matches	Eight beach and fourteen indoor elite female players; 2,336 three-dimensional trajectories from playoff matches	Three-dimensional trajectory analysis of active play time	In both disciplines 80% of rallies lasted up to 10 s and players covered 4.5 to 10 m during 60% of rally play, but distance covered and player load values in beach volleyball rallies were up to 23% higher, with the unstable sand surface elevating explosive demands relative to indoor play.
Medeiros et al. (2024)	Validity and reliability of My Jump 2® app to measure the vertical jump on elite women beach volleyball players	Eleven elite female players performing six countermovement jumps in a sand-filled box on a force platform	Video-based mobile application (My Jump 2) validated against a force platform	Inter-observer agreement was excellent for flight time, jump height and peak power (ICC 0.91 to 0.97), and no significant differences were detected between the force platform and the application for any of the three variables, supporting the application as a low-cost field alternative on sand.
Marzano-Felisatti et al. (2025a)	Validation of the WIMU PRO™ Device for Jump Detection in Beach Volleyball: A Gender-Based Analysis during Official Competitions	Eleven players (six female, five male) recorded during 42 one-set official matches	Inertial device (WIMU PRO) compared against high-definition camera observational analysis	Overall jump detection sensitivity was high (96.29%), with a small difference between sexes and additional variation attributable to individual players and to the technical action associated with the jump, indicating that device accuracy is action-dependent rather than uniform.
Figueira et al. (2025)	Comparative analysis of external and internal loads in preparation male volleyball and beach volleyball matches	Twelve national-level male players across three beach volleyball and one indoor volleyball session	Inertial units (VXSport Omni) with heart rate and energy expenditure recording	External load variables did not differ between disciplines except for a higher count of jumps below 20 cm in beach volleyball, whereas internal responses were greater on sand, including higher

Author (Year)	Full title of the included study	Sample and setting	Monitoring technology	Key findings
				average and peak heart rate, more time above 90% of maximum heart rate and greater energy expenditure.
Pino-Ortega et al. (2026)	Comparative analysis of recording system for collecting kinematic data in beach volleyball	Twelve beach volleyball matches from one tournament comprising 469 rallies	Global navigation satellite system compared with ultra-wideband local positioning system	Statistically significant differences were observed between the satellite and ultra-wideband systems for kinematic variables including total, explosive and speed-zone distance, accelerations, decelerations and speed, indicating that data obtained from different tracking technologies are not interchangeable in beach volleyball.
de Souza et al. (2026)	Validity and reliability of the my jump® 2 app to measure vertical jump performance in beach volleyball players	Twenty-six male players performing four vertical jump types on sand	Video-based mobile application (My Jump 2) compared with two-dimensional video analysis	Reliability indices were low to moderate (ICC 0.447 to 0.594) with substantial measurement error and minimal detectable change on sand, indicating that mobile application jump assessment is markedly less dependable in the field sand environment than under controlled sand-box conditions.

Table 5. Classification of the included studies by design, monitoring modality, thematic cluster and outcome domain

Author (Year)	Research design	Monitoring modality	Thematic cluster	Primary outcome domain
Link (2014)	Applied software development and evaluation	Computer vision and video-based tracking	Automated event and action recognition	Positional data capture and analysis workflow
Gomez et al. (2014)	Algorithm development and comparative validation	Computer vision and video-based tracking	Automated event and action recognition	Tracking accuracy for players and ball
Hank et al. (2016)	Observational cross-sectional match analysis	Computer vision and video-based tracking	Match and activity profiling	Horizontal displacement and rally duration
Kautz et al. (2017)	Algorithm development and comparative validation	Machine learning and data-mining analytics	Automated event and action recognition	Activity classification accuracy
Song et al. (2019)	System design and experimental verification	Machine learning and data-mining analytics	Tactical pattern modelling	Predicted cooperation success and action transfer
Nunes et al. (2020)	Observational case study across competitions	GNSS and local positioning systems	Internal load and physiological response	Activity profile and heart rate zone distribution
Wenninger et al. (2020)	Comparative model evaluation on archival data	Machine learning and data-mining analytics	Tactical pattern modelling	Tactical behaviour classification accuracy

