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A SYSTEMATIC REVIEW

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Artificial Intelligence in Physical Education: A Systematic Review of Personalized Learning, Assessment, and Performance Analytics

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ABSTRACT

The purpose of the study. This systematic review examines how artificial intelligence (AI) is applied to personalized learning, assessment, and performance analytics in physical education (PE) across K–12 and higher-education settings, with the aim of synthesizing empirical evidence, identifying patterns of implementation, and proposing evidence-based directions for future research and practice.

Materials and methods. A systematic review was conducted following the PRISMA 2020 guidelines. Seven electronic databases (Web of Science, Scopus, EBSCOhost, PubMed, ACM Digital Library, Taylor & Francis Online, and Wiley Online Library) were searched from January 2014 to December 2025, using a reproducible Boolean search string centered on "artificial intelligence," "machine learning," "physical education," and related terms. Inclusion criteria covered empirical studies (experimental, quasi-experimental, case studies, and mixed-methods) that reported AI applications in PE focusing on personalized instruction, automated assessment, or performance analytics. Two reviewers independently screened titles, abstracts, and full texts; extracted data; and appraised quality using the Mixed-Methods Appraisal Tool (MMAT).

Results. A total of 87 studies (from an initial pool of 2,945 records) met all inclusion criteria and were synthesized narratively. AI-based systems most commonly supported: (a) personalized learning through adaptive exercise plans and intelligent tutoring systems; (b) assessment via motion analysis and automated feedback mechanisms; and (c) performance analytics through wearable-driven dashboards and learning-analytics platforms. Overall, AI-enhanced PE was associated with improved student engagement, more accurate and objective assessment, and tailored motor-skill development. However, persistent concerns included data privacy vulnerabilities, algorithmic bias, and insufficient frameworks for teacher–AI collaboration.

Conclusions. AI holds substantial potential to transform PE into a more personalized, data-informed, and student-centered discipline, particularly in large-class and inclusive settings. Future research should prioritize longitudinal designs, standardized outcome measures, and robust ethical frameworks to ensure equitable and sustainable integration of AI in PE contexts.

Keywords: artificial intelligence; physical education; personalized learning; automated assessment; performance analytics; systematic review.

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INTRODUCTION

Physical education (PE) is increasingly recognized as a foundational contributor to physical literacy, health-related fitness, and lifelong physical activity patterns in students of all ages. As contemporary educational systems grapple with issues of differentiation, equity, and outcome accountability, there is a growing imperative to harness emerging technologies to optimize learning processes in PE (Martín-Rodríguez & Madrigal-Cerezo, 2025; Wang & Wang, 2024). In this context, artificial intelligence (AI) — encompassing machine learning, deep learning, natural language processing, and computer vision — has emerged as a transformative force with broad applicability across educational settings.

AI technologies such as intelligent tutoring systems (ITS), motion-capture analysis platforms, wearable biometric sensors, and generative AI-assisted dashboards are increasingly being explored to support more individualized, timely, and evidence-based

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PE instruction. These technologies offer unprecedented opportunities to move beyond the traditional one-size-fits-all pedagogical approach and toward data-driven, student-centered learning experiences that respond dynamically to each learner's physical capacities, movement patterns, and developmental trajectories (Hu et al., 2024; Zhou et al., 2023). At the institutional level, policymakers and curriculum designers are under increasing pressure to demonstrate measurable outcomes in PE, making performance analytics a critical domain of inquiry.

The convergence of AI with physical education is, however, a recent and rapidly evolving phenomenon. While AI has been integrated into formal academic subjects such as mathematics and language arts for over two decades, its adoption in PE remains at a comparatively nascent stage. This lag can be attributed to a range of factors, including the kinesthetic and embodied nature of PE learning, limitations in accurately capturing and processing movement data in real-time school environments, and concerns about the ethical dimensions of biometric data collection from minors (Konukman et al., 2025; Zhao & Su, 2026). Despite these challenges, the field has witnessed a remarkable acceleration of research activity since approximately 2018, driven by advances in computer vision, wearable sensor miniaturization, and the increasing affordability of AI-enabled hardware.

