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AI-enabled wearable monitoring of athletes' psychological states: a systematic literature review

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ABSTRACT

The meeting point of artificial intelligence and wearable sensing has quietly reshaped precision sport psychology. Athletes can now be monitored continuously, with cognitive and emotional states tracked at the individual level, something traditional self-report methods never quite captured. Yet the evidence on how AI actually turns physiological signals into psychological insight is scattered across sport science, engineering, and digital health. This systematic review follows the PRISMA 2020 framework to pull that evidence together. A structured Scopus search returned 112 records published between 2020 and 2025. After duplicates were removed and screening ran in two stages, 74 studies fell away at the title-and-abstract stage and 28 more after full-text assessment. That left 10 studies for qualitative synthesis, with 40 contextual records supporting the analysis. Eligible studies had to involve athlete populations, wearable physiological sensing, AI or machine-learning techniques, and psychological, cognitive, or affective outcomes. Three themes stood out. Electroencephalography combined with deep learning dominates cognitive-state classification. Multimodal integration of cardiac, electrodermal, muscular, and respiratory signals supports emotion and stress recognition. And telling psychological stress apart from physical stress remains the core methodological hurdle. What the evidence shows is that personalized, real-time psychological feedback is technically within reach, but it is still held back by small samples, laboratory settings, and limited external validation. Future work should push toward ecologically valid field studies, standardized labeling of psychological states, explainable AI models, and stronger data privacy for athletes. That is the path to real deployment in competitive sport.

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Introduction

Competitive sport increasingly relies on continuous measurement and computational analysis, yet psychological monitoring remains less standardized than physical monitoring. Wearable sensors can capture cortical and peripheral biosignals, while machine-learning models can map these signals to psychological or cognitive labels. The challenge is not merely sensing: psychological states are context-dependent, labels vary across studies, and physical exertion can alter the same physiological signals used to infer mental state. Recent sport-psychology evidence also shows that anxiety, self-efficacy, and concentration are important performance-relevant constructs, reinforcing the need to define psychological outcomes explicitly before they are modeled (Yusuf et al., 2025; Firmansyah et al., 2024).

In this review, the term precision sport psychology is used descriptively rather than as an established diagnostic or indexing term. It refers to individualized, technology-assisted monitoring and interpretation of athletes' psychological, cognitive, and affective states, with the intention of supporting training, competition, recovery, or decision-making. This operational definition distinguishes the review from broader athlete monitoring because a study must contain both (a) physiological or wearable sensing and (b) an explicit psychological, cognitive, or affective target.

Evidence already demonstrates several feasible routes. Portable EEG combined with deep learning has been used to classify mental focus and cognitive states; multimodal physiological fusion has been applied to emotion recognition; and wearable inertial or peripheral biosignals have been explored for flow-like states and stress. However, the apparent performance of these models is highly study-specific because labels, sample composition, experimental induction, and validation procedures differ. The present review therefore treats reported accuracy as a within-study result rather than as evidence of general clinical or competitive validity.

Recent work also points toward real-time and closed-loop systems. Deep architectures have improved classification of EEG-derived mental states, while multimodal physiological models have increased the amount of information available to an affective classifier. At the same time, context-aware and self-supervised approaches suggest that longer, ecologically valid data streams may eventually reduce the gap between laboratory prototypes and real-world athlete monitoring. These developments make a critical synthesis timely, particularly because continuous mental-state inference has implications for athlete autonomy, privacy, competitive integrity, and the interpretation of sensitive psychological information.

The first gap concerns population specificity. A large portion of physiological-AI research that appears relevant to sport psychology is derived from gaming or general-population experiments rather than athlete cohorts. Such evidence can inform methods, but it should not be treated as direct evidence for athletes because exercise, competitive pressure, training load, and sport-specific context can alter physiological signatures. The present review therefore separates athlete studies from contextual evidence and does not use non-athlete studies as core evidence for the athlete-specific conclusions.

The second gap concerns construct validity. Psychological states are defined inconsistently: stress may be elicited by cognitive tasks or inferred from peripheral biosignals; emotion may be represented as discrete categories or as arousal-valence dimensions; and flow may be represented through coach labels or behavioral proxies. This heterogeneity means that similar labels may describe different underlying constructs. A systematic synthesis therefore needs to record not only the sensor and model, but also the construct definition, labeling procedure, and validation strategy.

The pace of technology adoption makes this synthesis urgent. Wearable and AI systems are increasingly proposed for individualized training and performance support, but deployment decisions should be based on evidence that is transparent about population, setting, validation, and uncertainty. The purpose of the present review is not to establish a clinical diagnostic technology, but to determine how far the current athlete literature has progressed toward trustworthy psychological-state monitoring.

Accordingly, this review was designed to systematically map wearable sensing modalities and AI methods used to monitor athletes' psychological, cognitive, and affective states; compare how the target constructs are defined, labeled, and validated; and identify methodological, ecological, and ethical barriers to translation. The review is a systematic literature review reported using PRISMA 2020, with a Scopus sampling frame covering 2020–2025 and a narrative/thematic synthesis because the included outcomes are too heterogeneous for quantitative pooling. The primary outcomes are the sensing modalities, AI methods, psychological constructs, reported model performance, validation approach, and barriers to real-world deployment.

RQ1: Which wearable sensing modalities and artificial-intelligence methods are used to monitor athletes' psychological, cognitive, and affective states, and how effective are they reported to be?

The second question moves from method to psychological substance. Which mental constructs, such as stress, emotion, focus, flow, resilience, and recovery-related states, have actually been operationalized through wearable AI, and how are they defined and labeled? Answering it produces a critical account of construct validity and the labeling heterogeneity that currently limits cumulative progress.

RQ2: Which psychological, cognitive, and affective constructs have been operationalized through AI-driven wearable monitoring in athletes, and how consistent are their definitions and measurements?

The third question addresses translation and limitation. What barriers, whether methodological, ecological, or ethical, stand between current prototypes and deployable, personalized precision sport psychology? Answering it contributes a forward-looking research agenda. The novelty of this review lies in isolating the specific intersection of athlete, wearable, AI, and psychology, and in holding it to a strict data-integrity standard: no finding is asserted beyond its source evidence.

RQ3: What methodological, ecological, and ethical barriers stand in the way of translating AI-driven wearable monitoring into deployable precision sport psychology, and what future directions follow?

Method

Research Design and Framework

A systematic literature review design was used because the question spans sport psychology, wearable sensing, machine learning, and digital-health research. Reporting followed PRISMA 2020. The protocol logic specified the research questions, Scopus search string, eligibility criteria, extraction fields, appraisal approach, and thematic synthesis before interpretation. Because the evidence combined classification, exploratory field, and applied modeling studies with non-comparable outcomes, the synthesis was narrative and thematic rather than meta-analytic.

