Vol. 7, No. 1, 2026, pp. 553-566
DOI: https://doi.org/10.29210/08jces693300

Contents lists available at Journal ELORA

Journal of Counseling, Education and Society
ISSN: 2716-4896 (Print) , ISSN 2716-4888 (Electronic)

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

Wearable sensing and deep learning for human activity and action recognition in sport and physical activity: a systematic review

Nilma Zola[1], Ifdil Ifdil[*)1], M. Fahli Zatrahadi[2]
[1] Center for Educational Neuroscience, Trauma, and Human Behavior, Universitas Negeri Padang
[2] UniversitasIslam Negeri Sultan Syarif Kasim, Indonesia

Article Info

Article history:

Received Jul 12th, 2026
Revised Aug 20th, 2026
Accepted Sep 11th, 2026

Keyword:

Human activity recognition,
Wearable sensors,
Deep learning,
Sports monitoring,
Artificial intelligence

ABSTRACT

The fast merging of sensors which can be worn, the interconnected network of things, and the power of artificial intelligence changed the game in measuring movements during sports and physical activity, however, the information on how such systems can detect various athletic activities is still scattered mainly within engineering, sports-science, and health fields. In this systematic review the authors gathered studies which used wearable or vision-based sensors with different forms of machine/deep-learning models to identify human actions and activities during sporting and physical activity scenarios. Scopus, PubMed, and ScienceDirect were searched in compliance with PRISMA 2020 and 658 records were found. After removing 10 duplicates, 648 were screened, 50 full texts were evaluated, and 20 studies were found eligible. These were peer-reviewed English-language publications or reviews published within the last five years (2021 to 2026). Main topics of the research are the combination of inertial and multimodal sensors with the attention-based and hybrid convolutional-recurrent architectures that have yielded a high level of recognition performance for sports actions, together with the trend in research focusing on free-living, edge-deployable, and personal monitoring. The review points to key areas for further research being generalisability, standardised reporting, and athlete-centred validation.

Corresponding Author:

Ifdil Ifdil,
Center for Educational Neuroscience, Trauma, and Human Behavior, Universitas Negeri Padang
Email: ifdil@fip.unp.ac.id

Introduction

Sport and physical activities, through them, have the ability to create abundant records of movement that, by interpreting, one of the most essential things to improve performance, prevent injury, and promote public health have become. The improvements in the technology of wearables and AI today allow the movement of the athletes to be captured continuously and be automatically analyzed, thus the evaluation is transferred from the lab to the playground as well as daily life. (Madrigal-Cerezo et al., 2026; Morouço et al., 2024). The wearable systems that include inertial, electrophysiological, and pressure sensors along with the machine learning not only support data-driven decision making but also allow large-scale monitoring and guidance, such as coaching or feedback to athletes. (Madrigal-Cerezo et al., 2026; Sun et al., 2022)

Predicting human activity via machines is the capability at work when a system identifies actions from sensors or other devices like cameras, a kind of artificial vision system. It was also a great challenge for sport scientists to recognize tennis strokes, weightlifts or even change of training loads, because these sport-related activities are highly complex, very quick, and they have kinetic chains involving lots of joints, muscles and bones (Fujii et al., 2021). The recognition of such actions is therefore much easier than distinguishing walking from sitting. This challenge gives grounds to an integrative review of the development and validation of AI-based recognition techniques specifically in sports and physical activity settings.

So far, studies mainly dealt with using wearables and AI in areas outside sport. There have been overviews of wearable devices for measuring vital signs and cardiovascular health indicators (Miao et al., 2023; Sun et al., 2022), artificial intelligence applications based on gait data (Harris et al., 2022), the use of biosensors in healthcare enhanced with AI (Wang et al., 2023), and the employment of optical fibers and stretchable strain sensors to human motion measurement (Alqaderi et al., 2025; Li et al., 2025). Likewise, there are AI works on sports medicine and orthopaedics as in Baghbani et al. (2025) and Smaranda et al. (2024) and the use of new and rehabilitation technologies (Takáč et al., 2025). These reviews, however, primarily address the feasibility and versatility of these technologies, and not their use to the recognition of sport-related activity and actions.

New developments support a more concentrated review. Sensor technology has advanced from simple accelerometers and now covers a wide variety of multimodal and autonomous systems incorporating self-powered sensors including triboelectric and smart-textile devices (Ahmed et al., 2025; Dong et al., 2024; Zhou et al., 2026) while in the data modeling side there is a shift toward a more accurate representation of the temporal and spatial information by using attention-based networks and a combination of deep networks. Besides this, non-invasive biomedical and physiological sensing methods such as lactate biosensing for athletic performance monitoring (Yang et al., 2025) and activity evaluation via the principle of bioimpedance (Jacobs et al., 2026) are further increasing the amount and variety of signals that a machine can extract for a recognition task. It is obvious that publication output has accelerated substantially in the past three years so now more than ever it is the right time for a systematic overview.

Even with the progress being made, the body of work still presents a first problem: the evidence on AI-based recognition of sport activity and action is scattered among such disciplines as engineering, computer science, sports science, and health science, so it leaves no consolidated record of sensing modality and model families use and their performance. Studies frequently use very different benchmark and evaluation data. Therefore, it often becomes hard to compare different models or to figure out which ones can be applied in actual training settings (Caso et al., 2026a, b; Kaur et al., 2024). As a result, practitioners are at a loss where to go from an objective of monitoring a feature or an indicator to finding and building a suitable combination of a sensor and an analytics model.

A second issue concerns the methodology and the studies usually do very basic checks on the models by running them with data from lab or benchmark sources that have a completely different distribution than the actual sporting situation. Generalisability is a big concern here and the data about sampling, participants and outcomes are not very consistent (Sun, 2022). Also, rarely the aspects of device-embedded efficiency vs model complexity, multimodal fusion management and the reproducibility of a model are evaluated in a coherent and systematic manner. Without such a systematic evaluation we wouldn't be able to find out whether some studies are the ones showing real results that can be relied upon or they are just a few preliminary steps that are promising.

This literature review aims to resolve the problem that many in the field have expressed namely that the work published about sport and physical activity using AI recognition via wearable devices and vision methods, is still not well synthesized together despite the increasing momentum of the literature.

The paper reviews a body of literature using a very detailed plan to identify and describe with an explicit, repeatable method the ways of wearable and vision-based AI to human activity and human action in sports activity and physical activity as well as it provides a critical evaluation of the strength and reliability of the evidence available. Bringing together such studies will help people in sport training who are making technological choices with a large number of alternatives and will give designers of wearable products a clear understanding of the user requirements that they ought to take into account when developing future products.

Review of the literature in this article adds value in at least three ways: first, it provides a comprehensive taxonomy from sensing inputs to modeling; secondly, it delivers a critique of the methods and quality of research conducted thus far; third, it presents a research programme for the future. In order to present a comprehensive picture of the field, a set of three research questions have been posed and the synthesis is structured around them.

RQ1: What sensing modalities and signal types have been used by AI for human activity and action recognition in sport and physical activity contexts? It is through RQ1 that a sensing design space map is being given.

