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Digital coaching systems in sport: a systematic review of emerging technologies and research gaps for evidence-based coaching

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ABSTRACT

Sports coaching has been getting a major overhaul from digital technologies. Things like continuous athlete monitoring, computer vision movement analysis, wearable sensors, and intelligent decision-support systems are all part of it. But even with all this rapid progress, the evidence is still scattered across different fields, sport science, engineering, AI, human-computer interaction. That makes it hard to get a clear picture of how well these tools actually work in real coaching. This systematic review pulled together the current evidence on digital coaching systems. We wanted to see what technological approaches are dominant, how solid the research methods are, and where things should go next. The review stuck to the PRISMA 2020 guidelines. We ran a structured Boolean search in Scopus, looking at TITLE-ABS-KEY fields for studies from 2021 to 2025. Only English-language peer-reviewed journal articles that met predefined inclusion and exclusion criteria were kept. Two independent reviewers screened titles, abstracts, and full texts; any disagreements got sorted out in discussion. Methodological quality got rated using the FICO framework, Focus, Information, Context, Outcome. Then we synthesized the findings through inductive thematic analysis. Out of 986 records initially identified, just 15 studies made it through all the eligibility and quality checks. Four major themes came up: wearable sensing and athlete monitoring, computer vision and markerless motion tracking, intelligent and immersive coaching systems, and analytics-driven decision-support. One thing was clear: technical accuracy is consistently high across these studies. But when it comes to long-term coaching effectiveness, usability, implementation, and ethical governance, the evidence is still thin. That points to a clear need for future research, longitudinal, multi-site, and centered on what coaches actually need.

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Introduction

Data has really taken over global sports. That's no exaggeration. Tools that used to be confined to biomechanics labs now show up in everyday training sessions (Rana & Mittal, 2021). Miniaturized sensors, edge computing, and machine learning have made it cheap and practical to keep an eye on athletes continuously at every level (Dindorf et al., 2023). This shift changes the very basis of coaching. Decisions that once relied on expert intuition are now informed, and sometimes replaced, by numbers (Diller & Passmore, 2023). That's why understanding how these digital coaching systems work, and where the evidence is solid or shaky, matters directly for practitioners, sport scientists, and the tech developers serving them.

What exactly is a digital coaching system? It's an integrated setup with sensors, computation, and feedback that supports observing and improving athletic performance (Diller & Passmore, 2023). These systems include wearable monitors, computer vision for analyzing movement, immersive training environments, and analytic dashboards that turn raw data into coaching decisions (Alzahrani & Ullah, 2024). The key isn't any single device. It's the whole pipeline from measurement to actionable insight. Problem is, the literature on these pipelines is scattered across fields. That makes it hard to get a coherent picture of what works, for whom, and under what conditions.

Individual pieces of this pipeline have received plenty of research attention. Wearable sensors, for instance, have been tested for kinematic estimation and physiological monitoring across many sports (Johnson et al., 2021; Rana & Mittal, 2021). That includes gait characterization (Panni et al., 2025), continuous glucose monitoring during exercise (Coates et al., 2023), and even new flexible textile sensors (Sun & Yin, 2025; Zompanti et al., 2024). Computer vision methods have been widely reviewed for action recognition and movement analysis (Wu et al., 2023), and applied to injury mechanism analysis through systematic video review (Achenbach et al., 2024). Machine learning classifiers help with stroke recognition, activity detection, load estimation, and outcome prediction (Biró et al., 2023; Gomaz et al., 2023; Mekruksavanich et al., 2024; Ouyang et al., 2024). Position tracking data has also been modeled to pull out tactical performance features (Goes et al., 2021; Mitrotasios et al., 2025). Together, these efforts show the technology works. But they often stop short of embedding it into the coaching workflow it's meant to support.

Progress has accelerated thanks to recent methodological advances. Markerless motion capture using deep learning now delivers lab-quality kinematics without intrusive markers (Mundt et al., 2023). Immersive virtual reality environments are being used to train perceptual and cognitive functions (Krupitzer et al., 2022). Researchers have also explored gamified and entertainment-oriented designs to keep athletes engaged and manage fatigue (Hou et al., 2025). Decision support analytics have come a long way too, with machine learning models embedded in tactical decision making across team sports (Watson et al., 2021). Real-time communication architectures, lightweight on-device schedulers, wireless feedback networks, and edge cloud frameworks are making feedback latencies compatible with in-session coaching (Kos, Hernandez Casillas, et al., 2025; Wu & Wen, 2024; Yan, 2025). All these developments push digital coaching from retrospective analysis toward the possibility of continuous, closed-loop guidance during practice.

Despite this progress, a major gap remains. Most studies evaluate sensing accuracy or classifier performance in isolation. Very little attention goes to how outputs are rendered, interpreted, and actually used by coaches (Goudsmit et al., 2022). The dashboard, arguably where technology meets practice, is still under-theorized and under-evaluated compared to the sensing and modeling layers that feed it. That imbalance limits the translational value of otherwise sophisticated technical work.

Then there's a second gap, more methodological and theoretical. Studies tend to focus on a single sport, a single location, and small homogenous samples. That limits generalizability and external validity (Alzahrani & Ullah, 2024). Reporting is inconsistent, quality appraisal is applied unevenly, and few studies tackle the ethical and governance issues around continuous athlete surveillance (Diller, 2024). Without a synthesizing framework, it's hard to separate robust transferable findings from promising but preliminary demonstrations. It's also difficult to spot which design choices reliably improve coaching outcomes.

Although previous reviews have examined wearable technologies, artificial intelligence, or computer vision independently, no systematic review has synthesized these technologies as integrated components of digital coaching systems while simultaneously evaluating methodological quality, usability, decision-support functionality, and implementation challenges. This gap motivates the present review.