Search Strategy

Searches were performed in Scopus using the TITLE-ABS-KEY fields. The search combined wearable/physiological sensing, AI/machine learning, psychological outcomes, and athlete/sport terms. The exact search string was:

> TITLE-ABS-KEY(("wearable*" OR "sensor*" OR "EEG" OR "biosignal*" OR "physiological signal*") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("psycholog*" OR "emotion*" OR "mental" OR "stress" OR "affective" OR "cognitive") AND ("athlet*" OR "sport*" OR "player*"))

The screening frame was limited to English-language, peer-reviewed journal articles published from 2020 through 2025 and meeting the predefined population, technology, method, and outcome criteria. The supplied Scopus export records the publication window but does not preserve the exact calendar date on which the database query was executed; this is reported as a reproducibility limitation. No language, date, or document-type filter was embedded in the query itself so that the initial retrieval remained broad, with the eligibility criteria applied during screening.

Database and Information Sources

Scopus was selected because it spans sport science, biomedical engineering, sensor technology, and computer science, which are all represented in this topic. However, Scopus was the only database used in the archived review. PsycINFO, SPORTDiscus, PubMed, and Web of Science were not searched, and systematic citation chaining was not documented. We therefore do not claim database saturation and explicitly treat single-database sampling as a source of selection bias.

Eligibility Criteria

The eligibility framework was applied to the population, technology, method, and outcome dimensions. A record entered the core synthesis only when all dimensions were satisfied. The key correction made during revision was to separate athlete evidence from contextual evidence: records with gaming or general-population samples were not counted as athlete studies, even when the technology or AI method was directly relevant to sport psychology.

Table 1. Inclusion and exclusion criteria applied during screening.

Criterion	Inclusion	Exclusion
Language	English-language full text	Non-English
Document type	Peer-reviewed journal article	Conference paper, book chapter, editorial, note
Publication period	2020–2025	Published before 2020
Population	Athletes / sport-performance context	Non-athlete or purely clinical population
Technology	Wearable or physiological sensing	No wearable/physiological signal
Method	AI / machine-learning analysis	No computational modeling component
Outcome	Psychological, cognitive, or affective	Purely physical/biomechanical outcome only
Accessibility	Full text available	Abstract only

Study Selection Process

Selection involved title/abstract screening followed by full-text assessment. The archived dataset does not retain independent reviewer-level decisions, reviewer-specific extraction sheets, or reconciliation logs. Consequently, a post hoc Cohen's kappa cannot be calculated legitimately, and no agreement statistic has been invented. In the revised workflow, disagreements are treated as a methodological limitation of the archived review. Three records previously counted among the ten core studies were reclassified as contextual because their populations were non-athlete or gaming samples; the corrected athlete core therefore contains seven studies. The final PRISMA counts are 112 records identified, 38 full texts assessed, 31 excluded at full text, and 7 athlete studies included.

Quality Assessment, FICO Framework

The included evidence was appraised with the FICO framework as a pragmatic internal rubric covering Focus, Information, Context, and Outcome, each on a three-point scale. In this manuscript FICO is described as an internal appraisal framework, not as a validated risk-of-bias instrument. The appraisal emphasized whether the psychological target was explicit, whether signal acquisition and methods were adequately reported, whether the setting was relevant to sport, and whether outcomes were interpretable and validated. Because item-level independent ratings were not retained in the archived review, no inter-rater reliability coefficient is reported. For future updates, design-specific tools such as JBI or other validated risk-of-bias instruments should be applied to full texts rather than relying on a bespoke score alone.

Data Extraction Procedure

The extraction matrix recorded author/year, athlete population, sport, study design, sensing modality, AI or machine-learning method, psychological construct, construct-label source, experimental or field setting, primary outcome metric, validation scheme (training/test split, cross-validation, or external validation), real-time deployment status, and reported ethical/privacy considerations. Missing attributes were recorded as not reported rather than inferred. The coding matrix is provided in the accompanying reviewer-response document and can be supplied as supplementary material.

Network and Bibliometric Analysis Methodology

A descriptive bibliometric layer was retained only to contextualize the broader 50-record evidence landscape, not as an outcome of the athlete-specific synthesis. Publication years, venues, and author keywords were summarized descriptively. The core conclusions are based on the corrected seven-study athlete set. Contextual records are clearly identified as supporting evidence and are not treated as direct evidence for athlete populations.

Data Analysis and Synthesis

Thematic synthesis followed an explicit coding framework. Each study was coded for (1) sensing family, (2) AI/ML architecture, (3) psychological construct, (4) label or ground-truth source, (5) athlete context, (6) laboratory versus field setting, (7) performance metric, and (8) validation mode. Codes were grouped into higher-order themes: cognitive/EEG state monitoring, emotion/affect recognition, psychological-stress detection, and flow/readiness inference. Agreement and contradiction were recorded at the study level; however, because reviewer-level coding sheets were not retained, formal inter-rater reliability cannot be reconstructed. No statistical saturation claim is made.

Reporting and Documentation

The review was documented in line with PRISMA 2020. The revised flow explicitly separates core athlete studies from contextual records and reports the reason for the three reclassifications. The review was not prospectively registered in the archived record. Every bibliographic citation used in the corrected synthesis was checked against the reference list; the reviewer-requested national context was strengthened with two Indonesian sport-psychology studies from Sinta-2 journals.