RQ2: What is the main set-up of machine and deep learning that are involved and which recognition performance and method validation have been covered? It is through RQ2 that a comparison of modeling choices and evidential powers will be made clear.

RQ3: What is the landscape of application areas as well as the key methodological difficulties that have been revealed by the review and what should be the focus for future research? Through RQ3, a list of topics, issues and challenges will arise that bridge between technical possibility and athlete-centered real-world deployment. The three questions together will be used to carry out the first PRISMA synthesis that takes into consideration sport-specific AI activity recognition as a complete unit of research rather than a by-product of general HAR.

Method

Research design and framework

A systematic literature review (SLR) design was adopted because it offers a transparent, replicable procedure for identifying, appraising, and synthesising evidence on a defined question (Tranfield et al., 2003). Reporting followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021), which updates the original PRISMA guidance (Moher et al., 2009). The design was chosen over a narrative review to minimise selection bias and to make the study-selection and appraisal steps auditable.

Search strategy

The research questions were decomposed with the PICO framework to structure concept identification. Population (P): individuals engaged in sport, exercise, or physical activity, including athletes and general participants. Intervention/interest (I): wearable or vision-based sensing systems coupled with AI/machine-learning models for activity or action recognition and monitoring. Comparison (C): across sensing modalities and model architectures (no active comparator required). Outcome (O): recognition or classification performance and monitoring application outcomes. Each PICO element was expanded into a cluster of synonyms and combined with Boolean operators.

The search targeted title, abstract, and keywords using field-code restriction (TITLE-ABS-KEY in Scopus with equivalent fields in the other databases). Truncation captured word variants (e.g., sport* for sport, sports, sporting; wearable* for wearable, wearables). The exact Boolean string was:

("wearable" OR "inertial sensor*" OR "IMU" OR "accelerometer*" OR "EMG" OR "EEG" OR "triboelectric" OR "smart textile*" OR "computer vision") AND ("human activity recognition" OR "action recognition" OR "activity classification" OR "motion recognition" OR "pose estimation") AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "neural network*" OR "CNN" OR "LSTM" OR "transformer") AND ("sport*" OR "athlete*" OR "exercise" OR "physical activit*" OR "training")*

The string was piloted and refined iteratively: an initial broad string returned a large volume of clinical and smart-home records, so the sport/physical-activity cluster and the recognition cluster were tightened to improve precision while preserving recall for sport-relevant work.

Database and information sources

The primary database was Scopus, complemented by PubMed and ScienceDirect to broaden coverage across engineering and health literatures. The bibliographic export used for screening and synthesis was the Scopus metadata file, which served as the authoritative record set for all counts reported below. The search was executed in 2026 and restricted to the 2021–2026 window to reflect the current generation of AI and wearable technology.

Eligibility criteria

Inclusion and exclusion criteria were specified a priori (Table 1). Records had to be peer-reviewed articles or reviews, published in English between 2021 and 2026, that reported an AI-based recognition or monitoring model applied to wearable or vision data in a sport, exercise, or physical-activity context, with full text available.

Table 1. Inclusion and exclusion criteria.

Criterion	Inclusion	Exclusion
Language	English	Non-English
Document type	Article, Review	Conference paper, erratum, retracted item, book/chapter, note, letter
Publication period	2021–2026	Before 2021

Population / context	Sport, exercise, athlete, or physical-activity setting	Smart-home, elderly-care, clinical-only, surveillance, or classroom contexts
Intervention/interest	Wearable or vision sensing + AI/ML for activity/action recognition or monitoring	Sensor fabrication without AI-based sport recognition; no recognition/monitoring outcome
Outcome	Recognition/classification performance or monitoring outcome	Wrong outcome (e.g., emotion, body temperature only)
Accessibility	Full text available	Abstract only / inaccessible

Study selection process

Selection proceeded in three stages. First, duplicate records were removed using normalised title and DOI matching. Second, titles and abstracts were screened against the eligibility criteria to exclude off-topic and ineligible document types. Third, full texts of the remaining reports were assessed for eligibility, with reasons recorded for each exclusion. The process and counts are reported in the PRISMA 2020 flow diagram (Figure 1).

Quality assessment

Methodological quality was appraised with the Mixed Methods Appraisal Tool (MMAT), version 2018 (Hong et al., 2018), which accommodates the heterogeneous quantitative and mixed designs expected in this literature. For each study, the design category was first classified, and the corresponding five MMAT criteria were rated Yes (1), Can't tell/Partial (0.5), or No (0). One included report was a narrative review; because MMAT does not cover reviews, it was appraised with the equivalent JBI critical-appraisal checklist and flagged accordingly. Consistent with MMAT developer guidance, no study was excluded on quality score alone; studies scoring below 60% were retained but flagged as lower methodological confidence. Appraisal was conducted by the review team; as a single-team appraisal, a formal inter-rater kappa was not computed. Because appraisal relied substantially on abstracts and available full texts, scores should be read as indicative. A per-study summary appears in Table 2.

Table 2. MMAT/JBI quality-appraisal summary of included studies (Q1–Q5 rated 1 / 0.5 / 0).

Author(s), Year	Study design	Q1	Q2	Q3	Q4	Q5	Total	Category
Zhang et al. (2026)	Quantitative descriptive	1	1	0.5	1	0.5	4	High
Chen & Zhang (2026)	Narrative review (JBI)	-	-	-	-	-	-	High (JBI)
Sigcha et al. (2026)	Quantitative descriptive	1	1	1	1	1	5	High
Sun et al. (2024)	Quantitative descriptive	1	1	0.5	1	0.5	4	High
Jin et al. (2025)	Quantitative descriptive	1	1	1	1	0.5	4.5	High
Alonazi et al. (2026)	Quantitative descriptive	1	1	0.5	1	0.5	4	High
Zhao et al. (2023)	Quantitative descriptive	1	0.5	0.5	1	0.5	3.5	Medium
Zohirov et al. (2025)	Quantitative descriptive	1	1	1	1	0.5	4.5	High
Duarte et al. (2025)	Quantitative descriptive	1	1	0.5	1	0.5	4	High
Aydin et al. (2026)	Quantitative non-randomized	1	1	1	1	0.5	4.5	High
Yuan et al. (2026)	Quantitative descriptive	1	1	0.5	1	0.5	4	High
Xi et al. (2026)	Quantitative descriptive	1	1	0.5	1	0.5	4	High
Burenbatu et al. (2025)	Quantitative descriptive	1	1	0.5	1	0.5	4	High
Mekruksavanich et al. (2024)	Quantitative descriptive	1	1	1	1	0.5	4.5	High
Zhi et al. (2026)	Quantitative descriptive	1	1	0.5	0.5	0.5	3.5	Medium
Wang et al. (2025)	Quantitative descriptive	1	0.5	0.5	1	0.5	3.5	Medium
Skublewska-Paszkowska et al. (2023)	Quantitative descriptive	1	1	1	1	0.5	4.5	High
Mekruksavanich et al. (2022)	Quantitative descriptive	1	1	0.5	1	0.5	4	High
Rattanasateankij et al. (2025)	Mixed methods	1	0.5	0.5	1	0.5	3.5	Medium
Wieland et al. (2025)	Quantitative descriptive	1	1	1	1	0.5	4.5	High

Data extraction procedure

A structured form captured, for each study, the authors, year, source, study design, sensing modality, AI/ML model family, application theme, and principal findings. Extraction was performed directly from the source records and full texts; where a field was not reported in the source export, this was recorded rather than inferred.

