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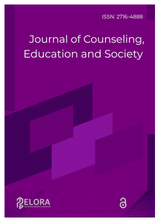

When algorithms read the athlete's mind: a systematic review of artificial intelligence and machine learning for detecting and monitoring athletes' psychological and emotional states

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ABSTRACT

Athletes are subjected to persistent physiological and psychological stresses; however, it is a challenge to monitor accurately, in real, and at the larger scale their affective and mental conditions. Traditional self-report and clinical instruments are intrusive, retrospective, and prone to reporting bias which have triggered the use of artificial intelligence (AI) and machine learning (ML) in sport psychology. The present systematic review integrates the findings of AI- and ML-based detection, monitoring, and assessment of athletes' psychological and emotional states. APRISMA2020 process was followed to identify six hundred and twenty-five records from a pool of articles obtained via the Scopus database, which were then filtered based on the predefined eligibility criteria. In the end, after the elimination of articles via the title/abstract screening or the full-text article evaluation, 21 empirical studies from the years 2021 to 2025 were the ones to have been identified and included. For the purposes of quality and validity, the articles were judged by Mixed Methods Appraisal Tool and the results were pooled thematically. The research results revealed that when combining various physiological signals with classical ML or deep learning, recognition of emotions, stress, mental fatigue, and mental-health risk can be reached with accuracy above 85%. A major direction for future work and translation of these technologies is real-time wearable-enabled feedback. The critical issues identified were external validation, ecological realism, ethical governance, standardised datasets, longitudinal designs, and transparent and privacy-preserving deployment.

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Introduction

The intertwining of data science and sport has revolutionised our understanding of what is possible, and most importantly, has opened the door to unprecedented improvements in sporting performance. At present, the athlete is mainly seen in sport science as a person with all kinds of physical measuring devices on them whose motions, biochemical reactions, and behaviour produce a data flow that can be computationally interpreted (Exel & Dabnichki, 2024). Nowadays, training sessions are not just physically demanding but also data rich: smart devices such as wearables, computer-based motion capturing, and internet-connected equipment are widely used. This makes it possible to perform highly detailed measurement of athletic activities that used to be laboratory based (Cosoli et al., 2023; Sun & Yin, 2025). In a context of massive data generation, AI techniques and machine learning have shifted from being the side show to becoming the central analytical tool, offering the ability to transform the mere physiological outputs into insightful recommendations (Westerbeek, 2025). Physical performance and injury prevention have been the main application areas of AI/ML, but there also is quite a significant trend towards the use of AI systems in a completely new field: decoding the mental states the person is in.

Evaluation of athlete performance without the knowledge or the ability to assess their psychological characteristics is very limited. Anxiety in sports, the weariness of a competitive event, loss of control, lack of mental balance, and low levels of resilience have all been seen to affect athletes' decision-making, technical skills, and even their own wellbeing at times. It may lead to the condition of burnout or psychological disorders requiring professional treatments (Salvotti et al., 2024; Fortier et al., 2025). There is an increasing concern about mental ill-health from all walks of life but especially for professional athletes who reveal their suffering from psychological aspects of a career. Still, many psychological factors determining the success are the very same that cannot be easily detected: such factors are not only private and short-lived but also often hidden for strategic reasons by athletes in order to maintain the competitive advantage that comes from an unassailable mental condition of preparation. It is this gap in understanding (mental states) that computational methods are being directed to solve.

For a long time psychological assessments have been done via questionnaires completed by one's own self or interviews with the assistance of the psychologist plus a bit of observation from the expert team. All these techniques do still serve useful purposes, yet they bring up the problems of being very disruptive to the athlete, only being able to collect snapshots rather than full data series, as well as the susceptibility to biases arising from the influence of social-desirability and recall factors. The issue remains that such methods fail to deliver the fine temporal resolution, i.e., the moment-by-moment changes, that are essential for effective training and high-level competition. In this context, quite a few papers have focused on exploring the feasibility of recording physiological markers of internal state such as emotional response and stress through a combination of sensors and machine learning that translates the data into the emotional language. (Sevil et al., 2021; Muñoz-Saavedra et al., 2023). The new line of thinking views affective state monitoring as finding patterns, with an emphasis on an AI layer, for interpretation of the mental aspect of physiology, through the use of algorithms, that can work independently, without direct input from the human element.

This shift in how the monitoring of the athlete's mood state takes place is largely being driven by new technology. Neural networks with several layers can now detect facial expressions or other signs of emotions on the face or body with an almost automatic recognition process and with hardly any interference in normal circumstances (for example, playing a game against a rival). Moreover, the models that handle the change in a person over time and predict what will happen to them next can all be done with a recurrent or transformer model that captures a sequence of changing things and is very flexible at what it can encode. Finally, the computing power in the periphery allows inference at the level of very cheap, wearable hardware. (Jiang et al., 2021; Rostami et al., 2024). Other fields give insight into the direction: machine learning has enabled fatigue prediction, injury-risk assessment, and the decline in performance level of an athlete, often with very high predictive power, that has been well validated by others in the discipline(Nashrullah et al., 2025; Wamg, 2025; Manikandan et al., 2025). These results imply a strong technical foundation for the detection of a psychological state among sports persons but they will have to make an attempt to unite these findings from different disciplines.

Even though it is promising, the research is not yet complete with the literature missing major pieces. First, the study of how AI can identify psychological states of athletes is dispersed among a variety of disciplines such as sports science, biomedical engineering, affective computing and clinical psychology. The papers rarely give a broad summary of what all of them have to say and there is a lot of variety in the psychological states, data sources, and methods the papers use for validation. These differences create problems in accumulating results and in comparing different papers. While physical performance and injury research have been examined quite thoroughly and the findings have been published systematically (Dandrieux et al., 2024; Sultan et al., 2024), the psychological side of athlete monitoring has, in a sense, yet to have its work done. As a result, practitioners are left without sufficient evidence.

