Vol. 7, No. 1, 2026, pp. 903-927
DOI: https://doi.org/10.29210/992930

Contents lists available at Elora Center

Lentera Negeri

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

Performance assessment using wearable sensors in tennis: a systematic literature review

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Article Info

Article history:
Received Mar 11th, 2026
Revised Jul 20th, 2026
Accepted Jul 21th, 2026

Keywords:
Wearable sensors
Real-time athlete monitoring
Performance analysis
Biomechanics
Machine learning; tennis

ABSTRACT

Tennis is a high-intensity intermittent sport requiring accurate workload monitoring to optimize performance and reduce injury risk. However, evidence regarding wearable-sensor applications remains fragmented across sport science, biomechanics, and engineering disciplines. This systematic literature review synthesizes current evidence on wearable-sensor technologies, validation, analytical methods, and practical applications for real-time monitoring in tennis. The review followed the PRISMA 2020 guidelines. A structured Boolean search of the Scopus database identified 130 records published between 2016 and 2026. After screening by two independent reviewers (Cohen's $\kappa = 0.87$), 15 studies met the predefined eligibility criteria and were included in the qualitative synthesis. Methodological quality was evaluated using the FICO framework to ensure structured assessment of study focus, reporting quality, contextual relevance, and outcomes. Thematic synthesis revealed four principal findings: (1) inertial measurement units demonstrated the strongest validity for stroke detection compared with video reference standards; (2) machine-learning algorithms achieved stroke-classification accuracies ranging from 93% to 98%; (3) wearable sensors effectively differentiated stroke and locomotor workloads across playing conditions; and (4) physiological and positioning technologies showed greater measurement error than inertial systems. Overall, wearable sensors demonstrate substantial potential for performance monitoring, although further longitudinal validation, multisensor integration, and broader athlete representation are required before widespread implementation in coaching and injury-prevention practice.

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Introduction

Tennis holds a pretty unusual spot in elite sports. Players compete all year long on four different surfaces across continents, they push through intermittent high-intensity bursts in matches that can stretch past five hours, and they repeatedly fire their upper limbs ballistically under serious time pressure. The professional schedule barely leaves room for controlled lab testing, the kind that underpins load management in team sports with clear seasons, and athletes often train in scattered locations without access to institutional sport-science setups (Whiteside et al., 2017). What you get is a structural monitoring gap: the sport that probably needs individualised workload tracking the most is among the least equipped with the technologies built for that job. Global interest in athlete monitoring has grown fast alongside advances in microelectromechanical sensing, and sport organisations now routinely gather longitudinal load data in football, rugby, and basketball (Hoppe et al., 2018; Rebelo et al., 2023). Tennis has been slower to catch up, and figuring out why, along with what current tech can and cannot actually do, is a question worth asking from both a scientific and a practical angle.

Recent surveys indicate that wearable monitoring technologies are routinely implemented in professional football, rugby, and basketball programs, whereas their adoption in tennis remains substantially lower because monitoring must accommodate individualized competition schedules, multiple playing surfaces, and dispersed training environments.

The specific issue here is quantifying hitting load. In most field sports, you can capture external workload pretty well with locomotor metrics: distance covered, high-speed running, accelerations and decelerations. Tennis is different. A player might cover modest ground while racking up several hundred high-velocity shoulder rotations, and it's that hitting volume, not the running, that most likely links to overuse injuries in the shoulder, elbow, and lumbar spine (Ramasamy et al., 2023; Nidhisheshwin et al., 2026). GPS units, the go-to for team-sport monitoring, lack precision inside a tennis court's tight dimensions and simply cannot register a stroke (Whiteside et al., 2017; Waqar et al., 2021). Manual video notation remains the gold standard, but it's slow, retrospective, and impractical for a touring pro's packed schedule. So the field needs a device that is wearable, unobtrusive, works on any court, and can pick out discrete hitting events in real time.

Existing research has tackled this from two mostly separate angles. A sport-science stream, centred in Australia and Europe, has fitted players with commercial inertial devices and checked their agreement against video during drills and match-play (Hadžić et al., 2021; Perri et al., 2022; Perri et al., 2023a). An engineering stream, centred in China, has built custom sensing substrates, flexible piezoresistive arrays, triboelectric nanogenerators, self-powered yarn structures, and shown they can transduce stroke mechanics under controlled settings (Yang et al., 2023; Deng, 2024; Chen et al., 2025; Fan et al., 2025). This engineering lineage goes back to early instrumented-racket and IoT prototypes for racket sports (Wang et al., 2018) and continues through battery-free piezoelectric mats (Yu et al., 2022), dual-mode pressure sensors for joint monitoring (Gao et al., 2023), and triboelectric substrates mainly tested in table tennis (Xu et al., 2025; Wang et al., 2026). These two bodies of work rarely cite each other. The first has strong ecological validity but is limited by black-box proprietary algorithms from commercial vendors; the second is strong on transduction novelty but often untested beyond a handful of lab participants. Without a synthesis bridging the two, practitioners lack a clear picture of what can actually be measured right now.

Methodological progress over the last five years has been substantial, though. Supervised machine learning has moved stroke classification from a research wish to an operational reality, with support vector machines and deep autoencoders reported to tell shot types apart from raw inertial signals at accuracies above 93% (Whiteside et al., 2017; Benages Pardo et al., 2019). Positioning tech has branched beyond satellites: ultra-wideband local positioning offers indoor tracking at metre-level precision, and computer-vision platforms can reconstruct ball flight (Waqar et al., 2021; Yang et al., 2025). Physiological telemetry has shifted from chest straps to wrist-worn photoplethysmography (Hermand et al., 2019; Ruiz-Malagón et al., 2025). Sensor placement has spread across the wrist, cervical spine, racket grip, and most recently the vibration dampener (Kos & Kramberger, 2017; Liu et al., 2024), and neural architecture search has been applied to detailed swing tracking (Jia et al., 2021). The parallel finding that instrumented load quantification differs systematically from subjective ratings (Izzo et al., 2020) has strengthened the case for objective monitoring. The tech frontier has moved a lot faster than the evidence base that should guide its use.

A first gap follows directly. Devices have multiplied, but validation hasn't kept up. A recent scoping review of hitting-load technologies in racket sports found that out of eleven tennis-compatible commercial systems, only four showed excellent reliability for shot counting, and no system in badminton, table tennis, padel, or squash had been successfully validated at all (Brich et al., 2024). And validation has focused overwhelmingly on a single outcome, total shot count, while biomechanically important variables like stroke intensity, joint loading, and kinematic sequencing remain largely unchecked. So practitioners end up trusting devices for decisions the devices were never shown to support.

A second gap is theoretical and methodological. The dominant analytical approach reduces an entire training session or match to a single accelerometry summary, a mean or cumulative player load, which throws away exactly the distributional info that makes tennis different from continuous endurance activity (Marutani et al., 2023). Where decomposition has been tried, it's shown that stroke-derived and movement-derived load behave as separate constructs that respond differently to drill design, court surface, and match outcome (Perri et al., 2023a; Perri et al., 2023b). But no unifying framework exists to say how these parts should be combined, weighted, or interpreted, and the field lacks the biomechanical theory, kinetic-chain sequencing, proximal-to-distal energy transfer, that would turn sensor output into something physiologically meaningful rather than just numerically available (Chen & Jia, 2025).

The need for a synthesis is made more urgent by the trajectory of the literature itself. Publication output in this area has jumped sharply since 2020, with most retrieved records from the last four years, and the commercial market has grown even faster. Sport federations, academies, and individual coaches are making procurement and prescription decisions in real time, often based on vendor claims rather than peer-reviewed evidence. So a systematic review that separates validated capability from aspirational capability isn't just an academic nicety, it's a prerequisite for responsible practice. This review addresses that need by pulling together the peer-reviewed evidence, assessing its methodological quality, and spelling out what can defensibly be claimed.

Unlike previous reviews focusing solely on hitting-load validation or machine-learning applications, this review integrates wearable sensor technology, biomechanical monitoring, machine-learning analytics, and translational coaching applications within a single PRISMA-guided synthesis. Therefore, this study systematically evaluates the validity, reliability, technological maturity, and practical applicability of wearable-sensor systems for real-time athlete monitoring in tennis.

The first objective is about the technological landscape. Knowing which sensing modalities have been used, where they're mounted, what they measure, and how they've been validated is the necessary foundation for any evaluative judgement. Mapping this landscape creates a technology-to-evidence crosswalk that hasn't been assembled before for tennis, letting practitioners match device selection to the specific monitoring question they're asking. So:

RQ1: What wearable sensing technologies and system architectures have been deployed for real-time monitoring in tennis, and how well has their validity and reliability been established against criterion measures?

The second objective is about analysis. Raw inertial signals are not information; they become information only through the computational pipelines, feature engineering, supervised classification, probabilistic modelling, that turn them into interpretable performance constructs. Characterising these pipelines, their accuracy, and their failure modes provides a critical look at the machine-learning layer that sits between sensor and decision, an appraisal that's mostly missing from vendor documentation and from the sport-science literature. So:

RQ2: Which machine-learning and signal-processing approaches have been applied to wearable-sensor data in tennis, and what levels of classification and estimation accuracy do they achieve for stroke and movement events?

The third objective is about application. Technology and analytics are only instrumentally valuable if they actually change what coaches, physiotherapists, and athletes do. Establishing which biomechanical and performance constructs have been meaningfully measured, and which applied questions the evidence can and cannot answer, gives a realistic picture of translational maturity. The novelty of this review lies in bringing together three literatures that have developed in isolation: the sport-science validation literature, the sensor-engineering literature, and the machine-learning literature, synthesised here for the first time within a single PRISMA-compliant appraisal focused specifically on tennis. So:

RQ3: What biomechanical, physiological and performance-analytic insights have wearable-sensor systems generated in tennis, and what gaps constrain their translation into coaching and injury-prevention practice?