Bibliometric and descriptive analysis

Descriptive analyses summarised the annual publication output of the retrieved corpus and the distribution of sensing modalities and model families across the included studies. These analyses were used to characterise the field and to contextualise the thematic synthesis rather than to draw inferential conclusions.

Data analysis and synthesis

Findings were combined using thematic synthesis (Thomas & Harden, 2008). Study findings were coded, grouped into descriptive themes aligned with the three research questions, and developed into analytical themes addressing sensing design, modelling approach, and application and deployment. Synthesis emphasised agreements, contradictions, and nuances across studies rather than listing them individually.

Reporting and documentation

The review is reported in accordance with the PRISMA 2020 checklist (Page et al., 2021). All record counts derive from the authoritative bibliographic export, and the selection funnel is documented in Figure 1.

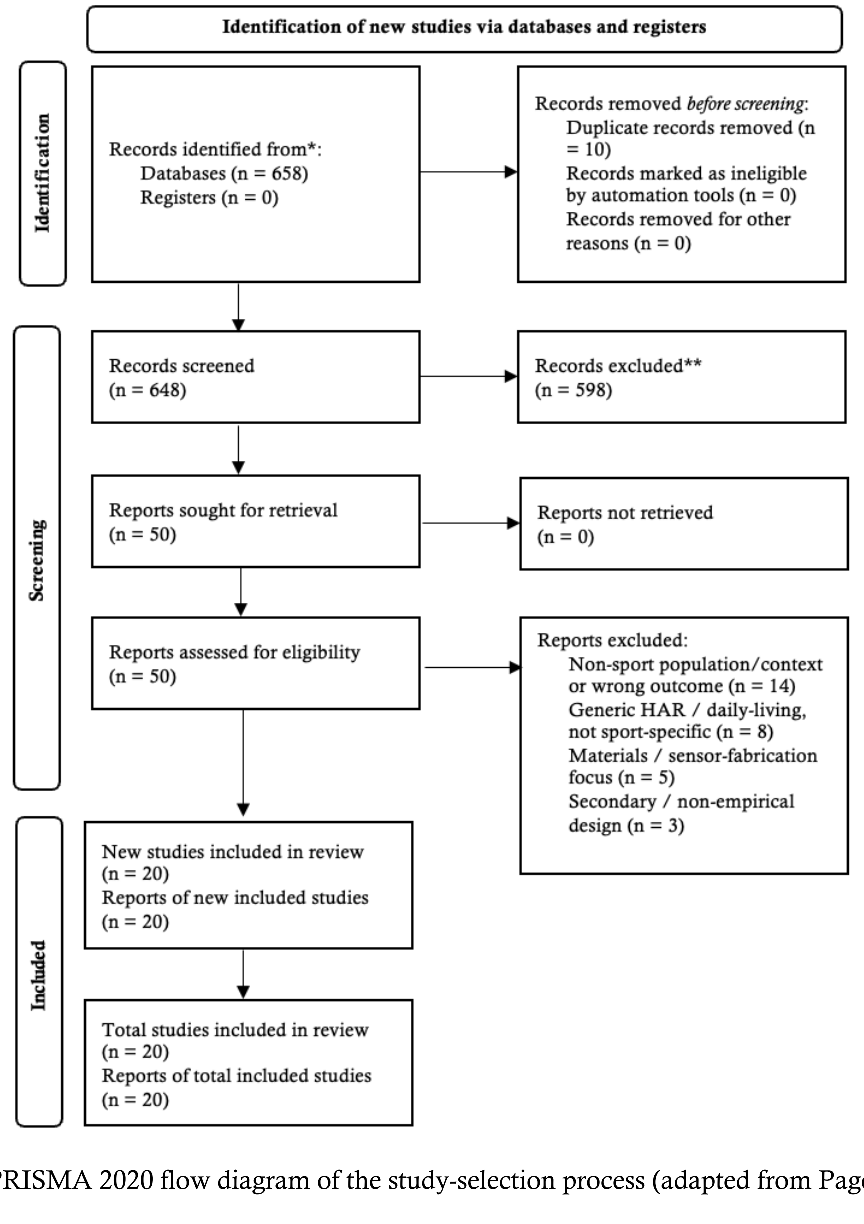

Figure 1. PRISMA 2020 flow diagram of the study-selection process (adapted from Page et al., 2021).

Results and Discussions

Study-selection results

The structured search of Scopus, PubMed, and ScienceDirect identified 658 records. Removing 10 duplicates left 648 records for title-and-abstract screening, at which stage 598 records were excluded as ineligible document types or as outside the sport-specific AI-recognition scope. Fifty full-text reports were assessed for eligibility, of

Journal of Counseling, Education and Society
Vol. 7, No. 1, 2026, pp. 553-566

which 30 were excluded: 14 for a non-sport population/context or wrong outcome, 8 as generic daily-living HAR, 5 for a material - or sensor-fabrication focus without sport-specific AI recognition, and 3 as secondary or non-empirical designs. Twenty studies met all criteria and were included in the synthesis (Figure 1). The included studies span 2022–2026, confirming that this is a recent and fast-moving evidence base.

Descriptive characteristics

Table 3 summarises the included studies, and Table 4 classifies them by application theme, sensing modality, model family, and outcome. The corpus retrieved by the search grew steadily across the review window, from 51 records in 2021 to 193 in 2026 (Figure 2), mirroring the broader acceleration of AI and wearable research in sport.

Table 3. Summary of included studies.