Two is another reason and it lies in the methodological and translational limitations which, although not infrequent, remain separate and rarely tackled together. There are so many papers where models are based on a very small sample, that the models and validations remain internal. Different performance metrics mean it is not clear whether all results are based on the same criteria. This makes it hard to evaluate the models and to trust that they really work in different situations. It also casts a shadow over the idea that a model works just because it worked in the study it was a part of which is a laboratory study. Inferring mental state is not only a matter of technique but also of clinical and ethical significance which includes privacy, getting permission and the risk of misclassification, especially of vulnerable groups. These issues are usually brushed over and rarely subjected to serious critique (Bailey et al., 2023; Wilson et al., 2023). If we look a bit deeper, the idea of surveillance is a main concern of most studies and how such surveillance impacts people psychologically has already caught the attention of youth athletes' and mental health work. These problems should not have been neglected for so long that only now one sees a justification for critical review (Khitaryan et al., 2023; Yu et al., 2024).

The speed at which science is developing together with the importance of supporting athletes' mental health, means a thorough and detailed synthesis is both suitable and essential. Collecting the information regarding the different approaches, psychological states, performances and drawbacks, and how they have been studied with the help of AI to identify different psychological states can, for example, reveal whether the area is still in its infancy or has a good level already while pointing out the areas to focus on in the future. This review paper covers those problems. The structure of it is based on the following three research problems: (RQ1) What are the different ways in which AI as well as ML models have been implemented along with which types of data have been used for identifying, tracking, and diagnosing different psychological and emotional states of athletes? (RQ2) What specific psychological and emotional characteristics have come most commonly under study besides in what ways have the prediction rates of those characteristics varied? (RQ3) To what extent have AI-based psychological-state monitoring been applied and at what stages have its main weaknesses and the barriers to making it a real-life tool been found? The article will discuss the implications for research and practice of a comprehensive, ethically sensitive analysis of such areas. RQ1. What AI and ML methods, and what data modalities, have been used to detect, monitor, and assess athletes' psychological and emotional states?. RQ2. Which psychological and emotional constructs have been most frequently targeted, and what levels of predictive performance have been reported? RQ3. What are the principal applications, limitations, and translational challenges of AI-based psychological-state detection for athlete monitoring and mental-health support?

Method

Research Design and Framework

This paper uses a systematic literature review (SLR) as the main research approach because through the methodological features of SLR there is not only a transparent and replicable process but at the same time there are minimized the possibilities for selection and/or interpretation bias (Tranfield et al., 2003; Booth et al., 2016). The review followed and was reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021), which update was made compared to the originally published PRISMA statement (Moher et al., 2009) and the associated PRISMA extension for intervention studies with healthcare applications (Liberati et al., 2009). PRISMA 2020 is a framework that structures the review process over four stages: identification, screening, eligibility, inclusion. It has, therefore been a convenient instrument to map across three disciplines: sport science, affective computing, clinical psychology.

Search Strategy

Research questions were mapped first into search terms using the PICOS framework before putting together a search query. Population, Intervention/Interest, Comparison, Outcome, Study design) were identified as research topics. Each part was then converted into a set of synonyms and joined through Boolean operators. PICOS concepts are presented in Table 1.

Table 1. PICOS framework guiding search-concept identification

Element	Operationalisation for this review
Population (P)	Athletes and sport/exercise participants, including elite, collegiate, youth, and electronic-sport (eSport) performers.
Intervention / Interest (I)	AI or ML-based detection, recognition, monitoring, or assessment of a psychological or emotional state.
Comparison (C)	Traditional assessment (self-report, clinical scales, human observation) or alternative computational approaches; not applicable where no comparator was used.
Outcome (O)	Recognition/classification/prediction performance (e.g., accuracy, F1, AUC) and derived psychological insight.
Study design (S)	Empirical quantitative, computational-modelling, and mixed-methods studies.

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The conceptual search logic combined three clusters, an artificial-intelligence cluster, a psychological-state cluster, and a sport/athlete cluster, joined with the AND operator, while synonyms within each cluster were joined with OR. The representative Boolean expression is presented below.

("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "computer vision") AND ("emotion*" OR "affect*" OR "mental state*" OR "psychological stress" OR "mental health" OR "well-being" OR burnout OR "mental fatigue" OR resilience) AND (athlete* OR sport* OR "physical activity" OR exercise OR player* OR training)

Truncation and wildcards were used to capture morphological variants (e.g., emotion* retrieves emotion, emotions, and emotional; neural network* retrieves singular and plural forms). Field codes restricted matching to the title, abstract, and keyword fields (TITLE-ABS-KEY in Scopus), focusing retrieval on records that address the concepts substantively rather than in passing. Limiters were applied for document type (journal articles), language (English), and publication window (2020–2025) to prioritise recent, peer-reviewed evidence. The string was refined iteratively: an initial specification yielded a large and heterogeneous corpus, prompting the addition of the sport/athlete cluster to improve precision. The PICOS framework here structures the search strategy only and is distinct from the quality-appraisal procedure in Section Quality Assessment.