Author (Year)	Research design	Monitoring modality	Thematic cluster	Primary outcome domain
Schmidt et al. (2021)	Criterion validation (field and laboratory)	Wearable inertial measurement units	Device validity and reliability	Jump count precision and jump height error
Bellinger et al. (2021)	Observational cross-sectional tournament analysis	GNSS and local positioning systems	External load quantification	External output and contextual modulators
Bozzini et al. (2021)	Longitudinal observational season monitoring	GNSS and local positioning systems	External load quantification	Internal and external seasonal training load
João et al. (2021)	Observational pilot competition analysis	GNSS and local positioning systems	Match and activity profiling	Player load, distance and acceleration by position
Tometz et al. (2022)	Longitudinal validation across a preseason	GNSS and local positioning systems	Internal load and physiological response	Concurrent internal and external load metrics
Schleitzer et al. (2022)	Device development and criterion validation	Wearable inertial measurement units	Jump load and jump detection	Automatic jump detection and height estimation
Nicklas et al. (2022)	Experimental exploratory design	Wearable eye-tracking	Perceptual-cognitive monitoring	Fixation frequency and duration under pressure
Medeiros et al. (2023)	Longitudinal observational case study	GNSS and local positioning systems	External load quantification	Player load, jumps and changes of direction
Marzano-Felisatti et al. (2024)	Observational cross-sectional competition analysis	Wearable inertial measurement units	External load quantification	Distance, acceleration and deceleration profiles
Hank et al. (2024)	Observational cross-sectional comparative analysis	Computer vision and video-based tracking	Match and activity profiling	External load compared across surfaces and positions
Medeiros et al. (2024)	Criterion validation against force platform	Video-based mobile applications	Device validity and reliability	Flight time, jump height and peak power agreement
Marzano-Felisatti et al. (2025a)	Criterion validation during official competition	Wearable inertial measurement units	Jump load and jump detection	Jump detection sensitivity by sex and action
Figueira et al. (2025)	Comparative experimental field design	Wearable inertial measurement units	Internal load and physiological response	External load, heart rate and energy expenditure
Pino-Ortega et al. (2026)	Comparative device concurrent analysis	GNSS and local positioning systems	Device validity and reliability	Agreement between satellite and ultra-wideband data
de Souza et al. (2026)	Criterion validation and reliability study	Video-based mobile applications	Jump load and jump detection	Reliability, measurement error and agreement on sand

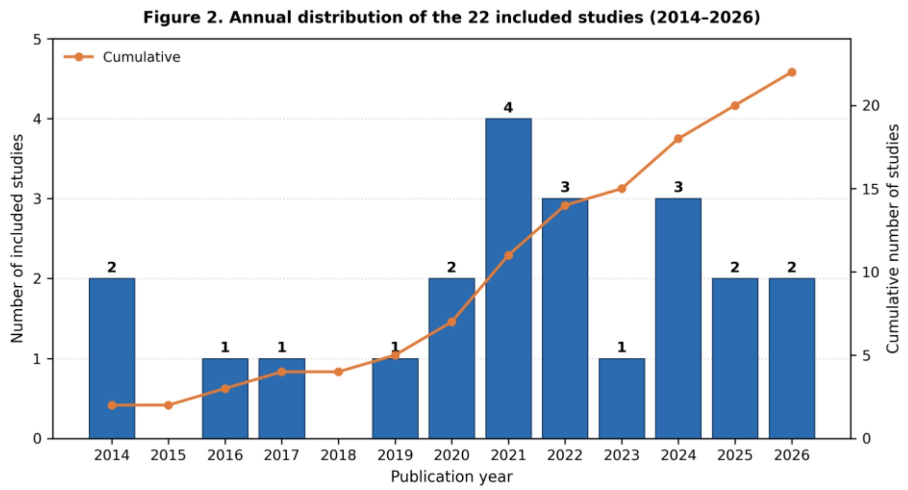

Figure 2. Annual distribution of the 22 included studies between 2014 and 2026, with cumulative curve.