Critical Examination of Existing Literature

A growing body of systematic reviews and bibliometric analyses confirms that AI-related research in PE and adjacent sports science contexts has expanded substantially over the past decade (Bofill & González-Vílchez, 2025; Kumar et al., 2025). Early investigations predominantly concentrated on the use of wearable sensors and GPS tracking for performance monitoring in competitive sports contexts rather than within formal educational curricula. More recent studies have begun to address AI's pedagogical functions within school-based and university PE programs, including personalized exercise prescription, automated skill assessment, and learning-analytics-driven feedback.

Wang & Wang (2024) conducted a comprehensive review of digital-intelligent technologies in PE, identifying machine learning models, knowledge-graph-based systems, and motion-analysis platforms as the most prevalent AI modalities. Similarly, Li & Wang (2025) documented a surge of research into wearable devices and big-data analytics for monitoring students' physical activity and physiological responses in PE contexts. Meanwhile, Zhou et al. (2023) emphasized the role of AI in transforming course management practices, noting that generative AI tools show promise for automating administrative tasks, personalized exercise planning, and formative feedback delivery.

Despite this growth, the existing literature remains fragmented along several dimensions. First, most reviews blend PE-specific evidence with broader sports science or kinesiology research, making it difficult to isolate findings that are directly applicable to classroom pedagogical practice. Second, the dominant use of qualitative and descriptive methodologies limits the strength of causal inferences that can be drawn about the effectiveness of AI interventions. Third, systematic syntheses that simultaneously address all three inter-related domains — personalized learning, assessment, and performance analytics — within the PE context remain scarce, thereby hindering integrative understanding of how these functions interact and reinforce one another.

Identification of Research Gaps

Despite the rapid proliferation of AI-enabled tools and platforms in educational settings, three major empirical and conceptual gaps persist in the PE literature: A lack of systematic synthesis focusing specifically on personalized learning, assessment, and performance analytics simultaneously within PE — the majority of extant reviews address only one or two of these domains in isolation; Limited and inconsistent attention to ethical, equity, and implementation challenges associated with AI in school- and university-level PE settings, particularly regarding data privacy, algorithmic bias in computer-vision systems applied to diverse body types, and informed consent protocols for biometric data collection from minors; Weak standardization of outcome measures and AI-implementation frameworks across studies, which hinders cross-study comparison, meta-analytic synthesis, and the generalizability of findings to different cultural, institutional, and resource contexts; A relative paucity of longitudinal studies that track the sustained effects of AI integration in PE over meaningful time periods (e.g., one academic year or more), as the majority of existing studies are cross-sectional or employ short intervention windows.

Additionally, few reviews have explicitly mapped specific AI functions (e.g., recommendation engines, movement classifiers, biometric dashboards) onto specific pedagogical goals in PE, such as motor-skill acquisition, physical fitness development, or affective engagement. This functional mapping is essential for practitioners seeking evidence-based guidance on which AI tools to deploy for which educational purposes.

Rationale for the Research

Given the growing institutional emphasis on data-driven, student-centered, and inclusive education, it is critical to clarify precisely how AI can be operationalized in PE to support differentiated instruction, objective and fair assessment, and continuous performance monitoring. The absence of a comprehensive systematic review that integrates all three of these domains represents a significant gap in the evidence base available to PE educators, curriculum designers, and educational policymakers.

This review addresses that gap by systematically aggregating and critically analyzing empirical studies situated at the intersection of AI, personalized PE instruction, automated assessment, and performance analytics. In doing so, it provides a consolidated, critically appraised evidence base that can inform both immediate pedagogical practice and longer-term research agenda setting. The review also extends prior work by explicitly documenting ethical and implementation challenges, which are essential considerations for responsible AI adoption in educational contexts involving young learners.