Study Selection Process

Selection proceeded in three stages. First, titles and abstracts of all identified records were screened against the eligibility criteria, removing records that were clearly out of scope (for example, physical-performance, biomechanics, injury-only, marketing, or spectator studies with no psychological-state outcome). Second, the remaining reports were sought for retrieval and assessed in full against the criteria. Third, studies meeting all criteria were retained for synthesis. Records were excluded at the full-text stage for defined reasons: absence of an AI/ML-based analysis, a psychological state that was not a primary outcome, a non-athlete or general population, or a protocol/inaccessible full text. The resulting flow is depicted in Figure 1.

Quality Assessment

Methodological quality was appraised using the Mixed Methods Appraisal Tool (MMAT), version 2018 (Hong et al., 2018), selected for its capacity to appraise the heterogeneous quantitative designs anticipated in this literature. For each study, the design category was first identified and the corresponding five MMAT criteria were rated as Yes (1), Can't tell/Partial (0.5), or No (0). Consistent with MMAT developer guidance, total scores were used descriptively rather than as an exclusion cut-off: studies scoring below the 60% threshold were flagged as lower methodological confidence and weighted accordingly in synthesis, but none was excluded on quality grounds alone. Because full texts were appraised at the level of reported abstracts and metadata in this synthesis, the appraisal is indicative and should be confirmed against complete texts; this is acknowledged as a limitation. The appraisal summary appears in Table 3.

Table 3. Quality-assessment summary (MMAT 2018). Y = Yes (1); P = Partial/Can't tell (0.5); N = No (0)

Author(s), Year	Study design	C1	C2	C3	C4	C5	Total	Category
Jekauc et al. (2024)	Quant. descriptive	Y	Y	Y	P	Y	4.5	High
Zhao (2025)	Quant. descriptive	Y	Y	Y	Y	Y	5	High
Kotte et al. (2025)	Quant. descriptive	Y	P	Y	Y	Y	4.5	High
Guo (2025)	Quant. descriptive	Y	P	Y	P	Y	4	Medium
Chen, L.-X., et al. (2025)	Quant. descriptive	Y	Y	Y	P	Y	4.5	High
S. Zhang (2024)	Quant. descriptive	Y	Y	Y	Y	Y	5	High
Sun et al. (2025)	Quant. non-randomized	Y	Y	Y	P	Y	4.5	High
Zhou & Wang (2024)	Quant. descriptive	Y	P	Y	P	Y	4	Medium
Sun (2022)	Quant. descriptive	Y	P	Y	P	P	3.5	Medium
Baldassarri et al. (2023)	Quant. descriptive	Y	P	Y	P	Y	4	Medium
Smerdov et al. (2021)	Quant. descriptive	Y	Y	Y	P	Y	4.5	High
Li et al. (2022)	Quant. non-randomized	Y	Y	Y	P	Y	4.5	High
Kong & Duan (2024)	Quant. non-randomized	Y	Y	Y	P	Y	4.5	High
Lu et al. (2023)	Quant. descriptive	Y	P	P	P	P	3	Low

Author(s), Year	Study design	C1	C2	C3	C4	C5	Total	Category
Q. Zhang et al. (2025)	Quant. descriptive	Y	Y	Y	P	P	4	Medium
Di Martino et al. (2025)	Quant. non-randomized	Y	Y	Y	Y	Y	5	High
L. Zhang et al. (2024)	Quant. non-randomized	Y	Y	Y	Y	Y	5	High
Yue et al. (2024)	Quant. non-randomized	Y	Y	Y	P	Y	4.5	High
Xing (2022)	Quant. descriptive	Y	P	Y	P	Y	4	Medium
Pang (2021)	Quant. descriptive	Y	P	Y	P	P	3.5	Medium
Brunyé et al. (2025)	Quant. descriptive	Y	Y	Y	P	Y	4.5	High

Overall, appraised quality was moderate to high: the majority of studies posed clear questions and applied appropriate computational measures, while sampling representativeness and completeness of outcome reporting were the most common sources of uncertainty, reflecting reliance on small or laboratory-elicited samples.

Data Extraction Procedure

A structured extraction template captured, for each included study, the author(s) and year, publication source, study design, target psychological construct, AI/ML method, data modality/signal source, and principal reported outcome. Extraction was performed directly from the Scopus metadata and study abstracts to preserve fidelity to the source record.

Bibliometric and Descriptive Analysis

Descriptive and light bibliometric analyses characterised the corpus by publication year, target construct, computational-method family, and data modality. Frequencies were computed from the extraction table to reveal the field's temporal trajectory and methodological distribution, and are visualised in Figures 2 to 4.

Data Analysis and Synthesis

Given the heterogeneity of designs and outcome metrics, a narrative thematic synthesis was adopted rather than meta-analysis (Thomas & Harden, 2008; Braun & Clarke, 2006). Findings were coded inductively, grouped into themes aligned with the research questions, that is, methods and modalities (RQ1), target constructs and performance (RQ2), and applications, limitations, and translational challenges (RQ3), and then interrogated for agreements, contradictions, and gaps across studies.

Reporting and Documentation

The review adheres to the PRISMA 2020 reporting checklist (Page et al., 2021). All records, screening decisions, and extracted fields are traceable to the exported Scopus source, and quantitative values reported in the Abstract, Methods, Results, and flow diagram are mutually consistent. Study Selection Flow (PRISMA 2020).