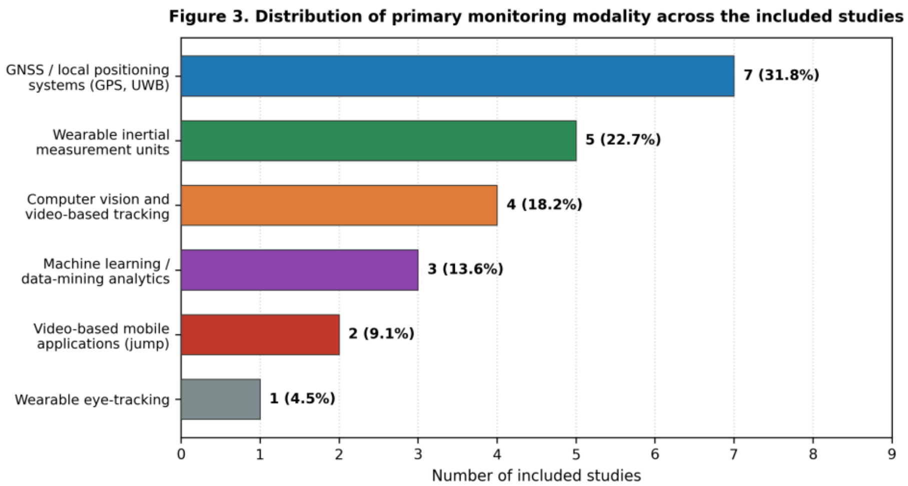

Figure 3. Distribution of the primary monitoring modality across the 22 included studies.

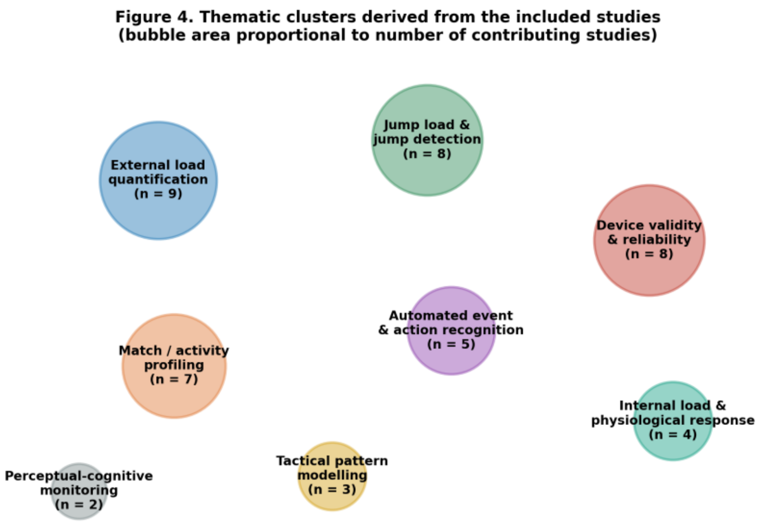

Figure 4. Thematic clusters derived from the included studies; bubble area is proportional to the number of contributing studies.

Thematic Synthesis

Findings for RQ1: Monitoring systems and the constructs they quantify

The first research question asked which monitoring systems are deployed in beach volleyball and what constructs they quantify. Across the synthesis, the field looks as though it has settled into a partially integrated ecosystem. Positioning technologies handle displacement. Inertial technologies cover jump activity and mechanical intensity. Vision-based technologies take care of events, trajectories, and technical actions. Studies have drawn on 10 Hz satellite positioning to derive distance covered, velocity zones, acceleration and deceleration counts, and composite player load, both in official competition and across entire competitive seasons (Bellinger et al., 2021; João et al., 2021; Bozzini et al., 2021). Electronic performance and tracking systems that fuse inertial and positioning sensing have carried those same constructs into youth competition and into direct comparisons of beach and indoor specialists (Marzano-Felisatti et al., 2024). What gets measured, in other words, is predominantly external, mechanical, and displacement-based.

Inertial measurement units go after a construct positioning systems capture poorly, namely the vertical component of the game. They have been used to count jumps during match play with high precision, to estimate jump height, and to tell jump types apart by technical action (Schmidt et al., 2021; Schleitzer et al., 2022; Marzano-Felisatti et al., 2025a). Video-based mobile applications sit in an adjacent slot, quantifying discrete jump performance in field-testing rather than in continuous monitoring contexts (Medeiros et al., 2024; de Souza et al., 2026). Taken together, these studies make jump load the construct that has drawn the most concentrated instrumentation effort in the discipline. That makes sense, given how central jumping is to both performance and overuse risk in a two-player game.

