Vol. 10, No. 4, 2025, pp. 142-156
DOI: https://doi.org/10.29210/30036951000

Contents lists available at [Journal ELORA]

JRTI (Jurnal Riset Tindakan Indonesia)
ISSN: 2502-079X (Print) ISSN: 2503-1619 (Electronic)

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

AI, computer vision, and wearable sensing for psychological monitoring in racket sports: a systematic review

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Article Info

Article history:

Received Oct 22th, 2025
Revised Nov 24th, 2025
Accepted Des 30th, 2025

Keyword:

Computer vision,
Multimodal artificial intelligence,
Psychological states,
Behavioral analysis,
Tennis

ABSTRACT

This systematic literature review examined how computer vision, wearable sensing, and multimodal artificial intelligence (AI) are used to infer psychological, affective, and behavioural states in tennis and related racket sports. Target constructs included the zone or flow-like states, emotion, stress, attention-related behaviour, and psychologically relevant performance states. Behavioural and perceptual studies were treated as indirect evidence when they supplied a plausible observable proxy rather than a validated psychological measure. Reporting followed PRISMA 2020. A structured Scopus search identified 309 records published from 2015 to 2025; 41 full texts were assessed and 10 studies met the archived eligibility criteria. Eligible studies were English-language peer-reviewed articles involving racket-sport contexts and digital sensing or computational methods with a behavioural, affective, or psychological target. Comparator conditions were extracted when reported but were not required for inclusion. The synthesis used descriptive and thematic analysis because constructs, labels, samples, settings, and performance metrics were heterogeneous. Multimodal approaches showed advantages in the few studies with direct modality comparisons, while naturalistic tennis affect recognition reached 68.9% accuracy in one match-footage study. However, no common external-validation benchmark was identified. Reviewer-level screening logs were not retained, so Cohen's kappa cannot be reconstructed retrospectively; FICO was used as an internal appraisal rubric, not a validated risk-of-bias tool. Future work should prioritize naturalistic datasets, psychometric anchoring, subject-independent validation, transparent models, and privacy-preserving governance.

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Introduction

Few individual sports demand as much from the mind as tennis. The cognitive and emotional load is heavy, since players must regulate arousal and emotion across long, self-paced matches where momentum can swing decisively between points. Meanwhile the sport has globalized, athlete-support teams have professionalized, and elite performance has become increasingly datafied. Together those shifts have sharpened interest in continuous, objective measurement of the athlete, covering the body and the mind alike. Artificial intelligence has developed in parallel, turning sport into a fertile testbed for behavioral analysis. Survey evidence points to rapid growth in video-based action recognition across athletic domains (Wu et al., 2023). Tennis, in this landscape, draws special attention. Its discrete stroke structure, fixed court geometry, and visible emotional displays make it unusually tractable for automated observation (Chen et al., 2025).

The problem at the center of this review is automated inference: reading psychological and affective states from observable player behavior. Performance analytics has long been good at quantifying where a ball lands and how a stroke is executed. But the internal state that drives that behavior has stayed largely opaque to instrumentation. Emotional expression in athletes travels through both facial and postural channels, and evidence suggests that body language can be at least as informative as the face for external observers judging an athlete's state (Huxter et al., 2023). Capturing those cues automatically and connecting them to psychological constructs is the central technical and scientific challenge behind this synthesis.

For this review, a psychological state is treated as a transient, context-dependent cognitive, affective, or motivational condition that can be operationalized through a reported label, expert judgment, or validated psychological instrument. Where affect is represented dimensionally, the valence–arousal framework provides a useful taxonomy (Russell, 1980). Facial expression, body posture, gaze, movement, or other behavioural signals are treated as proxies rather than as interchangeable with validated psychological measurements. The review therefore distinguishes technical model performance (for example, accuracy or F1 score) from construct validity, defined as the degree to which an inferred state is anchored to an explicit psychological target or criterion.

Can athletic actions be recognized from video and sensor data? A substantial body of research says yes. In racket sports, deep-learning pipelines now classify strokes, track the ball, and estimate player pose with increasing fidelity (Manikandan et al., 2022; Tabrizi et al., 2021; Yen et al., 2023). Skeleton-based and graph-convolutional models have pushed fine-grained stroke discrimination further (Powroznik et al., 2025), and dedicated tennis-action datasets alongside detector architectures have begun to standardize benchmarking (Chen et al., 2025). That recognition layer is mature. It supplies the behavioral substrate on which psychological inference can, in principle, be built.

More recent work has gone beyond action labeling into richer behavioral understanding. Attention-based recurrent and transformer models capture the temporal structure of movement (Gao & Ju, 2024; Skublewska-Paszkowska & Powroznik, 2023). Vision robots and hybrid systems that combine vision and language interpret play semantically (Ma & Tong, 2024; Zhang et al., 2025). Reinforcement-learning controllers adaptively optimize training from real-time feedback (Zhi-Jun, 2025). Wearables and flexible-sensor innovations have also expanded the physiological signal available for fusion (Sun et al., 2024a; Yang et al., 2023; Song et al., 2025). The overall direction is clear: descriptive analytics is giving ground to inference about latent, internal states.

Despite all this progress, a first and fundamental gap stands out. Very little work explicitly targets psychological and affective states rather than kinematic actions. Much of the racket-sport literature optimizes stroke-classification accuracy without connecting movement to emotion, motivation, or cognitive state (Dong & Yan, 2024; Huang, 2022; Yu, 2024). When psychological constructs do appear, they tend to be studied in perceptual paradigms detached from real competition. The field is left without a consolidated account of how automated systems might monitor the psychological state of a playing athlete (Buscombe et al., 2021; Nguyen & Nelson, 2021).