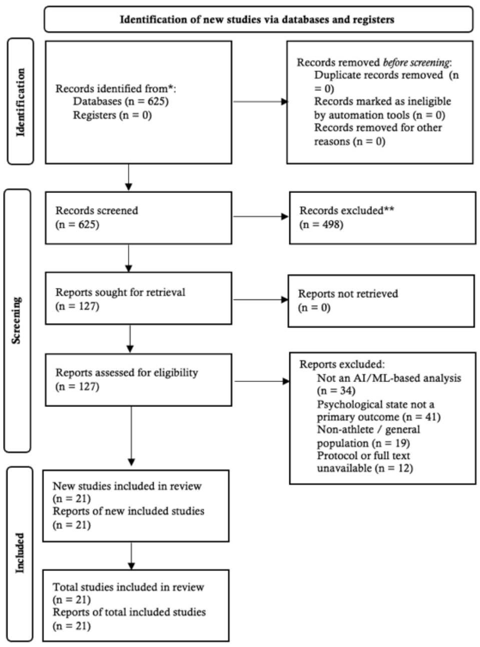

Figure 1. PRISMA 2020 flow diagram of the study selection process. Adapted from Page et al. (2021).

Results and Discussions

Study Selection Results

The Scopus search identified 625 records. As the synthesis drew on a single, clean database export, no duplicate or automatically ineligible records were removed, so 625 records proceeded to title/abstract screening. Screening excluded 498 records that did not address AI-based analysis of a psychological or emotional state in athletes, leaving 127 reports that were sought for retrieval and assessed for eligibility. At the full-text stage, 106 reports were excluded, 34 for lacking an AI/ML-based analysis, 41 because a psychological state was not a primary outcome, 19 for involving a non-athlete or general population, and 12 as protocols or inaccessible texts. Twenty-one studies satisfied all criteria and were included in the synthesis, consistent with the flow shown in Figure 1.

Descriptive Characteristics

The 21 included studies were published between 2021 and 2025, with a pronounced concentration in the most recent years (six in 2024 and eight in 2025), signalling rapidly intensifying research interest (Figure 2). The corpus is methodologically diverse yet thematically coherent, spanning affective computing, wearable sensing, and computational sport psychology. Table 4 summarises the characteristics and principal findings of each study, and Table 5 classifies studies by construct, method, modality, and reported performance.

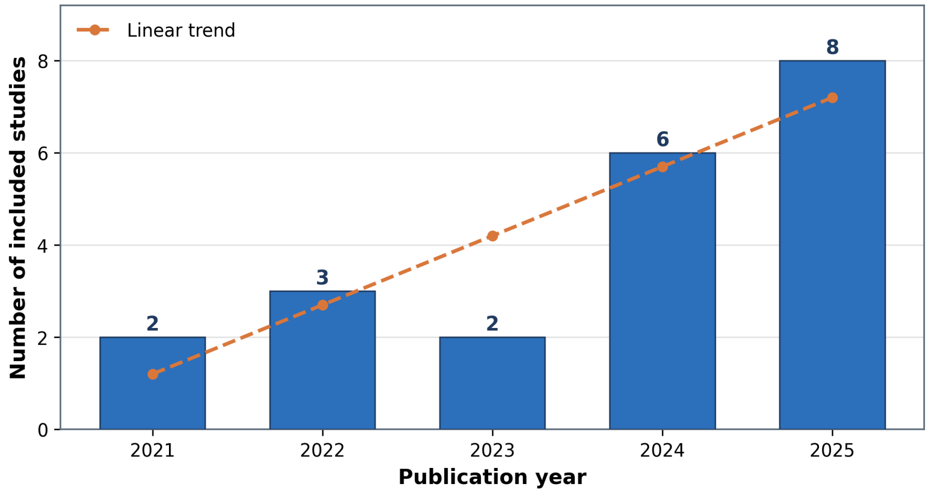

Figure 2. Annual distribution of included studies (2021–2025).

Table 4. Characteristics and principal findings of included studies

Author(s) (Year)	Full title	Source	AI/ML method	Key findings
Jekauc et al. (2024)	Recognizing affective states from the expressive behavior of tennis players using convolutional neural networks	Knowledge-Based Systems	Deep learning (CNN)	CNN recognition of affective states from tennis players' bodily expressions in real matches reached up to 68.9% accuracy, matching or exceeding human observers; negative affect was detected more reliably.
Zhao (2025)	Enhancing psychological resilience and decision-making in basketball players through emerging technologies	Scientific Reports	Classical ML (SVM/RF/GBM)	Wrist-worn IMU features with SVM/Random Forest/Gradient Boosting inferred players' psychological resilience (84.7%) and decision-making quality (78.3%); leave-one-subject-out validation gave 79.4% and 73.1%.
Kotte et al. (2025)	Deep learning-based EEG mental state classification to support mental focus in female cricketers	Discover Artificial Intelligence	Deep learning (CNN/TL)	EEG (Muse 2) with wavelet time–frequency imaging and transfer-learning CNNs classified calm/focus/neutral states; AlexNet reached 99.34% (92% cross-validated),