A different family of constructs comes from vision-based and analytical technologies. Automated tracking systems pull player and ball positions, plus contact time points, straight from video (Gomez et al., 2014), and integrated toolsets turn those positional streams into structured tactical analysis for coaching staff (Link, 2014). Machine learning pushes this further into classification and prediction. Some approaches recognise sport-specific actions from wearable sensor signals (Kautz et al., 2017). Others classify tactical behaviour across large archival game datasets (Wenninger et al., 2020). Still others predict cooperation success and identify action transfer sequences within a data-mining architecture (Song et al., 2019). Outside these three families, a single study applied wearable eye-tracking to quantify gaze behaviour during teammate interaction under performance pressure (Nicklas et al., 2022), and several positioning studies added heart rate telemetry to represent internal load alongside external output (Nunes et al., 2020; Tometz et al., 2022; Figueira et al., 2025). So RQ1 resolves into a taxonomy of six modalities. Together they quantify external displacement, jump activity, physiological strain, technical-tactical events and, in one instance, visual attention.

Findings for RQ2: Validity and reliability on sand

Eight of the 22 studies reported direct validation or reliability evidence. The findings were heterogeneous and should not be reduced to a single universal threshold. Schmidt et al. (2021) reported jump-count precision of 0.975 and recall of 0.836–1.000 across jump types, while Marzano-Felisatti et al. (2025a) reported 96.29% overall jump-detection sensitivity in official competition. Medeiros et al. (2024) reported excellent inter-observer agreement for flight time, jump height, and peak power (ICC 0.91–0.97) under controlled sand-box conditions, whereas de Souza et al. (2026) reported low-to-moderate reliability on open sand (ICC 0.447–0.594). These results demonstrate that measurement quality depends on the construct, instrument, reference standard, and environmental context.

Validation of video-based mobile applications illustrates the importance of ecological context. Under controlled sand-box conditions on a force platform, Medeiros et al. (2024) reported ICC values of 0.91–0.97 and no significant differences between the application and criterion measures for flight time, jump height, or peak power. In contrast, de Souza et al. (2026) found ICC values of 0.447–0.594 on open sand, together with substantial measurement error and minimal detectable change. The two studies therefore should not be treated as contradictory; rather, they define different boundary conditions for the same class of tool.

Positioning-system comparability is another distinct validity problem. Across 469 rallies, Pino-Ortega et al. (2026) found statistically significant differences between GNSS and ultra-wideband systems in total, explosive, and speed-zone distance, acceleration, deceleration, and speed. The evidence therefore does not support treating outputs from competing positioning infrastructures as interchangeable. For computer vision, Gomez et al. (2014) reported that the better of two tracking algorithms correctly tracked 82.6% of frames for front players, with occlusion and camera perspective remaining major sources of error.

Algorithmic studies require a different interpretation from criterion-validation studies. Kautz et al. (2017) compared a deep convolutional neural network with conventional classifiers for activity recognition, while Wenninger et al. (2020) compared multiple machine-learning architectures for tactical classification. Their results demonstrate model-dependent classification performance rather than instrument validity against a physical reference standard. Accordingly, classification accuracy is reported as algorithmic performance and is not conflated with measurement validity or reliability.

Findings for RQ3: Applications, limitations and gaps

The third research question covered practical application, limitations, and gaps. What the corpus offers most directly is a set of competition reference values. Rally structure looks highly consistent across independent datasets. In elite female competition, mean rally duration is 7.27 s and 83.7% of rallies finish within 10 s (Hank et al., 2016). A later elite comparison put 80% of rallies below 10 s and found 60% of court coverage between 4.5 and 10 m (Hank et al., 2024). Mean horizontal displacement of 9.39 m per rally and 287.5 m per set gives conditioning design a defensible target. And the reported 23% elevation of rally distance and player load relative to indoor play quantifies the extra mechanical cost of the sand surface.

The second applied contribution has to do with specifying training relative to competition. Longitudinal case monitoring of a world top-level team showed that formal matches, match warm-up, physical training, and technical-tactical training generate systematically different demands in field time, player load, jump counts, distance, and change of direction (Medeiros et al., 2023). Seasonal monitoring of collegiate athletes told a similar story, with differing exposure between travelling and non-travelling squad members across a competitive season (Bozzini et al., 2021). Positional analysis added another layer, showing that defenders and blockers diverge in player load, intensity distribution, and within-match trajectory (João et al., 2021; Nunes et al., 2020). The implication is that load prescription should be individualised, role-specific, and squad-status-specific, not an undifferentiated team programme.