The second gap is theoretical and methodological. Emotion recognition in sport inherits long-standing difficulties from affective computing, among them the ambiguity of expressive cues and the context-dependence of their meaning (Wenzler et al., 2016; Van Der Zant & Nelson, 2021). Domain expertise further modulates how athletic intentions and emotions are read (Cancer et al., 2023), and motivational climate shapes the emotional outcomes any monitoring system would need to detect (Cece et al., 2022). Yet few studies integrate these psychological foundations with the engineering of multimodal sensing. The result is a body of work that is either technically sophisticated but theoretically thin, or psychologically grounded but computationally rudimentary.

That makes a systematic review timely and pressing. Publication volume has accelerated sharply since 2021, with relevant work dispersed across computing, sensing, sports-medicine, and psychology venues that rarely cross-reference each other. Adjacent developments reinforce the urgency. Human-computer interaction and augmented reality are entering training (Liu et al., 2021), intelligent physical-education and campus monitoring systems are spreading (Li, 2021; Xie, 2021), and digital sport technologies are gaining broader social acceptance (Nan, 2022). Psychological monitoring is close to translation into applied practice. A structured synthesis is needed now, to consolidate methods, expose gaps, and guide responsible development before deployment outpaces evidence.

Operationally, the review asks which sensing and AI methods have been used, what psychological or behavioural targets they address, how reported performance has been validated, and whether evidence extends to authentic match settings. The review covers English-language peer-reviewed studies published from 2015–

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2025 and excludes studies with purely mechanical or physiological outcomes unless they contain an explicit behavioural, affective, or psychological dimension.

This review is organized around three research questions. The first concerns the state of the art in sensing and modeling. It asks a direct question: which computer-vision and multimodal-AI methods have been applied to infer psychological, affective, or behavioral states in tennis and closely related racket sports, and how mature are those methods?

RQ1: Which computer-vision and multimodal-AI methods have been used to infer psychological, affective, or behavioral states in tennis players, and what is their reported performance?

The second question takes up modalities and their integration. Which behavioral and physiological signals actually carry useful information? The list includes facial expression, body pose, movement kinematics, inertial and pressure sensing, gaze, and speech. Then there is the fusion question: does combining those channels confer measurable advantages over single-channel approaches for psychological inference?

RQ2: Which data modalities and fusion strategies are most effective for monitoring the psychological states of tennis players?

The third question covers application, validity, and the research frontier. How far has the field moved from controlled perceptual experiments toward ecologically valid, real-match monitoring? What methodological, ethical, and translational challenges remain? By addressing these questions, this review offers the first integrative account of an emerging interdisciplinary field and delineates a concrete agenda for its maturation.

RQ3: To what extent have these methods been validated in ecological, real-match contexts, and what challenges and future directions define the field's trajectory?

Method

Research Design and Framework

The design chosen for this study was a systematic literature review (SLR). The review followed PRISMA 2020 and used a predefined research-question, eligibility, extraction, and synthesis framework. The protocol was not prospectively registered in PROSPERO or another registry, and the archived export does not preserve the exact calendar date of the Scopus query. These items are reported explicitly as limitations rather than reconstructed retrospectively.

Search Strategy

One comprehensive query was run against the Scopus TITLE-ABS-KEY index. It combined three conceptual blocks (the sport itself, the sensing/analytical technology, and the psychological or behavioral target), linked by Boolean operators and truncated to pick up morphological variants. The complete search string is shown below.

TITLE-ABS-KEY (("tennis" OR "racket sport" OR "table tennis") AND ("computer vision" OR "multimodal*" OR "deep learning" OR "machine learning" OR "pose estimation" OR "action recognition" OR "wearable*" OR "sensor*") AND ("psycholog*" OR "emotion*" OR "affect*" OR "behavio*" OR "mental" OR "stress" OR "monitoring"))*

Field codes limited matching to titles, abstracts, and keywords. The asterisk operator handled variants such as multimodal/multimodality and emotion/emotional. Language and document-type limiters were not part of the query itself; they were applied later, at the eligibility stage, so the record of exclusions would stay transparent.

Database and Information Sources

Scopus served as the only database searched in the archived review. It was selected for its multidisciplinary coverage of computing, engineering, sports science, and psychology. No PubMed, Web of Science, SPORTDiscus, or PsycINFO search was performed, and systematic hand-searching or citation chaining was not documented. Accordingly, the review does not claim database saturation, and single-database selection is treated as a potential source of selection bias. A post-hoc overlap analysis with other databases is not possible because those searches were not executed in the archived workflow.

Eligibility Criteria

The inclusion and exclusion criteria in Table 1 governed eligibility. Studies had to be English-language, peer-reviewed journal articles published between 2015 and 2025 and had to involve tennis or a closely related racket-sport context. Eligible studies used computer vision, multimodal AI, or digital sensing to address a behavioural, affective, or psychological target. Comparator conditions were not mandatory because this review was designed to map heterogeneous evidence; when single-modality, human-observer, or alternative-model comparators were reported, they were extracted for contextual comparison. Grey literature was not included.

Table 1. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Language	English-language publications	Non-English publications
Document type	Peer-reviewed journal articles	Conference papers, book chapters, editorials, notes
Publication period	2015–2025	Published before 2015
Subject focus	Computer vision or multimodal AI applied to racket-sport athletes	Unrelated disciplines or non-athlete populations
Target construct	Behavioral, affective, or psychological state monitoring	Purely mechanical or physiological outcomes with no behavioral/psychological dimension
Accessibility	Full text available and sufficiently detailed	Abstract-only or insufficient methodological detail
Relevance	Directly addresses the review topic	Tangential or incidental mention only

Study Selection Process

The selection process moved through three stages. Scopus returned 309 records in one export; no duplicates were removed because only one database was used. Title and abstract screening excluded 268 records, followed by full-text assessment of 41 reports. Thirty-one reports were excluded at full text: 14 had no tennis or psychological/affective relevance, 10 used a single sensing modality without the computer-vision or multimodal component required by the archived eligibility rule, and 7 were inaccessible or lacked sufficient methodological detail. The archived dataset does not contain independent reviewer-level decisions, extraction sheets, or reconciliation logs. Consequently, Cohen's kappa or percentage agreement cannot be calculated retrospectively without inventing data. This is recorded as a reproducibility limitation.