Author(s) (Year)	Full title	Source	AI/ML method	Key findings
				enabling real-time mental-focus feedback.
Guo (2025)	Fine grain emotional intelligent recognition method for athletes based on multi physiological information fusion	International Journal of Biometrics	Fuzzy neural network	Bayesian fusion of ECG/EMG/EDA/respiration with fuzzy neural networks achieved fine-grained athlete emotion recognition (97.5% average rate; 1.41 s).
Chen, L.-X., et al. (2025)	A Data-Driven Study on Monitoring and Assessment of Psychological Stress in Athletes' Training	Journal of Network Intelligence	Classical ML (KNN+optimisation)	Multi-physiological signals (HR, GSR, RR, SpO2) with a Harris-Hawk-Optimisation-KNN model enabled accurate real-time monitoring of athletes' psychological stress during training.
S. Zhang (2024)	RDA-MTE: an innovative model for emotion recognition in sports behavior decision-making	Frontiers in Neuroscience	Deep learning (Transformer/ResNet)	The RDA-MTE deep model (ResNet-50 + bidirectional attention + Transformer encoder) recognised emotions for sports behaviour decision-making, reaching 83.5% (FER-2013) and 88.9% (CK+).
Sun et al. (2025)	Application of Cluster Analysis Algorithm in Pattern Recognition and Personalized Management of Athletes' Psychological States During Competitions	Journal of Cases on Information Technology	Clustering (K-means)	K-means clustering of wearable HR/EEG/EDA data categorised athletes' states (high-stress, resting, concentrated) at 86.3% accuracy with 1.3 s feedback latency and significant post-implementation gains.
Zhou & Wang (2024)	Athlete's facial emotion recognition method based on multi physiological information fusion	International Journal of Reasoning-based Intelligent Systems	Classical ML (LS-SVM)	Wavelet features fused across ECG/respiration/pulse/skin conductance with LS-SVM recognised athletes' facial emotions with F1 > 0.97 and <300 ms latency.
Sun (2022)	Abnormal emotion Detection of Tennis Players by Using Physiological Signal and Mobile Computing	International Journal of Information System Modeling and Design	Classical ML (classifier)	Portable pulse-wave sensing with wavelet denoising and time/frequency features recognised over 90% of tennis players' abnormal pre-competition emotions via mobile computing.
Baldassarri et al. (2023)	Wearables and Machine Learning for Improving Runners' Motivation from an Affective Perspective	Sensors	Classical ML	A wearable measuring electrodermal activity with ML models deduced runners' emotions in real time and adapted music to raise motivation within the DJ-Running application.
Smerdov et al. (2021)	Detecting Video Game Player Burnout with the Use of Sensor Data and Machine Learning	IEEE Internet of Things Journal	Deep learning (Transformer/GRU)	Physiological sensor data with transformer/GRU models predicted eSports players' encounter outcomes as burnout/decline indicators, forecasting a losing encounter 10 s ahead in 88.3% of cases (ROC-AUC 0.71).
Li et al. (2022)	Effects of psychological fatigue on college	Eurasip Journal on Wireless	AI signal processing (ERP)	AI signal-processing of event-related potentials (error-related negativity) quantified mental fatigue/burnout in

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Author(s) (Year)	Full title	Source	AI/ML method	Key findings
	athletes' error-related negativity based on artificial intelligence computing method	Communications and Networking		college athletes; fatigue significantly altered reaction time and error monitoring.
Kong & Duan (2024)	Boxing behavior recognition based on artificial intelligence convolutional neural network with sports psychology assistant	Scientific Reports	Deep learning (BERT+3D-ResNet)	A BERT + 3D-ResNet model fused boxers' pre-competition psychological dimensions (anxiety, self-confidence) with action data, classifying boxing behaviour at 96.9% accuracy.
Lu et al. (2023)	Application of mobile sensors based on deep neural networks in sports psychological detection and prevention	Preventive Medicine	Deep learning (LSTM)	A low-power LSTM neural processor on mobile/IoT inertial sensors detected sports psychological/mental fatigue to support monitoring and prevention.
Q. Zhang et al. (2025)	Evaluation of the effects of the body on athletes' emotions and motivational behaviors from the perspective of big data public health	Frontiers in Psychology	Classical ML (PSO-KNN/SVM)	PSO-KNN and PSO-SVM classifiers recognised athletes' emotional and tension states; baseline-removed PSO-KNN performed best, indicating preprocessing sensitivity in affect recognition.
Di Martino et al. (2025)	The Role of Sports in Building Resilience: A Machine Learning Approach to the Psychological Effects of the COVID-19 Pandemic on Children and Adolescents	Sports	Classical ML (CHAID/clustering)	CHAID decision-tree and clustering on 1,702 youths (8–18 y) showed sport participation and longer training experience were protective against pandemic-related depression, anxiety and post-traumatic stress.
L. Zhang et al. (2024)	An artificial intelligence tool to assess the risk of severe mental distress among college students in terms of demographics, eating habits, lifestyles, and sport habits: an externally validated study using machine learning	BMC Psychiatry	Classical ML (ensemble)	An externally validated ensemble ML tool (LR/XGBoost/DT/KNN/RF/SVM) predicted severe mental distress among college students from demographics, eating, lifestyle and sport habits.
Yue et al. (2024)	Study on the sports biomechanics prediction, sport biofluids and assessment of college students' mental health status transport based on artificial neural	MCB Molecular and Cellular Biomechanics	ANN + expert system	An ANN + expert-system model assessed college students' mental-health status (DASS-21) during suspended yoga classes and quantified exercise-intervention effects.

Author(s) (Year)	Full title	Source	AI/ML method	Key findings
	network and expert system			
Xing (2022)	Sportsman's Mental State Evaluation and Early Warning Method Based on Intelligent CNN	Scientific Programming	Deep learning (CNN/NLP)	A CNN text-classification model with LIWC features identified psychological-distress signals from student-forum text to support early warning in university/sport populations.
Pang (2021)	Psychological Crisis Intervention of College Sports Majors Based on Big Data Analysis	Revista de Psicologia del Deporte	Classical ML (decision tree)	A decision-tree model mining psychological-census and social-network text predicted and longitudinally tracked psychological-crisis risk among college sport majors.
Brunyé et al. (2025)	Inferring Mental States via Linear and Non-Linear Body Movement Dynamics: A Pilot Study	Sensors	Classical ML	Body-movement dynamics with ML predicted acute stress with moderate-to-high accuracy (linear spectral features most informative); workload and uncertainty were less separable.