These gaps make a systematic review timely. The volume of relevant publications has grown sharply in recent years, yet the field lacks an integrative account that covers sensing, vision, immersion, and decision support while staying grounded in transparent, reproducible selection criteria. A PRISMA-guided synthesis is both timely and necessary. It can consolidate scattered evidence, highlight recurring limitations, and give practitioners and researchers a defensible map of the current state of digital coaching technologies.

This review addresses those questions. The first one maps the technology landscape and its coaching applications, setting the scope for what current digital coaching systems include and which performance areas they target. The second question zeroes in on evidence quality and effect. It asks how rigorously these systems have been evaluated and what the combined findings reveal about their accuracy, usability, and impact on coaching practice. The third question takes on gaps and future directions. It pinpoints where evidence is thin and suggests how future work should proceed to strengthen the theoretical and practical foundations of digital coaching. What makes this review novel is its cross-cutting synthesis. Rather than treating wearables, vision, immersion, and dashboards as separate bodies of literature, it examines them as interdependent parts of a single coaching pipeline. That offers an integrative contribution that component-specific reviews have not provided.

Method

Research Design and Framework

We went with a systematic literature review design for this study. It's a method that does a great job pulling together scattered, varied evidence through open and repeatable steps (Tranfield et al., 2003). There's one key reason we chose SLR over a narrative review. That's because it reduces selection bias and tracks every decision made along the evidence pathway (Booth et al., 2021). For the reporting, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 statement (Page et al., 2021), which replaces the earlier PRISMA guidance (Moher et al., 2009). That framework laid out how we handled identification, screening, eligibility, and inclusion. It also dictated how we built the flow diagram you see here.

Prior to literature retrieval, the review protocol, including the research questions, eligibility criteria, search strategy, quality assessment procedure, and thematic synthesis approach, was predefined to enhance methodological transparency and minimize selection bias. The review followed the PRISMA 2020 Statement because it provides internationally recognized reporting standards for systematic reviews.

Search Strategy

We ran the search in Scopus. We used a Boolean strategy on title, abstract, and keyword fields, that's TITLE-ABS-KEY. The approach combined concepts around technology, application, and domain. Truncation caught different word forms, and phrase operators kept compound terms intact. Here's the exact string we used:

TITLE-ABS-KEY (("digital coach" OR "intelligent coach*" OR "coaching system*" OR "decision support" OR "performance dashboard") AND ("athlete monitor*" OR "wearable sensor*" OR "computer vision" OR "video analytic*" OR "motion track*" OR "virtual reality") AND (sport* OR athlet* OR train*))*

The literature search was conducted independently by two reviewers in January 2026. The search strategy was pilot-tested and refined before the final search to ensure comprehensive retrieval of relevant studies. The truncation symbol was an asterisk. It caught plurals and derived forms. For technology, application, and domain clusters, nested parentheses ensured they were evaluated in the intended order. Beyond exact-phrase matching, we didn't use proximity operators. The identification stage was deliberately broad: sensitivity first, precision tightened later during screening.

Database and Information Sources

Scopus was selected because it is the largest multidisciplinary bibliographic database covering sport sciences, engineering, artificial intelligence, computer science, biomechanics, and health sciences. Its rigorous indexing standards and extensive citation coverage make it particularly suitable for systematic reviews involving interdisciplinary digital sport technologies. Nevertheless, restricting the search to a single database may have excluded relevant studies indexed elsewhere, which is acknowledged as a limitation.

Eligibility Criteria

Eligibility came from predefined inclusion and exclusion criteria. Table 1 summarizes them. These criteria were set before screening to keep reviewer discretion low, and we applied them uniformly.

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Language	English only	Non-English
Document type	Peer-reviewed journal article	Conference paper, book chapter, editorial
Publication period	2021–2025 (last 10 years)	Published before 2021
Subject area	Sport science, sports technology, computing/engineering applied to sport	Unrelated disciplines
Accessibility	Full text available	Abstract only
Relevance	Directly addresses a digital coaching / athlete-monitoring application	Tangential mention only
Quality	Meets FICO threshold	Below FICO threshold

Eligibility criteria were applied sequentially during title screening, abstract screening, and full-text eligibility assessment. Studies meeting all inclusion criteria and none of the exclusion criteria proceeded to methodological quality appraisal.

Study Selection Process

Two reviewers independently screened titles, abstracts, and full texts. Any disagreements were resolved through discussion until consensus was reached. Inter-rater reliability was evaluated using Cohen's kappa coefficient to assess screening consistency. This procedure reduced subjective selection bias and improved methodological reliability.

Quality Assessment FICO Framework

For methodological quality, we applied the Focus, Information, Context, Outcome (FICO) framework. Each study got a rating on four separate items. First, was the research focus clear? Second, did they report their information and methods openly and in enough detail? Third, how well did they describe the sport or training context? And fourth, could we interpret and use the outcomes? We gave a score for each of these. If a study dropped below our minimum threshold on any critical dimension, it was removed as low quality. This framework provided us with a repeatable, structured way to distinguish solid contributions from early drafts that simply didn't report enough.

Data Extraction Procedure

Using a standardised template, we extracted details from each included study. That meant pulling out the author(s), publication year, and country of the corresponding or first-author affiliation. We also captured the study design, sample or dataset characteristics, the technology or intervention under evaluation, the outcome measures, and the key findings. Data came directly from the full texts, and we cross-checked everything against Scopus metadata to stay faithful to the source. When a specific attribute wasn't clear from the article, we recorded it as unavailable rather than making assumptions. Data extraction was independently performed by two reviewers using a standardized extraction form. Extracted information was cross-checked, and discrepancies were resolved through consensus.