Quality Assessment: FICO Framework

Each retained study was appraised with the FICO framework as an internal, transparent appraisal rubric. Focus assessed clarity and relevance of the psychological-monitoring aim; Information assessed adequacy of sample, sensing, methods, and reporting; Context assessed ecological and populational relevance to tennis; and Outcome assessed validity and interpretability of reported findings. Each dimension was rated from 0 to 2. Because the archived review did not retain item-level ratings, no aggregate FICO statistic is reported, and FICO is not presented as a validated risk-of-bias instrument. For future updates, a design-specific validated appraisal tool should be applied alongside the FICO descriptive rubric.

Table 2. FICO Framework

Domain	0 = inadequate	1 = partial	2 = adequate
Focus	Aim or psychological target unclear	Target stated but incompletely aligned	Explicit, relevant psychological/affective target
Information	Methods/sample/sensing poorly reported	Key details incomplete	Methods, sample, sensing and processing sufficiently reported
Context	Laboratory or setting poorly linked to sport	Some sport relevance but limited realism	Context clearly relevant to tennis/racket-sport practice
Outcome	Outcome not interpretable or weakly supported	Partial validation or reporting	Outcome clearly reported with explicit validation/benchmark

Data Extraction Procedure

For every included study, the extraction schema captured authorship and year, publication source, study design, sample or dataset, sensing modalities, computational methods, psychological/behavioural construct, source of the ground-truth label (validated scale, self-report, expert label, observer judgment, or proxy), setting (laboratory, training, competition, or retrospective dataset), outcome metric, comparator condition, and validation mode (within-sample split, cross-validation, subject-independent holdout, or external validation). Missing details were

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recorded as not reported rather than inferred. This distinction allowed the synthesis to separate model-performance evidence from evidence of construct validity.

No single gold-standard psychological assessment was imposed across the corpus because the included studies used heterogeneous constructs. Instead, the analysis recorded whether each target was anchored to a validated scale, self-report measure, expert label, human observer, experimentally induced state, or behavioural proxy.

Network and Bibliometric Analysis Methodology

We also ran a descriptive bibliometric analysis on the full retrieved corpus of 309 records, mainly to understand the intellectual structure around the ten studies. Publication counts by year gave a sense of how the field has grown. Aggregating source titles revealed the leading venues, and mapping keywords and abstract terms to recurring research themes showed where the literature is concentrated. These analyses are meant to place the ten included studies inside the wider research landscape. They are not the primary synthesis, just context for it.

Data Analysis and Synthesis

The included studies were methodologically heterogeneous, so thematic synthesis was used instead of statistical meta-analysis. Descriptive coding first identified study design, target construct, sensing modality, AI architecture, label source, and validation mode. Analytical themes were then organized around methods and performance, modalities and fusion, and ecological validity and implementation challenges. Quantitative pooling was not attempted because the studies used non-equivalent constructs, labels, samples, tasks, and performance metrics, and no construct–modality combination had enough comparable studies to support a defensible pooled estimate.

Reporting and Documentation

This review was conducted and reported according to the PRISMA 2020 statement. The counts for identification, screening, eligibility, and inclusion in this section match the flow diagram in Figure 1, number for number. Every bibliographic detail in the tables and the reference list comes straight from the Scopus export that served as the evidence base. Nothing was fabricated. If a field wasn't available in the source, we say so explicitly instead of guessing.