A third applied contribution concerns the relationship between internal and external load. Comparative field testing found external load variables largely equivalent between beach and indoor sessions, except for a higher count of low-amplitude jumps on sand. Internal responses, however, were consistently greater on sand: higher average and peak heart rate, more time above 90% of maximum heart rate, and higher energy expenditure (Figueira et al., 2025). The practical implication is clear. Rely on external metrics alone and you will systematically underestimate the physiological cost of beach volleyball. Any framework built exclusively on distance or player load will misrepresent what athletes are actually going through.

The corresponding limitations are structural. Sample sizes are small, often confined to one team or one tournament. Designs are overwhelmingly cross-sectional; the corpus contains only three longitudinal monitoring studies. Criterion measures are heterogeneous, spanning force platforms, three-dimensional motion capture, and retrospective video annotation. And no included study linked technology-derived load to prospectively recorded injury outcomes. Sex-specific validation is only partial, with a single study explicitly analysing detection accuracy by sex. So RQ3 gets this answer. The technology supports descriptive profiling and role-specific load prescription with reasonable confidence. Individualised threshold setting, cross-system benchmarking, and injury risk prediction are still out of reach.

Comparative and Critical Analysis of Methodological Approaches

Methodologically, the corpus splits into three traditions that rarely interact. First is the engineering tradition, which covers algorithm development and device validation studies. It prioritises internal validity, uses criterion referencing, and reports classification or agreement statistics, but it often operates on small or laboratory-constrained samples. Second is the applied sport science tradition, covering competition and season monitoring studies. It prioritises ecological validity in official competition yet generally takes manufacturer-reported accuracy on faith, without independent verification. Third is the analytical tradition, the machine learning and data-mining contributions. These run on archival datasets of substantial scale but sit largely detached from the physiological and training questions that motivate applied monitoring.

Design frequencies mirror that division. Observational cross-sectional analyses were the most common, with criterion validation studies next. Only three longitudinal designs appeared, along with one experimental laboratory-field hybrid and one exploratory experimental design. Randomised or controlled interventional designs were entirely absent. That is unsurprising, since the review's inclusion criteria centre on measurement rather than intervention. Still, it constrains any causal inference about whether monitoring-informed practice actually changes performance or injury outcomes.

Chronologically, a methodological evolution is visible. The earliest included work centred on vision-based tracking and analysis toolsets, which simply reflected the technological options available at the time

(Link, 2014; Gomez et al., 2014). The middle period brought learning-based classification (Kautz et al., 2017) and the first large-scale positioning studies. The most recent period is dominated by device validation and comparative analysis, sex-stratified validation and direct comparison of competing positioning infrastructures among them (Marzano-Felisatti et al., 2025a; Pino-Ortega et al., 2026). That progression, from capability demonstration toward measurement scrutiny, is typical of a maturing measurement field. Even so, the evidence base remains front-loaded with feasibility work relative to confirmatory application.

Discussion

Interpretation and theoretical implications

The synthesis suggests that the principal constraint is not a lack of sensing capability but a mismatch between measurement assumptions and the mechanical properties of sand. Biomechanical studies in the included evidence show lower power output, altered rate of force development, and changes in joint mechanics on sand (Giatsis et al., 2018, 2022, 2023). These findings provide a plausible mechanism for the observed divergence between robust jump counting and less dependable jump-height estimation. The interpretation should nevertheless remain bounded by the small samples and study-specific reference standards: the present review supports a surface-dependent measurement problem, but it does not establish that all monitoring devices share the same error mechanism.

The dissociation between external and internal load that shows up in the corpus extends existing theoretical accounts of load in team sport. Conventional models treat external load as the imposed dose and internal load as the individual response, and the two are expected to covary. Beach volleyball breaks that expectation. Moving the body through a deformable surface demands mechanical work, and outdoor play adds a thermoregulatory cost, so internal response inflates without any proportional increase in the displacement metrics that positioning systems record. Session rating of perceived exertion has been shown to function as a valid internal load indicator across genders and competitive levels in beach volleyball, though with limitations for tactical training and games. That is consistent with this interpretation, and it reinforces the case for monitoring in parallel rather than treating one type of load as a substitute for the other (Lupo et al., 2020).