Title	Author(s), Year	Source	Key findings
High-sensitivity flexible triboelectric nanogenerator sensor based on recycled PA66 for the monitoring of soccer player lower limb training	Zhang et al. (2026)	Materials Research Bulletin	High-sensitivity self-powered triboelectric sensor (up to 32.36 V/N; 91 ms response) enables accurate real-time monitoring of soccer players' lower-limb training loads.
Energy-Efficient and Self-Powered Smart Sensors for Real-Time Basketball Training-Load Monitoring: Mechanisms, Applications, and Future Directions	Chen & Zhang (2026)	International Journal of Energy Research	Reviews self-powered sensing and edge intelligence for continuous basketball training-load monitoring; energy efficiency and multisensor fusion identified as key enablers.
Robust Assessment of Free-Living Physical Behaviors and Activity Intensity Using Dual-Wearable Multitask Learning: Development and Evaluation Study From the Multicenter WEALTH Project	Sigcha et al. (2026)	JMIR mHealth and uHealth	Dual-wearable multitask learning classifies seven physical-behaviour categories and three intensity levels robustly under free-living conditions, outperforming lab-trained single-sensor baselines.
EEG-powered cerebral transformer for athletic performance	Sun et al. (2024)	Frontiers in Neurorobotics	A multimodal EEG-based cerebral Transformer captures athletes' neural states, improving the accuracy and real-time performance of sports-performance analysis over unimodal methods.
Wearable sensing for badminton stroke recognition with one-dimensional convolutional neural network	Jin et al. (2025)	Scientific Reports	A two-IMU wearable network with a one-dimensional CNN accurately classifies badminton strokes, providing a portable alternative to video- and optical-based technique analysis.
Attention-Based Multimodal Framework for Athlete-Performance Analysis and Rehabilitation Monitoring Using Vision and Wearable Sensors	Alonazi et al. (2026)	Bioengineering	An attention-based multimodal framework fusing vision and wearable signals supports movement-pattern analysis, injury prevention, and rehabilitation monitoring in sport.
Simulation of sports training recognition system based on internet of things video behavior analysis	Zhao et al. (2023)	Preventive Medicine	An IoT video-behaviour-analysis system recognises sports-training actions, enabling more objective evaluation of the physical-training process.
EMG-Based Recognition of Lower Limb Movements in Athletes: A Comparative Study of Classification Techniques	Zohirov et al. (2025)	Signals	Time- and frequency-domain EMG features with comparative classifiers accurately recognise lower-limb movements in 25 athletes and identify the best-performing feature-classifier combinations.
Intelligent Sports Weights	Duarte et al. (2025)	Sensors	A low-power embedded CNN coupled to weights classifies exercise-trajectory correctness in real time, enabling unsupervised weightlifting feedback that may reduce injury risk.
A Robust Deep Learning Framework for Skill Level Discrimination in Tennis Strokes Using Bilateral IMU Measurements	Aydin et al. (2026)	Sensors	A hierarchical CNN-BiLSTM on bilateral IMU data discriminates elite from amateur players across 4,594 strokes, supporting objective skill assessment and talent identification.

Title	Author(s), Year	Source	Key findings
An IoT-enabled CRNN framework for secure wearable sensor-based activity recognition in physical education	Yuan et al. (2026)	Scientific Reports	An IoT-enabled CRNN models the spatiotemporal dependencies of wearable-sensor signals to recognise complex activities in physical-education settings, with explicit attention to secure data handling.
Multimodal human action recognition and personalized sports health promotion: a deep learning framework integrating wearable sensor fusion	Xi et al. (2026)	Frontiers in Neurorobotics	A Transformer-GCN framework synchronising physiological and behavioural signals improves sports action recognition and drives personalized health-promotion recommendations.
Real-time monitoring of lower limb movement resistance based on deep learning	Burenbatu et al. (2025)	Alexandria Engineering Journal	MMTL-Net jointly predicts resistance levels and recognises activities in real time with high accuracy and computational efficiency for rehabilitation and athletic-training use.
Recognition of sports and daily activities through deep learning and convolutional block attention	Mekruksavanich et al. (2024)	PeerJ Computer Science	A hybrid CNN-BiGRU-CBAM model improves recognition of sports and daily activities by jointly exploiting spatial, temporal, and attention mechanisms.
High-performance pressure sensors based on twisted-structure graphene fibers for motion training	Zhi et al. (2026)	Chemical Engineering Journal	High-performance twisted-graphene-fibre pressure sensors deliver wide-range, highly sensitive signals suitable for wearable motion-training monitoring.
Analysis of Mechanical Damage in Dance Training Under Artificial Intelligence Behavior Constraints	Wang et al. (2025)	International Journal of High Speed Electronics and Systems	AI behaviour-constraint modelling links movement patterns to injury risk, supporting the analysis and prevention of mechanical injuries in dance training.
Temporal Pattern Attention for Multivariate Time Series of Tennis Strokes Classification	Skublewska-Paszkowska et al. (2023)	Sensors	Temporal-pattern-attention networks classify four basic tennis strokes from 3D data and demonstrate how the content of the input signal affects classification accuracy.
Multimodal Wearable Sensing for Sport-Related Activity Recognition Using Deep Learning Networks	Mekruksavanich et al. (2022)	Journal of Advances in Information Technology	A multimodal wearable deep-learning framework recognises fine-grained sport-related activities that simple, single-modality HAR systems cannot distinguish.
Training Stress, Sleep Behaviour, and Recovery Self-Regulation in Elite Female Boxers: A Behavioural Pattern Analysis Using Data-Driven Methods	Rattanasateankij et al. (2025)	Journal of Mind and Behavior	A data-driven framework integrating physiological and behavioural signals classifies readiness patterns in elite female boxers, improving on subjective coach observation. (DOI not available in source file.)
Enhancing Sensor-Based Human Activity Recognition With Multiresolution Wavelet-Attention	Wieland et al. (2025)	IEEE Sensors Journal	A pretrained multiresolution wavelet-attention block improves sensor-based HAR across eight benchmark datasets spanning sports and other domains.

Table 4. Classification of included studies by design, theme, sensing modality, and model family.

Author(s), Year	Design	Theme / focus	Sensing modality	AI/ML model
Zhang et al. (2026)	Quantitative descriptive	Sensor development & training-load monitoring	Triboelectric flexible sensor	Sensor + ML motion classification
Chen & Zhang (2026)	Narrative review (JBI)	Basketball training-load monitoring	Self-powered / triboelectric (review)	Edge / on-device intelligence
Sigcha et al. (2026)	Quantitative descriptive	Free-living physical-behaviour & intensity classification	Dual accelerometers	Multitask ML/DL

Author(s), Year	Design	Theme / focus	Sensing modality	AI/ML model
Sun et al. (2024)	Quantitative descriptive	Athlete neural-state & performance monitoring	Wearable EEG (multimodal)	Transformer
Jin et al. (2025)	Quantitative descriptive	Badminton stroke recognition	Dual IMU (wrist)	1D-CNN
Alonazi et al. (2026)	Quantitative descriptive	Athlete-performance & rehabilitation monitoring	Vision + wearable (multimodal)	Attention-based deep learning
Zhao et al. (2023)	Quantitative descriptive	Sports-training action recognition	IoT video / vision	Deep-learning behaviour analysis
Zohirov et al. (2025)	Quantitative descriptive	Lower-limb movement recognition	Surface EMG	Comparative classical ML
Duarte et al. (2025)	Quantitative descriptive	Weightlifting technique & injury prevention	Embedded inertial (on-weights)	CNN (on-chip)
Aydin et al. (2026)	Quantitative non-randomized	Tennis skill-level discrimination	Bilateral IMU	CNN-BiLSTM (hierarchical)
Yuan et al. (2026)	Quantitative descriptive	Activity recognition in physical education	Wearable multimodal	CRNN (CNN-RNN)
Xi et al. (2026)	Quantitative descriptive	Action recognition & personalized health promotion	Multimodal wearable (12-dimensional)	Transformer-GCN hybrid
Burenbatu et al. (2025)	Quantitative descriptive	Training & rehabilitation monitoring	Wearable motion sensing	MobileNetV3 multitask (MMTL-Net)
Mekruksavanich et al. (2024)	Quantitative descriptive	Sports & daily-activity recognition	Accelerometer + physiological trackers	CNN-BiGRU-CBAM
Zhi et al. (2026)	Quantitative descriptive	Sensor development & motion training	Graphene-fibre pressure sensor	Sensor + ML motion recognition
Wang et al. (2025)	Quantitative descriptive	Dance-training injury analysis & prevention	Motion analysis (AI behaviour constraints)	AI behaviour-constraint model
Skublewska-Paszkowska et al. (2023)	Quantitative descriptive	Tennis-stroke classification	3D motion capture (vision)	Temporal Pattern Attention
Mekruksavanich et al. (2022)	Quantitative descriptive	Sport-related activity recognition	Multimodal wearable	Deep S-HAR networks
Rattanasateankij et al. (2025)	Mixed methods	Athlete readiness monitoring	Physiological + behavioural data	Data-driven ML classification
Wieland et al. (2025)	Quantitative descriptive	Sensor-based HAR methodology	Wearable sensors	Wavelet-attention block (MRWA)