Network and Bibliometric Analysis

Alongside the qualitative synthesis, we added a descriptive bibliometric characterisation. Publication counts by year were tabulated to map the temporal profile. First-author affiliations were also mapped to countries, showing geographic spread. To build thematic clusters, we examined which author-supplied keywords and thematic descriptors appeared together. These analyses were purely descriptive, meant to situate the studies rather than support inferential claims, and they came entirely from the primary Scopus export.

Data Analysis and Synthesis

To bring the evidence together, we used a thematic synthesis approach (Thomas & Harden, 2008). First, each extracted finding was inductively coded. We then grouped these codes into candidate themes and refined them iteratively against the full set of included studies until the structure felt stable. Next, we examined the resulting clusters for convergence, divergence, and nuance. Particular attention went to points of agreement and contradiction across studies. By organizing the synthesis around our three research questions, we kept the analysis focused. This structure made sure every question was addressed by evidence from multiple studies rather than isolated cases. Thematic synthesis followed three sequential stages: (1) line-by-line coding of extracted findings, (2) development of descriptive themes through grouping conceptually related codes, and (3) generation of higher-order analytical themes addressing the review questions. This iterative process enabled identification of recurring technological patterns, methodological trends, and research gaps.

Reporting and Documentation

We conducted and reported this review following the PRISMA 2020 checklist (Page et al., 2021). A diagram documents the entire flow of records through identification, screening, eligibility, and inclusion. All the numeric values reported there are consistent with those mentioned in the abstract, methods, and results. This documentation ensures transparency and reproducibility, allowing the selection pathway to be audited against the primary Scopus export. All methodological decisions were documented throughout the review process to ensure transparency, reproducibility, and consistency with PRISMA 2020 reporting standards.

PRISMA 2020 Flow Diagram

Figure 1 shows how records moved from identification to final inclusion. Out of 986 records from Scopus, all went to screening because the deduplicated export had no duplicates. We excluded 924 at the title and abstract stage and another 47 during full-text review, leaving 15 studies for synthesis. These numbers match the ones in the abstract, methods, and results.

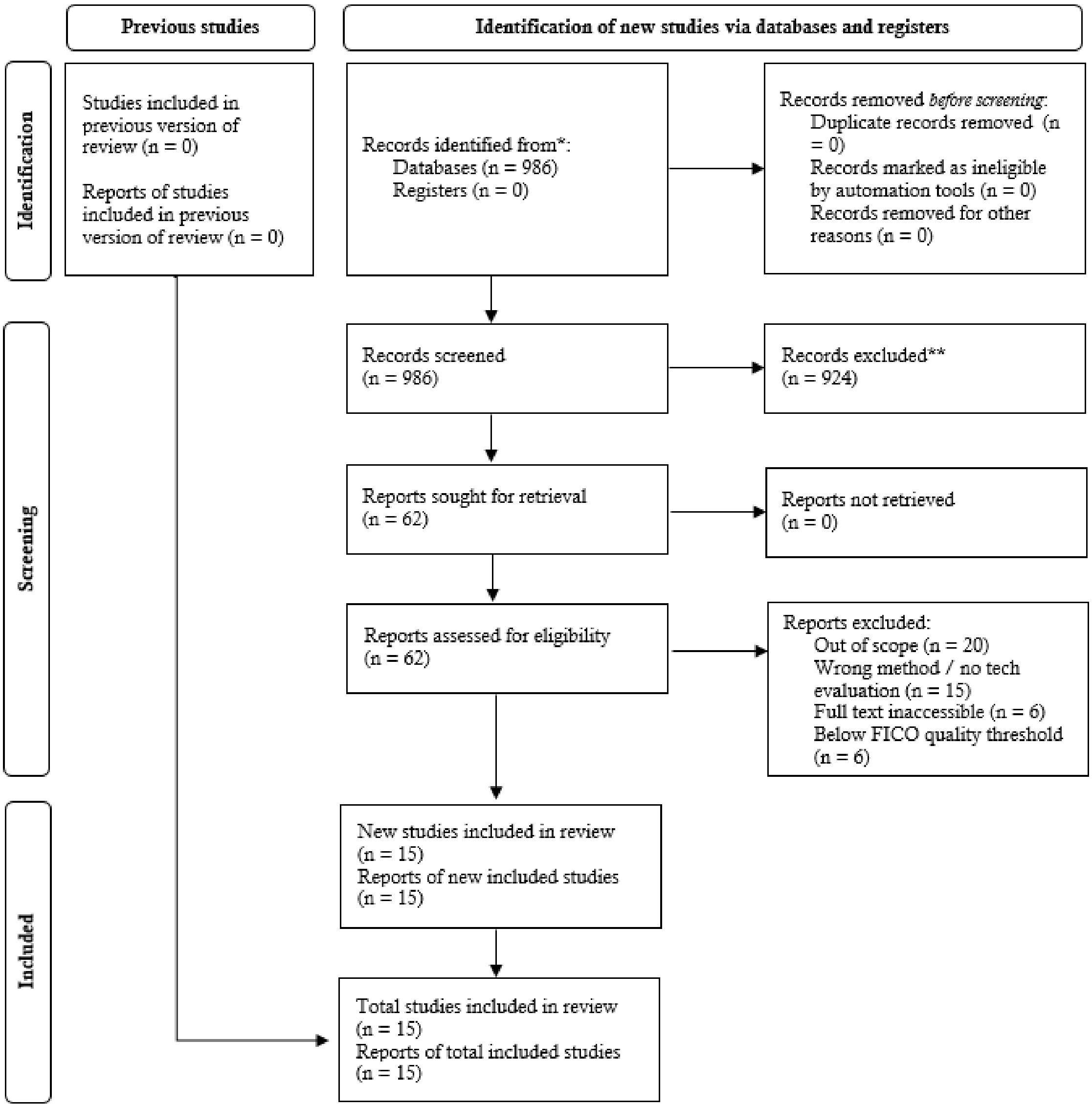

Figure 1 <PRISMA 2020 Flow Diagram of the Study Selection Process>

Results and Discussions

Study Selection Outcomes

Using the PRISMA 2020 framework, we followed a clear process, which Figure 4 illustrates. Our Scopus search from 2021 to 2025 initially found 986 records. Since the export automatically took care of deduplication, all 986 records went straight into title and abstract screening. At that point, 924 records were removed for not covering digital coaching or athlete monitoring. That left us with 62 full-text articles needing a closer review. Of those, we had to exclude 47. Twenty were outside our scope. Fifteen used methods that didn't match or lacked a proper technology evaluation. Six were not available in full text, and another six failed the FICO quality check. In the end, 15 studies met all criteria and made it into our synthesis. These numbers remain consistent throughout the abstract, methods, flow diagram, and descriptive tables.