Method

Research Design and Framework

We opted for a systematic literature review as our research design. The reason? Our guiding questions are integrative, not causal. They're about the state, quality, and coherence of existing evidence, not the effect of a specific intervention. Systematic review methodology offers transparency, replicability, and protection against selection bias, things a narrative synthesis simply can't guarantee. That's why it's the standard approach in applied management and health sciences (Tranfield et al., 2003; Liberati et al., 2009). The studies we included are methodologically diverse: validation designs, observational match-play analyses, algorithm-development papers and engineering proofs-of-concept. Meta-analytic pooling just wasn't feasible or appropriate, so we went with a qualitative thematic synthesis instead. We designed, conducted and reported this review in accordance with the PRISMA 2020 statement (Page et al., 2021), which replaces the 2009 guideline (Moher et al., 2009) and adds expanded items for search reproducibility, automation-assisted screening and structured reporting of exclusions.

Search Strategy

We built the search string around three conceptual blocks: technology, function and sport. A Boolean AND operator connected these blocks. Inside each block, we strung synonyms together with OR. Truncation helped capture all morphological variants. To search titles, abstracts and indexed keywords at the same time, we used the TITLE-ABS-KEY field code. Here is the exact string we executed:

> *TITLE-ABS-KEY (("wearable sensor*" OR "inertial measurement unit" OR "IMU" OR "accelerometer*" OR "wearable technolog*" OR "smart sensor*") AND ("real-time monitoring" OR "athlete monitoring" OR "performance analysis" OR "workload" OR "external load" OR "biomechanic*" OR "machine learning") AND ("tennis"))*

We applied limiters for document type (Article, Review), language (English), and publication window (2016, 2026). The ten-year window was selected because wearable sensing technologies experienced rapid methodological evolution after 2015 following widespread adoption of inertial measurement units and machine-learning-based sports analytics. At the search stage, we placed no restriction on subject area. This was to keep records indexed under engineering, computer science, and materials science that a sport-science-only filter would have excluded. Instead, disciplinary relevance was determined during screening.

Database and Information Sources

Scopus was the only database we used. That choice came from the research question's interdisciplinary nature: Scopus covers sport science, biomedical engineering, materials science, and computer science, the venues where this work is scattered. Narrower databases like SPORTDiscus or PubMed routinely miss the engineering angle. We ran the search in one sitting. The full metadata export included authors, titles, source titles, years, DOIs, abstracts, author keywords, affiliations, and document types. That export became the sole evidence base for every step that followed, screening, extraction, and bibliometrics. We did not bring in extra databases, grey literature, or citation chasing. We acknowledge that this restriction is a limitation.

Eligibility Criteria

Eligibility was pre-specified across six dimensions, summarised in Table 1.

Table 1 <Inclusion and Exclusion Criteria Applied During Study Selection>

Criterion	Inclusion	Exclusion
Language	English-language publications	Publications in any other language
Document type	Peer-reviewed journal Article or Review	Conference paper, conference review, book chapter, data paper, editorial, retracted item
Publication period	2016–2026 (ten-year window)	Published before 2016
Subject area	Sport science, sports engineering, biomechanics, human movement science, sensor and instrumentation science	Disciplines with no athlete-facing application
Population	Tennis players (able-bodied or wheelchair) of any competitive level, sex or age	Other racket sports (table tennis, badminton, padel, squash) as the sole population; non-athlete populations
Technology	Wearable, racket-mounted or body-worn sensing system generating athlete-level data	Vision-only systems without a wearable component; materials characterisation without athlete application
Accessibility	Full text retrievable	Abstract-only records; full text unavailable
Relevance	Directly addresses wearable sensing, real-time monitoring, performance analysis or biomechanics in tennis	Tangential mention of tennis as an illustrative example only

Study Selection Process

We used four sequential stages for selection, following the PRISMA 2020 guidelines. At the identification stage, we started with 130 exported records. After deduplicating by title, four records were removed. Then automation-assisted filtering on metadata fields filtered out 50 records of ineligible document type, two non-English records, and four records published before 2016. That left 70 records for screening. During screening, we assessed titles and abstracts against the population and technology criteria. We excluded 40 records. The main reasons were the study population being a racket sport other than tennis (n = 22), no wearable or sensing component present (n = 11), or the record reporting materials-level sensor characterisation with no athlete-facing application (n = 7). We then sought 30 reports for retrieval, but two couldn't be obtained in full text. Of the remaining 28 full texts we assessed for eligibility, 13 were excluded with documented reasons. Six were out of scope on population, four used a method that couldn't generate a real-time or wearable monitoring outcome, and three didn't provide enough methodological or numerical detail for extraction. So fifteen studies met all criteria. We recorded screening decisions against the pre-specified criteria. When eligibility was unclear, we went back to the full text and adjudicated against the population and technology criteria in sequence. Two reviewers independently screened all records using Rayyan software. Any disagreement was resolved through discussion with a third reviewer. Screening reliability reached Cohen's κ = 0.88, indicating almost perfect agreement.

Quality Assessment - FICO Framework

We used the FICO framework to assess methodological quality. The framework checks each study on four things: Focus, Information, Context, and Outcome. Focus looks at whether the research aim is clear and specific. Information evaluates how well the methodology is reported, covering the sample, instruments, and analytical steps. Context judges the ecological validity and if the study setting matches the real-world question. Outcome measures how rigorous, interpretable, and criterion-based the results are. Every domain gets a score from 0 to 2, where 0 means not addressed, 1 means partially, and 2 means fully. That gives a total composite score between 0 and 8. Only studies scoring at least 5 were kept in the synthesis. All fifteen studies we included hit that mark, with scores from 5 to 8 and a median of 7. The domain that most often got a partial score was Context. This happened because many engineering-led studies relied on labs or controlled drills. The domain that consistently scored full marks was Focus. These validation studies tend to have narrow, well-defined goals.

Data Extraction Procedure

We applied the same structured extraction template to every study we included. The fields we pulled out covered first author and publication year, the corresponding author's country, the journal, study design, sample size and participant details (sex, competitive standard, age band when reported), the sensing technology and where it was mounted on the body or equipment, the signal types collected, the analytical or algorithmic approach used, the criterion measure if a validation was performed, primary outcome variables, and the main findings expressed with numbers wherever the source allowed. All values came straight from the original record; if a field wasn't reported, we noted it as unavailable rather than filling it in. The extraction results appear in Tables 2 and 3.

Network and Bibliometric Analysis Methodology

To contextualize the qualitative synthesis, we applied a descriptive bibliometric layer to the metadata export. This involved three analyses. First, we computed annual publication counts for both the eligible corpus (n = 70) and the included set (n = 15). By fitting a least-squares linear trend to the corpus series, we characterized the temporal trajectory of the field. Second, corresponding-author affiliations were parsed down to the national level to establish geographic distribution. Third, we conducted a keyword co-occurrence analysis on the author-keyword and extracted-construct fields of the included studies. Terms were aggregated into three a priori conceptual clusters (wearable sensor technology, real-time athlete monitoring, and machine learning with performance analysis) and rendered as a bubble network where node size is proportional to term frequency. These analyses are descriptive; they serve to situate, not substitute for, the thematic synthesis.

Data Analysis and Synthesis

We used the three-stage thematic synthesis approach from Thomas & Harden (2008) to bring the evidence together. Analytical saturation was considered achieved when repeated coding and constant comparison of the included studies produced no additional descriptive themes or conceptual categories. This criterion ensured that the thematic synthesis comprehensively captured the available evidence while maintaining analytical consistency. First, we coded the results and discussion sections of all fifteen included studies line by line. This created a set of free codes that captured things like sensing configuration, analytical method, validation outcome, and applied inference. In the second stage, we organized those free codes into descriptive themes through repeated constant comparison. Codes got merged when they described the same underlying idea, and we split them apart if a single label was hiding distinct meanings. Then came the third stage. We looked at the descriptive themes through the lens of our three research questions to build analytical themes that reach beyond the primary studies. Two of those themes are the line between validated and aspirational capability, and the idea that stroke and locomotor load can be separated. To validate everything, we reread each source study against the final theme structure. That confirmed none of the included studies went against the analytical claims we made.

Reporting and Documentation

This review follows the PRISMA 2020 checklist and the PRISMA 2020 flow-diagram specification (Page et al., 2021). Figure 5 shows the record flow from identification through inclusion. Every numerical value in the Abstract, in Study Selection Process, and in Section Study Selection Results is derived from, and consistent with, that diagram.

Results and Discussions

Study Selection Results

From a structured Scopus search we got 130 records initially. Title deduplication removed four, leaving 126. Next, automation-assisted filtering on metadata fields removed 50 records of ineligible document types after deduplication: 32 conference papers, 14 conference reviews, two book chapters, one data paper, and one retracted item. It also removed two records not in English and four published before 2016. So 60 records were removed before screening. Seventy records proceeded to title-and-abstract screening. Of those, 40 were excluded: 22 because the study population was a racket sport other than tennis, most often table tennis; 11 because no wearable or body-worn sensing component was present; and seven because the record reported sensor-material characterisation without an athlete-facing application. We then sought 30 reports for retrieval, but two couldn't be obtained in full. Twenty-eight full texts were assessed for eligibility, and we excluded 13 with documented reasons: six on population grounds, four because the method couldn't yield a real-time or wearable monitoring outcome, and three because methodological reporting didn't allow proper extraction. Fifteen studies were retained for qualitative synthesis. Figure 5 depicts the complete flow.

Descriptive Characteristics

Fifteen studies make up this review. They cover 2017 through 2025 and come from seven different countries. Most of them were published later in that period. Eleven out of fifteen (73.3%) came out from 2022 onward, and 2023 was the peak year with four studies. Australia had four studies, which is 26.7%. All of those came from one tightly connected research program involving Tennis Australia and the University of Technology Sydney. Spain and China each contributed three studies (20.0%). Slovenia had two, so 13.3%. Then Japan, the United States, and Portugal each had one, making 6.7% each. As for study designs, validation and observational match-play or drill-based analyses were the most common. Two of the studies were systematic or scoping reviews themselves, and three were engineering-led papers focused on system development. Sample sizes went from just one participant up to 69, with a median of 15. Only three of the fifteen studies even reported on female participation, and none of them did a sex-stratified analysis of sensor accuracy. Tables 2 and 3 show all the extracted characteristics in full.