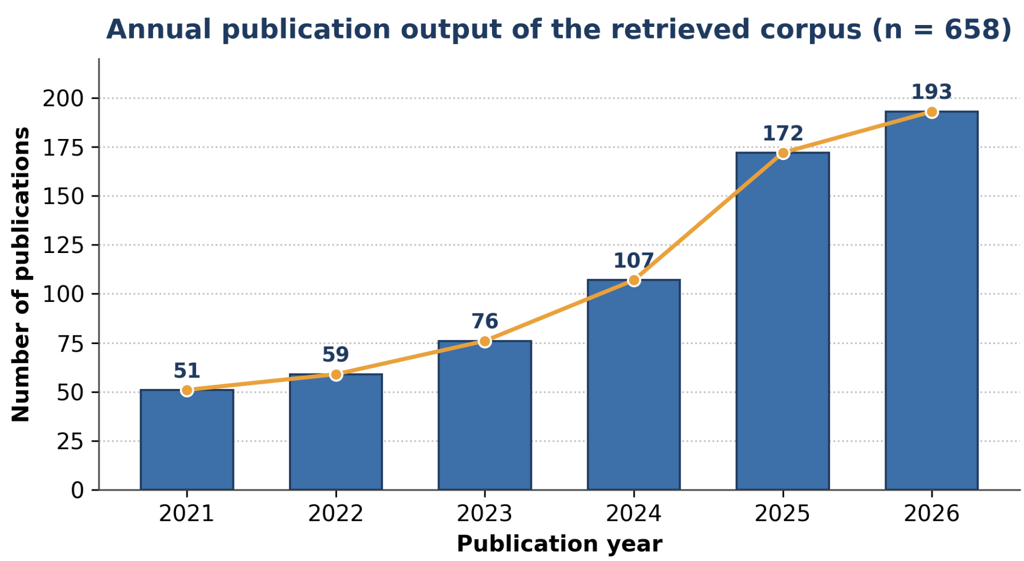

Figure 2. Annual publication output of the retrieved corpus (2021–2026; n = 658).

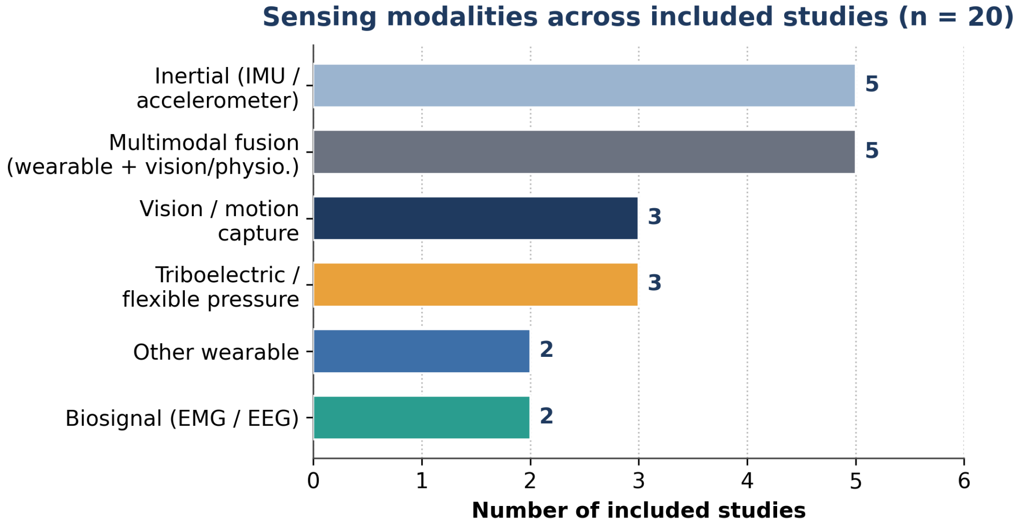

Figure 3. Distribution of sensing modalities across the 20 included studies.

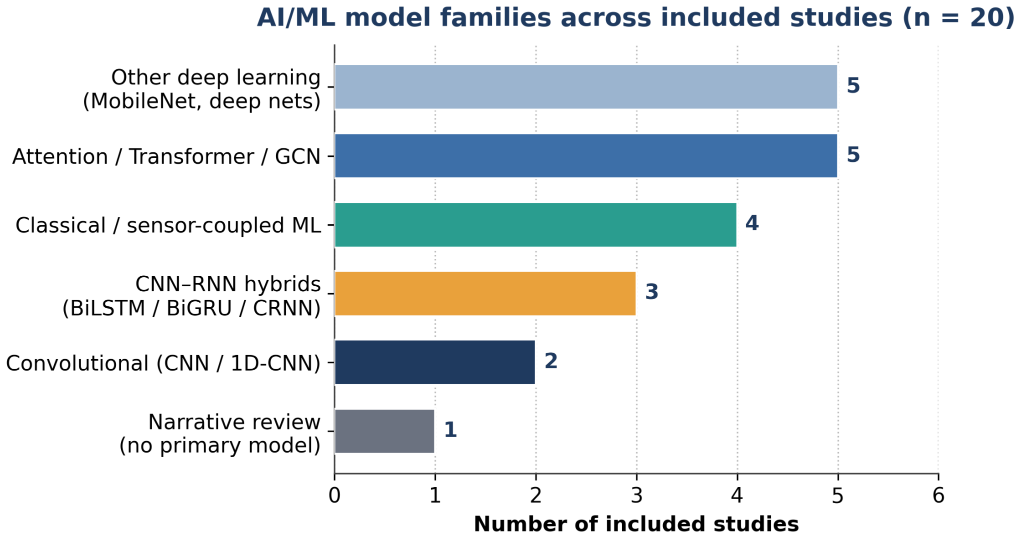

Figure 4. Distribution of AI/ML model families across the 20 included studies.

Thematic synthesis

Findings for RQ1 - sensing modalities and signal types

If we look at the studies that have been included, it is inertial and multimodal sensing that the space of the design is made up of mainly (Figure 3). Inertidal measurement units and accelerometers were by far the most common modality for capturing wrist and limb movement patterns for stroke and activity detection (Aydin et al., 2026; Jin et al., 2025; Mekruksavanich et al., 2024; Sigcha et al., 2026). The second category is based on electrophysiological data with surface electromyography for the classification of lower limb movements in athletes (Zohirov et al., 2025) and for wearable electroencephalography to the athletes' neural states during performance (Sun et al., 2024). The third group of the studies is on self-powered and flexible sensing, which is the frontier of materials science, including triboelectric nanogenerator devices for soccer training and twisted-graphene-fibre pressure sensors for motion training (Zhang et al., 2026; Zhi et al., 2026) as well as one paper discussing the topic of self-powered sensing in basketball load monitoring (Chen & Zhang, 2026).