Table 5. Classification of included studies by construct, method, and data modality

Author(s) (Year)	Psychological construct	AI/ML method	Data modality	Outcome
Jekauc et al. (2024)	Emotion/Affect	Deep learning (CNN)	Facial/visual behaviour	Acc up to 68.9%
Zhao (2025)	Resilience & decision-making	Classical ML (SVM/RF/GBM)	IMU/motion	84.7% / 78.3%
Kotte et al. (2025)	Mental focus/cognitive state	Deep learning (CNN/TL)	EEG	99.34% (92% CV)
Guo (2025)	Emotion/Affect	Fuzzy neural network	Multi-physiological fusion	97.5% rate
Chen, L.-X., et al. (2025)	Psychological stress	Classical ML (KNN+optimisation)	Multi-physiological fusion	Real-time; high acc.
S. Zhang (2024)	Emotion/Affect	Deep learning (Transformer/ResNet)	Facial/visual behaviour	83.5% / 88.9%
Sun et al. (2025)	Psychological stress	Clustering (K-means)	Multi-physiological fusion	86.3% acc.
Zhou & Wang (2024)	Emotion/Affect	Classical ML (LS-SVM)	Multi-physiological fusion	F1 > 0.97
Sun (2022)	Emotion/Affect	Classical ML (classifier)	PPG/pulse	>90% detection
Baldassarri et al. (2023)	Emotion/Affect	Classical ML	EDA	Real-time affect
Smerdov et al. (2021)	Burnout/mental fatigue	Deep learning (Transformer/GRU)	Multi-physiological fusion	88.3% (AUC 0.71)
Li et al. (2022)	Burnout/mental fatigue	AI signal processing (ERP)	EEG	Sig. ERN effects
Kong & Duan (2024)	Anxiety/competitive state	Deep learning (BERT+3D-ResNet)	Facial/visual behaviour	96.9% acc.
Lu et al. (2023)	Burnout/mental fatigue	Deep learning (LSTM)	IMU/motion	Detection framework

Author(s) (Year)	Psychological construct	AI/ML method	Data modality	Outcome
Q. Zhang et al. (2025)	Emotion/Affect	Classical ML (PSO-KNN/SVM)	Multi-physiological fusion	~56.7% (PSO-KNN)
Di Martino et al. (2025)	Mental health risk (anx/depr/PTSD)	Classical ML (CHAID/clustering)	Questionnaire/behavioural	Protective effects
L. Zhang et al. (2024)	Mental health risk (distress)	Classical ML (ensemble)	Questionnaire/behavioural	Externally validated
Yue et al. (2024)	Mental health risk (DASS)	ANN + expert system	Questionnaire/behavioural	DASS-21 modelling
Xing (2022)	Mental health risk (distress)	Deep learning (CNN/NLP)	Text/social media	Text-based warning
Pang (2021)	Mental health risk (crisis)	Classical ML (decision tree)	Text/social media	Risk prediction
Brunyé et al. (2025)	Psychological stress	Classical ML	IMU/motion	Moderate–high acc.

Across the corpus, target constructs clustered into emotion and affect recognition (the largest group), mental-health risk and distress, psychological stress, mental fatigue and burnout, and a smaller set addressing resilience and decision-making, cognitive focus, and competitive anxiety (Figure 3). Methodologically, classical or traditional ML predominated, followed by deep learning, with a tail of clustering, fuzzy-neural, expert-system, and signal-processing approaches; data modalities were led by multi-physiological signal fusion, followed by facial/visual behaviour, inertial motion, questionnaire/behavioural data, EEG, and text/social-media sources (Figure 4).

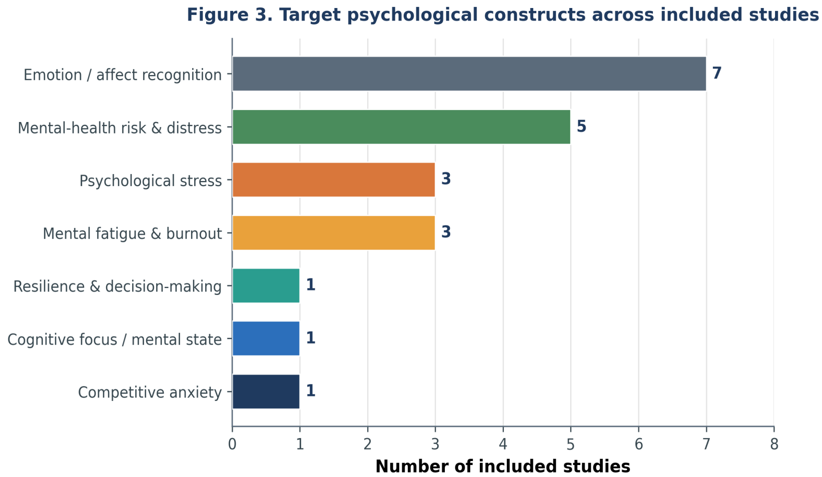

Figure 3. Target psychological constructs across included studies.