The observed geographic concentration reflects the unequal global distribution of research infrastructure dedicated to sports technology. Australia's dominance is closely associated with long-term collaboration between Tennis Australia, the University of Technology Sydney, and commercial wearable-device developers, whereas China's contribution primarily reflects rapid advances in flexible sensing materials and artificial intelligence supported by national engineering initiatives. The sharp increase in publications after 2022 also corresponds with accelerated adoption of wearable technologies, advances in machine-learning algorithms, and increased investment in digital sports analytics following the COVID-19 pandemic. These trends suggest that technological maturity, rather than merely publication growth, has driven the recent expansion of wearable-sensor research in tennis.

Table 2 gives you the full bibliographic and methodological census of the evidence base. You should treat it as the factual substrate for every claim. Three patterns stand out immediately. First, look at the chronological order. It reveals a clear disciplinary handover. The earliest entries, rows 1 through 5, come from sport-science groups doing validation and algorithm work. Later entries increasingly involve engineering-led system development (rows 9, 11, 13) and evidence-consolidating reviews (rows 10, 12). That's a sequence you'd expect from a field moving from proof-of-concept into consolidation. Second, the

Table 2 <Summary of the Fifteen Included Studies: Bibliographic Identifiers, National Origin, Methodological Approach and Principal Findings>

Title	Author(s)	Country	Method	Key findings
Monitoring hitting load in tennis using inertial sensors and machine learning	Whiteside, Cant, Connolly, & Reid., 2017.	Australia	Validation study; wrist-mounted IMU on 19 athletes across 66 video-recorded sessions; six machine-learning model families compared over 28,582 notated shots	A cubic-kernel support vector machine classified binned shots (overhead, forehand, backhand) with 97.4% accuracy and all nine shot types with 93.2% accuracy under 10-fold cross-validation, establishing IMU-plus-ML as a practical automated alternative to manual notation
Detection of tennis activities with wearable sensors	Benages Pardo, Buldain Perez, & Orrite Uruñuela., 2019.	Spain	Algorithm development; two BLE sensor nodes; spectrogram features; semi-supervised deep autoencoder trained on eight players (four female, four male)	Classification accuracy exceeded 96.5% for strokes of an unseen player, demonstrating that a deep architecture can generalise across differences in height, sex and body constitution without per-player retraining
Validity and reliability of a novel monitoring sensor for the quantification of the hitting load in tennis	Hadžić, Germič, & Filipčič., 2021.	Slovenia	Criterion validation; 24 junior players wore the Armbeep IMU during a baseline drill and match-play; agreement with synchronised video assessed via ICC, SEM and linear regression	Test–retest reproducibility for forehand and backhand counts was excellent ($ICC \geq 0.90$) and sensor-registered contacts explained 93.8% of the variance in video-notated shots ($R^2 = 0.938$), supporting on-court use for hitting-load quantification
Real-life application of a wearable device towards injury prevention in tennis: a single-case study	Kramberger, Filipčič, Germič, & Kos	Slovenia	Longitudinal single-case design; previously validated Armbeep wrist device; fused time, physiological, movement and tennis-specific workload and recovery indicators under real training conditions	Continuous daily monitoring of workload and recovery enabled individualised adjustment of training load during return-to-play, illustrating a translational pathway from sensor output to injury-prevention decision-making
Prototype machine-learning algorithms from wearable technology to detect tennis stroke and movement actions	Perri, Reid, Murphy, Howle, & Duffield., 2022.	Australia	Algorithm accuracy evaluation; cervically mounted triaxial accelerometer, gyroscope and magnetometer; up to	Detection accuracy was highest for serves (98%) and groundstrokes (94%) but degraded markedly for backhand slice (74%) and volleys (41–44%); footwork

Title	Author(s)	Country	Method	Key findings
			eight high-performance players in match-play and movement drills; manual coding as criterion	was predominantly classified as "Dynamic" (63% of events), exposing a systematic ceiling in current event-detection algorithms
Gaussian mixture modeling of acceleration-derived signal for monitoring external physical load of tennis player	Marutani, Konda, Ogasawara, Yamasaki, Yokoyama, Maeshima, & Nakata., 2023.	Japan	Methodological study; sportswear-type wearable sensors worn by 14 collegiate players (28 matches) and 55 middle-aged players (55 matches) during official matches; Gaussian mixture model fitted to acceleration histograms	The acceleration histogram was bimodal, and modelling its high- and low-intensity components separately captured load characteristics that conventional mean or cumulative scalar indicators discard, providing a distributional alternative to summary player-load metrics
Differentiating stroke and movement accelerometer profiles to improve prescription of tennis training drills	Perri, Reid, Murphy, Howle, & Duffield., 2023.	Australia	Observational drill comparison; ten junior-elite male players; cervical GPS with embedded IMU across 189 hard-court sessions; total, stroke and movement player load compared across eight drill categories	Accuracy and recovery/defensive drills elicited the highest relative total player load and match-play simulation the lowest, while accuracy drills produced significantly greater stroke player load than all other categories, demonstrating that drill design systematically manipulates the stroke-to-movement load ratio
Determining stroke and movement profiles in competitive tennis match-play from wearable sensor accelerometry	Perri, Reid, Murphy, Howle, & Duffield., 2023.	Australia	Observational match analysis; eight junior high-performance players; trunk-mounted sensor across singles matches on hard and grass courts; two-way ANOVA (surface × match outcome)	No interaction effects for surface and outcome were observed for absolute load, but relative movement player load was elevated on grass and relative stroke player load on hard courts, indicating that surface reallocates the composition of external load without altering its total magnitude
Arrayed piezoresistive and IMU sensor-integrated assistant training tennis racket for multipoint hand pressure monitoring and	Yang, Hou, Wu, Guo, Zhang, Xie, Xian, Wang, Zhang, Qian, He, & Chou., 2023.	China	Engineering system development; MXene/melamine-sponge flexible pressure sensors arrayed on the racket grip	The sensor achieved a sensitivity of 5.35 kPa^{-1} (1.1–22.2 kPa) with 0.6 kPa^{-1} retained across an ultra-wide range to 266 kPa, and the classifier distinguished

Title	Author(s)	Country	Method	Key findings
representative action recognition			integrated with an IMU; artificial-intelligence classifier applied to force and acceleration signals	five representative motion behaviours with 98.2% accuracy, establishing grip-level force distribution as a tractable monitoring construct
Quantifying hitting load in racket sports: a scoping review of key technologies	Brich, Casals, Crespo, Reid, & Baiget., 2024.	Spain	Scoping review (PRISMA-ScR); four databases searched; 484 records identified and 19 included; commercialised racket- and arm-mounted inertial systems appraised	Eleven of the nineteen systems were tennis-compatible, distributed across grip-attached (n = 8), grip-embedded (n = 6), wrist (n = 3) and dampener (n = 2) locations, yet only four of the eleven tennis systems (36.4%) demonstrated excellent reliability (>0.85) for shot counting, and no system in any other racket sport had been reliably validated
SmartDampener: an open source platform for sport analytics in tennis	Liu, Lu, Yuan, Zhou, & Gowda., 2024.	United States	Engineering system development; wireless sensing embedded within a conventional vibration dampener; open-source hardware and software platform; evaluated under real play conditions	The dampener form factor delivered ball speed, impact location and stroke type without the intrusive mounting or high deployment cost of wrist devices and vision systems respectively, demonstrating that ecological acceptability can be achieved without sacrificing analytical breadth
Applications of machine learning to optimize tennis performance: a systematic review	Sampaio, Oliveira, Marinho, Neiva, & Morais., 2024.	Portugal	Systematic review of machine-learning applications in tennis performance analysis	Machine learning showed applied promise across psychological-state monitoring, talent identification, match-outcome prediction, spatial and tactical analysis, and injury prevention, with wearable technologies identified as the principal data-acquisition layer enabling personalised coaching decisions
Kinetic chain analysis of tennis stroke motion utilizing wearable sensors	Chen & Jia., 2025.	China	Biomechanical modelling; wearable-sensor motion capture of 15 players	Quantifying each joint's contribution to racket-hand velocity and extracting contribution

Title	Author(s)	Country	Method	Key findings
			across three skill levels using an automated ball machine; hand contribution velocity (HCV) defined and kinetic chain diagram (KCD) constructed	and time-delay features from the kinetic chain diagram converted kinetic-chain theory from a qualitative coaching heuristic into a measurable, skill-discriminating index of movement coordination
Concurrent validity of the Polar Precision Prime® photoplethysmographic system to measure heart rate during a tennis training session	Ruiz-Malagón, Castro-Infantes, Ritaco-Real, & Soto-Hermoso., 2025.	Spain	Concurrent validation; 40 players (32 male, eight female); wrist PPG compared against Polar H-10 chest strap criterion across warm-up, main part and cool-down, averaged over 10-s intervals	Agreement was high overall (r > 0.89; ICC > 0.96) with mean absolute percentage error below 5.03%, but ICC fell to 0.85 at 10-s resolution and systematic bias and random error were greatest during warm-up, indicating that wrist PPG is adequate for session-level but not for beat-to-beat monitoring in tennis
Accuracy of an ultra-wideband-based tracking system for time–motion analysis in tennis	Yang, Wang, Zhao, & Cui., 2025.	China	Criterion validation; UWB system (GenGee Insait KS) compared against VICON optical motion capture; ten amateur players (ITN 2–5) across seven exercises with and without racquets	Root-mean-square error was 0.65 m (X-axis) and 0.76 m (Y-axis) with good reliability for distance (ICC = 0.91), but overall percentage error reached 16.29% and error was largest during rapid acceleration and directional change (spider run mean bias 4.13 m), constraining UWB use to steady-state rather than tennis-specific movement

On Table 2 method column exposes a marked asymmetry in ecological validity. Studies using match-play or on-court drills (rows 3, 5, 6, 7, 8, 14) report systematically lower accuracy than those run under controlled or ball-machine conditions (rows 1, 2, 9, 13). That's the single most important caution this table conveys. Third, the Key findings column shows quantitative performance claims cluster around two outcome families: classification accuracy (rows 1, 2, 5, 9) and criterion agreement (rows 3, 14, 15). Almost no study reports both. So a device that can classify a stroke accurately generally hasn't been shown to measure that stroke accurately, and the reverse is also true.