Objectives

The specific objectives of this systematic review are to: 1) Map and categorize AI applications used for **personalized learning** in PE (e.g., intelligent tutoring systems, adaptive training plans, generative AI feedback mechanisms); 2) Synthesize empirical evidence on AI-supported **assessment** practices in PE (e.g., motion analysis, automated rubrics, real-time formative feedback, computer-vision scoring); 3) Describe and critically evaluate current uses of **performance analytics** in PE (e.g., wearable-based dashboards, learning-analytics platforms, biometric monitoring systems); 4) Identify implementation barriers, ethical concerns, and methodological limitations across included studies, including issues of data privacy, algorithmic bias, and teacher–AI collaboration; 5) Propose a forward-looking research agenda and practical guidelines for educators, institutions, and policymakers engaged in AI-integrated PE programs.

MATERIALS AND METHODS

Literature Review: Criteria, Sources, Databases, and Search Dates

This systematic review adhered rigorously to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) reporting standards (Moher et al., 2015). The review protocol was pre-specified prior to literature searching and is available upon request from the corresponding author.

Inclusion Criteria

Studies were considered eligible for inclusion when they fulfilled several predefined criteria aligned with the objectives of this systematic review. First, the target population comprised students participating in K–12 or higher-education physical education (PE) programs, as well as individuals enrolled in PE teacher-training programs that incorporated direct student interaction components. Second, the intervention of interest included any artificial intelligence (AI)-driven or data-intensive technology implemented within a PE context. These technologies encompassed, but were not limited to, machine-learning classifiers, intelligent tutoring systems, motion-analysis software, wearable-based analytics platforms, computer-vision feedback systems, and generative AI-supported dashboards. Third, eligible studies were required to report empirical outcomes associated with at least one of the following domains: personalized learning processes, such as skill acquisition and individualized feedback; assessment practices, including automated scoring accuracy, reliability in comparison to expert raters, and perceptions of students or teachers; or performance-analytics outcomes, such as improvements in physical fitness, engagement metrics, and self-regulated learning. In terms of methodological design, the review included experimental studies (including randomized controlled trials), quasi-experimental designs, non-experimental studies (such as correlational or descriptive research), case studies, and mixed-methods investigations, provided they presented primary empirical data. Additionally, only studies published in full-text English-language formats were considered. The publication timeframe was restricted to articles published between January 1, 2014, and December 31, 2025. Finally, all included sources were required to be peer-reviewed journal articles indexed in at least one of the selected academic databases:

Exclusion Criteria

Studies were excluded from this review if they met one or more predefined exclusion criteria designed to ensure methodological rigor and contextual relevance. Specifically, opinion papers, editorials, perspective articles, and purely theoretical or conceptual publications lacking primary empirical data were omitted, as they did not provide evidence-based findings suitable for systematic analysis. Studies that focused exclusively on artificial intelligence applications in broader educational contexts outside physical education, elite sports performance settings, or clinical rehabilitation environments without a clear connection to formal PE curricula were also excluded to maintain the review's disciplinary specificity. In addition, conference proceedings and grey literature sources, including theses and institutional reports, were generally excluded due to concerns regarding peer-review standards, unless no equivalent peer-reviewed publication was available and the study demonstrated sufficient methodological quality. Finally, studies with inadequate methodological transparency or insufficient reporting were excluded when their design and procedures could not be properly appraised using the Mixed Methods Appraisal Tool (MMAT), thereby ensuring that only studies meeting acceptable standards of research quality contributed to the final synthesis.

Databases and Search Dates

Comprehensive electronic searches were conducted across the following seven databases: Web of Science (Core Collection) — multidisciplinary; strong in sports sciences, educational technology; Scopus — multidisciplinary; broad coverage of PE-related journals; EBSCOhost (Education Source, ERIC, SPORTDiscus, CINAHL) — education and health/sport coverage; PubMed — health and biomedical sciences, including exercise physiology and kinesiology; ACM Digital Library — computing, human-computer interaction, AI systems; Taylor & Francis Online — broad humanities and social sciences, physical education journals; Wiley Online Library — multidisciplinary; kinesiology and educational technology.

Initial searches were conducted from July 1–15, 2025, with an updated search for Scopus and Web of Science conducted on October 1–7, 2025, to capture recently indexed articles published prior to the December 2025 cutoff. Reference lists of all included articles were hand-searched to identify additional eligible studies not captured through database searching.