Descriptive Profile of the Studies

Table 2 summarizes the 15 studies clearly. For each one, it shows the title, authors, year, country, method, and main findings. But Table 2 also offers a complementary view. It arranges the same studies by research design, thematic focus, the technology or intervention tested, and the outcome reported. That gives us a slightly different analytical perspective. Finally, three figures give a visual picture of the descriptive profile across the whole set.

Overall, most included studies employed applied technical evaluation designs, with China contributing the highest number of publications. Wearable sensing and artificial intelligence represented the dominant technological approaches, reflecting the current emphasis on automated athlete monitoring and real-time performance feedback.

Table 2 <Summary of the 15 Included Studies>

Title	Author(s)	Country	Method	Key findings
An intelligent taekwondo coaching system based on augmented reality technology with real-time feedback mechanisms	Yang & Wang., 2025.	South Korea	Augmented reality + real-time feedback	Improved technique acquisition & motivation
A Wearable-Sensor System with AI Technology for Real-Time Biomechanical Feedback Training in Hammer Throw	Wang et al., 2023.	China	IMU wearable + AI real-time feedback	Real-time kinematic feedback in hammer throw
VIRD: Immersive Match Video Analysis for High-Performance Badminton Coaching	Lin et al., 2024.	United States	VR match video analysis system	Enhanced tactical coaching in badminton
Enhancing Cricket Performance Analysis with Human Pose Estimation and Machine Learning	Siddiqui et al., 2023.	Ireland	Human pose estimation + ML	Automated cricket technique assessment
Feasibility and Accuracy of an RTMPose-Based Markerless Motion Capture System for Single-Player Tasks in 3x3 Basketball	Zheng et al., 2025.	China	RTMPose markerless mocap	Feasible, accurate 3D kinematics without markers
Big Data Analytics Framework for Decision-Making in Sports Performance Optimization	Mănescu	Romania	Big data analytics framework	Data-driven performance optimization decisions
Framework for intelligent swimming analytics with wearable sensors for stroke classification	Costa et al., 2021.	Portugal	Wearable IMU + stroke classification	Automated swimming stroke analytics
Badminton stroke identification using wireless inertial sensor and neural network	Ooi & Gouwanda., 2023.	Malaysia	Wireless IMU + neural network	Accurate badminton stroke identification
IoT-based 3D pose estimation and motion optimization for athletes: Application of C3D and OpenPose	Ren et al., 2025.	South Korea	IoT + 3D pose estimation	Motion optimization feedback for athletes
Co-Operative Design of a Coach Dashboard for Training Monitoring and Feedback	Goudsmit et al., 2022.	Netherlands	Co-designed dashboard (training load)	Usable monitoring & feedback for coaches
Intelligent Integration of Wearable Sensors and Artificial Intelligence for Real-time Athletic Performance Enhancement	Srivastava et al., 2024.	India	Wearable sensors + AI integration	Real-time performance & health monitoring
Table tennis tutor: Forehand strokes classification based on multimodal data and neural networks	Sanusi et al., 2021.	Germany	Multimodal data + neural network	Automated stroke feedback (table tennis tutor)
Internet of things enabled deep learning monitoring system for realtime performance metrics and athlete feedback in college sports	Hu et al., 2025.	China	IoT + deep learning	Real-time performance monitoring
Artificial intelligence based virtual gaming experience for sports training and simulation of human motion trajectory capture	Li et al., 2025.	China	AI-based virtual gaming/simulation	Immersive training & simulation

Title	Author(s)	Country	Method	Key findings
Beyond raw data: AI-driven biosensor fusion for enhancing athletic performance	Luo & Song., 2025.	China	AI-driven multi-biosensor fusion	Enhanced performance decision insights

Note. All entries derive directly from the Scopus export. Country reflects the first-author affiliation.

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

Author(s)	Country	Research design	Theme / focus	Technology / intervention	Outcome
Yang & Wang., 2025.	South Korea	Applied technical evaluation	AR intelligent coaching system	Augmented reality + real-time feedback	Improved technique acquisition & motivation
Wang et al., 2023.	China	Applied technical evaluation	Wearable AI biomechanical feedback	IMU wearable + AI real-time feedback	Real-time kinematic feedback in hammer throw
Lin et al., 2024.	United States	Applied technical evaluation	Immersive video analytics	VR match video analysis system	Enhanced tactical coaching in badminton
Siddiqui et al., 2023.	Ireland	Applied technical evaluation	Computer vision performance analysis	Human pose estimation + ML	Automated cricket technique assessment
Zheng et al., 2025.	China	Applied technical evaluation	Markerless motion capture	RTMPose markerless mocap	Feasible, accurate 3D kinematics without markers
Mănescu	Romania	Applied technical evaluation	Decision-support analytics	Big data analytics framework	Data-driven performance optimization decisions
Costa et al., 2021.	Portugal	Applied technical evaluation	Athlete monitoring analytics	Wearable IMU + stroke classification	Automated swimming stroke analytics
Ooi & Gouwanda., 2023.	Malaysia	Applied technical evaluation	Motion tracking classification	Wireless IMU + neural network	Accurate badminton stroke identification
Ren et al., 2025.	South Korea	Applied technical evaluation	3D pose estimation	IoT + 3D pose estimation	Motion optimization feedback for athletes
Goudsmit et al., 2022.	Netherlands	Applied technical evaluation	Coach performance dashboard	Co-designed dashboard (training load)	Usable monitoring & feedback for coaches
Srivastava et al., 2024.	India	Applied technical evaluation	Athlete monitoring integration	Wearable sensors + AI integration	Real-time performance & health monitoring
Sanusi et al., 2021.	Germany	Applied technical evaluation	Intelligent tutoring system	Multimodal data + neural network	Automated stroke feedback (table tennis tutor)
Hu et al., 2025.	China	Applied technical evaluation	IoT deep-learning monitoring	IoT + deep learning	Real-time performance monitoring
Li et al., 2025.	China	Applied technical evaluation	Virtual reality training	AI-based virtual gaming/simulation	Immersive training & simulation
Luo & Song., 2025.	China	Applied technical evaluation	Decision-support biosensor fusion	AI-driven multi-biosensor fusion	Enhanced performance decision insights