Another four set of clusters are about vision and motion-capture data, which include tennis-stroke classification and IoT-based sports-training action analysis (Skublewska-Paszkowska et al., 2023; Zhao et al., 2023). The methodologically most ambitious researches, on the other hand, bring together multiple aforementioned streams at once: multimodal frameworks for instance, pair vision with wearer sensors to identify sports performance and rehabilitation (Alonazi et al., 2026); others blend physical and movement signals to detect a sport-related activity (Mekruksavanich et al., 2022; Yuan et al., 2026); one even matches twelve-dimensional physiological and behavioural data for one's individualised health promotion (Xi et al., 2026). A common observation is that the fusion of signals is sought precisely in those domains where single-modality data fails at representing details of sport actions sufficiently, in line with the general idea that a simple sensing cannot fully describe what athletes do (Fujii et al., 2021).

Findings for RQ2 - model families, performance, and validation

The selection of model types seems to be grouped into few different categories (refer to Figure 4). The most prevalent categories included self-supervising and/or attention mechanisms-based architectures. They also incorporated transformers or graph-augmentation features and employed these kinds of models not only in deep learning state estimation but also in multi-modality athlete analysis, tennis-stroke time series data, and benchmark HAR (Alonazi et al. [2026], Skublewska-Paszkowska et al. [2023], Sun et al. [2024], Wieland et al. [2025], Xi et al. [2026]). In contrast, where spatial and temporal features were both important (e.g. in the problem of distinguishing different tennis skills or recognising physical-educational activities), the authors opted to implement Hybrid Networks: CNN-BiLSTM, CNN-BiGRU with attention, and CRNN (Aydin et al. [2026], Mekruksavanich et al. [2024], Yuan et al. [2026]). On one hand, purely convolutional models, which are a type of one-dimensional or on-chip CNNs, have been used for a range of recognition tasks on portable and embedded devices (e.g. badminton and weightlifting), (Duarte et al. [2025], Jin et al. [2025]). On the other hand, lightweight and efficient backbones like MobileNetV3 have allowed real-time multitask monitoring (Burenbatu et al. [2025]). Classical machine learning classifiers have been still helpful for biosignal and readiness classifications (Rattanasateankij et al. [2025], Zohirov et al. [2025]).

Overall, the reported performance was mostly excellent, and a number of the papers mentioned that the use of combination and attention modules gave rise to significant performance gains as these systems were tested for complex, or contextual actions. (Mekruksavanich et al. [2022, 2024], Wieland et al. [2025]) Despite this, there was variation in validation approaches. Several works were able to test their models across different public benchmarks and real-world user studies, thus providing evidence that their models could generalise well, (Sigcha et al. [2026], Wieland et al. [2025]). On the other side of the coin, other works have limited their validations to small or laboratory-controlled samples, and this has hindered their external validity- something that has also been found in wearables literature (Sun et al. [2022]). Furthermore, there were quite a number of instances where the details about participants, data collection and measurement of outcomes were either missing or of poor quality. Hence it's not surprising to see the variety of MMAT scores in Table 2.

Findings for RQ3 - applications, challenges, and directions

Application areas basically consist of technique and skill analysis (Aydin et al., 2026; Skublewska-Paszkowska et al., 2023), training-load and activity monitoring (Zhang et al., 2026), injury prevention and rehabilitation (Alonazi et al., 2026), and the personal health promotion and readiness (Rattanasateankij et al., 2025). These aspects are in harmony with broader recommendations for the athlete-centred coaching and rehabilitation with wearable AI (Madrigal-Cerezo et al., 2026). The ongoing methodological issues include the ability to generalise beyond the use of controlled data sets, the choice between efficiency and accuracy on-device deployment, how to perform principled combinations in multimodal data sources and the ability to replicate results. As an answer to RQ3, it is expected that the field will develop from recognition of concepts to monitoring tools that are both deployable and personal, which however will demand standardised data collection and report formats, resource-conscious edge models as well as validation in a training environment.

Comparative and critical analysis

The majority of the papers methodologically fall into quantitative, descriptive categories of work where a model's results were developed and tested either from their own or benchmark data; genuine comparative and hypothesis-testing methodologies and prospective filed trials are exceptions rather than the norm. It is quite interesting to observe that with the years, a clear transition happened: earlier works relied on using convolutional and recurrent neural network frameworks, whereas more recently, attention modules, Transformer architecture, graph-based frameworks and multimodal fusion have become the main tools. Wearable and self-powered sensors are found predominantly in recent work, showing that the hardware innovation and modelling are starting to happen side by side. Less often employed are methods such as strict cross-subject/validation across different sites, quantifying uncertainties, and addressing the explainability gap related issues which practitioners trust and which are concerns in sports-medicine AI too (Baghbani et al., 2025; Smaranda et al., 2024).

Discussion

Interpretation

The synthesis indicates that AI-based recognition of sport activity and action has matured into a coherent field with characteristic sensing-and-model configurations, yet one whose evidential strength is uneven. The recurrent finding that multimodal fusion and attention mechanisms are reserved for the hardest recognition problems suggests that model complexity is being matched to task difficulty rather than adopted indiscriminately.

Theoretical implications

The results extend general HAR theory (Kaur et al., 2024) by showing that sport imposes distinctive demands-speed, variability, and kinetic-chain dependence-that reshape both sensing and modelling choices. This supports treating sport-specific recognition as a sub-field with its own design principles rather than a straightforward application of generic HAR.

Practical implications

For coaches and sports scientists, the sensing-to-model map clarifies that inertial wearables with convolutional or hybrid models suffice for many technique and load tasks, while multimodal, attention-based systems are warranted for fine-grained or physiologically informed monitoring (Morouço et al., 2024; Sigcha et al., 2026). For engineers, the demand for on-device, energy-aware recognition (Burenbatu et al., 2025; Chen & Zhang, 2026) should guide model and hardware co-design.

Comparison with prior reviews

Unlike reviews centred on clinical wearables, biosensors, or materials (Alqaderi et al., 2025; Li et al., 2025; Miao et al., 2023; Yang et al., 2025), this review foregrounds recognition of sport-specific activity and action, complementing rather than duplicating that literature. It also connects engineering advances to sports-science applications that biosensor-focused reviews leave implicit (Wang et al., 2023).

Contradictions

The literature disagrees on how far laboratory-trained models transfer to free-living sport: some studies report robust free-living performance (Sigcha et al., 2026), while others implicitly concede limited transfer through narrow evaluation. Differences in datasets, sensor placement, and reporting likely explain much of this divergence, underscoring the need for common benchmarks.