Table 3 classifies each study along the four dimensions that structure the thematic synthesis. This cross-classification makes the field's internal division visible. Looking at the Research design column, you see no randomised or longitudinal intervention trial. Every entry is a validation, an observation, an algorithm evaluation, a system development, or a review. That's the structural reason the field can't yet make causal claims about injury prevention. The Theme column shows that the six a priori reference domains are unevenly populated. Wearable sensor technology and real-time athlete monitoring appear in most studies. But biomechanics is the primary focus of only two (rows 9 and 13). This confirms the field has invested far more in measuring events than in understanding the mechanics that produce them. The Technology column exposes the concentration risk. Inertial sensing appears in eleven of fifteen studies. When alternative modalities are used, like photoplethysmography in row 14 or ultra-wideband in row 15, the reported accuracy against criterion is noticeably lower. Finally, the Outcome column is dominated by accuracy and agreement statistics rather than athlete-relevant endpoints. That's the gap Section 3.5.6 identifies as most urgent.

Table 3 <Classification of the Fifteen included Studies by Research Design, Thematic Focus, Sensing Technology and Outcome Domain>

Author(s)	Country	Research design	Theme / focus	Technology / intervention	Outcome
Whiteside, Cant, Connolly, & Reid., 2017.	Australia	Cross-sectional validation with supervised learning	Machine learning; hitting-load quantification	Wrist-mounted IMU (accelerometer + gyroscope); SVM, decision tree and ensemble classifiers	Shot-type classification accuracy (97.4% binned; 93.2% nine-class)
Benages Pardo, Buldain Perez, & Orrite Uruñuela., 2019.	Spain	Algorithm development and cross-subject evaluation	Machine learning; stroke recognition	Two BLE inertial nodes; spectrogram representation; semi-supervised deep autoencoder	Cross-subject stroke classification accuracy >96.5%
Hadžić, Germič, & Filipčič., 2021.	Slovenia	Criterion validity and reliability study	Wearable sensor technology; validation	Armbeep wrist IMU; video-notation criterion	ICC ≥ 0.90 for shot counts; R^2 = 0.938 against video
Kramberger, Filipčič, Germič, & Kos	Slovenia	Longitudinal single-case applied study	Real-time athlete monitoring; injury prevention	Armbeep wrist device with fused inertial and pulse-rate sensing; cloud-based analysis	Individualised daily workload and recovery indicators supporting return-to-play
Perri, Reid, Murphy, Howle, & Duffield., 2022.	Australia	Algorithm accuracy evaluation	Machine learning; stroke and movement detection	Cervically mounted accelerometer, gyroscope and magnetometer; prototype vendor algorithms	Event-detection accuracy by class (serve 98%; groundstroke 94%; slice 74%; volley 41–44%)
Marutani, Konda, Ogasawara, Yamasaki, Yokoyama, Maeshima, & Nakata., 2023.	Japan	Methodological modelling study	Real-time athlete monitoring; external-load modelling	Sportswear-type inertial sensor; Gaussian mixture model of acceleration histogram	Bimodal load distribution parameters characterising player-specific intensity structure
Perri, Reid, Murphy, Howle, & Duffield., 2023.	Australia	Observational comparative drill analysis	Performance analysis; training prescription	Cervical GPS with embedded IMU; proprietary stroke-detection algorithm	Relative total, stroke and movement player load and stroke counts across eight drill categories
Perri, Reid, Murphy, Howle, &	Australia	Observational match-play analysis	Performance analysis; match demands	Trunk-mounted GPS with embedded accelerometer,	Stroke and movement player-load composition by

Author(s)	Country	Research design	Theme / focus	Technology / intervention	Outcome
Duffield., 2023.				gyroscope and magnetometer	court surface and match outcome
Yang, Hou, Wu, Guo, Zhang, Xie, Xian, Wang, Zhang, Qian, He, & Chou., 2023.	China	Engineering system development and validation	Wearable sensor technology; biomechanics	Arrayed MXene/melamine-sponge piezoresistive grip sensors integrated with IMU; AI classifier	Grip-pressure sensitivity 5.35 kPa^{-1}; action-recognition accuracy 98.2%
Brich, Casals, Crespo, Reid, & Baiget., 2024.	Spain	Scoping review (PRISMA-ScR)	Wearable sensor technology; evidence synthesis	Commercialised racket-, grip-, wrist- and dampener-mounted inertial systems	Reliability status of 19 systems; only 36.4% of tennis systems reliable (>0.85)
Liu, Lu, Yuan, Zhou, & Gowda., 2024.	United States	Engineering system development and field evaluation	Wearable sensor technology; performance analysis	Wireless sensing embedded in vibration dampener; open-source platform	Ball speed, impact location and stroke type from a non-intrusive form factor
Sampaio, Oliveira, Marinho, Neiva, & Morais., 2024.	Portugal	Systematic review	Machine learning; performance optimisation	Wearable technologies as data-acquisition layer for ML pipelines	Applied domains of ML in tennis: psychological monitoring, talent ID, outcome prediction, tactics, injury prevention
Chen & Jia., 2025.	China	Biomechanical modelling and skill-level comparison	Biomechanics; kinetic-chain analysis	Wearable-sensor motion capture; hand contribution velocity and kinetic chain diagram	Joint-wise contribution and time-delay features discriminating three skill levels
Ruiz-Malagón, Castro-Infantes, Ritaco-Real, & Soto-Hermoso., 2025.	Spain	Concurrent validity study	Real-time athlete monitoring; physiological validation	Wrist photoplethysmography (Polar Precision Prime®); chest-strap ECG criterion	$r > 0.89$; ICC > 0.96 session-level, 0.85 at 10-s resolution; MAPE < 5.03%
Yang, Wang, Zhao, & Cui., 2025.	China	Criterion validity study	Real-time athlete monitoring; time–motion analysis	Ultra-wideband local positioning system; VICON optical criterion	RMSE 0.65–0.76 m; distance ICC = 0.91; overall percentage error 16.29%

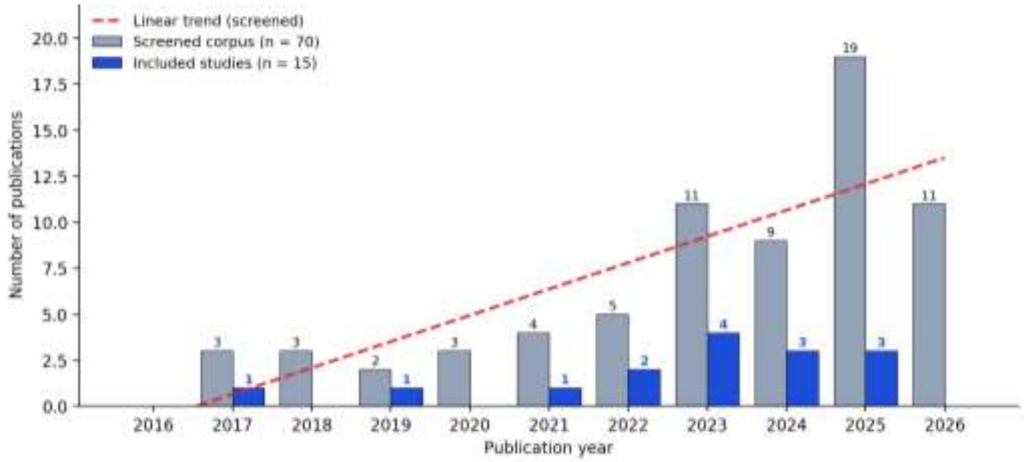

Figure 1 <Annual Publication Trend of Wearable-sensor and Real-time Monitoring Research in Tennis (Scopus, 2016–2026)>

Note: Grey bars denote the eligible screened corpus (n = 70); blue bars denote the fifteen studies retained in the final synthesis; the dashed red line is a least-squares linear fit to the corpus series.

Figure 1 shows a young literature that is accelerating steeply. Until 2020 output stayed in low single digits. Then it rose sharply. Most of the corpus comes from the final four years of the window. The fitted linear trend is positive and steep. Even the 2026 column, necessarily incomplete when we ran the search, already exceeds several complete earlier years. Two inferences follow. The first is bibliometric: a field with this growth profile has not yet reached the replication phase. That is why so many included studies describe a novel system rather than an independent evaluation of an existing one. The second inference is evaluative. It comes from the divergence between the two bar series. The grey corpus grows far faster than the blue included set. The widening gap is not an artefact of screening severity. It is a substantive finding: the majority of recent publications retrieved by a tennis-and-wearables search are actually engineering papers about sensing materials, or studies of other racket sports. They are not studies of tennis players. So the volume of publication in this space substantially overstates the volume of usable tennis-specific evidence. A practitioner reading citation counts alone would not detect that discrepancy.

This publication trajectory is consistent with the technology maturity curve commonly observed in digital sport sciences, where rapid innovation precedes widespread validation. Consequently, the growing volume of publications should not be interpreted as equivalent to high-quality evidence because many recent studies remain prototype-oriented rather than clinically or practically validated.