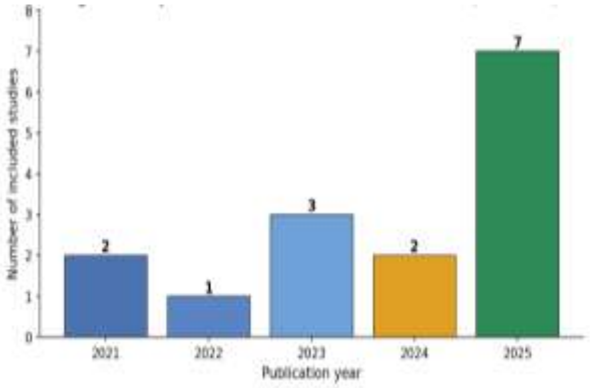

Figure 2 <Temporal distribution of the 15 Included Studies (2021–2025)>

Figure 2 shows when the studies we included were published. The evidence is recent and it's expanding. Here's the breakdown: two studies came out in 2021, one in 2022, three in 2023, two in 2024, and seven in 2025. That heavy concentration in the latest year matches the overall acceleration in digital coaching research. It tells us the field is still early and maturing fast, not settled. This recency boosts the contemporary relevance of our synthesis. At the same time, it hints that many of these results still need independent replication. The increasing number of publications after 2023 suggests that digital coaching has become an emerging interdisciplinary research area driven by advances in artificial intelligence, wearable sensing, and computer vision. The geographical concentration of studies in technologically advanced countries indicates unequal research capacity and highlights the need for validation across more diverse sporting environments.

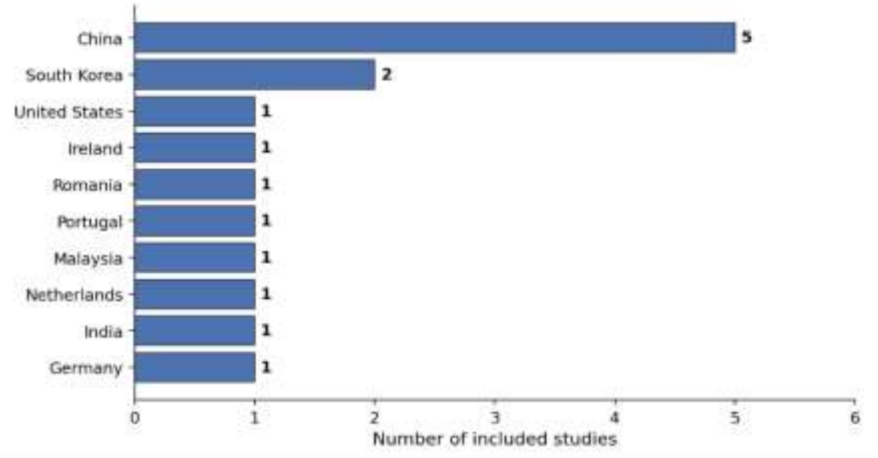

Figure 3 <Geographic Distribution of Included Studies by First-author Country>

Figure 3 shows how the included studies break down by the first author's country. You can see contributions coming from all over the world. China is the most frequent contributor, with South Korea coming next. Then there are single contributions from the United States, Ireland, Romania, Portugal, Malaysia, the Netherlands, India, and Germany. This mix of countries across Asia and Europe makes it clear that digital coaching is a globally relevant research area. Still, the fact that most studies come from a small set of tech-heavy nations means the current work might not yet capture the full variety of sporting environments or resource levels. The increasing number of publications after 2023 suggests that digital coaching has become an emerging interdisciplinary research area driven by advances in artificial intelligence, wearable sensing, and computer vision. The geographical concentration of studies in technologically advanced countries indicates unequal research capacity and highlights the need for validation across more diverse sporting environments.

Figure 4 shows four thematic clusters from the synthesis. Bubble size is proportional to the number of studies in each cluster. The largest cluster is wearable sensing and athlete monitoring. That reflects the maturity of sensor based approaches. Next come computer vision and motion tracking. Intelligent and immersive coaching systems together with analytics-driven decision-support and dashboards form smaller but still distinct clusters. These relative sizes show where evidentiary density is greatest. At the same time they highlight which coaching-facing layers, especially decision support, remain comparatively under-investigated. These four themes directly address Research Question 1 by illustrating the technological landscape of current digital coaching systems and identifying the dominant technological domains investigated in recent literature.