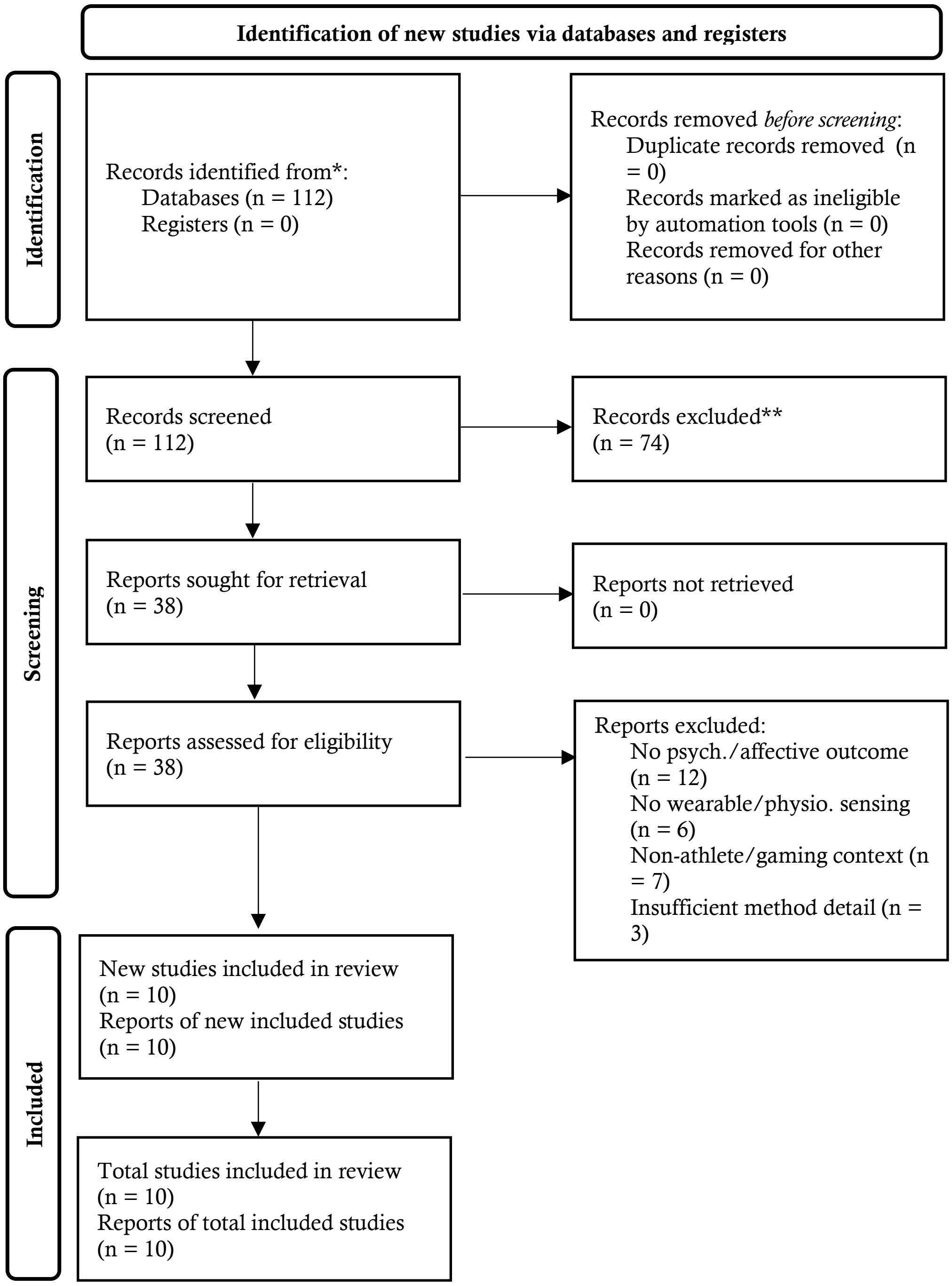

Figure 1. PRISMA 2020 flow diagram of study identification, screening, eligibility, and inclusion.

Results and Discussions

Result

Study Selection Results

The Scopus search returned 112 records. No duplicate titles or DOIs were identified within the single exported database set, so all 112 records entered title-and-abstract screening. Seventy-four were excluded at this stage: 30 had no athlete or sport focus, 14 had no AI or machine-learning component, 16 focused on hardware or material development without a psychological application, and 14 addressed unrelated clinical or general-population domains. Thirty-eight full texts were then assessed. At full text, 12 lacked a psychological or affective outcome, 6 lacked wearable or physiological sensing, 10 were non-athlete or gaming populations, and 3 lacked sufficient methodological detail. Seven studies therefore met the athlete-specific eligibility criteria and formed the core synthesis. The three reclassified non-athlete/gaming records were retained only as contextual literature.

Corpus context and core evidence

The broader contextual corpus contained 50 records published between 2021 and 2025, with the largest annual counts in 2024 and 2025. These descriptive patterns are useful for locating the topic within the wider AI/wearable literature, but they should not be confused with the athlete-specific evidence base. The corrected core comprises seven athlete studies: three EEG classification studies, three multimodal physiological/affective modeling studies, and one wearable IMU study targeting a flow-like state. The core studies span female cricket, table tennis, elite tennis, running, and mixed athlete samples, illustrating a still-small but sport-specific evidence base.

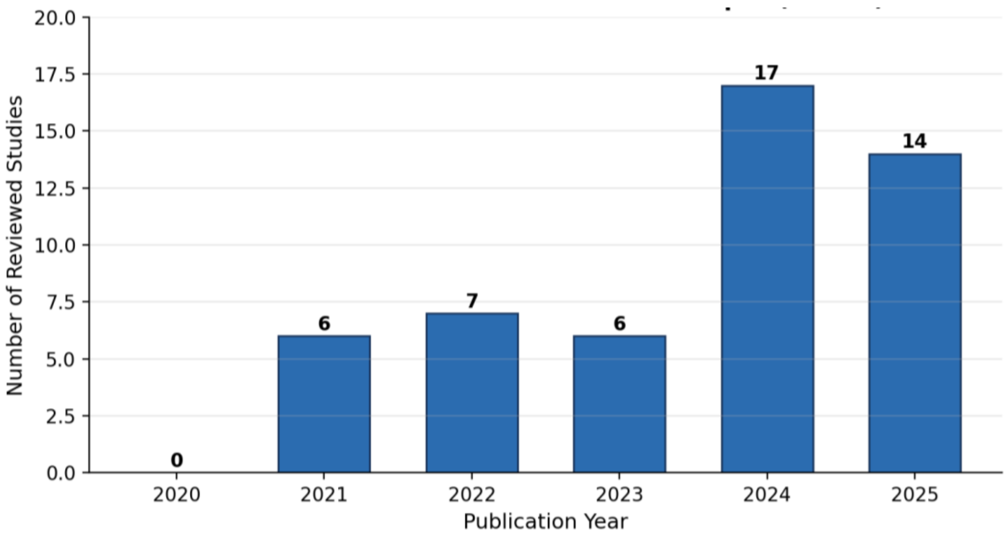

Figure 2. Annual distribution of the 50 reviewed records (2020–2025).