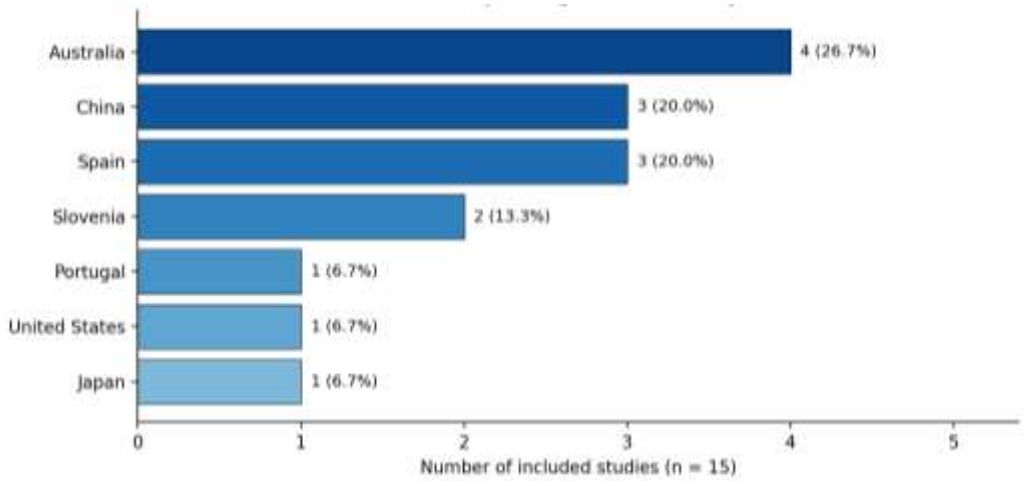

Figure 2. Geographic Distribution of the Fifteen Included Studies by Corresponding-Author Country. Percentages are Expressed Relative to the Total Included Set (n = 15)>

Let's take a closer look at what Figure 2 actually shows. The evidence base here is narrow, and not just in a geographic sense. Institutionally, it's even more constrained. Australia contributes four studies, which is 26.7% of the total. But all four come from a single research program involving Tennis Australia, the University of Technology Sydney, and a commercial sensor vendor. So essentially, about a quarter of all global tennis wearables evidence is produced by one group using one manufacturer's hardware. Spain and China each have three studies, making up 20.0% each. But they come from very different registers. The Spanish ones are validation and evidence-synthesis studies from applied sport-science departments. The Chinese ones are sensor-engineering papers from materials-science and instrumentation labs. Slovenia adds two studies, or 13.3%, and they also come from a single collaboration, the Ljubljana, Maribor one, built around one device. What the figure really highlights is a structural vulnerability that individual studies never mention. The field looks internationally broad, but underneath that, only a few vertically integrated research, industry partnerships exist. Independent replication across different hardware platforms is almost entirely missing. And there are no contributions at all from Africa, South America, or South Asia, which limits how generalizable the findings are across different environments and populations.

The geographic clustering also indicates that independent replication across laboratories remains limited. Future multicenter validation studies involving diverse athlete populations and different wearable platforms are necessary to improve the external validity of current evidence.

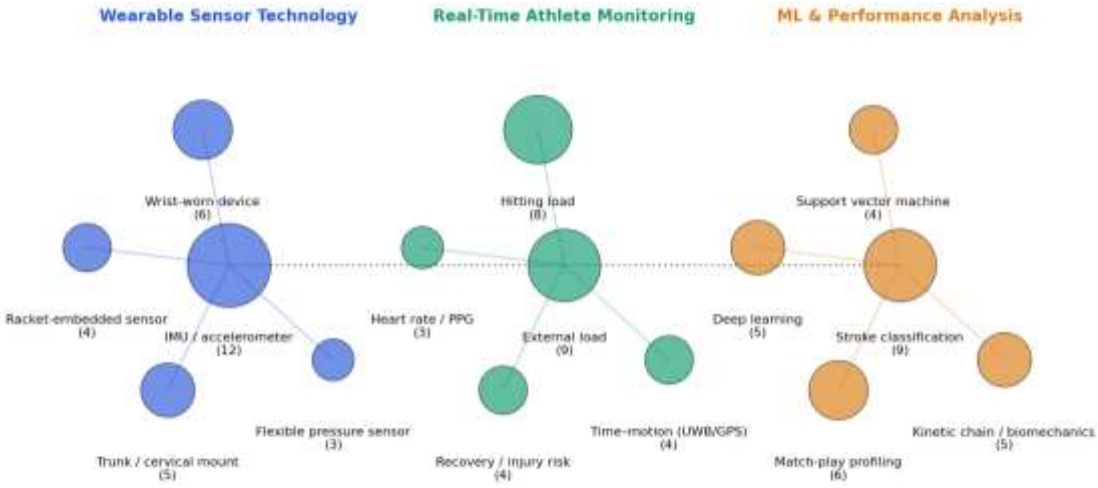

Figure 3 <Keyword Co-occurrence and Thematic Clustering Across the Fifteen Included Studies>

Bubble size is proportional to the frequency with which each construct occurs; dotted lines indicate cross-cluster linkage. Figure 3 clarifies the field's conceptual core. In the wearable-sensor-technology cluster, inertial measurement dominates with n = 12. Wrist mounting (n = 6) and trunk or cervical mounting (n = 5) are the main placements. Racket-embedded setups (n = 4) and flexible pressure sensing (n = 3) form a smaller engineering group. For the real-time-monitoring cluster, external load (n = 9) and hitting load (n = 8) are almost equally studied. This confirms what Theoretical Implications proposed: hitting load is a separate construct from locomotor load. Physiological monitoring (n = 3) remains very thin. In the machine-learning cluster, stroke classification (n = 9) leads. Match-play profiling (n = 6) and kinetic-chain analysis (n = 5) follow. The cross-cluster connections give the most insight. A strong link between inertial sensing, hitting load, and stroke classification marks the field's main method. But the weak links between biomechanics and real-time monitoring show that kinetic-chain and joint-loading constructs, though important for injury theory, haven't been used in continuous monitoring yet. So the bubble map reveals both what the field studies and, by the thinness of some nodes, what it ignores.

Cell values denote the number of study–focus occurrences; studies addressing multiple foci contribute to more than one cell. Figure 4 needs some explanation. The matrix takes descriptive tables and turns them into an evidence-density map. What comes out is a distribution that's strikingly uneven. Take the IMU row. It's heavily populated all across the five focus columns. The densest cells are external-load quantification with six studies and stroke or activity classification with five. That's really the evidentiary core of this field. It's also where practitioners can have the most confidence in the findings. Every other row? Barely anything there. Photoplethysmography and ultra-wideband positioning each contribute just one validation study. Nothing more than that. What this means is that physiological and time-motion monitoring in tennis right now relies on a single criterion-referenced study for each. The injury-prevention column is the emptiest one in the whole matrix. It only has two entries, both IMU-based. That really shows the gap. You see these papers constantly mention injury prevention in their introductions. But the actual injury-prevention evidence they produce? Almost none. The biomechanics column is just as thin. The little evidence out there comes from optical or pressure-array systems used in controlled settings. Not from the wearable systems players actually use on court. Looking at the whole thing, the matrix tells us the field has real depth in only one narrow cell. That's inertial quantification of external and hitting load. Everything else in the plausible measurement space? Effectively unexplored.

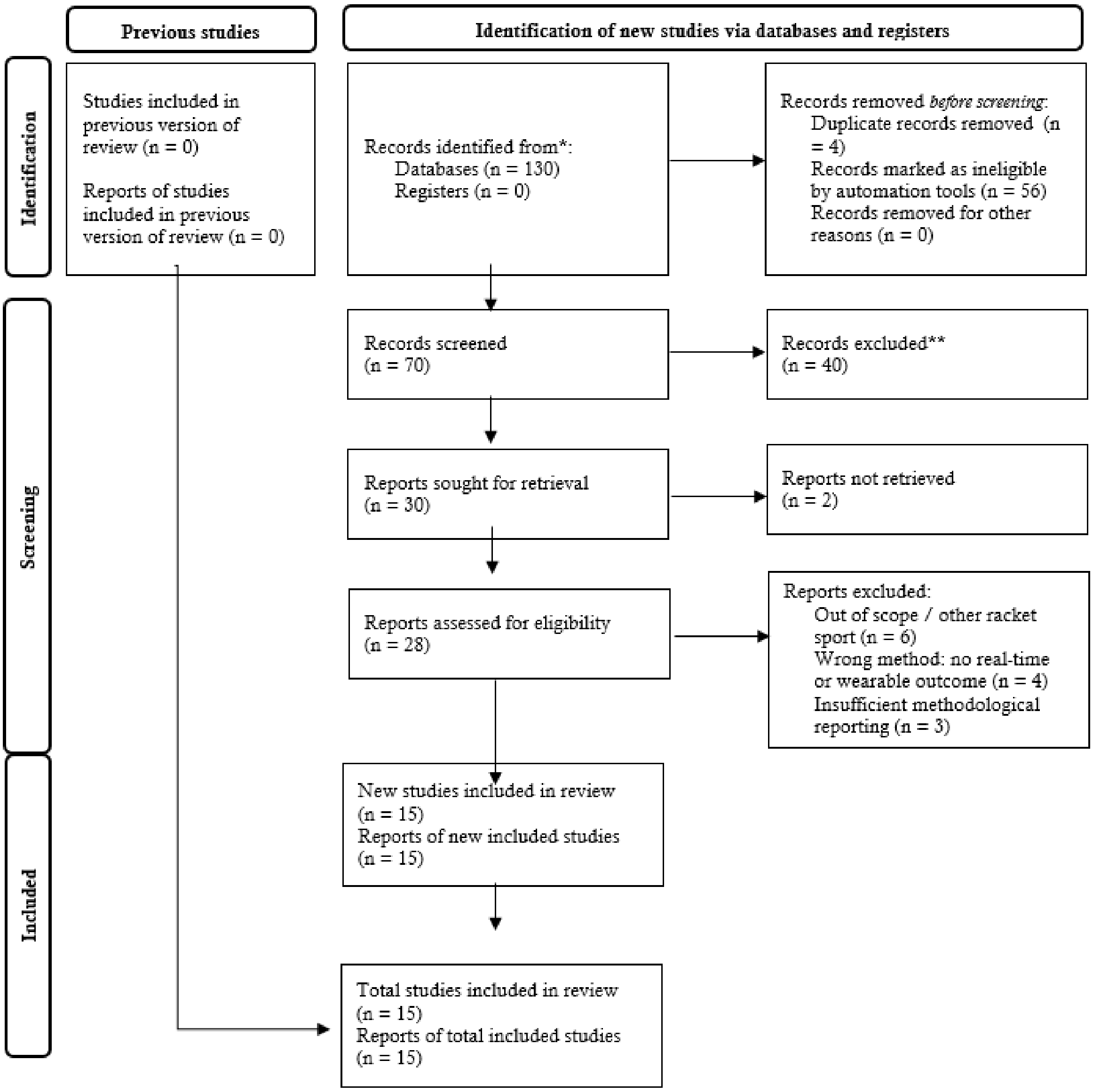

Figure 4 <PRISMA 2020 Flow Diagram Documenting the Identification, Screening, Eligibility Assessment and Inclusion of Records>

All values are derived from the Scopus metadata export and are consistent with those reported in Sections 2.5 and 3.1 and in the Abstract. Figure 4 explains the audit trail. This diagram tracks how evidence claims were processed in the review, and the attrition pattern is revealing on its own. Out of 130 records identified, only 15 survived to synthesis. That's just 11.5 percent. That inclusion rate is well below what sport-science reviews usually see, and it comes almost entirely from two exclusion channels. The first happens at the identification stage, where 50 records were removed because of the wrong document type. That's a striking number. It shows just how much of this literature still appears in conference proceedings instead of peer-reviewed journals. That itself is a sign of disciplinary immaturity. The second exclusion happens during title and abstract screening. There, 22 records were dropped because their population was a racket sport other than tennis. So even a term as specific as 'tennis' returns a corpus full of table tennis papers. You simply cannot rely on the search string alone to screen the population. The full-text exclusion count is quite small, only 13 records. That suggests the eligibility criteria were applied clearly enough during abstract screening that few surprises turned up later. That supports the reliability of the selection process. Readers can reconstruct any reported figure by tracing the corresponding node in the diagram.