Research gaps

Three gaps stand out: the scarcity of cross-subject, cross-site, and prospective field validation; the absence of standardised datasets, metrics, and reporting for sport-specific recognition; and the limited attention to explainability and uncertainty that practitioner adoption requires.

Limitations of this review

First, the authoritative export was Scopus-based, so despite searching additional databases the retrievable corpus may under-represent some venues. Second, quality appraisal relied substantially on abstracts and available texts, so ratings are indicative. Third, the review synthesised heterogeneous outcomes narratively rather than meta-analytically, because datasets and metrics were not comparable.

Future research agenda

Future work should (i) build and share standardised, multi-site sport-recognition datasets with common evaluation protocols; (ii) develop energy-aware, edge-deployable models validated prospectively in training and competition; and (iii) integrate explainability, uncertainty quantification, and athlete-centred outcomes so that recognition translates into trusted coaching and health decisions (Madrigal-Cerezo et al., 2026; Takáč et al., 2025).

Summary answers

In brief, RQ1 is answered by a layered sensing space with inertial and multimodal signals at its centre; RQ2 by the dominance of attention-based and hybrid deep models whose strong performance is tempered by uneven validation; and RQ3 by a clear but incomplete transition toward deployable, personalised, athlete-centred monitoring.

Conclusions

Based on the guidelines provided, this review combined 20 recent studies on wearable and vision-based AI for human activity and action recognition during sport and physical activity. It is stated that using inertial and multimodal sensors and employing attention-based and hybrid convolutional-recurrent models, the sport actions with fine-grained details can be recognised with very accurate results (RQ1, RQ2). Furthermore, the area of research goes from a scenario of laboratory benchmarks to free-living, edge-deployable, and personal monitoring (RQ3). The main outcome is an integrated sensing-to-model map and a critical appraisal which together explain how technical choices should be determined based on the objectives of the monitoring. For the practitioners, from this review, one is given the guidelines on how a sensor and a model are chosen in a particular case in coaching, load management and rehabilitation. This review, however, has several drawbacks in terms of Scopus-anchored corpus, abstract-based appraisal and narrative synthesis. The future development of field would depend on having standardised datasets and reporting, energy-aware edge models, and a prospective, athlete-centred validation.

Acknowledgments

Acknowledge anyone who has helped you with the study, including: Researchers who supplied materials, reagents, or computer programs; anyone who helped with the writing or English, or offered critical comments about the content, or anyone who provided technical help. State why people have been acknowledged and ask their permission. Acknowledge sources of funding, including any grant or reference numbers. Please avoid apologize for doing a poor job of presenting the manuscript.

References

Ahmed, A., Hasan, E.U., & Hasseni S.-e.-i. (2025). Smart and Sustainable: A Global Review of Smart Textiles, IoT Integration, and Human-Centric Design. Sensors, 25(23). https://doi.org/10.3390/s25237267

Alhaddad, A.Y., Aly, H., Gad, H., Al-Ali, A., Sadasivuni, K.K., Cabibihan J.-j., & Malik, R.A. (2022). Sense and Learn: Recent Advances in Wearable Sensing and Machine Learning for Blood Glucose Monitoring and Trend-Detection. Frontiers in Bioengineering and Biotechnology, 10. https://doi.org/10.3389/fbioe.2022.876672

Alonazi, M., Abro, I.A., Abdelhaq, M., Alsaqour, R., Jalal, A., & Liu, H. (2026). Attention-Based Multimodal Framework for Athlete-Performance Analysis and Rehabilitation Monitoring Using Vision and Wearable Sensors. Bioengineering, 13(7). https://doi.org/10.3390/bioengineering13070718

Alqaderi, A.I.J., & Ramakrishnan, N. (2025). Carbon-based flexible strain sensors: Recent advances and performance insights in human motion detection. Chemical Engineering Journal, 513. https://doi.org/10.1016/j.cej.2025.162609

Aydin, E.H., & Aydemir, O. (2026). A Robust Deep Learning Framework for Skill Level Discrimination in Tennis Strokes Using Bilateral IMU Measurements. Sensors, 26(10). https://doi.org/10.3390/s26103273

Baghbani, S., Mehrabi, Y., Movahedinia, M., Babaeinejad, E., Joshaghanian, M., Amiri, S., & Shahrezaee, M. (2025). The revolutionary impact of artificial intelligence in orthopedics: comprehensive review of current benefits and challenges. Journal of Robotic Surgery, 19(1). https://doi.org/10.1007/s11701-025-02561-5

Burenbatu, Liu, Y., & Lyu, T. (2025). Real-time monitoring of lower limb movement resistance based on deep learning. Alexandria Engineering Journal, 111, 136–147. https://doi.org/10.1016/j.aej.2024.09.031

Caso, S., Furley, P., & Jordet, G. (2026). Using video-notational analysis to examine soccer players' behaviours. International Journal of Sport and Exercise Psychology, 24(4), 739–759. https://doi.org/10.1080/1612197X.2025.2477165

Chen, D., & Zhang, H. (2026). Energy-Efficient and Self-Powered Smart Sensors for Real-Time Basketball Training-Load Monitoring: Mechanisms, Applications, and Future Directions. International Journal of Energy Research, 2026(1). https://doi.org/10.1155/er/5311498

Dong, K., Tianmei, L., Sheng, F., & Peng, X. (2024). Advances in smart textiles oriented to personalized healthcare; [面向个性化健康医疗的智能纺织品研究进展]. Fangzhi Xuebao/Journal of Textile Research, 45(1), 240–249. https://doi.org/10.13475/j.fzxb.20221106002

Duarte, O.D.S., Jacinto, G., Véstias, M., & Policarpo Duarte, R. (2025). Intelligent Sports Weights. Sensors, 25(12). https://doi.org/10.3390/s25123808

Fujii, K. (2021). Data-driven analysis for understanding team sports behaviors. Journal of Robotics and Mechatronics, 33(3), 505–514. https://doi.org/10.20965/jrm.2021.p0505

Harris, E.J., Khoo I.-h., & Demircan, E. (2022). A Survey of Human Gait-Based Artificial Intelligence Applications. Frontiers in Robotics and AI, 8. https://doi.org/10.3389/frobt.2021.749274

Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., Gagnon, M.-P., Griffiths, F., Nicolau, B., O'Cathain, A., Rousseau, M.-C., & Vedel, I. (2018). Mixed Methods Appraisal Tool (MMAT), version 2018. Registration of Copyright (#1148552), Canadian Intellectual Property Office, Industry Canada.