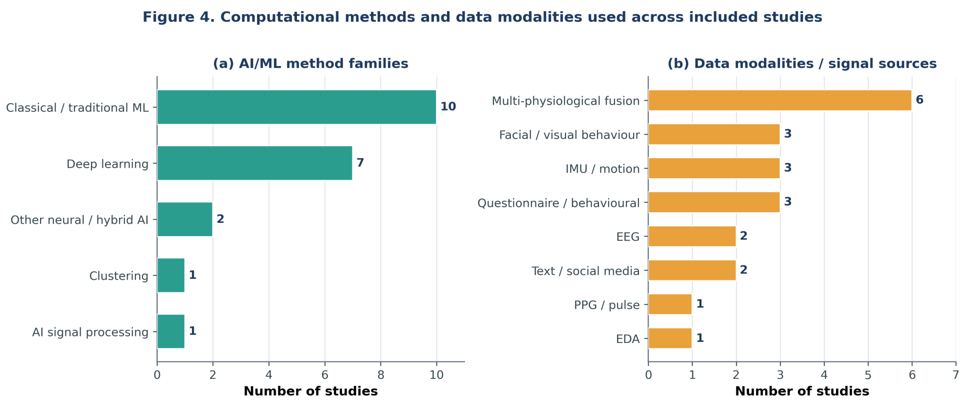

Figure 4. Computational methods (a) and data modalities (b) used across included studies.

Thematic Synthesis

RQ1 - Methods and data modalities

The reviewed studies reveal a clear methodological topography. Multi-physiological signal fusion emerged as the dominant sensing paradigm: several studies combined electrocardiography, electromyography, electrodermal activity, respiration, and related signals, then applied fusion and classification pipelines to recognise affective and stress states (Guo, 2025; Zhou & Wang, 2024; L.-X. Chen et al., 2025). Classical ML remained the workhorse, with support-vector machines, k-nearest neighbours, decision trees, ensembles, and clustering recurring across the corpus (Zhao, 2025; Q. Zhang et al., 2025; Sun et al., 2025). In parallel, deep learning has advanced rapidly, encompassing convolutional networks for facial and bodily expression (Jekauc et al., 2024; S. Zhang, 2024), transfer-learning CNNs for EEG (Kotte et al., 2025), and recurrent or transformer architectures for temporal physiological and behavioural sequences (Smerdov et al., 2021; Lu et al., 2023; Kong & Duan, 2024).

Beyond physiology, the field draws on a widening set of modalities. Facial and bodily expression captured through computer vision supports naturalistic affect recognition (Jekauc et al., 2024; S. Zhang, 2024), while inertial measurement units enable movement-based inference of psychological states (Zhao, 2025; Brunyé et al., 2025). Text and social-media signals extend detection to psychological distress and crisis risk via natural-language processing (Xing, 2022; Pang, 2021), and questionnaire-plus-behavioural data feed predictive models of mental-health risk (Di Martino et al., 2025; L. Zhang et al., 2024; Yue et al., 2024). This modality breadth mirrors trends in adjacent monitoring literatures, where wearable ECG, textile sensors, and edge-deployed models are increasingly standard (Cosoli et al., 2023; Sun & Yin, 2025; Rostami et al., 2024). Taken together, the answer to RQ1 is that athlete psychological-state detection is a multi-modal, multi-method enterprise in which physiological fusion and classical ML remain central, even as deep learning and richer sensing rapidly expand the design space.

RQ2 - Target constructs and reported performance

The constructs most frequently targeted were emotion and affect, psychological stress, mental fatigue and burnout, and broader mental-health risk. Emotion recognition attracted the largest concentration of work and often reported high accuracy: fine-grained multi-physiological fusion achieved recognition rates around 97% (Guo, 2025; Zhou & Wang, 2024), pulse-wave sensing detected over 90% of abnormal pre-competition emotions (Sun, 2022), and CNN-based recognition of naturalistic tennis expressions reached approximately 69%, matching or exceeding human observers in a demanding real-world setting (Jekauc et al., 2024). Stress and mental-state monitoring likewise reported strong performance, with clustering and optimisation-augmented classifiers exceeding 86% and delivering near-real-time feedback (Sun et al., 2025; L.-X. Chen et al., 2025), and movement-based models predicting acute stress with moderate-to-high accuracy (Brunyé et al., 2025).

Fatigue, burnout, and mental-health risk formed a second axis of evidence. Neurophysiological and sensor-based approaches quantified mental fatigue and its behavioural consequences (Li et al., 2022; Lu et al., 2023), while sensor-and-model pipelines flagged performance decline and burnout in eSport athletes (Smerdov et al., 2021). At the population level, externally validated ensembles and expert systems predicted severe mental distress and mapped mental-health status from lifestyle, sport, and questionnaire data (L. Zhang et al., 2024; Yue et al., 2024; Di Martino et al., 2025). Reported accuracies were frequently high, but they must be read against heterogeneous datasets, metrics, and validation regimes; headline figures such as 99% EEG classification (Kotte et al., 2025) coexist with more modest results under stricter, subject-independent validation (Zhao, 2025; Q. Zhang et al., 2025). The answer to RQ2, therefore, is that AI can index a broad spectrum of athlete psychological constructs with often impressive accuracy, yet cross-study comparability is limited and optimistic performance may not survive rigorous, ecologically valid testing.

Comparative and Critical Analysis

Comparing methodological approaches exposes an evolution from bespoke, hand-crafted feature pipelines toward end-to-end deep architectures and real-time, edge-deployed systems. Early and physiologically grounded studies leaned on wavelet features and kernel classifiers (Sun, 2022; Zhou & Wang, 2024), whereas more recent work integrates attention mechanisms, transfer learning, and multimodal fusion (S. Zhang, 2024; Kotte et al., 2025; Kong & Duan, 2024). This maturation parallels developments in affective computing and wearable analytics more broadly, where multimodal and personalised models outperform single-signal, one-size-fits-all designs (Muñoz-Saavedra et al., 2023; Gutiérrez-Martín et al., 2022; Sevil et al., 2021). Consistent with this, individualised and personalised classification consistently outperforms generic pipelines, underscoring the limits of population-level models for idiosyncratic affective signals (Worsey et al., 2021), and the broader convergence of rehabilitation, exercise, and digital-wellness technologies is reshaping how such tools reach practice (Y. Chen et al., 2025). Nevertheless, several designs remain underused: longitudinal and subject-independent validation, causal or explanatory modelling, and prospective field deployment are comparatively rare, echoing gaps noted in fatigue- and injury-prediction reviews (Nashrullah et al., 2025; Dandrieux et al., 2024). The dominant reliance on small, laboratory-elicited samples constrains external validity and may inflate reported accuracy.