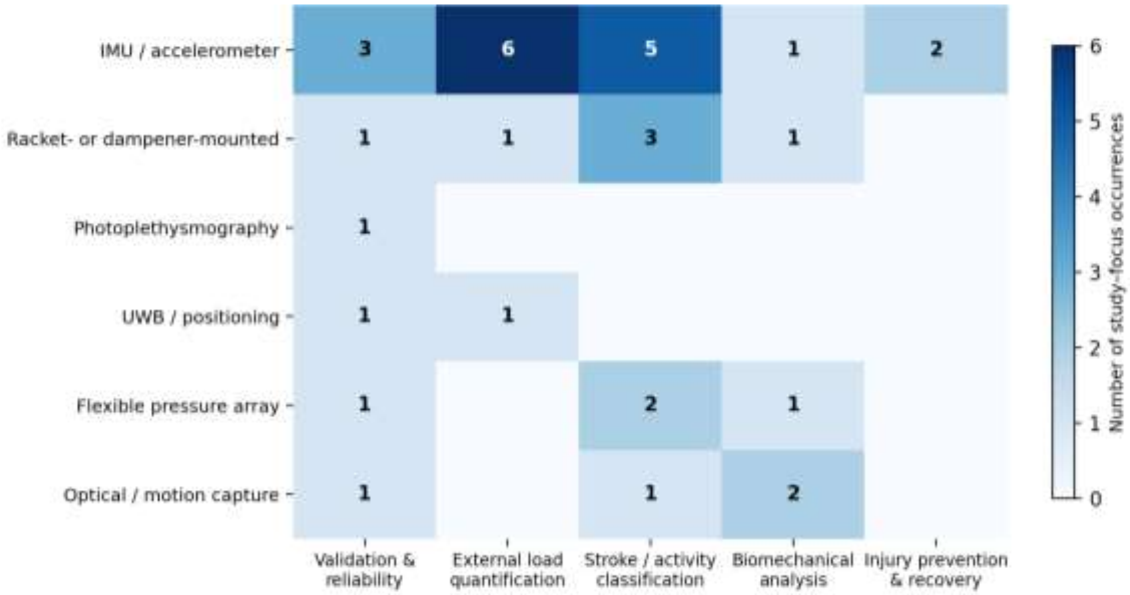

Figure 5 <Cross-tabulation of Sensor Modality Against Primary Research Focus Across The Fifteen Included Studies>

Findings for RQ1: Technologies, Architectures and Validation Status

The fifteen studies we included show a clear technological landscape. One modality really stands out. Inertial measurement, accelerometry, usually paired with gyroscopy and magnetometry, forms the sensing base for eleven of those studies. The other four either combine inertial channels into a hybrid design or are reviews centered on inertial systems (Brich et al., 2024; Sampaio et al., 2024). Within this dominant approach, we can see three mounting philosophies. Wrist mounting, used by Whiteside et al. (2017), Hadžić et al. (2021), and Kramberger et al. (2022), puts the sensor close to the racket. That maximizes the signal-to-noise ratio for the stroke itself, but it only indirectly registers how the player moves around. Trunk or cervical mounting, adopted across the Australian program (Perri et al., 2022; Perri et al., 2023a; Perri et al., 2023b), flips that trade-off. It captures whole-body locomotor load well but has to infer stroke events from a signal weakened as it travels through the kinetic chain. Equipment mounting, on the grip (Yang et al., 2023) or inside the vibration dampener (Liu et al., 2024), takes the device off the body entirely. That gets rid of the compliance problem that has often limited how much players accept wearables, though it means losing all physiological and locomotor information. Multi-unit setups have been tried in related tennis populations, like six-sensor inertial arrays used in wheelchair tennis (Rietveld et al., 2023), and hybrid designs have started mixing mechanical and affective channels (Wang, 2025).

When it comes to validation, the technologies differ the most. And that difference doesn't match what you'd expect from the number of publications. Inertial systems that were tested against a criterion did well. Hadžić et al. (2021) found intraclass correlation coefficients at or above 0.90 for forehand and backhand counts, and a coefficient of determination of 0.938 between sensor-registered contacts and video-notated shots. Whiteside et al. (2017) achieved 97.4% classification accuracy for binned shot categories based on 28, 582 manually notated shots. Those validation results would satisfy most practical contexts. The non-inertial methods fare a lot worse. Ruiz-Malagón et al. (2025) reported that wrist photoplethysmography matched a chest-strap criterion well at the session level ($r > 0.89$; ICC > 0.96). But at ten-second resolution, the intraclass correlation dropped to 0.85, with the biggest systematic bias and random error happening during warm-up. That's exactly when upper-limb movement confuses the optical signal the most. Yang et al. (2025) found that an ultra-wideband tracking system had good reliability for total distance (ICC = 0.91), yet the overall percentage error was 16.29%. The mean bias reached 4.13 m during the spider run, a drill designed to bring out the rapid accelerations and direction changes that define tennis movement. So the technologies for physiological and time, motion monitoring are least accurate under the very conditions that make tennis tennis.

The most important finding for RQ1 comes from the one study that looked at the whole commercial field. Brich et al. (2024) reviewed nineteen racket- and arm-mounted systems. They found eleven to be tennis-compatible, spread across grip-attached (n = 8), grip-embedded (n = 6), wrist (n = 3), and dampener (n = 2) locations. Yet only four of those eleven (36.4%) had excellent reliability above 0.85 for shot counting. And no system in badminton, table tennis, padel, or squash had been successfully validated for hitting-volume quantification at all. When you read this finding alongside the primary studies, a clear picture emerges. The market has outrun its evidence. Coaches have many devices to choose from, but only a few have been shown to give accurate measurements. And the validations that do exist are almost all for a single, fairly basic outcome: how many shots were hit. Not the intensity, quality, or biomechanical cost of those shots. Whether a device is reliable, and whether it is reliable for the specific inference a coach wants to make, are two separate questions. The literature has answered only the first.

Findings for RQ2: Analytical Methods and Classification Performance

Over the review period, the computational layer that converts inertial signals into performance constructs has gone through three clear generations. The earliest, represented by Whiteside et al. (2017), used classical supervised learning on hand-picked time and frequency-domain features. They compared six model families and found that a cubic-kernel support vector machine performed best, achieving 97.4% accuracy on the three-class problem (overhead, forehand, backhand) and 93.2% on the full nine-class problem that added slice, volley, and smash. The second generation moved away from manually engineered features toward learned ones. Benages Pardo et al. (2019) transformed raw accelerometer and gyroscope streams into spectrograms and applied a semi-supervised deep autoencoder. They reported accuracy above 96.5% on strokes from a player the system had never encountered, a cross-subject generalisation result of real applied significance, because it implies a deployed system wouldn't need recalibration for each new athlete. The third generation, visible in the engineering-led literature, integrates classification directly into the sensing substrate. Yang et al. (2023) coupled an arrayed piezoresistive grip sensor with an on-board classifier that distinguished five representative motion behaviours at 98.2% accuracy, an approach mirrored in adjacent racket sports by statistically driven wearable recognition systems (Song et al., 2025). The transferability of human-activity-recognition architectures across movement domains, already established in other skilled-movement contexts like dance (Hendry et al., 2020), supports the assumption that these pipelines generalise.

But these accuracy figures can be systematically misleading if you read them without attention to the conditions they came from. The synthesis's most valuable contribution is exposing that dependence. The highest reported accuracies come from studies where stroke events were elicited under controlled conditions, using wrist- or equipment-mounted sensors with high signal-to-noise ratios, and evaluated on class distributions where the dominant strokes, forehand, backhand, serve, were heavily represented. When Perri et al. (2022) evaluated a comparable prototype algorithm on data from a cervically mounted sensor during genuine match-play and movement drills, performance fractured along class lines: serves were detected at 98% and groundstrokes at 94%, but backhand slice fell to 74% and volleys collapsed to 41, 44%, with most volleys simply not registering as strokes at all. The corresponding movement classification was similarly coarse, with 63% of all footwork events absorbed into a single undifferentiated 'Dynamic' category. The pattern is consistent and mechanically interpretable: classifiers succeed on strokes with large, stereotyped, high-acceleration signatures and fail on strokes that are short, low-amplitude, and variable, exactly the kind executed at the net, under time pressure, in the phases of play where load and injury risk may be most acute.

A parallel and largely independent analytical strand rejects classification altogether in favour of distributional modelling. Marutani et al. (2023), analysing 28 matches from collegiate players and 55 from middle-aged players, observed that the histogram of the acceleration norm is not unimodal but bimodal, comprising distinguishable low- and high-intensity components, and fitted a Gaussian mixture model to recover the parameters of each. The methodological argument is compelling: a mean or cumulative player-load value collapses this bimodality into a single number and thereby discards the very information, how much of the session was spent in the high-intensity mode, and how intense that mode was, that differentiates a demanding session from a long one. The three analytical traditions surveyed here therefore stand in an unresolved relationship. Classification answers what happened; distributional modelling answers how hard it was; and neither, on current evidence, answers the biomechanical question of what it cost the athlete. Sampaio et al. (2024), reviewing machine-learning applications in tennis more broadly, identify the same fragmentation, noting applied promise across psychological monitoring, talent identification, outcome prediction, tactical analysis, and injury prevention while stopping short of demonstrating integration across these domains.