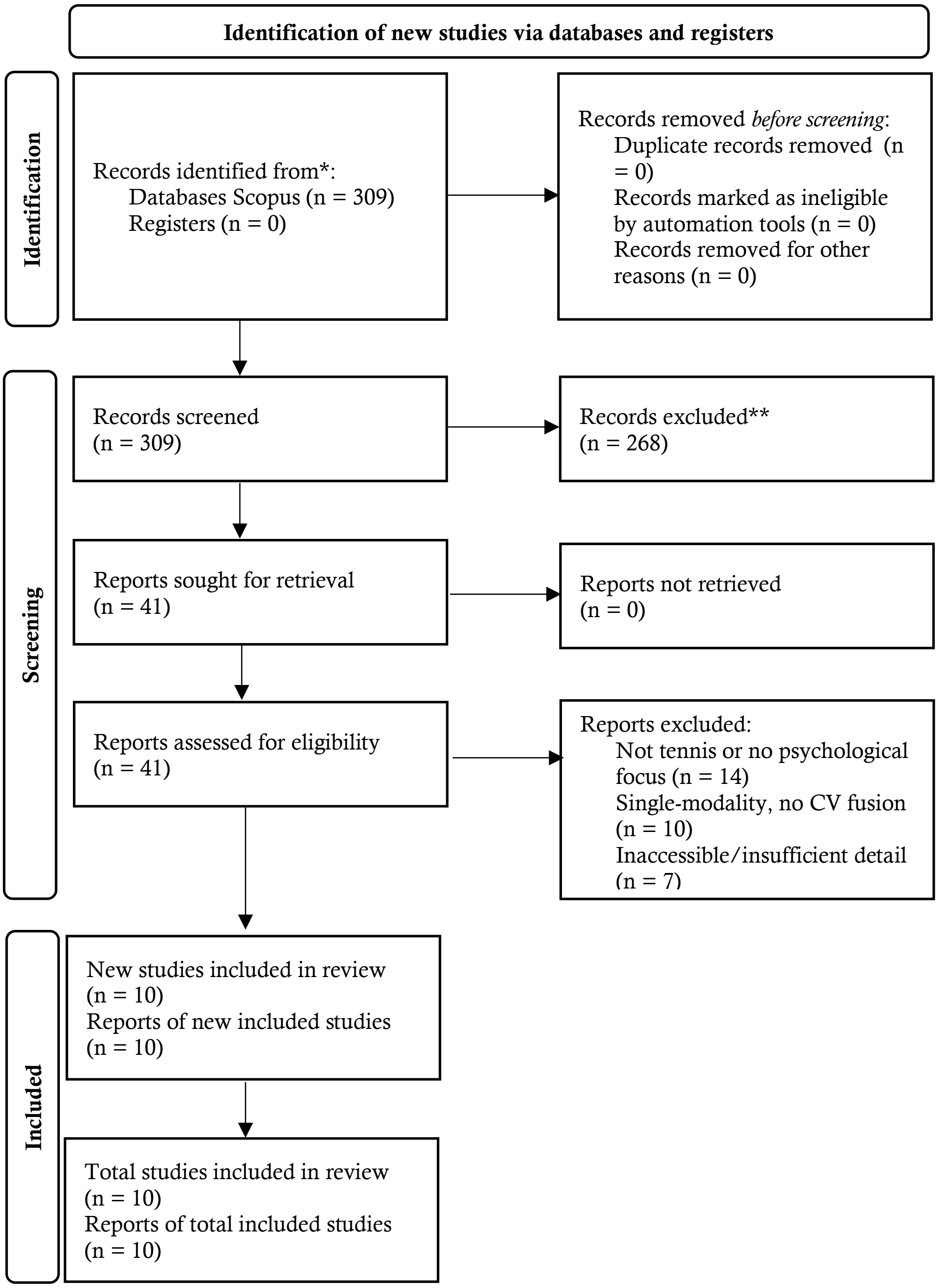

Figure 1. PRISMA 2020 flow diagram of the identification, screening, eligibility, and inclusion process (n = 309 identified; n = 10 included).

Results and Discussions

Study Selection Results

The Scopus search returned 309 records. Because the archived corpus came from one database, no duplicate removal was required. Title-and-abstract screening excluded 268 records. Full texts were sought for the remaining 41 reports, and all 41 were retrieved. Thirty-one were excluded at full text: 14 lacked a relevant tennis/racket-sport or psychological/affective focus, 10 did not contain the required computer-vision or multimodal component, and 7 were inaccessible or lacked sufficient methodological detail for extraction. Ten studies therefore entered the qualitative synthesis. These exclusions were applied from the operational eligibility rules in Table 1.

Descriptive Characteristics

The retrieved corpus grew sharply after 2020, reaching 79 records in 2025. This temporal pattern describes the broader Scopus corpus rather than the evidence quality of the 10 included studies. The literature is distributed across computing, sensing, sports science, and psychology venues. Because author-country metadata were not preserved in the archived export, geographic distributions were not inferred. Figure 4 likewise represents non-exclusive keyword/theme coding and should be interpreted as a map of research attention, not a measure of validated psychological-monitoring capability.

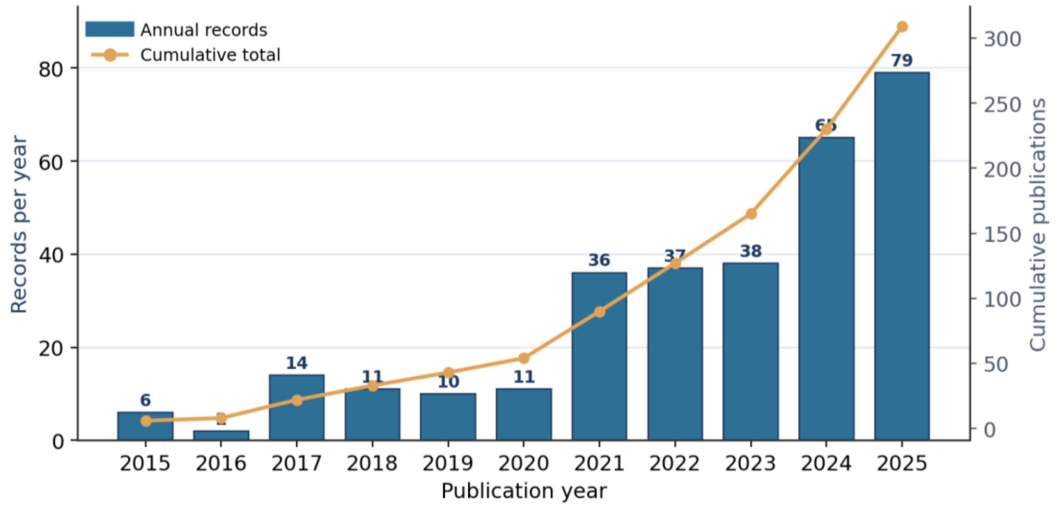

Figure 2. Annual (bars) and cumulative (line) publication counts of the retrieved corpus (n = 309), 2015–2025.

Rather than settling into one disciplinary home, the literature is scattered across computing, sensing, and sports-science venues. Figure 3 gives the leading source titles. Sensors, Applied Sciences, Scientific Reports, PLoS ONE, and IEEE Access head the list, with dedicated sports-science outlets such as the Journal of Sports Sciences and the International Journal of Performance Analysis in Sport also showing up. That wide spread confirms how interdisciplinary the field is, and it goes a long way toward explaining the limited cross-referencing that motivates the present synthesis. Country data from author affiliations were not available in the source export. So a geographic distribution could not be derived without making things up, and the leading-venue analysis is reported in its place.