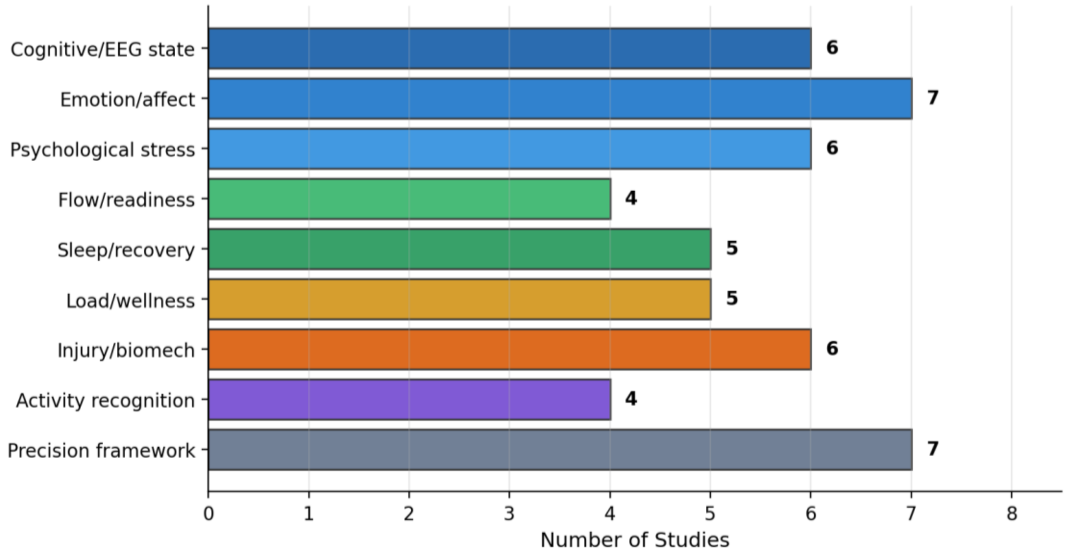

Figure 3. Thematic distribution of the reviewed corpus.

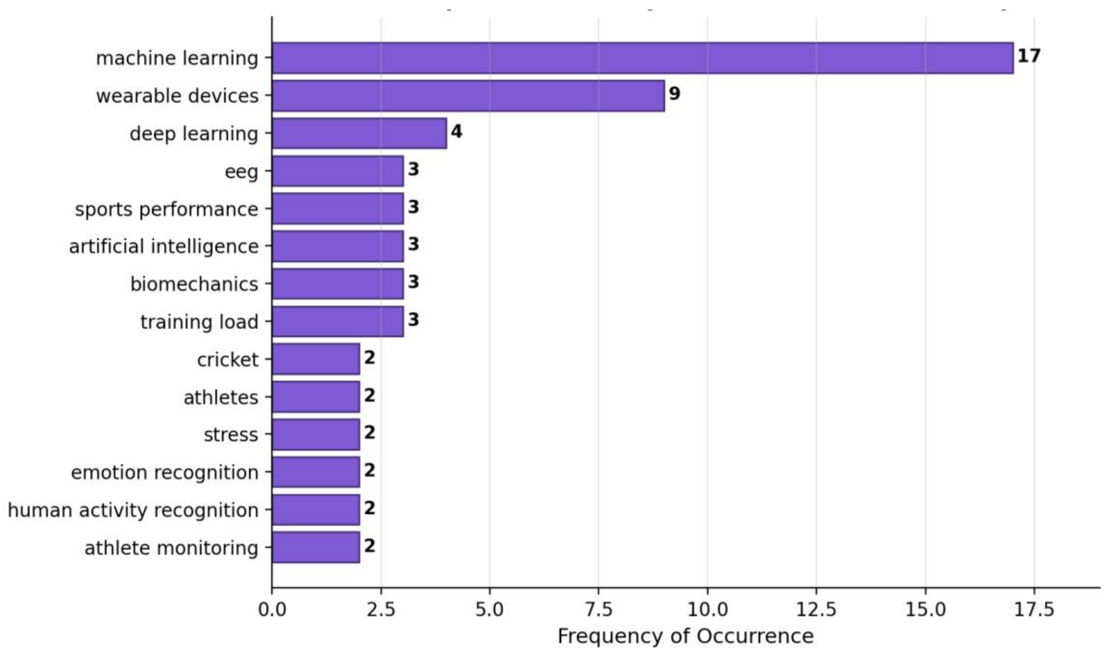

Figure 4. Most frequent author keywords across the reviewed corpus.

Table 2. Summary of the ten included studies (all bibliographic data drawn from the Scopus export).

Title	Author(s)	Year	Method / Technology	Key Findings
Deep-learning EEG mental-state classification for mental focus in female cricketers	Kotte et al.	2025	Portable EEG (Muse 2) + CNNs (AlexNet, ResNet, XceptionNet)	Wavelet-transformed EEG classified calm, focus, and neutral states with high accuracy, supporting personalized mental-focus training for female athletes.
EEG signal analysis with machine learning for psychological balance detection of athletes	Jiang & He	2023	EEG + CNN/LSTM machine learning	Machine-learning analysis of pre-competition EEG detected athletes' psychological balance, indicating value for psychological preparation.
Analyzing brain waves of table-tennis players with machine learning for stress classification	Tsai et al.	2022	EEG + multiple ML classifiers (incl. XGBoost)	Comparative modeling of stress-test EEG identified classifiers with optimal accuracy for stress detection in players.
Fine-grained emotional recognition for athletes via multi-physiological fusion	Guo	2025	ECG/EMG/EDA/respiration fusion + Bayesian + fuzzy neural networks	Bayesian fusion of multiple physiological signals improved fine-grained emotion-recognition accuracy and reduced recognition time in athletes.
Toward detecting the zone of elite tennis players through wearable technology	Havlucu et al.	2022	IMU wearable + coach labels + recurrent neural network	An RNN predicted the flow-like 'zone' state from IMU data and coach labels, demonstrating psychological-state inference from commercial wearables.
Athlete's facial-emotion recognition via multi-physiological fusion	Zhou & Wang	2024	ECG/respiration/pulse/EDA + wavelet + LS-SVM	Fusing physiological features with least-squares SVM improved accuracy

Title	Author(s)	Year	Method / Technology	Key Findings
Wearables and machine learning for improving runners' motivation from an affective perspective	Baldassarri et al.	2023	Wearable physiological signals + ML emotion models	and speed of athletes' facial-emotion recognition. Machine-learning models inferred runners' emotions in training to inform affect-aware, motivation-enhancing feedback.

Table 3. Classification of included studies by design, psychological construct, technology, and outcome.