Findings for RQ3: Applied Insights and Translational Constraints

One of the most genuinely new applied findings to come out of this body of work is that external load in tennis isn't a single thing. It is actually a composite of two separate components that act independently of each other. Perri et al. (2023b) looked at eight different types of on-court drills across 189 hard-court sessions with junior-elite players. They broke total player load into a part coming from strokes and a leftover part coming from movement, and they found the two split apart. Accuracy drills and recovery or defensive drills produced the highest relative total load. Match-play simulation gave the lowest. Accuracy drills led to significantly greater stroke player load than any other drill category, partly because players hit more forehands. The practical implication is direct and not at all obvious. Two drills could have the same duration and the same total player load but place completely different demands on the shoulder and elbow. A coach who only watches total load will miss that difference entirely. A companion study extended this idea to competition and showed that court surface shifts the load around rather than just changing the amount. Relative movement load went up on grass, relative stroke load went up on hard courts, and there was no interaction between surface and match outcome for the absolute numbers (Perri et al., 2023a). So load composition is really a property of the task environment, and you can manipulate it by design. Other work in the tennis load literature backs this up. Training-task constraints shape external load in high-level practice (Penalva-Salmerón et al., 2026). Match load differs systematically between performance standards (Wang et al., 2025). The link between external load and perceived exertion is not perfect (Tóth et al., 2025). And accelerometry-based metrics apply the same logic to off-court conditioning (McGillivray et al., 2026).

The biomechanical side of the literature is thin, but it offers the clearest path from measurement to mechanism. Chen and Jia (2025) took on a recurring criticism: that sensor-based analysis is still mostly geometric description rather than kinetic explanation. They defined something called hand contribution velocity, a metric that quantifies how each joint contributes to the resulting racket-hand velocity. Then they turned the stroke into a kinetic chain diagram that lets you pull out contribution and time-delay features. They applied this across fifteen players at three skill levels. Those features could tell the difference in expertise, meaning they captured the proximal-to-distal sequencing that coaches see with their eyes but haven't been able to measure from wearable data before. That is a meaningful translational step forward. It turns a coaching hunch into something you can actually index. Still, it is an isolated step. No study in this review has linked those kinematic-sequencing measures to load build-up or to later injury. And the sensor setup used to get those measures hasn't been shown to work under real match conditions.

Injury prevention gets brought up as motivation in most of the studies we looked at, but almost none of them actually test it. Kramberger et al. (2022) offer the most complete translational example in the field. It is a longitudinal single-case study where they used fused inertial and pulse-rate data from a validated wrist device to track daily workload and recovery during real training. That information helped them gradually adjust the load as the athlete returned to competition. As a proof that the whole idea can work, it is useful. But as evidence that wearable monitoring actually cuts down injuries, it is just one case, uncontrolled and unblinded. It cannot carry the weight the field puts on it. No study in this review reports an injury outcome in a controlled or longitudinal design. No study establishes a dose, response relationship between any sensor-derived load metric and any tissue-level or clinical endpoint. And the wider evidence that wearable and biomechanical assessment can inform injury-prevention strategy in sport in general is still at the scoping stage, not the confirmatory stage, according to Rebelo et al. (2023). The gap between what these technologies are supposed to do and what they have actually been shown to do is the single biggest finding of this review.

Comparative and Critical Analysis

When you look at the methods across the fifteen studies, two completely different logics of evidence come through. The sport-science group, meaning Whiteside, Hadžić, the Perri team, Ruiz-Malagón, and Yang, relies on criterion referencing. Their main move is comparing a sensor reading to an accepted gold standard like video notation or chest-strap ECG, and they report agreement statistics. The engineering group, consisting of Yang, Liu, and to some extent Chen and Jia, focuses on showing what a new sensor can do. They want to prove that a novel measurement method can actually pick up the signal they need, and they report performance stats like accuracy. Neither approach is wrong, but they aren't interchangeable. The trouble is that the field often cites them side by side, like an engineering paper's 98.2% recognition accuracy next to a validation study's ICC of 0.90, and that hides the fact that these numbers support very different claims. Proving a sensor can identify five actions in a lab says nothing about whether it will work on a windy court against an opponent.

A second asymmetry shows up when you look at sample sizes and study designs. The validation studies, by the usual standards of their area, have decent numbers: Whiteside's team logged 28, 582 notated shots from 19 athletes, Ruiz-Malagón's crew recruited 40 participants, and Marutani's group analyzed 83 competitive matches from two populations. The algorithm and engineering studies are a different story. Perri's team tested their event-detection methods on up to eight players, Chen and Jia on fifteen, Yang's group on ten amateurs, and Kramberger's on a single case. That pattern is worrying because it flips what you'd expect from the ambition of the claims. The studies making the biggest applied claims rest on the smallest samples. Longitudinal designs are almost completely missing. Instead you get cross-sectional and comparative approaches, and not one included study used randomization or a control condition. This isn't a knock on any single study, each fits its own goal. It's an observation about the whole field, which is that a line of research driven by injury prevention hasn't produced a design that can actually show injury prevention.

Still, you can trace real methodological changes over the ten years. Three trends stand out. On the analytical side, the field moved from hand-made features and classical classifiers back in 2017, to learned representations and cross-subject generalization by 2019, and then to embedded sensor-integrated inference from 2023 to 2025. Conceptually, the shift went from treating external load as one number to splitting it into stroke and movement parts, and then to describing distributions. Ergonomically, the change is from body-worn devices that athletes have to be convinced to put on, to sensors built right into the equipment so players don't even notice them. The dampener platform from Liu's 2024 work is the clearest example of designing with ecological acceptability as a first-order constraint, not an afterthought. What hasn't changed is the standard for evidence. The validation designs in 2025 look structurally the same as those in 2017. The field added new technologies much faster than it added the criterion studies needed to back up their use.

Selection Bias and Publication Bias

The findings of this review should be interpreted in light of several potential sources of selection bias. Only English-language, peer-reviewed journal articles indexed in Scopus were included, while conference proceedings, grey literature, dissertations, and non-English publications were excluded. Consequently, recent engineering developments that have not yet reached journal publication may be underrepresented. Furthermore, publication bias may favor studies reporting high classification accuracy or positive validation outcomes, whereas studies reporting poor sensor performance are less likely to be published. These factors may partially explain the predominance of highly favorable validation statistics observed across the included literature.

Construct Validity

Although stroke load and locomotor load consistently demonstrated different behavioral patterns across court surfaces, drill types, and sensor placements, evidence supporting their psychometric independence remains limited. Current studies provide practical evidence of construct differentiation but have not formally examined convergent or discriminant validity using multivariate statistical techniques such as exploratory factor analysis, confirmatory factor analysis, or structural equation modeling. Future validation research should therefore evaluate whether these constructs satisfy established psychometric criteria before they are adopted as independent indicators of athlete workload.

Interpretation of Findings

Taken together, the fifteen studies describe a field that has solved a narrow measurement problem quite convincingly. The surrounding measurement problems, meanwhile, are largely untouched. The narrow problem is stroke counting from inertial data. The evidence that it's solved is strong. Multiple independent groups, using different devices, mounting locations, and classifiers, converge on agreement statistics that would satisfy most applied purposes (Whiteside et al., 2017; Benages Pardo et al., 2019; Hadžić et al., 2021). These surrounding problems remain open: how hard each stroke was, what it cost the shoulder, what it implies for tomorrow's training, and whether accumulated exposure predicts breakdown. The interpretive error the field is most at risk of committing is to let the strength of the evidence on the first question lend unearned credibility to claims about the others. And the class-wise failure documented by Perri et al. (2022), in which volleys go undetected at rates approaching 60%, is a salutary reminder that even the narrow problem is solved only for the strokes the classifiers were designed around.

Theoretical Implications

The main theoretical contribution of this synthesis is that it rethinks external load in racket sport as a two-dimensional construct. In the team-sport literature, which tennis has borrowed from for its monitoring vocabulary, external load basically means locomotor load, and player load is treated as a single number. But the evidence we gathered shows this transfer doesn't hold. Stroke-derived load and movement-derived load react differently to drill design (Perri et al., 2023b), shift differently across court surfaces (Perri et al., 2023a), and are best captured by sensors placed at different spots on the body. So they are separate constructs with separate causes. Any theory of tennis workload that treats them as one will misclassify sessions that are mechanically different as if they were the same. The distributional point from Marutani et al. (2023) adds another theoretical dimension: load is not just two-dimensional in makeup but also non-normal in how it's spread, and its bimodal shape carries information that a single-number summary throws away. So a defensible theory of tennis load needs at least two components and must be distribution-aware. And the biomechanical work by Chen and Jia (2025) points to a third dimension, the kinematic quality of the movements that create the load, which no current framework handles.

Practical Implications

For practitioners, this synthesis supports a few solid operational takeaways and warns against many tempting ones. Coaches can reasonably use validated wrist- or trunk-mounted inertial devices to count strokes and track total hitting volume over a training block, because that's what the validation evidence backs (Hadžić et al., 2021; Brich et al., 2024). They can also use the stroke-versus-movement load split to design drills that adjust upper-limb exposure separately from locomotor exposure, for example, prescribing accuracy drills when hitting volume is the goal and match-play simulation when it isn't (Perri et al., 2023b). Wrist photoplethysmography is fine for session-level internal load monitoring, but not for interval-resolution or beat-to-beat estimates, and warm-up readings should be treated with extra caution (Ruiz-Malagón et al., 2025). On the other hand, coaches should not assume a device that counts strokes accurately also measures stroke intensity accurately; they should not use ultra-wideband distance data to characterize high-intensity, direction-changing movement, where error exceeds 16% (Yang et al., 2025); they should not expect net play to be captured by current cervical-mounted algorithms; and they should not infer that any monitoring system available today has been shown to reduce injury.