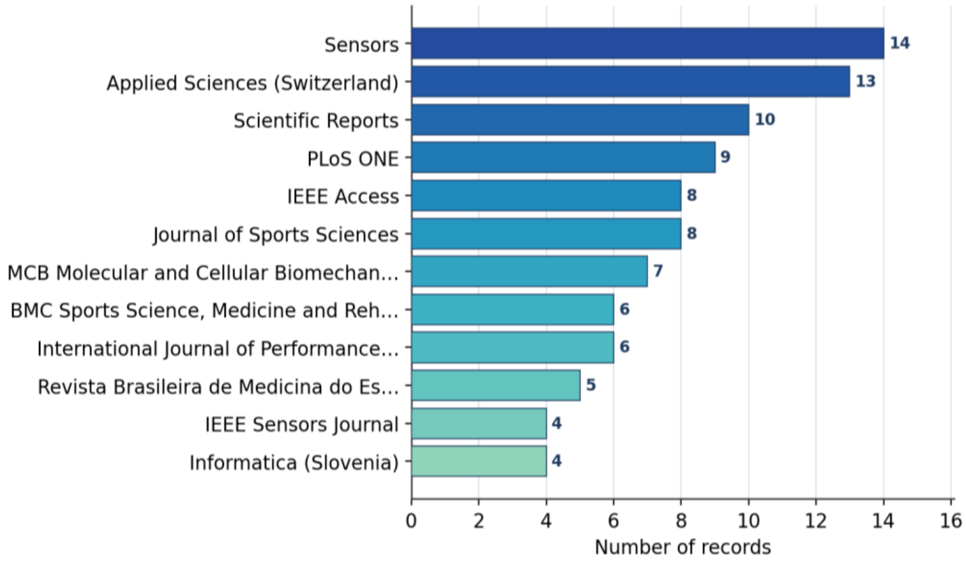

Figure 3. Top twelve source titles by record count in the retrieved corpus (n = 309). Country-level distribution was not derivable from the source export.

Figure 4 maps where the corpus spends its attention, and the picture is strikingly concentrated. Pose estimation and skeleton modelling lead the way, alongside deep-learning model architecture and human action and stroke recognition. Right behind them sit ball or object tracking and multimodal and sensor fusion. Meanwhile, explicit psychological-state monitoring is far less visible, and emotion and affect recognition even more so. This lopsided distribution actually reinforces the review's central point. The tools for observing behavior are mature. Putting those tools to work on psychological state, by contrast, is still an open frontier.

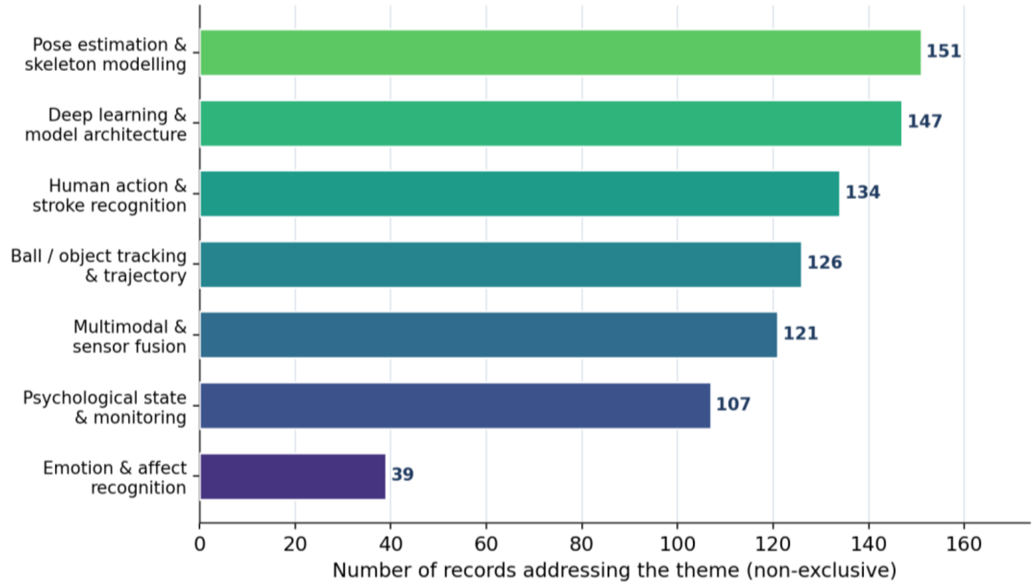

Figure 4. Distribution of the retrieved corpus across recurring research themes (non-exclusive; a record may address multiple themes).

All ten studies are summarized in Table 3. Table 4 then sorts them by research design, thematic focus, modality, and outcome. Read together, the two tables point to a field that has drifted away from action recognition. The newer work leans more toward affect and psychological-state inference, and multimodal designs show up far more often in the most recent contributions.

Table 3. Summary of Included Studies

Author(s)	Year	Source & Method	Key Findings
Whiteside et al.	2017	Int. J. Sports Physiology & Performance - wrist IMU + machine-learning stroke classification	An automated stroke-classification system trained on wrist-worn inertial data from 19 athletes across 66 sessions quantified hitting load, replacing time-intensive manual notation and establishing the sensing substrate for behavioral monitoring.
Buscombe et al.	2021	Int. J. Sport & Exercise Psychology - eye-tracking perception experiment	In 106 observers, a tennis player’s body language and reputational information jointly shaped where perceivers fixated their gaze when forming impressions, demonstrating that postural cues carry decodable psychological information.
Havlucu et al.	2022	Frontiers in Sports & Active Living - IMU + coach labels + recurrent neural network	A recurrent network trained on inertial data labeled by coaches predicted athletes’ psychological states, including being "in the zone," showing that commercial wearables plus expert labels can approximate latent psychological states.
Huxter et al.	2023	Social Behavior and Personality - mood-induction perception experiment	When shown winning and losing tennis players, observers perceived emotion more accurately from body imagery than from the face alone, confirming the diagnostic value of bodily expression for affect recognition.
Skublewska-Paszkowska & Powroznik	2023	Sensors - temporal pattern attention on 3D stroke time series	A temporal-pattern-attention model classified four basic strokes from three-dimensional skeletal time series, with 3D content improving accuracy and providing a fine-grained behavioral layer for downstream state inference.