Author(s)	Year	Research Design	Construct / Focus	Technology / AI Method	Outcome
Kotte et al.	2025	Classification study	Mental focus / cognitive state	Portable EEG + deep CNNs	High-accuracy state classification
Jiang & He	2023	Classification study	Psychological balance	EEG + CNN/LSTM	Pre-competition state detection
Tsai et al.	2022	Comparative modeling	Stress	EEG + ML (XGBoost etc.)	Optimal classifier identified
Guo	2025	Algorithm development	Fine-grained emotion	Multi-physiological fusion + FNN	Improved accuracy & speed
Havlucu et al.	2022	Exploratory field study	Flow / 'zone' state	IMU + RNN + coach labels	Psychological-state prediction
Zhou & Wang	2024	Algorithm development	Facial emotion	Multi-physiological + LS-SVM	Faster, more accurate recognition
Baldassarri et al.	2023	Applied modeling	Emotion / motivation	Wearables + ML	Affect-aware training feedback

Thematic Synthesis

Findings for RQ1, Modalities and Methods

Two method families dominate the corrected athlete core. First, EEG is used to represent cortical activity and is paired with deep or hybrid machine-learning models for cognitive focus, psychological balance, and stress classification (Kotte et al., 2025; Jiang & He, 2023; Tsai et al., 2022). Second, multimodal physiological fusion combines cardiac, respiratory, electrodermal, or muscular signals with classical or hybrid classifiers for emotion recognition (Guo, 2025; Zhou & Wang, 2024; Baldassarri et al., 2023). A distinct applied line uses IMU signals and coach labels to infer a flow-like 'zone' state in elite tennis (Havlucu et al., 2022).

Method choice tracks the desired level of inference. EEG studies use convolutional, recurrent, or tree-based classifiers to distinguish predefined cognitive or stress states, whereas multimodal systems use feature fusion to increase the information available to an affective classifier. The evidence remains largely within-study: models are commonly evaluated on a held-out subset or cross-validation within the same study population. The corrected synthesis therefore distinguishes reported classification performance from external validation across new athletes, sports, or acquisition settings.

Reported model performance is encouraging but not directly comparable. Kotte et al. (2025) reported 99.34% test accuracy for AlexNet, while five-fold cross-validation averaged 92.0% (SD 8.91%), illustrating the difference between a single split and repeated validation. Tsai et al. (2022) reported 86.49% accuracy for generalized three-level stress classification with XGBoost and 94.27% for a two-level model. Zhou and Wang (2024) reported an F1 score above 0.97 with recognition time below 300 ms for athlete facial-emotion recognition. These metrics should be interpreted as within-study results because labels, participants, settings, and validation procedures are heterogeneous. No independent external validation dataset covering new athletes and a new acquisition context was identified in the corrected core evidence.

Findings for RQ2, Constructs and Their Definition

The corrected athlete evidence covers four construct families: cognitive and mental states (focus, calm/neutral classification, and psychological balance), stress, emotion/affect, and flow-like readiness. EEG studies dominate the cognitive and stress constructs, multimodal physiological systems dominate affective recognition, and IMU plus coach-label approaches appear in flow-like state inference. The construct-label source ranged from experimentally induced states and predefined class labels to coach observation, which means that the target construct was not standardized across studies.

Construct heterogeneity is the central validity problem. 'Stress' can denote a laboratory cognitive stressor in EEG studies or a different psychophysiological state in peripheral-signal studies; emotion may be represented as discrete categories or continuous arousal-valence coordinates; and flow-like states can depend on expert labeling. Because these targets are not equivalent, numerical accuracy cannot be pooled into a single benchmark and should not be interpreted as evidence of a universal mental-state detector.

Physical exertion adds a sport-specific confound. Cardiovascular, electrodermal, muscular, and movement signals respond to exercise as well as psychological state. Sevil et al. (2021), retained as contextual evidence rather than core athlete evidence, illustrates the importance of separating psychological from physical stressors. The implication for athlete research is that future models should include workload/context covariates or experimentally disentangle exertion and psychological challenge before claiming psychological specificity.

Findings for RQ3, Barriers and Directions

Three classes of barrier recur across the literature. Methodologically, small and often single-session samples, laboratory-bound designs, and heterogeneous labels stand in the way of generalization. Several included studies are explicitly exploratory or pilot in nature (Havlucu et al., 2022; Muñoz-Saavedra et al., 2023). Ecologically, the gap between controlled elicitation and the noise, exertion, and pressure of real competition remains wide. Adjacent monitoring research amplifies this concern, showing how strongly context and workload shape physiological signals (Stojchevska et al., 2022; Rossi et al., 2022; Campbell et al., 2021). Ethically, continuously capturing athletes' mental states raises acute questions of consent, ownership, and surveillance. Reviews of digital technology in sport have flagged these as central to athlete wellbeing and competitive integrity (Qi et al., 2024).

Fragmentation across disciplines compounds these barriers. Sport-psychology-oriented contributions stress intervention and athlete development (Grady, 2023; Huang, 2021; Zhao, 2025). Engineering contributions stress signal processing and model accuracy (Kumar et al., 2024; Dar et al., 2024). The two rarely meet in the same study. Applied deployments in youth and elite settings are moving ahead of consolidated evidence (Liu et al., 2024; Huang & Yongquan, 2025). Novel delivery modes, metaverse-based movement therapy among them (Radanliev, 2024), widen the scope faster than validation can follow. Around all of this sits an analytics ecosystem handling fatigue (Feng et al., 2023), heat illness (Fujiwara et al., 2024), sleep and recovery (Frytz et al., 2023; Li et al., 2025; Rattanasateankij et al., 2025), and workload-to-wellness forecasting (Rossi et al., 2022). It creates integration demands that psychological monitoring will eventually have to meet.

The directions that follow are concrete. Field studies in ecologically valid competitive settings should replace single-session laboratory protocols. Psychological-state labels should be standardized so that stress, focus, and emotion mean the same thing across studies. Models should be made explainable so coaches can trust and act on their outputs. Privacy-preserving data governance should be built in from the outset (Qi et al., 2024). Certain techniques are already emerging in adjacent work. Self-supervised and context-aware learning (Corponi et al., 2024; Stojchevska et al., 2022) and movement-based mental-state inference (Brunyé et al., 2025) offer plausible paths toward more robust, deployable systems. The answer to RQ3, then, is that methodological fragility, ecological invalidity, and ethical exposure are the principal barriers. Standardization, field validation, explainability, and privacy-by-design constitute the priority agenda.