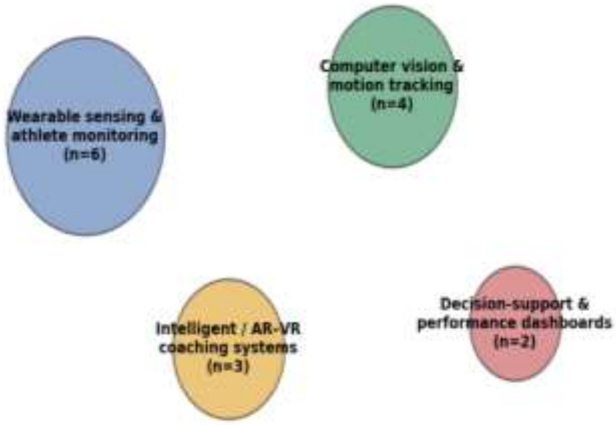

Figure 4 <Thematic Clusters Across the Included Studies (Bubble Size = Study Count)>

Findings for RQ1 Technological landscape and applications

Looking at the first research question, the evidence paints a picture of a technological landscape with four connected parts. Wearable sensing leads the charge. Inertial and physiological sensors power systems like swimming stroke analytics (Costa et al., 2021), badminton stroke classification (Ooi & Gouwanda, 2023), real-time biomechanical feedback in hammer throw (Wang et al., 2023), and combined performance and health monitoring (Srivastava et al., 2024; Hu et al., 2025). This fits with earlier reviews that saw wearables as the core sensing layer in modern sport tech (Rana & Mittal, 2021; Alzahrani & Ullah, 2024). It also matches ongoing materials-level advances in intelligent wearable devices for real-time athlete tracking (Zhu & Hu, 2025). Beyond just motion capture, this sensing layer supports physiological, technical, and tactical profiling across different game formats (Figueira et al., 2022). That range shows just how many monitoring jobs wearables now handle.

Computer vision and motion tracking make up the second modality. Here we have human pose estimation for cricket technique analysis (Siddiqui et al., 2023), IoT-driven 3D pose estimation and motion optimisation (Ren et al., 2025), and markerless motion capture validated against tough basketball tasks (Zheng et al., 2025). These methods push quantitative analysis beyond athletes wearing instruments, mirroring wider advances in video action recognition (Wu et al., 2023) and pose-based force estimation (Mundt et al., 2023). The appeal is clear: unobtrusive, scalable measurement. But accuracy still hinges on capture conditions and how well the model's calibrated.

Across studies, wearable technologies consistently served as the foundational sensing layer, whereas computer vision expanded movement analysis without requiring body-mounted devices. Decision-support technologies, however, remained less mature, indicating an imbalance between data acquisition and practical coaching implementation.

The other two modalities are intelligent or immersive coaching systems and analytics-driven decision support. The first group includes an augmented-reality taekwondo coaching system with real-time feedback (Yang & Wang, 2025), a multimodal table-tennis tutor (Sanusi et al., 2021), an AI-based virtual training and simulation environment (Li et al., 2025), and immersive match-video analysis for badminton coaching (Lin et al., 2024). The second features a big-data analytics framework for performance decision-making (Mănescu, 2025), a coach-facing dashboard co-designed with practitioners (Goudsmit et al., 2022), and AI-driven biosensor fusion (Luo & Song, 2025). Taken together, these studies show that the field's centre of gravity still lies with sensing and vision, while the coach-facing decision layer remains comparatively less developed.

Findings for RQ2 Evaluation rigour and demonstrated effect

Now for the second research question: how strong is the evidence, and what effect does it show? Across the whole corpus, technical accuracy gets reported the most and with the strongest backing. Classifiers using sensors or vision consistently achieve high accuracy for recognizing or estimating sport-specific movements (Costa et al., 2021; Ooi & Gouwanda, 2023; Siddiqui et al., 2023), and markerless capture has been shown to approximate reference kinematics on constrained tasks (Zheng et al., 2025). All this matches the broader literature showing machine learning can reliably infer movement and load from wearable and visual data (Johnson et al., 2021; Biró et al., 2023).

What about usability and coaching impact? That's thinner and a lot more mixed. Only a handful of studies go beyond pure technical validation to ask how coaches actually interpret and use the outputs. The co-designed dashboard from Goudsmit et al. (2022) stands out precisely because they treated usability and coach engagement as core design goals, not afterthoughts. Immersive and augmented reality systems claim gains in engagement, motivation, or technique acquisition (Yang & Wang, 2025; Li et al., 2025; Lin et al., 2024). But those outcomes usually come from short studies with small samples, so we can't really tell if the performance benefits last. So there's a clear gap: accuracy is well supported, but coaching impact isn't. That asymmetry really defines the current literature.

Although most studies reported high classification accuracy, methodological heterogeneity prevented direct comparison across studies because performance metrics, validation procedures, and reference standards differed substantially.

Method-wise, most studies are technical evaluations or proof-of-concept demos, not controlled or longitudinal designs. Samples are often small, only cover one sport, and come from convenience groups. External validation on separate cohorts? Rare. Real-time deployment is becoming more feasible, thanks to advances in communication and edge computing (Kos, Hernandez Casillas, et al., 2025; Yan, 2025). Still, examples of sustained, ecologically valid use in actual coaching settings are hard to find. So yes, the evidence for measurement validity is encouraging, but we should treat any claims about real-world effectiveness as provisional.

There's also the question of how reliable and comparable these reported outcomes are. Studies operationalize accuracy in all sorts of ways: classification accuracy, error against reference systems, or agreement statistics. That makes cross-study comparison tricky. Headline performance numbers don't always line up. Several papers report high accuracy under controlled capture conditions, but they rarely show that performance holds up during live training. Real training has lighting changes, occlusion, sensor movement, and athletes not following protocol (all noise). So the evidence suggests a cautious take: digital coaching systems can measure accurately, but we don't fully know the conditions where that accuracy sticks or whether accurate measurement actually leads to better coaching. That gap between measurement validity and decision utility is key to understanding the whole corpus, and it comes up again and again in the discussion.