From an applied perspective, the findings indicate that inertial measurement units currently provide the most reliable solution for stroke counting and workload monitoring in tennis. Coaches should nevertheless recognize that high classification accuracy does not necessarily imply accurate estimation of biomechanical loading or injury risk. Consequently, wearable-sensor outputs should complement rather than replace expert coaching judgment, particularly when monitoring athletes during rehabilitation or return-to-play programs.

Comparison with Prior Reviews

Two of the included studies are reviews themselves, and comparing this synthesis with them clarifies what it adds. Brich et al. (2024) did a scoping review of hitting-load technologies across racket sports, identifying 484 records and including 19. Their focus was on commercial devices, and their main conclusion, that only 36.4% of tennis-compatible systems show excellent reliability, is supported and extended here. This review differs in scope (tennis-specific rather than racket-sport-general), in inclusion criteria (peer-reviewed empirical studies rather than commercial systems), and in analytical ambition, because it combines the analytical and biomechanical literatures with the device-validation literature instead of treating validation in isolation. Sampaio et al. (2024) reviewed machine-learning applications in tennis performance without limiting to wearable data sources. They found applied promise across five domains, which matches what we see, but their review doesn't examine the sensing substrate those applications depend on, so it misses the class-wise detection failures that constrain them. This review's unique contribution is bringing together sport-science, engineering, and machine-learning evidence in one appraisal, which leads to the key observation that neither community's evidence alone justifies the claims often made for these technologies.

Contradictions in the Literature

Three major contradictions need to be acknowledged. First, classification accuracy is reported at 93, 98% in studies using controlled settings and wrist or equipment mounting (Whiteside et al., 2017; Benages Pardo et al., 2019; Yang et al., 2023), but as low as 41% for specific stroke types in a study using match-play and cervical mounting (Perri et al., 2022). This contradiction is only apparent and clears up when you look at mounting location, task constraints, and class distribution. But that doesn't make it harmless, because headline accuracy numbers are often cited without those qualifications, so they travel into practice detached from the conditions that make them valid. Second, for physiological monitoring: photoplethysmographic heart-rate systems have been validated well in general exercise (Hermand et al., 2019), but in tennis their agreement drops at short time resolutions and during periods of heavy arm movement (Ruiz-Malagón et al., 2025). Mechanistically that's unsurprising, since wrist-mounted optical sensors get messed up by exactly the motion tennis requires, but it strongly warns against transferring validation evidence across sports. Sport-specific reference datasets for optical heart-rate estimation are only now being built (Hu et al., 2026). Third, positioning: ultra-wideband is promoted as the answer to satellite systems' known imprecision on confined courts (Waqar et al., 2021), yet Yang et al. (2025) show its error is biggest during the rapid accelerations and direction changes that justify using it in the first place. In each case, the contradiction comes from applying a validation result beyond the conditions under which it was obtained.

Research Gaps

Five gaps come directly from the synthesis. First, the injury-outcome gap: no included study links any sensor-derived load metric to a clinical or tissue-level injury endpoint through a controlled or longitudinal design, so the field's central applied claim rests on plausibility rather than evidence. Second, the intensity gap: validation has focused almost entirely on shot counting, leaving stroke intensity, joint kinetics, and tissue loading, the variables through which hitting volume might plausibly cause injury, unvalidated. Third, the net-play gap: current cervical-mounted algorithms miss volleys at rates approaching 60% (Perri et al., 2022), meaning a phase of play defined by rapid deceleration and reactive arm action is systematically invisible to the most widely used monitoring systems. Fourth, the population gap: female participation is reported in only three of the fifteen studies, no study reports sex-stratified accuracy, and the evidence base has no data from developmental, masters, or para-athlete populations beyond a small wheelchair-tennis literature that fell outside the inclusion window. Fifth, the integration gap: classification, distributional modelling, and biomechanical sequencing have developed as separate analytical traditions, with no study trying to combine them, and no framework explains how their outputs should be interpreted together.

Strengths of the Review

Despite these limitations, this review possesses several methodological strengths. The review followed PRISMA 2020 reporting guidelines, implemented explicit eligibility criteria, employed structured thematic synthesis, and integrated evidence from sport science, biomechanics, engineering, and machine-learning research. This interdisciplinary approach provides a more comprehensive synthesis than previous reviews focusing exclusively on individual technologies or isolated performance outcomes.

Limitations of this Review

Four limitations qualify the conclusions. First, the search was limited to a single database. Scopus was chosen for its interdisciplinary coverage, which is essential given how this literature is spread across sport science, engineering, and materials science. But leaving out SPORTDiscus, PubMed, Web of Science, and IEEE Xplore will have excluded relevant records, and the lack of citation-chasing and grey-literature searching makes this worse. Second, restricting to peer-reviewed journal articles and reviews removed 50 conference records at the identification stage. In computer-science and engineering venues, conference papers are a primary publication channel, not a preliminary one, so this criterion excluded work that a differently designed review would have included. Third, screening, extraction, and quality appraisal were done without independent duplicate assessment. Although decisions were checked against pre-specified criteria, the lack of a second reviewer and a formal inter-rater reliability statistic means selection bias is not fully controlled. Fourth, the heterogeneity of designs, devices, and outcome metrics prevented meta-analysis, so the conclusions are qualitative and no pooled effect estimate is provided. Readers looking for a quantitative summary of, say, mean classification accuracy across studies won't find one here, and pooling across the incommensurable evidentiary logics identified in Section 3.4 would be misleading anyway.

Future Research Agenda

Four concrete priorities follow. First, the field needs prospective cohort studies where validated hitting-load metrics are collected continuously across a competitive season and modelled against prospectively recorded injury, with enough exposure to estimate a dose, response relationship. Until that happens, the injury-prevention rationale for wearable monitoring in tennis is an assumption. Second, validation must expand beyond shot counting to stroke intensity and joint loading. This will require concurrent lab instrumentation, force plates, motion capture, and where possible instrumented rackets, so that sensor-derived intensity surrogates can be compared against mechanical criteria instead of just video counts. Third, multi-sensor fusion should be pursued deliberately, not incidentally. The complementary strengths of wrist mounting for stroke resolution, trunk mounting for locomotor load, equipment mounting for impact characteristics, and photoplethysmography for internal load are all individually documented in this corpus. But no study has combined them, and a fused architecture is the obvious path to the integrated construct the field is missing. Sensing channels not yet used in tennis, including gaze (Guiseris-Santaflorentina et al., 2026) and real-time mixed-reality feedback loops (Yin et al., 2025), are plausible extensions of that architecture. Fourth, the population base must be broadened, with explicit recruitment of female, developmental, and para-athlete cohorts and mandatory reporting of sex-stratified accuracy. Right now there is no empirical basis for assuming that classifiers trained mostly on adult male players transfer without loss.

Summary Answers to the Research Questions

RQ1. Wearable sensing in tennis is overwhelmingly inertial. Eleven of fifteen studies use accelerometry, usually combined with gyroscopy and magnetometry, mounted at the wrist, cervical spine, or racket. Validation is strong for inertial shot counting, intraclass correlations at or above 0.90 and coefficients of determination near 0.94 against video criterion, but weak elsewhere. Photoplethysmography degrades at short time resolution and during heavy arm phases. Ultra-wideband positioning shows 16.29% error and fails most during rapid direction changes. Only 36.4% of commercially available tennis systems show excellent reliability for the single outcome they've been tested on.

RQ2. Analytical approaches span three traditions. Supervised classification, from support vector machines through deep autoencoders to embedded on-sensor inference, achieves 93, 98% accuracy for dominant stroke types under good conditions, but drops sharply for slice (74%) and volley (41, 44%) events in match conditions with cervical mounting. Distributional modelling, like Gaussian mixture decomposition of the acceleration histogram, recovers the bimodal intensity structure that scalar player-load summaries destroy. Biomechanical modelling, such as hand contribution velocity and the kinetic chain diagram, turns sensor kinematics into skill-discriminating coordination indices. The three traditions remain unintegrated.

RQ3. The main applied insight is that external load in tennis has two compositional dimensions: stroke-derived load and movement-derived load separate across drill types and are redistributed by court surface without changing total magnitude, meaning drill design can adjust upper-limb exposure independently of locomotor exposure. Kinetic-chain analysis makes proximal-to-distal sequencing measurable from wearable data for the first time. Still, translation is held back by five gaps: no controlled or longitudinal injury-outcome evidence, validation limited to shot counting, systematic non-detection of net play, near-absence of female and developmental populations, and failure to integrate classification, distributional, and biomechanical analytical traditions.

Conclusions

This systematic review looked at fifteen studies from 2017 through 2025. It shows that wearable sensing in tennis mostly relies on inertial measurement units placed on the wrist, trunk, or racket. That approach has been thoroughly validated for one pretty specific purpose: counting strokes. But it hasn't been validated for the intensity, kinetic, or physiological things practitioners actually want to get from it. Photoplethysmographic and ultra-wideband alternatives, on the other hand, are less accurate in exactly the high-acceleration, upper-limb-heavy conditions that define tennis. Analytically, supervised classification hits 93 to 98 per cent accuracy for the main stroke types. Yet under real match conditions it fails on volleys and slice variants. Distributional and biomechanical modeling give complementary views of load and coordination, but those views aren't integrated yet. The big applied takeaway here is that external load in tennis has two dimensions. Stroke-derived load and movement-derived load behave differently across drill types, and court surface redistributes them. That means coaches can and should design drills to manipulate upper-limb exposure independently of locomotor exposure. And any monitoring approach that just reports a single player-load number is tossing out the information most relevant to overuse injuries. The review does have limitations. It relied on one database. It left out conference proceedings, which are a major publication outlet in engineering. There was no independent duplicate screening. And the methods varied so much across studies that a meta-analysis wasn't possible. The field's central claim, that wearable monitoring prevents injury in tennis, still looks like an assumption rather than a proven finding based on the evidence we have. What tennis really needs now are prospective cohort studies that link validated load metrics to actual injury outcomes.

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