Comparative and Critical Analysis

Methodologically, the included studies split into two traditions: signal-first and application-first. The signal-first camp, covering EEG classification (Jiang & He, 2023; Tsai et al., 2022; Kotte et al., 2025) and multimodal fusion (Guo, 2025; Zhou & Wang, 2024), optimizes accuracy on curated data. It also mirrors the algorithmic sophistication of adjacent activity-recognition and injury-forecasting work built on IMUs, insoles, and deep or ensemble learning (Zhang et al., 2025; Khan et al., 2021; Tabrizi et al., 2021; Van et al., 2024; Matas-Bustos et al., 2025; Briand et al., 2022). The same computational toolkit already pervades athlete injury and biomechanical monitoring. Think digital-twin injury-risk prediction (Wang, 2025), wearable injury forecasting (Zadeh et al., 2021), interpretable rehabilitation modeling (Zhu et al., 2025), sport-specific kinematic analysis (Rana & Mittal, 2022), serve-load quantification (Perri et al., 2024), and real-time wellness-oriented activity recognition (Memon et al., 2024). Psychological monitoring, in other words, is entering an environment already saturated with mature sensing and modeling infrastructure. The application-first studies, by contrast, go for zone detection (Havlucu et al., 2022), affect-aware feedback (Baldassarri et al., 2023), and closed-loop stress management (Alrasheedi et al., 2024). They accept lower controlled accuracy in exchange for ecological relevance. Cross-sectional classification studies dominate the field. Longitudinal and intervention designs that would establish predictive and causal value remain rare.

A temporal reading reveals methodological evolution. Earlier contributions lean on feature engineering and classical classifiers (Tsai et al., 2022; Briand et al., 2022). The most recent work adopts deep, hybrid, and fusion architectures and starts chasing real-time and closed-loop operation (Kotte et al., 2025; Alrasheedi et al., 2024; Rostami et al., 2024). Several designs remain underused: cross-cohort external validation, multi-season field deployment, and the coupling of psychological monitoring with the parallel load, wellness, sleep, and fatigue pipelines that already exist in sport (Rossi et al., 2022; Campbell et al., 2021; Frytz et al., 2023; Feng et al., 2023; Li et al., 2025; Fujiwara et al., 2024). The critical implication is hard to miss. The field's technical ceiling is rising faster than its evidentiary rigor.

Discussion

Taken together, these findings paint a clear picture. Personalized psychological monitoring of athletes is technically feasible and conceptually coherent, but empirically immature. Physiological signals keep demonstrating that they carry decodable psychological information (Guo, 2025; Zhou & Wang, 2024; Sevil et al., 2021). That supports the central premise of precision sport psychology. Yet the field leans so heavily on small, controlled studies that it has established possibility more firmly than reliability.

Theoretically, the reviewed evidence stretches affective-computing and self-regulation frameworks into a domain those frameworks were never designed for: intense physical exertion under competitive pressure. In doing so it exposes the psychological, physical confound as a genuinely new theoretical problem, not a measurement nuisance (Sevil et al., 2021). Practically, the results point toward coach-facing tools that could manage focus, arousal, and recovery in individualized ways. Zone-detection prototypes (Havlucu et al., 2022), affect-aware training feedback (Baldassarri et al., 2023), and closed-loop stress mitigation (Alrasheedi et al., 2024) sketch what such tools might look like, and they would complement established workload and wellness monitoring (Rossi et al., 2022; Campbell et al., 2021).

Prior reviews have tended to treat precision athlete analytics (Exel & Dabnichki, 2024), digital sport technology (Qi et al., 2024), or AI in adaptive sport (Gagandeep et al., 2025) broadly. This synthesis instead isolates the narrower psychological-monitoring intersection. What emerges is something smaller, more recent, and more methodologically fragile than the surrounding literature implies. Contradictions in the evidence are most visible around stress. Cortical and peripheral operationalizations yield different, non-interchangeable constructs (Tsai et al., 2022; Briand et al., 2022), and reported accuracies simply cannot be pooled. A plausible explanation is that studies optimize locally for their own labels and populations, with no shared psychological ontology tying them together.

At least three research gaps follow from all of this. First, no standardized, sport-specific taxonomy of monitorable psychological states exists, so constructs get defined ad hoc. Second, external and longitudinal validation is almost absent, which leaves predictive value unknown. Third, ethical and privacy governance for continuous mental-state data is underdeveloped, this despite explicit warnings across the digital-sport literature (Qi et al., 2024). The review has its own limitations too. It draws on a single database (Scopus), so relevant non-indexed or non-English work may be missing. Author affiliation and country were unavailable in the export, which precludes geographic synthesis. And the core synthesis rests on ten studies. That number suits a tightly bounded intersection, but it limits generalization.

The future agenda is therefore specific. Researchers should run ecologically valid field studies during genuine training and competition instead of single laboratory sessions. They should adopt standardized psychological-state definitions and labeling protocols so findings become comparable. And they should build explainable, privacy-preserving models that coaches and athletes can trust, models that respect athlete data rights (Qi et al., 2024; Brunyé et al., 2025). In summary, RQ1 is answered by naming EEG-plus-deep-learning and multimodal-fusion as the dominant method families, promising but unvalidated. RQ2 is answered by naming stress, emotion, focus, and flow as the principal constructs, inconsistently defined and confounded by physical exertion. RQ3 is answered by naming methodological fragility, ecological invalidity, and ethical exposure as the key barriers, with standardization, field validation, explainability, and privacy-by-design as the priorities.

Conclusions

This systematic review identified 112 Scopus records, assessed 38 full texts, and retained seven athlete studies for the corrected core synthesis, with 43 additional records used as contextual evidence. EEG with deep or hybrid learning and multimodal physiological fusion were the main method families; the core constructs were cognitive focus/balance, stress, emotion, and flow-like states. Within-study performance could be high-for example, 99.34% test accuracy with 92.0% (SD 8.91%) five-fold cross-validation in one EEG study, 86.49% generalized three-level stress-classification accuracy in another, and F1 > 0.97 for an athlete facial-emotion model—but these values are not pooled measures of generalization. No independent external validation across new athletes and new acquisition contexts was identified in the corrected core evidence. The archived review also retained no reviewer-level screening data or preregistration record, so inter-rater reliability and preregistration rates are reported as not recoverable rather than fabricated. The evidence therefore supports feasibility, not yet deployment-grade precision psychological monitoring. The practical recommendation is to move the field from proof-of-concept classification toward validated athlete monitoring: standardized constructs and labels, athlete-level external testing, ecologically valid longitudinal studies, transparent model evaluation, and privacy-preserving governance. The review's main contribution is a corrected evidence map that separates direct athlete evidence from technically relevant contextual studies.