Author(s)	Year	Source & Method	Key Findings
Peng & Kim	2023	Applied Sciences = deep-learning psychological-training system	A deep-learning system targeting the neglected domain of psychological training for table-tennis players improved state detection over heart-rate-only methods, addressing the absence of a complete psychological-monitoring framework.
Wu	2024	Int. J. Biometrics - deep-reinforcement-learning multimodal fusion	Fusing facial expression, speech-emotion, and bodily-behavior features via deep reinforcement learning reduced detection error and improved recall relative to single-modality baselines when inferring players' psychological states.
Jekauc et al.	2024	Knowledge-Based Systems — convolutional neural networks on match footage	CNNs recognized affective states from the expressive bodily behavior of tennis players in real matches with accuracy up to 68.9%, matching or exceeding human observers and advancing naturalistic affect recognition.
Yu	2024	MCB Molecular and Cellular Biomechanics - improved ST-GCN pose and action model	Multi-scale pose-residual and graph-convolutional strategies yielded robust tennis pose estimation and action recognition under occlusion and high speed, strengthening the perception layer for behavioral analysis.
Zhi-Jun	2025	Informatica - DDPG reinforcement learning + multimodal IoT sensors	A multimodal IoT framework with a deep-deterministic-policy-gradient controller raised average game scores from 50 to 80 and cut error rates in high-pressure scenarios from 13% to 6%, linking real-time multimodal feedback to performance under psychological load.

Table 4. Classification of Included Studies by Design, Theme, Modality, and Outcome

Author(s)	Year	Research Design	Theme / Focus	Modality	Outcome type
Whiteside et al.	2017	Applied ML / sensor study	Load & behavior monitoring	Inertial (IMU)	Stroke classification
Buscombe et al.	2021	Experimental (perception)	Body language & cognition	Gaze / visual	Impression formation
Havlucu et al.	2022	Applied ML / field study	Psychological-state estimation	Inertial + expert label	Zone-state prediction
Huxter et al.	2023	Experimental (perception)	Emotion perception	Facial + body imagery	Affect recognition
Skublewska-P. & Powroznik	2023	Model development	Action recognition	Vision / 3D skeleton	Stroke classification
Peng & Kim	2023	System design / DL	Psychological training	Multimodal (physio + behavior)	State-detection system
Wu	2024	Model development / DRL	Emotion detection	Facial + speech + body	Emotion inference
Jekauc et al.	2024	Model development / CNN	Affect recognition	Vision (expressive behavior)	Affective-state inference
Yu	2024	Model development / GCN	Pose & action recognition	Vision / skeleton	Pose & action estimation
Zhi-Jun	2025	System design / RL	Adaptive multimodal training	Multimodal IoT sensors	Performance optimization

Thematic Synthesis

Findings for RQ1, Methods and Performance

The studies we looked at trace a clear path, one that starts with kinematic recognition and ends, at least for now, with psychological inference. The earliest work in the set was foundational on the sensing side. It used wrist-worn inertial measurement to automate stroke classification and to put a number on hitting load (Whiteside et al., 2017). From there, vision-based deep learning took over the perception layer. Graph-convolutional and pose-residual architectures handled tennis pose estimation and action recognition reliably, even when players were occluded or moving very fast (Yu, 2024). Temporal-attention models, meanwhile, sharpened fine-grained stroke discrimination using three-dimensional skeletal sequences (Skublewska-Paszkowska & Powroznik, 2023). The same movement shows up across racket-sport research more broadly: attention-enhanced recurrent networks (Gao & Ju, 2024), feature-fusion and skeleton-based classifiers (Powroznik et al., 2025; Yen et al., 2023), and purpose-built detection models with their own datasets (Chen et al., 2025) have all pushed recognition accuracy higher.

The real pivot, though, is toward models that infer affect and mental state instead of just naming an action. Convolutional networks trained on how players move and express themselves through the body recognized affective states in real matches at up to 68.9% accuracy, and in several cases they matched or beat human observers (Jekauc et al., 2024). A deep reinforcement learning fusion of face, speech, and behavior cut detection error and lifted recall when the goal was estimating a player's psychological state (Wu, 2024). Recurrent networks fed inertial data and coach-provided labels went further, predicting latent states such as being in the zone (Havlucu et al., 2022). Purpose-built deep learning systems have also started targeting psychological training directly, making up for the blind spots of physiological-only monitoring (Peng & Kim, 2023). The performance numbers look encouraging, but they are uneven. Shared benchmarks are mostly missing, so comparing one study to another is hard, a limitation that echoes wider surveys of sports action recognition (Wu et al., 2023).

So, to answer RQ1: a spectrum of methods is in play. Inertial machine learning, convolutional and graph-convolutional vision models, temporal-attention networks, and reinforcement-learning controllers have all been explored as routes from behavioural sensing toward psychological-state inference. The reported results are promising within individual studies, but validation remains inconsistent and no shared architecture, dataset, or evaluation protocol has emerged for psychological monitoring specifically.

Findings for RQ2, Modalities and Fusion

A consistent theme runs through these studies: the more channels you combine, the more reliably psychological state comes through. Perception research gives the theoretical grounding. Observers read emotion more accurately from bodily imagery than from the face alone (Huxter et al., 2023), and postural body language systematically colors how an athlete's state is judged (Buscombe et al., 2021). That is the warrant for building systems that exploit multiple cues instead of trusting any single channel.