The review also shows, theoretically, that the constructs currently measured sit unevenly across the determinants of performance. Research on decision making in beach volleyball defence has identified perceptual and anticipatory factors as central to expert performance (Schläppi-Lienhard & Hossner, 2015; Ittlinger et al., 2024). Perceptual training and gaze-cueing studies have shown that visual behaviour is modifiable and relevant to performance (Klostermann et al., 2015; Klatt & Smeeton, 2020). Evidence that base rate information gets used in real-world sequential decisions further underlines the cognitive sophistication of expert play (Link & Raab, 2022). Yet only one included study instrumented this domain (Nicklas et al., 2022). So the monitoring ecosystem quantifies the mechanical determinants of performance in detail, while the perceptual-cognitive determinants sit almost entirely uninstrumented.

Practical implications and comparison with prior reviews

Practically, the review yields four actionable recommendations. First, treat jump count as the primary inertial monitoring metric in beach volleyball. Whenever jump height feeds individual decision making, it should be reported with explicit measurement error, given how far count validity and height validity diverge (Schmidt et al., 2021; Marzano-Felisatti et al., 2025a). Second, anchor longitudinal monitoring to a single tracking infrastructure for the whole season, because satellite and ultra-wideband systems produce kinematic values that are simply not interchangeable (Pino-Ortega et al., 2026). Third, always pair external load monitoring with an internal load indicator, since sand and outdoor conditions inflate physiological strain independently of displacement (Figueira et al., 2025; Lupo et al., 2020).

Fourth, audit training design against competition demands instead of assuming it reproduces them. Within a single elite team, the divergence between formal match, warm-up, physical, and technical-tactical demands is well demonstrated, and it indicates that jump and change-of-direction exposure can be substantially under- or over-represented in the training week (Medeiros et al., 2023). Add the documented burden of overuse shoulder and spine complaints in volleyball populations, the distinct injury pattern seen in beach volleyball (Seminati & Minetti, 2013; Jiménez-Olmedo et al., 2018; Juhan et al., 2021), and the environmental heat risk recorded across more than a decade of world tour surveillance (Racinais et al., 2021). Audited exposure then looks like a tractable prevention strategy that can be implemented immediately.

Placing these findings against prior syntheses clarifies what this review adds. Earlier reviews of beach volleyball match analysis catalogued technical-tactical performance indicators drawn largely from manual observation (Medeiros et al., 2014; Alvarado-Ruano & López-Martínez, 2022). A recent review characterised physical performance and game demands without taking the measurement instrument as the unit of analysis (Marzano-Felisatti et al., 2025b). Reviews of injury and pathology built the epidemiological case for load management but never evaluated the tools available to deliver it (Jimenez-Olmedo & Penichet-Tomas, 2015). This review complements all of them by showing that the descriptive values reported across the applied literature rest on measurement systems whose agreement with one another has been formally rejected. That constraint qualifies the interpretation of every prior demand synthesis.

Limitations, research gaps and future agenda

Several contradictions in the literature deserve explicit acknowledgement. The most striking one concerns mobile application jump assessment. Excellent agreement shows up under sand-box laboratory conditions (Medeiros et al., 2024), yet low to moderate reliability shows up in open-field sand conditions (de Souza et al., 2026). A plausible reconciliation: in the laboratory, constrained foot placement, fixed camera geometry, and stable sand depth remove the sources of variance that dominate in the field. If that is right, then both findings are correct within their own boundary conditions, and neither generalises to the other.

A second contradiction concerns external load comparisons between disciplines. Three-dimensional trajectory analysis of elite playoff matches reported beach volleyball rally distance and player load exceeding indoor values by up to 23% (Hank et al., 2024). Inertial monitoring of preparation matches, by contrast, found no significant external load differences apart from low-amplitude jump counts, with the difference showing up instead in internal responses (Figueira et al., 2025). Competitive context, sex composition, and, critically, measurement modality all probably contribute to the divergence, which only reinforces the central methodological conclusion of this review. A third, more subtle tension concerns positional effects. Playing position did not influence horizontal distance covered in one elite female sample (Hank et al., 2016), yet position strongly differentiated player load and intensity distribution in others (João et al., 2021; Nunes et al., 2020). Positional differentiation, that suggests, lives in movement intensity and vertical activity rather than in aggregate displacement.