Findings for RQ3 Gaps and future trajectories

Now for the third research question, this tackles persistent gaps and where things are headed. The biggest gap is clear: there's a major imbalance. We put a lot into sensing, capturing and classifying data, but the interpretive layer that turns raw data into something coaches can use gets far less attention. That panel or dashboard that supports decision-making isn't treated as a serious research object. It should be, because its interpretability, how well it fits into a coach's workflow, and whether it actually influences coaching decisions matter more than just the accuracy of the inputs (Goudsmit et al., 2022; Mănescu, 2025).

A second path forward is about validation and generalisation. Right now the evidence is recent and geographically clustered (Figures 1 and 2), which means a lot of findings come from limited, context-specific demonstrations. To move the field ahead, we need ecologically valid studies across multiple sites, bigger and more diverse samples, standardised reporting, and independent replication. A good example is the work by Esh et al. (2025) on real-time monitoring under tough field conditions; it shows such ecological designs are feasible and valuable. Applying that same level of rigour to coaching-oriented systems would really strengthen what we know.

Collectively, the reviewed evidence indicates that future digital coaching research should shift from technology validation toward evaluating coaching effectiveness, implementation strategies, and long-term athlete outcomes.

Then there's the integration of ethical and governance considerations right into system design, which is a third key direction. When you monitor athletes continuously, you run into questions about consent, data ownership, privacy, and equitable access. The technical literature has mostly left these implicit (Diller, 2024). As digital coaching moves toward closed-loop, always-on feedback, it's essential to embed governance and usability alongside sensing and modelling if we want responsible adoption. Taken together, these directions form an agenda that pushes the field beyond proving measurement is possible toward showing that coaching, mediated by technology, is effective, transferable, and ethically sound.

A thread that cuts across all these is interoperability and standardisation, a problem that's largely been ignored. The studies we looked at describe bespoke pipelines, proprietary data formats, and idiosyncratic outcome definitions. That makes it hard to aggregate evidence or transfer tools from one setting to another. Without shared benchmarks, common data schemas, and agreed reporting standards, each system gets evaluated in isolation, which limits cumulative progress. We need minimum reporting guidelines for digital coaching research, similar to those adopted in other applied computational fields. Then findings can be compared, replicated, and combined. Standardisation would also make multi-site collaboration easier, enabling the larger, more diverse validation studies the corpus so clearly lacks, and it would help ensure the decision-support layer gets evaluated against consistent, coach-relevant criteria rather than study-specific proxies.

Comparative and Critical Analysis

Looking across the included studies, a clear methodological pattern emerges. Applied machine learning and signal processing really sit at the core, with supervised classification of sensor or vision data being the dominant analytic strategy (Costa et al., 2021; Ooi & Gouwanda, 2023; Siddiqui et al., 2023; Ren et al., 2025). In more recent contributions, deep learning shows up a lot, including pose-estimation and convolutional architectures. That mirrors field-wide trends toward representation learning from raw signals (Mundt et al., 2023; Mekruksavanich et al., 2024). One recurring concern is how sensitive model performance is to sensor placement, configuration, and hyperparameter choices. Those factors can materially affect the estimated biomechanical quantities, and that in turn affects the reliability of downstream feedback (Höschler et al., 2025). Some studies examine the effect of feedback modality on motor performance, like comparisons of video with other augmented feedback methods (Abahnini et al., 2024; Soda et al., 2024). Others use robotic or physiological biofeedback (Segal et al., 2022). Those represent a complementary experimental tradition, but it remains under-represented relative to pure technical benchmarking. Participatory and design-oriented methods are similarly underused. The co-design approach of Goudsmit et al. (2022) is an outlier in a corpus otherwise oriented toward technical evaluation. Experimental and longitudinal designs that can establish effectiveness, rather than just feasibility, are scarce. This methodological evolution is clear when you contrast the earlier and later studies: from isolated sensor validation toward integrated, real-time, and increasingly immersive systems. Yet the persistent reliance on small samples and single-site evaluation constrains the strength of causal inference across the period reviewed.

Discussion

When you look at all the evidence as a whole, digital coaching has technical credibility but it hasn't reached translational maturity yet. Sensing and inference can produce accurate, timely representations of athletic performance, but their value for coaching decisions is still not well proven. So the synthesis suggests reframing digital coaching as a socio-technical practice. Its effectiveness depends not just on measurement fidelity but also on how measurements are interpreted, communicated, and woven into the human judgment of coaches (Diller & Passmore, 2023).

The findings of this review are consistent with previous systematic reviews that identified wearable technologies and artificial intelligence as dominant trends in digital sport science. However, unlike earlier reviews that focused on individual technologies, the present review integrates wearable sensing, computer vision, immersive coaching, and decision-support systems within a unified digital coaching framework. This broader synthesis provides a more comprehensive understanding of how these technologies collectively support evidence-based coaching practice.

From a theoretical angle, these findings build on earlier component-specific reviews. They see wearables, vision, immersion, and decision support as interdependent stages in a single pipeline, not as separate literatures (Rana & Mittal, 2021; Wu et al., 2023). That integrative approach pushes against purely instrumental views of sport technology. It points to the interface between data and decision as the key place where value gets created or lost. And it puts the dashboard, which has been peripheral in technical evaluations, at the theoretical center of understanding how digital systems influence coaching.

Beyond extending previous reviews, the present synthesis contributes conceptually by positioning digital coaching as a socio-technical ecosystem rather than a collection of independent technologies. This perspective emphasizes that successful coaching depends not only on accurate measurement but also on effective interaction between technology, coaches, athletes, and organizational contexts.