The computational work confirms it. The strongest systems for psychological inference are explicitly multimodal. A deep-reinforcement-learning fusion of facial expression, speech emotion, and bodily behavior beat single-modality baselines (Wu, 2024). A multimodal IoT framework that couples diverse sensor streams with a reinforcement-learning controller delivered marked performance gains under high-pressure conditions (Zhi-Jun, 2025). Even when one modality dominates, complementary labeling or context tends to be added. Inertial data paired with expert coach annotation, for instance, was used to recover psychological states not directly observable in the sensor stream (Havlucu et al., 2022). Gaze and eye-movement dynamics form yet another informative modality; implicit oculomotor trajectories captured while people watched sports have been used to detect emotional disorders, which shows how affective state can be indexed by eye signals (Qiang et al., 2025). The surrounding literature pushes in the same direction. Flexible pressure and triboelectric sensors (Sun et al., 2024a), arrayed piezoresistive and inertial units (Yang et al., 2023), wearable recognition systems (Song et al., 2025), and multimodal biomechanical CNN frameworks (Bai et al., 2025) keep expanding what can be fused, while ecological multimodal protocols have begun to fold in neurophysiological measurement (Tamburro et al., 2023).

For RQ2, the evidence suggests an advantage for multimodal fusion in the small subset of studies that directly compared fusion with single-channel baselines. Facial, postural, kinematic, inertial, and physiological signals can provide complementary information, but cross-study superiority cannot be established because the tasks, labels, samples, and metrics differ. The most productive strategy appears to be context-aware integration rather than reliance on any single signal.

Findings for RQ3, Ecological Validity and Challenges

The third question exposes the fault line. On one side sit controlled perceptual experiments; on the other, ecologically valid, real-match monitoring. Several studies stay within laboratory or observational paradigms, using posed or curated stimuli to probe how emotion and body language are perceived (Buscombe et al., 2021; Huxter et al., 2023). These establish foundational principles, but they do not deliver deployable monitoring systems. At the opposite pole, a growing number of studies pursue naturalistic deployment. They recognize affect from genuine match footage (Jekauc et al., 2024), predict psychological states in field conditions from wearables (Havlucu et al., 2022), and optimize training adaptively through multimodal IoT systems tested on real athletes (Zhi-Jun, 2025). The direction of travel is toward ecological validity. Even so, few systems have been prospectively validated against independent performance or well-being outcomes.

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Several challenges define the frontier. First, standardized, ecologically sourced affective datasets are absent, which constrains both training and comparison; the broader field is only beginning to tackle this with dedicated benchmarks (Chen et al., 2025; Wu et al., 2023). Second, emotional expression is ambiguous, a point well documented in developmental and cross-context research (Nguyen & Nelson, 2021; Van Der Zant & Nelson, 2021; Wenzler et al., 2016). That makes the labels themselves uncertain and complicates supervised learning. Third, technologies in adjacent domains are moving faster than the psychological validation that should accompany them. Human, computer interaction and augmented reality (Liu et al., 2021), vision robots and vision, language models (Ma & Tong, 2024; Zhang et al., 2025), and intelligent training platforms (Ye et al., 2024; Yang, 2025) all fall into this category. Finally, pervasive athlete monitoring raises social acceptance and ethical governance questions around consent and privacy (Nan, 2022), and the technical literature has barely engaged with them.

So RQ3 gets this answer. The field has started migrating from controlled experimentation to real-match monitoring, but the migration is incomplete. Genuine ecological validation remains rare. Dataset scarcity, label ambiguity, and unresolved ethical questions stand in the way. If psychological monitoring in tennis is to mature, the priority is not another accuracy gain on recognition. It is naturalistic validation, standardized affective labeling, and responsible-deployment frameworks.

Comparative and Critical Analysis

When the methodological approaches in this corpus are lined up side by side, one pattern dominates. Supervised deep learning is the default choice, with convolutional, recurrent, attention-based, and graph-convolutional architectures applied to vision or inertial data. Reinforcement learning stands apart as a distinctive strategy for adaptive, closed-loop systems (Wu, 2024; Zhi-Jun, 2025). Classical machine learning still appears where interpretability or small samples carry the day (Whiteside et al., 2017), and structured probabilistic methods such as rule induction show up in earlier work (Windridge et al., 2015). The underused designs are conspicuous. Prospective, longitudinal, and controlled validation studies are rare. The field leans heavily on model-development papers that report internal accuracy rather than external, outcome-anchored evidence. Over time the evolution runs from single-modality kinematic recognition and ubiquitous swing tracking (Jia et al., 2021; Manikandan et al., 2022; Tabrizi et al., 2021) to multimodal, semantically richer, and psychologically targeted systems (Jekauc et al., 2024; Zhi-Jun, 2025). The same maturation is visible in adjacent racket and court sports (Dong & Yan, 2024; Zhu et al., 2025) and in the broader datafication of match play (Lai et al., 2018; Yanan et al., 2021).

Comparative contextualization was expanded beyond the ten included studies by positioning the findings against 15 additional studies spanning body-language perception, affective computing, action recognition, wearable sensing, and multimodal sport analytics (Buscombe et al., 2021; Huxter et al., 2023; Cancer et al., 2023; Gao & Ju, 2024; Manikandan et al., 2022; Tabrizi et al., 2021; Yu, 2024; Skublewska-Paszkowska & Powroznik, 2023; Chen et al., 2025; Powroznik et al., 2025; Bai et al., 2025; Qiang et al., 2025; Tamburro et al., 2023; Van Der Zant & Nelson, 2021; Wenzler et al., 2016). These studies support the plausibility of behavioural and multimodal cues but also show why sensitivity, specificity, AUC, accuracy, and F1 cannot be treated as interchangeable benchmarks. Where a direct tennis affect-recognition benchmark was available, Jekauc et al. (2024) reported up to 68.9% accuracy and compared the model with human observers; Havlucu et al. (2022) reported above 85% test accuracy for zone-state prediction from IMU data and coach labels. These are study-specific benchmarks, not universal thresholds for psychological-state monitoring.