Jacobs, I., Lowe, A., Garcia, L., & Zhang, H. (2026). Advancing physical activity monitoring through bioimpedance measurement: a review. Progress in Biomedical Engineering, 8(2). https://doi.org/10.1088/2516-1091/ae3671

Jin, G., & Li, X. (2025). Wearable sensing for badminton stroke recognition with one-dimensional convolutional neural network. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-25158-2

Kaur, H., Rani, V., & Kumar, M. (2024). Human activity recognition: A comprehensive review. Expert Systems, 41(11). https://doi.org/10.1111/exsy.13680

Li, L., Luo, Y., Wang, R., Huo, D., Song, B., Hao, Y., & Zhou, Y. (2025). Optical Fiber Sensing Technology for Sports Monitoring: A Comprehensive Review. Photonics, 12(10). https://doi.org/10.3390/photonics12100963

Madrigal-Cerezo, R., Domínguez-Sanz, N., & Martín-Rodríguez, A. (2026). Wearable Biosensing and Machine Learning for Data-Driven Training and Coaching Support. Biosensors, 16(2). https://doi.org/10.3390/bios16020097

Mekruksavanich, S., & Jitpattanakul, A. (2022). Multimodal Wearable Sensing for Sport-Related Activity Recognition Using Deep Learning Networks. Journal of Advances in Information Technology, 13(2), 132–138. https://doi.org/10.12720/jait.13.2.132-138

Mekruksavanich, S., Phaphan, W., Hnoohom, N., & Jitpattanakul, A. (2024). Recognition of sports and daily activities through deep learning and convolutional block attention. PeerJ Computer Science, 10. https://doi.org/10.7717/PEERJ-CS.2100

Miao, F., Wu, D., Liu, Z., Zhang, R., Tang, M., & Li, Y. (2023). Wearable sensing, big data technology for cardiovascular healthcare: current status and future prospective. Chinese Medical Journal, 136(9), 1015–1025. https://doi.org/10.1097/CM9.0000000000002117

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. PLoS Medicine, 6(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Morouço, P. (2024). Wearable Technology and Its Influence on Motor Development and Biomechanical Analysis. International Journal of Environmental Research and Public Health, 21(9). https://doi.org/10.3390/ijerph21091126

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Rattanasateankij, W., Senakham, T., Punthipayanon, S., Puttasimma, T., & Senakham, N. (2025). Training Stress, Sleep Behaviour, and Recovery Self-Regulation in Elite Female Boxers: A Behavioural Pattern Analysis Using Data-Driven Methods. Journal of Mind and Behavior, 46(3), 109–129.

Sigcha, L., Swenne, A., Hayes, G., Kuhnova, J., Cimler, R., Elavsky, S., Vetrovsky, T., Fezeu Kamedjie, L., Bouchan, J., Oppert J.-m., Harrington, J., Cardon, G., Hebestreit, A., Donnelly, A., Van de Ven, P., & Buck, C. (2026). Robust Assessment of Free-Living Physical Behaviors and Activity Intensity Using Dual-Wearable Multitask Learning: Development and Evaluation Study From the Multicenter WEALTH Project. JMIR mHealth and uHealth, 14, e94302. https://doi.org/10.2196/94302

Skublewska-Paszkowska, M., & Powroznik, P. (2023). Temporal Pattern Attention for Multivariate Time Series of Tennis Strokes Classification. Sensors, 23(5). https://doi.org/10.3390/s23052422

Smaranda, A.M., Drăgoiu, T.S., Caramoci, A., Afetelor, A.A., Ionescu, A.M., & Bădărău, I.A. (2024). Artificial Intelligence in Sports Medicine: Reshaping Electrocardiogram Analysis for Athlete Safety-A Narrative Review. Sports, 12(6). https://doi.org/10.3390/sports12060144

Sun, Q. (2024). EEG-powered cerebral transformer for athletic performance. Frontiers in Neurorobotics, 18. https://doi.org/10.3389/fnbot.2024.1499734

Sun, W., Guo, Z., Yang, Z., Wu, Y., Lan, W., Liao, Y., Wu, X., & Liu, Y. (2022). A Review of Recent Advances in Vital Signals Monitoring of Sports and Health via Flexible Wearable Sensors. Sensors, 22(20). https://doi.org/10.3390/s22207784

Takáč, P. (2025). Sports Injury Rehabilitation: A Narrative Review of Emerging Technologies and Biopsychosocial Approaches. Applied Sciences (Switzerland), 15(17). https://doi.org/10.3390/app15179788

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. BMC Medical Research Methodology, 8, 45. https://doi.org/10.1186/1471-2288-8-45

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British Journal of Management, 14(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Wang, C., He, T., Zhou, H., Zhang, Z., & Lee, C. (2023). Artificial intelligence enhanced sensors - enabling technologies to next-generation healthcare and biomedical platform. Bioelectronic Medicine, 9(1). https://doi.org/10.1186/s42234-023-00118-1

Wang, J., & Hao, J. (2025). Analysis of Mechanical Damage in Dance Training Under Artificial Intelligence Behavior Constraints. International Journal of High Speed Electronics and Systems, 34(2). https://doi.org/10.1142/S012915642440086X

Journal of Counseling, Education and Society
Vol. 7, No. 1, 2026, pp. 553-566

Wieland, C., & Pankratius, V. (2025). Enhancing Sensor-Based Human Activity Recognition With Multiresolution Wavelet-Attention. IEEE Sensors Journal, 25(14), 26920–26930. https://doi.org/10.1109/JSEN.2025.3571572

Xi, Y., Huang, T., & Yang, Z. (2026). Multimodal human action recognition and personalized sports health promotion: a deep learning framework integrating wearable sensor fusion. Frontiers in Neurorobotics, 20. https://doi.org/10.3389/fnbot.2026.1785114

Yang, H., & Yan, S. (2025). A comprehensive review of electrochemical lactate biosensors: Principles, innovations, and future perspectives. International Journal of Electrochemical Science, 20(10). https://doi.org/10.1016/j.ijoes.2025.101132

Yuan, J., Zhang, Y., & Chen, B. (2026). An IoT-enabled CRNN framework for secure wearable sensor-based activity recognition in physical education. Scientific Reports, 16(1). https://doi.org/10.1038/s41598-026-42082-1

Zhang, J., Li, Q., Li, J., Zhang, Y., Shen, Y., Zeng, L., Sun, G., & Xiao, C. (2026). High-sensitivity flexible triboelectric nanogenerator sensor based on recycled PA66 for the monitoring of soccer player lower limb training. Materials Research Bulletin, 194. https://doi.org/10.1016/j.materresbull.2025.113774

Zhao, J., Zhao, Y., & Wang, H. (2023). Simulation of sports training recognition system based on internet of things video behavior analysis. Preventive Medicine, 173. https://doi.org/10.1016/j.ypmed.2023.107611

Zhi, Y., Qin, Y., Zhu, J., Zhang, H., Zhang, Y., Li, Q., Li, W., & Zhang, H. (2026). High-performance pressure sensors based on twisted-structure graphene fibers for motion training. Chemical Engineering Journal, 545. https://doi.org/10.1016/j.cej.2026.179567

Zhou, J., Zhang, Q., Zhang, M., Aikebaier, S., Zhu, X., & Zhou, X. (2026). Flexible wearable medical devices: from material innovations and data processing to intelligent healthcare applications. Journal of Advanced Research, 83, 1195–1218. https://doi.org/10.1016/j.jare.2025.08.036

Zohirov, K., Makhmudjanov, S., Ruziboev, F., Berdiev, G., Temirov, M., Sherboboyeva, G., Achilova, F., Pardayeva, G., & Boykobilov, S. (2025). EMG-Based Recognition of Lower Limb Movements in Athletes: A Comparative Study of Classification Techniques. Signals, 6(3). https://doi.org/10.3390/signals6030045