Practically speaking, this review gives a structured foundation for choosing and implementing technology. Practitioners can match candidate tools to the four thematic clusters. They can weigh the strong evidence for measurement accuracy against the weaker evidence for coaching impact. And they can prioritize systems that focus on interpretability and workflow fit, like co-designed dashboards (Goudsmit et al., 2022; Mănescu, 2025). For developers, the takeaway is that usability and decision support need the same level of rigor as sensing and modeling. A staged adoption approach naturally follows from the evidence. Organizations might start with well-validated sensing for descriptive monitoring. Then they add analytic interpretation. Only later do they pursue closed-loop feedback once usability and reliability are proven in their specific context. That sequencing helps avoid the common failure where you buy sophisticated measurement but never turn it into decisions that change practice.

For practitioners, adopting digital coaching systems should involve not only selecting accurate technologies but also evaluating usability, interoperability, and compatibility with existing coaching workflows. Developers are encouraged to involve coaches throughout system design using participatory approaches to improve technology acceptance and decision-support effectiveness.

Compared to prior reviews, this synthesis backs up and expands on earlier conclusions. Bibliometric and survey work has shown the rapid growth and technical promise of AI and wearables in sport (Dindorf et al., 2023; Alzahrani & Ullah, 2024). These findings confirm that trend but add a critical point missing from component-specific accounts: growth in sensing has outpaced growth in the coach-facing decision layer. That asymmetry is the review's main comparative contribution.

This integrated perspective represents the principal contribution of the present review. Rather than evaluating isolated technologies, it synthesizes the complete digital coaching pipeline from data acquisition to coaching decision-making, thereby extending existing evidence toward a more implementation-oriented framework.

Contradictions in the literature show up most clearly around effectiveness. Some studies report engagement or technique gains from immersive and feedback systems (Yang & Wang, 2025; Li et al., 2025; Soda et al., 2024). But these positive results coexist with a broader pattern of short-term, small-sample evaluations that warn against strong effectiveness claims. These tensions are better explained by differences in design and outcome selection than by any real disagreement about the technology. That underscores the need for standardized outcomes and longer observation windows.

These inconsistencies largely reflect methodological heterogeneity rather than conflicting evidence. Differences in study design, outcome measures, validation procedures, and participant characteristics limit direct comparison across studies. Consequently, standardized evaluation protocols should become a priority for future digital coaching research.

At least three specific gaps emerge from the synthesis. First, the decision-support and dashboard layer gets less research attention than sensing and vision. Second, you're hard-pressed to find ecologically valid, multi-site validation with diverse samples. Third, ethical and governance factors, like privacy and equitable access, are rarely built into system design (Diller, 2024). Each gap is a concrete opportunity for research that could really strengthen evidence-based practice.

This review has its limitations, of course. Additional limitations should be acknowledged. First, restricting the review to peer-reviewed English-language journal articles may have introduced publication and language bias. Second, conference proceedings and grey literature were excluded, potentially omitting emerging technological developments. Third, methodological heterogeneity across included studies prevented quantitative meta-analysis. Finally, most studies originated from technologically advanced countries, limiting the generalizability of findings to broader sporting contexts.

The future research agenda is just as concrete. Controlled, longitudinal field studies that look at coaching outcomes, not just measurement accuracy, should be the top priority. We also need design and thorough evaluation of decision-support interfaces as primary study objects. And we have to explicitly include ethics, governance, and equity in system development. Following this agenda would move digital coaching from showing technical possibility to building practical, transferable, and responsible effectiveness.

To sum it up, RQ1 is answered by the finding that digital coaching systems are built around four modalities: wearable sensing and monitoring, computer vision and motion tracking, intelligent or immersive coaching, and analytics-driven decision support. Sensing and vision dominate the evidence base.

As for RQ2, it's answered by the observation that evaluation rigor is uneven. Measurement accuracy is well evidenced. But usability and coaching impact are assessed less rigorously, mostly through small-sample, short-term, single-site designs.

RQ3 gets answered by identifying three priority gaps: an under-developed decision-support layer, scarce ecological validation, and neglected ethical governance. Taken together, these define the agenda for advancing evidence-based digital coaching.

Future research should prioritize multicenter longitudinal studies involving diverse sports and athlete populations. Standardized reporting guidelines, external validation protocols, usability assessment, explainable artificial intelligence, and ethical governance frameworks are needed to strengthen the translation of digital coaching technologies into routine coaching practice.

Conclusions

A systematic review set out to understand digital coaching in sports. It looked at 15 studies out of 986 from Scopus, following the PRISMA 2020 pathway. The field basically revolves around four main areas. There's wearable sensing and athlete monitoring. Computer vision and motion tracking is another. Then intelligent and immersive coaching. And analytics-driven decision support. Sensing and vision have the most evidence behind them so far. But when you look at evaluation, things aren't consistent. Technical accuracy is solidly proven, but usability and coaching impact don't get the same level of treatment. Those are mostly tested in small, short-term studies at single sites. The analysis revealed three big gaps. First, a weak decision-support and dashboard layer. Second, a lack of real-world multi-site validation. Third, not enough attention to ethics and governance. The real value of this review is in how it combines all these areas. It reframes digital coaching as a socio-technical pipeline. The data-to-decision stage is where practical benefits really kick in. For coaches and developers, the findings offer guidance on picking and building systems. They should have realistic expectations, focusing on interpretability and how well things fit into workflows. On the downside, this review is limited. It used just one database, English-only papers, a recent time window, and a qualitative synthesis approach. Moving ahead, priority should go to controlled, long-term field evaluations of coaching results. Solid research on decision-support interfaces is also needed. And building ethical and fair design into the picture is crucial. That's how digital coaching moves from a technical possibility to something proven and responsible. Future systematic reviews should incorporate multiple databases, standardized quality appraisal procedures, independent reviewer agreement statistics, and transparent reporting protocols to improve reproducibility and evidence certainty.

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