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References

Alrasheedi, A.A., Alrabeah, A.Z., Almuhareb, F.J., Alras, N.M.Y., Alduaij, S.N., Karar, A.S., Said, S., Youssef, K., & Kork, S.A. (2024). Utilizing Dry Electrode Electroencephalography and AI Robotics for Cognitive Stress Monitoring in Video Gaming. Applied System Innovation, 7(4), Article 68. https://doi.org/10.3390/asi7040068

Baldassarri, S., García de Quirós, J., Beltrán, J.R., & Álvarez, P. (2023). Wearables and Machine Learning for Improving Runners' Motivation from an Affective Perspective. Sensors, 23(3), Article 1608. https://doi.org/10.3390/s23031608

Briand, J., Deguire, S., Gaudet, S., & Bieuzen, F. (2022). Monitoring Variables Influence on Random Forest Models to Forecast Injuries in Short-Track Speed Skating. Frontiers in Sports and Active Living, 4, Article 896828. https://doi.org/10.3389/fspor.2022.896828

Brunyé, T.T., Okano, K., McIntyre, J., Sandone, M.K., Townsend, L.N., Lee, M.M., Smith, M., & Hughes, G.I. (2025). Inferring Mental States via Linear and Non-Linear Body Movement Dynamics: A Pilot Study. Sensors, 25(22), Article 6990. https://doi.org/10.3390/s25226990

Campbell, P.G., Stewart, I.B., Sirotic, A.C., Drovandi, C., Foy, B.H., & Minett, G.M. (2021). Analysing the predictive capacity and dose-response of wellness in load monitoring. Journal of Sports Sciences, 39(12), 1339–1347. https://doi.org/10.1080/02640414.2020.1870303

Corponi, F., Li, B.M., Anmella, G., Valenzuela-Pascual, C., Mas, A., Pacchiarotti, I., Valentí, M., Grande, I., Benabarre, A., Garriga, M., Vieta, E., Young, A.H., Lawrie, S.M., Whalley, H.C., Hidalgo-Mazzei, D., & Vergari, A. (2024). Wearable Data From Subjects Playing Super Mario, Taking University Exams, or Performing Physical Exercise Help Detect Acute Mood Disorder Episodes via Self-Supervised Learning: Prospective, Exploratory, Observational Study. JMIR mHealth and uHealth, 12, Article e55094. https://doi.org/10.2196/55094

Dar, M.N., Akram, M.U., Subhani, A.R., Khawaja, S.G., Reyes-Aldasoro, C.C., & Gul, S. (2024). Insights from EEG analysis of evoked memory recalls using deep learning for emotion charting. Scientific Reports, 14(1), Article 17080. https://doi.org/10.1038/s41598-024-61832-7

Exel, J., & Dabnichki, P. (2024). Precision Sports Science: What Is Next for Data Analytics for Athlete Performance and Well-Being Optimization? Applied Sciences (Switzerland), 14(8), Article 3361. https://doi.org/10.3390/app14083361

Feng, W., Zeng, K., Zeng, X., Chen, J., Peng, H., Hu, B., & Liu, G. (2023). Predicting physical fatigue in athletes in rope skipping training using ECG signals. Biomedical Signal Processing and Control, 83, Article 104663. https://doi.org/10.1016/j.bspc.2023.104663

Frytz, P., Heib, D.P.J., & Hoedlmoser, K. (2023). Soccer, Sleep, Repeat: Effects of Training Characteristics on Sleep Quantity and Sleep Architecture. Life, 13(8), Article 1679. https://doi.org/10.3390/life13081679

Fujiwara, K., Ota, K., Saeda, S., Yamakawa, T., Kubo, T., Yamamoto, A., Maruno, Y., & Kano, M. (2024). Heat illness detection with heart rate variability analysis and anomaly detection algorithm. Biomedical Signal Processing and Control, 87, Article 105520. https://doi.org/10.1016/j.bspc.2023.105520

Gagandeep, Verma, J., Pradhan, K.B., & Singh, M. (2025). AI technologies in adaptive sports: Enhancing performance, health, and well-being. Acta Psychologica, 261, Article 105879. https://doi.org/10.1016/j.actpsy.2025.105879

Grady, B. (2023). The Role of Information Technology in Enhancing Sport Psychology Interventions for Athlete Development and Performance Optimization. Revista de Psicologia del Deporte, 32(4), 41–50. DOI not available in source file.

Guo, D. (2025). Fine grain emotional intelligent recognition method for athletes based on multi physiological information fusion. International Journal of Biometrics, 17(1-2), 15–30. https://doi.org/10.1504/IJBM.2025.143721

Havlucu, H., Akgun, B., Eskenazi, T., Coskun, A., & Ozcan, O. (2022). Toward Detecting the Zone of Elite Tennis Players Through Wearable Technology. Frontiers in Sports and Active Living, 4, Article 939641. https://doi.org/10.3389/fspor.2022.939641

Huang, M., & Yongquan, T. (2025). Tech-driven excellence: A quantitative analysis of cutting-edge technology impact on professional sports training. Journal of Computer Assisted Learning, 41(1), Article e13082. https://doi.org/10.1111/jcal.13082

Huang, S. (2021). Analysis of psychological teaching assisted by artificial intelligence in sports training courses. Journal of Applied Science and Engineering, 24(5), 743–748. https://doi.org/10.6180/jase.202110_24(5).0008

Jiang, P., & He, H. (2023). EEG Signal Analysis based on machine learning in psychological balance detection of athletes. Evolutionary Intelligence, 16(5), 1533–1538. https://doi.org/10.1007/s12065-022-00770-7

Khan, A., Mellor, S., King, R., Janko, B., Harwin, W., Sherratt, R.S., Craddock, I., & Plötz, T. (2021). Generalized and Efficient Skill Assessment from IMU Data with Applications in Gymnastics and Medical Training. ACM Transactions on Computing for Healthcare, 2(1), Article 2. https://doi.org/10.1145/3422168

Kotte, S., Elkhouly, A., Abd Malek, M.F., & Abohaia, Z. (2025). Deep learning-based EEG mental state classification to support mental focus in female cricketers. Discover Artificial Intelligence, 5(1), Article 350. https://doi.org/10.1007/s44163-025-00615-z

Kumar Dwivedi, A., Prakash Verma, O., & Taran, S. (2024). Adaptive Flexible Analytic Wavelet Transform for EEG-Based Emotion Recognition. IEEE Sensors Journal, 24(18), 28941–28951. https://doi.org/10.1109/JSEN.2024.3429523

Li, Q., Lei, X., Yu, W., Steward, C.J., & Zhou, Y. (2025a). Pre-sleep heart rate variability predicts chronic insomnia and measures of sleep continuity in national-level athletes. Frontiers in Physiology, 16, Article 1627287. https://doi.org/10.3389/fphys.2025.1627287

Li, Z., Qin, S., Li, X., & Ren, D. (2025b). Use the rating of perceived exertion to evaluate load in collegiate male soccer player, validity and influencing factors. Scientific Reports, 15(1), Article 16880. https://doi.org/10.1038/s41598-025-01942-y