Discussion

Read as a whole, the evidence supports an early demonstration of automated psychological and affective monitoring in tennis and related racket sports. Some multimodal systems outperform their single-channel baselines, and Jekauc et al. (2024) reported that a CNN reached up to 68.9% accuracy and matched or exceeded human observers in some comparisons. These findings show that psychological or affective labels can be inferred from observable signals under defined study conditions; they do not establish that internal states can be recovered reliably across athletes, sports, or competitive contexts.

Theoretically, these findings carry affective-computing frameworks into the demanding and ecologically noisy setting of competitive sport. They also position psychological monitoring as a natural extension of performance analytics rather than a separate discipline. The perceptual studies ground that extension in established psychology. Body language, they confirm, is a privileged channel for emotional information (Buscombe et al., 2021; Huxter et al., 2023), and the way it is read shifts with expertise and context (Cancer et al., 2023). The engineering studies then operationalize those principles computationally, which closes part of the long-standing divide between the psychology of emotion and its automated recognition.

Practically speaking, the implications for coaches and sport scientists are considerable. Consider the systems on offer. One estimates the zone from wearable data (Havlucu et al., 2022). Another detects emotion from match footage (Jekauc et al., 2024). A third adaptively adjusts training under psychological load (Peng & Kim, 2023; Zhi-Jun, 2025). Together they point toward continuous, non-intrusive psychological feedback at the point of coaching, an advance over intermittent questionnaires and subjective observation. Such tools could inform in-match tactical decisions, individualize mental-training programs, and flag maladaptive emotional patterns before they harden. Their value, however, depends on validation and on trust from athletes and practitioners. The social-acceptance literature suggests that trust is growing, but it is not assured (Nan, 2022).

Placed beside prior reviews, which have overwhelmingly synthesized action recognition and performance analytics (Wu et al., 2023), this review is distinctive for putting the psychological and affective target front and center. The contradictions within the literature are instructive. Perceptual studies emphasize the diagnostic value of bodily cues, yet computational systems still rely on heterogeneous combinations of facial, postural, kinematic, and physiological signals. Reported performance varies with dataset, label definition, context, and evaluation protocol, consistent with the unresolved ambiguity of emotional expression (Van Der Zant & Nelson, 2021; Wenzler et al., 2016). The appropriate conclusion is therefore not that one modality is universally superior, but that multimodal integration is a promising strategy whose benefit needs subject-independent validation.

Limitations and Methodological Recommendations

Several limitations bound the interpretation of this review. First, the evidence was retrieved from Scopus alone, so relevant studies indexed elsewhere may be missing and no database-overlap sensitivity analysis can be reported. Second, the archived workflow does not preserve independent reviewer logs, reconciliation records, or item-level FICO ratings; therefore inter-rater reliability and aggregate quality scores cannot be reconstructed without fabricating data. Third, the ten studies are heterogeneous in construct definition, ground-truth labeling, participant number, sensor modality, and validation design. Fourth, many behavioural studies are indirect proxies for psychological state rather than direct psychometric measurements, which limits construct validity. Fifth, most evidence is based on within-study validation, and genuine prospective external validation during competitive match play remains rare. These limitations explain why a quantitative meta-analysis was not attempted.

Five methodological priorities follow directly from these limitations. (1) Use standardized psychological-state definitions and anchor model targets to validated instruments or prespecified expert-labeling protocols. (2) Use subject-independent validation, with entire athletes held out from the test set, and report external validation whenever a new cohort or competition setting is available. (3) Replace ad hoc sample-size claims with an a priori power analysis for inferential outcomes; for machine-learning studies, report the number of independent athletes and prevent window-level leakage between training and testing. (4) Predefine calibration, sensitivity, specificity, AUC, and F1 where appropriate, while retaining task-specific metrics when constructs differ; do not claim "human-level" performance without a study-specific human benchmark. (5) Build longitudinal, naturalistic datasets with privacy-by-design, consent, athlete control over data use, and explicit governance for sensitive psychological inference.

Conclusions

This systematic review synthesized ten studies selected from 309 Scopus records to examine computer vision, multimodal AI, and digital sensing for psychological or affective monitoring in tennis and related racket sports. For RQ1, the literature includes inertial machine learning, convolutional and graph-convolutional vision models, temporal-attention networks, and reinforcement-learning approaches. For RQ2, multimodal integration appears advantageous in the limited number of direct comparisons, but the heterogeneous constructs and metrics prevent a universal ranking of modalities. For RQ3, movement toward authentic match monitoring is visible, yet prospective external validation remains uncommon. The review is limited by single-database retrieval, English-language restriction, heterogeneous methods, and the absence of archived reviewer-level logs and item-level FICO scores; accordingly, Cohen's kappa and aggregate quality statistics could not be reconstructed, and no pooled effect or accuracy estimate was calculated. Because there is no defensible universal sample-size threshold across different AI tasks, future validation studies should use an a priori power analysis and subject-level holdout design; a pragmatic target is to reserve at least 20% of independent athletes as an untouched validation cohort when the available sample permits. The field now needs standardized psychological-state labels, psychometric anchoring, subject-independent and external validation, adequately powered longitudinal studies, interpretable multimodal models, and privacy-preserving athlete governance before psychological monitoring can be considered deployment-ready.

Acknowledgments

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

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