Discussion

Interpreted collectively, the evidence indicates that the computational reading of athletes' psychological states has crossed a threshold of technical feasibility. Physiological, behavioural, and textual signals can be decoded into psychologically meaningful categories with accuracy that, in several cases, rivals human judgement (Jekauc et al., 2024). Theoretically, this supports a signal-based conception of affect in which emotion and stress leave measurable, learnable traces across multiple channels, and it foregrounds fusion, the integration of complementary modalities, as the mechanism that most consistently improves recognition (Guo, 2025; L.-X. Chen et al., 2025).

Theoretically, these findings both extend and complicate established sport-psychology frameworks. They operationalise constructs such as stress, resilience, and mental fatigue as continuously measurable states rather than periodic self-reports, inviting dynamic, within-person models of psychological functioning (Zhao, 2025; Brunyé et al., 2025). At the same time, the frequent reduction of rich affective experience to a small set of discrete labels risks oversimplifying constructs that theory treats as contextual and multidimensional, a tension the field has yet to resolve.

Practically, the clearest translational thread is real-time, wearable-enabled feedback intended to support athletes and inform coaches (Sun et al., 2025; Baldassarri et al., 2023). Such systems could enable early identification of maladaptive states, individualised load and recovery management, and timely mental-health support, complementing the injury- and performance-monitoring tools already entering practice (Wang, 2025; Manikandan et al., 2025; Sultan et al., 2024). For sport-science practitioners, the value lies less in headline accuracy than in continuous, low-burden monitoring that surfaces trends invisible to episodic assessment.

Compared with prior reviews, which have concentrated on physical performance, fatigue, or injury (Nashrullah et al., 2025; Dandrieux et al., 2024), this synthesis foregrounds the psychological dimension and shows it to be an active but fragmented frontier. Contradictions in the literature are instructive: very high accuracies reported under laboratory elicitation contrast with lower, more realistic figures under subject-independent validation (Kotte et al., 2025; Zhao, 2025), and the promise of objective measurement sits uneasily beside evidence that context and individual variability strongly shape affective signals (Q. Zhang et al., 2025). These divergences likely reflect differences in data provenance, validation rigour, and construct definition rather than genuine disagreement about feasibility.

Three research gaps stand out. First, external and ecological validity is underdeveloped: few models are validated across independent cohorts or in live competitive settings. Second, datasets and reporting are non-standardised, impeding comparison and cumulative progress and precluding meta-analysis. Third, ethical and governance questions, privacy, informed consent, data security, and the consequences of misclassification, are frequently acknowledged but rarely addressed in design, despite their salience for youth and vulnerable athletes (Bailey et al., 2023; Wilson et al., 2023; Khitaryan et al., 2023).

This review also has limitations. It drew on a single bibliographic database (Scopus), which, although broad, may omit relevant records indexed elsewhere; multi-database searching would strengthen coverage. Quality appraisal was conducted at the level of abstracts and metadata rather than full texts, so the MMAT ratings are indicative. Finally, the heterogeneity of designs and metrics permitted only narrative synthesis, not quantitative pooling. These constraints temper the strength of inferences but do not undermine the review's mapping function.

The future research agenda follows directly. Priority should be given to longitudinal, subject-independent, and field-deployed studies that test whether laboratory performance generalises to real training and competition; to shared, well-documented datasets and standardised reporting that enable comparison and meta-analysis; and to privacy-preserving, transparent, and consented deployment frameworks co-designed with athletes and clinicians. Integrating multimodal fusion with explainable models, and pairing detection with validated intervention pathways (Tan et al., 2024; Maxin et al., 2024; Yu et al., 2024), would move the field from proof-of-concept recognition toward tools that demonstrably protect and enhance athlete wellbeing.

In summary, the answers to the research questions are as follows. AI-based athlete psychological-state detection relies chiefly on multi-physiological fusion and both classical and deep-learning methods across a widening set of modalities (RQ1); it most often targets emotion, stress, fatigue/burnout, and mental-health risk, frequently with high but not always rigorously validated accuracy (RQ2); and its principal application is real-time monitoring and support, constrained by gaps in external validity, standardisation, and ethical governance (RQ3).

Conclusions

This systematic review merged 21 papers investigating machine learning (ML) and artificial intelligence (AI) based detection techniques for athletes' psychological as well as emotional states and explained, at what level the machine reading can achieve and the effect it makes. It is the case that RQ1 and RQ2 were mainly addressed by multi-physiological signal fusion and classical machine learning (ML) analysis, nowadays more often deep learning as well but mostly for emotion and affect, psychological stress, mental fatigue and burnout, and other mental-health risk conditions. The paper frequently states high performance measures. To RQ3, the leading practical outcome is real-time, wearables-based feedback while, external validation, ecological realism, standardized datasets, and ethical governance are still largely missing. The main result of the review is a comprehensive methodological as well as thematic picture of an interdisciplinary area, which gives sport-science coaches and workers a summary of facts they can be assured of and a terminology for evaluating these tools.

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