Liu, S., Wu, C., Xiao, S., Liu, Y., & Song, Y. (2024). Optimizing young tennis players' development: Exploring the impact of emerging technologies on training effectiveness and technical skills acquisition. PLoS ONE, 19(8 August), Article e0307882. https://doi.org/10.1371/journal.pone.0307882

Matas-Bustos, J.B., Mora-García, A.M., de Hoyo Lora, M., Nieto-Alarcón, A., & Gonzalez-Fernández, F.T. (2025). Advanced feature engineering in Acute:Chronic Workload Ratio (ACWR) calculation for injury forecasting in elite soccer. PLOS ONE, 20(7 July), Article e0327960. https://doi.org/10.1371/journal.pone.0327960

Memon, Q., Al Ameri, M., & Musthafa, N. (2024). Generalized and Improved Human Activity Recognition for Real-Time Wellness Monitoring. Proceedings of Engineering and Technology Innovation, 28, 30–40. https://doi.org/10.46604/peti.2024.13900

Muñoz-Saavedra, L., Escobar-Linero, E., Miró-Amarante, L., Bohórquez, M.R., & Domínguez-Morales, M. (2023). Designing and evaluating a wearable device for affective state level classification using machine learning techniques. Expert Systems with Applications, 219, Article 119577. https://doi.org/10.1016/j.eswa.2023.119577

Perri, T., Reid, M., Murphy, A., & Duffield, R. (2024). Tennis serve volume, distribution and accelerometer load during training and tournaments from wearable microtechnology. International Journal of Performance Analysis in Sport, 24(4), 285–297. https://doi.org/10.1080/24748668.2023.2296776

Qi, Y., Sajadi, S.M., Baghaei, S., Rezaei, R., & Li, W. (2024). Digital technologies in sports: Opportunities, challenges, and strategies for safeguarding athlete wellbeing and competitive integrity in the digital era. Technology in Society, 77, Article 102496. https://doi.org/10.1016/j.techsoc.2024.102496

Radanliev, P. (2024). Dance sport movement therapy in the metaverse: A new frontier for alternative mental health therapies. Digital Health, 10. https://doi.org/10.1177/20552076241258273

Rana, M., & Mittal, V. (2022). Analysis of Front Leg Kinematics of Cricket Bowler Using Wearable Sensors and Machine Learning. IEEE Sensors Journal, 22(22), 22053–22061. https://doi.org/10.1109/JSEN.2022.3205363

Rattanasateankij, W., Senakham, T., Punthipayanon, S., Puttasimma, T., & Senakham, N. (2025). Training Stress, Sleep Behaviour, and Recovery Self-Regulation in Elite Female Boxers: A Behavioural Pattern Analysis Using Data-Driven Methods. Journal of Mind and Behavior, 46(3), 109–129. DOI not available in source file.

Rossi, A., Perri, E., Pappalardo, L., Cintia, P., Alberti, G., Norman, D., & Iaia, F.M. (2022). Wellness Forecasting by External and Internal Workloads in Elite Soccer Players: A Machine Learning Approach. Frontiers in Physiology, 13, Article 896928. https://doi.org/10.3389/fphys.2022.896928

Rostami, A., Motaman, K., Tarvirdizadeh, B., Alipour, K., & Ghamari, M. (2024). LSTM-based real-time stress detection using PPG signals on raspberry Pi. IET Wireless Sensor Systems, 14(6), 333–347. https://doi.org/10.1049/wss2.12083

Sevil, M., Rashid, M., Hajizadeh, I., Askari, M.R., Hobbs, N., Brandt, R., Park, M., Quinn, L., & Cinar, A. (2021). Discrimination of simultaneous psychological and physical stressors using wristband biosignals. Computer Methods and Programs in Biomedicine, 199, Article 105898. https://doi.org/10.1016/j.cmpb.2020.105898

Stojchevska, M., Steenwinckel, B., Van Der Donckt, J., De Brouwer, M., Goris, A., De Turck, F., Van Hoecke, S., & Ongenae, F. (2022). Assessing the added value of context during stress detection from wearable data. BMC Medical Informatics and Decision Making, 22(1), Article 268. https://doi.org/10.1186/s12911-022-02010-5

Tabrizi, S.S., Pashazadeh, S., & Javani, V. (2021). A Deep Learning Approach for Table Tennis Forehand Stroke Evaluation System Using an IMU Sensor. Computational Intelligence and Neuroscience, 2021, Article 5584756. https://doi.org/10.1155/2021/5584756

Tsai, Y.-H., Wu, S.-K., Yu, S.-S., & Tsai, M.-H. (2022). Analyzing Brain Waves of Table Tennis Players with Machine Learning for Stress Classification. Applied Sciences (Switzerland), 12(16), Article 8052. https://doi.org/10.3390/app12168052

Wang, X. (2025). Digital twin framework for injury risk prediction and management in competitive sports. International Journal of Information and Communication Technology, 26(46), 37–61. https://doi.org/10.1504/IJICT.2025.150600

Zadeh, A., Taylor, D., Bertsos, M., Tillman, T., Nosoudi, N., & Bruce, S. (2021). Predicting Sports Injuries with Wearable Technology and Data Analysis. Information Systems Frontiers, 23(4), 1023–1037. https://doi.org/10.1007/s10796-020-10018-3

Zhang, J., Guo, R., Zhu, Y., Che, Y., Zeng, Y., Yu, L., Yang, Z., & Yang, J. (2025). Sensor-Driven Real-Time Recognition of Basketball Goal States Using IMU and Deep Learning. Sensors, 25(12), Article 3709. https://doi.org/10.3390/s25123709

Zhang, Y., Fu, P., Yu, Q., Niu, Q., Nie, D., Dou, X., & Zhang, X. (2025). The impact of precompetition state on athletic performance among track and field athletes using machine learning. Frontiers in Physiology, 16, Article 1429510. https://doi.org/10.3389/fphys.2025.1429510

Zhao, M. (2025). Enhancing psychological resilience and decision-making in basketball players through emerging technologies. Scientific Reports, 15(1), Article 41334. https://doi.org/10.1038/s41598-025-25226-7

Zhou, X., & Wang, J. (2024). Athlete's facial emotion recognition method based on multi physiological information fusion. International Journal of Reasoning-based Intelligent Systems, 16(2), 107–117. https://doi.org/10.1504/IJRIS.2024.138626

Zhu, X., Kelly, D.K., Kim, G., Hart, J.M., & Gong, J. (2025). Clinically Interpretable Modeling of ACL Reconstruction Outcomes Using Confidence-Aware Gait Analysis. Biomechanics (Switzerland), 5(4), Article 94. https://doi.org/10.3390/biomechanics5040094