Three specific research gaps follow from the synthesis. The first is the absence of prospective studies linking technology-derived load to injury or illness outcomes. No included study followed athletes long enough, or recorded health outcomes systematically enough, to actually test load-injury relationships. The second is the near-absence of instrumented perceptual-cognitive monitoring, despite converging evidence that decision making and visual behaviour discriminate expert performance in the sport and respond to training (Schläppi-Lienhard & Hossner, 2015; Klostermann et al., 2015; Grisi et al., 2021; Ittlinger et al., 2024). The third is the absence of multi-modal integration. No included study combined positioning, inertial, physiological, and vision-based streams within a single analytical framework, so the incremental information each modality contributes remains unquantified.

The review has five principal limitations. First, the current evidence identification relied on Scopus alone, so records unique to PubMed, Web of Science, or grey-literature sources may have been missed. Second, only English-language publications were eligible, which may introduce language bias. Third, the 22-study corpus is small and methodologically heterogeneous, preventing a meaningful pooled estimate of device agreement. Fourth, the FICO rubric is author-developed and involves interpretive judgement; it should therefore be treated as supplementary unless replaced or complemented by established design-specific appraisal tools. Fifth, the review was not prospectively registered. These limitations constrain external validity and should be reported explicitly rather than hidden by the high proportion of FICO-rated studies.

Future research should prioritise four areas: prospective multi-season monitoring linked to systematic injury and illness surveillance; sex- and action-stratified validation of wearable and video-based systems; direct cross-system agreement studies that establish whether conversion models are possible; and multimodal frameworks combining positioning, inertial, physiological, and perceptual-cognitive signals. These studies should report reference standards, sample characteristics, missing data, measurement error, and uncertainty explicitly so that practitioners can distinguish true change from device noise.

Overall, six monitoring modalities answer RQ1: satellite/local positioning, wearable inertial measurement units, computer vision, machine-learning analytics, video-based mobile applications, and wearable eye-tracking. RQ2 shows the strongest evidence for discrete event detection, especially jump counting, while jump height and high-intensity kinematic magnitudes remain less certain. Video-based applications are highly context-dependent, and competing positioning infrastructures cannot currently be assumed interchangeable. RQ3 indicates practical value for competition profiling, role-specific load prescription, and training-competition auditing, but not yet for injury prediction or universal individualised thresholds.

To summarise directly, six monitoring modalities answer RQ1. Jointly, they quantify external displacement, jump activity, physiological strain, automated event and tactical classification and, marginally, visual attention, while satellite and local positioning systems and wearable inertial units dominate the evidence base. RQ2, by comparison, is more uneven. Validity is acceptable for discrete event detection and aggregate displacement. Jump height and high-intensity kinematic magnitudes remain uncertain, and video-based mobile applications come across as strongly context-dependent. Between competing positioning infrastructures, validity is formally absent. For RQ3, current technology supports competition profiling, role-specific and squad-specific load prescription, and training-competition auditing. The caveats are familiar: small cross-sectional samples, heterogeneous criterion measures, incomplete sex-specific validation, and the absence of injury-linked longitudinal evidence and multi-modal integration.

Conclusions

This systematic review synthesised 22 peer-reviewed studies published between 2014 and 2026 on technology-based athlete monitoring in beach volleyball. Six monitoring modalities were identified, with satellite/local positioning and wearable inertial systems dominating the evidence base. Quantitative validation findings were construct-specific: jump detection showed high performance in official competition (96.29% sensitivity in one study; precision 0.975 and recall 0.836–1.000 in another), while jump-height and field-based mobile-app reliability were substantially less consistent (ICC 0.447–0.594 in open sand versus 0.91–0.97 under controlled sand-box conditions). GNSS and ultra-wideband outputs also differed significantly across multiple kinematic variables, precluding assumptions of interchangeability. The evidence therefore supports technology-assisted descriptive profiling and role-specific load monitoring, but not yet cross-device benchmarking, universal individual thresholds, or injury prediction. The main review limitations are single-database identification, English-only eligibility, small and heterogeneous primary samples, and the absence of pooled meta-analysis. Before the evidence can support high-stakes individualised decisions, future studies should use multi-database searches, independent multi-reviewer screening, established risk-of-bias tools, sex- and action-stratified validation, prospective injury surveillance, and multimodal integration.

Acknowledgments

The Authors would like to thank Faculty of Sport Sciences, Universitas Negeri Padang for providing excellent facilities, as well as for being very supportive of this research from the beginning. Authors also thank the team members who had generously shared their brilliant ideas, engaging discussion, and academic supports during the study.

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