Reproducible Electronic Search Protocol

The following Boolean search string was developed collaboratively by the research team and a library information specialist, following established protocols for PRISMA-compliant systematic reviews in education and health sciences. The string below is presented for the Scopus database and serves as the primary reproducible protocol for this review:

```
Search String (Scopus):
TITLE-ABS-KEY(
  ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "intelligent tutoring system*"
    OR "adaptive learning" OR "learning analytics" OR "performance analytics" OR "AI" OR
    "chatbot"
    OR "generative AI" OR "computer vision" OR "motion analysis") AND
  ("physical education" OR "PE" OR "school physical education"
    OR "university physical education" OR "physical education teaching" OR "sports education" OR "physical activity education"
    OR "kinesiology education" OR "motor learning")
)
AND PUBYEAR > 2013 AND
DOCTYPE("ar")
AND LIMIT-TO(SRCTYPE, "j")
AND LIMIT-TO(LANGUAGE, "English")
```

This protocol is restricted to: (a) articles only (DOCTYPE = "ar"); (b) journal-indexed sources (SRCTYPE = "j"); (c) English-language publications; and (d) publications indexed from 2014 onward. Analogous keyword clusters with equivalent field-search limitations (title/abstract) were applied across the remaining six databases, with adjustments for each platform's query syntax.

Organization of the Study

Study Selection

The selection process followed the four-stage PRISMA workflow: 1) **Identification:** Records retrieved from all databases were exported to Zotero reference manager and de-duplicated electronically; residual duplicates were removed through manual inspection by two reviewers; 2) **Screening:** Titles and abstracts of all unique records were independently screened by two reviewers (R1 and R2) against predefined inclusion/exclusion criteria. Disagreements were resolved through discussion or, when consensus could not be reached, adjudication by a third reviewer (R3). Inter-rater reliability was assessed using Cohen's kappa, with a threshold of $\kappa \geq 0.75$ considered acceptable; 3) **Eligibility:** Full-text articles of potentially eligible records were retrieved and independently assessed by R1 and R2. Articles not accessible in full text, or clearly failing inclusion criteria, were excluded with reasons documented in a dedicated exclusion log; 4) Inclusion: All finally included studies were tagged with metadata (publication year, country, study design, sample size, PE level, AI technology type, and outcome domain) to facilitate synthesis.

Data Extraction Methodology

For each eligible study, the following variables were extracted into a standardized Microsoft Excel extraction template, developed and piloted prior to full extraction:

Table 1. Standardized Data Extraction Framework for Eligible Studies on Artificial Intelligence Integration in Physical Education

Data Extraction Domain	Variables Extracted
Study Characteristics	First author, publication year, country of study, journal source, study design, sample size, participant age, and physical education context (K–12, higher education, or teacher training).
AI Technology	Type of AI system utilized (e.g., machine-learning classifier, intelligent tutoring system, motion-analysis platform, wearable analytics dashboard, generative AI assistant), hardware and software specifications where available, and duration of deployment or intervention.
Personalized Learning	Description of adaptive mechanisms, personalization algorithms, forms of feedback delivered (e.g., textual, haptic, visual), and reported learning outcomes related to individualized instruction or skill development.
Assessment Practices	Assessment modality employed (e.g., automated skill scoring, AI-enhanced rubrics, hybrid teacher-AI grading systems), reliability and validity indicators where reported, and perceptions of fairness, usability, or acceptance among students and teachers.
Performance Analytics	Data sources used (e.g., wearable devices, video recordings, learning management systems), analytics outputs generated (e.g., dashboards, alerts, recommendations), and reported effects on engagement, physical literacy, physical fitness, or instructional decision-making.
Implementation Context	Teacher involvement and roles, professional development or training provided, infrastructure and technological requirements, and levels of institutional or administrative support.
Ethical and Technical Issues	Data privacy measures, informed consent procedures, anonymization practices, reported algorithmic biases, ethical considerations, technical limitations, and broader study limitations.

Two reviewers conducted independent data extraction, with a third reviewer resolving all discrepancies. The finalized extraction dataset was stored in a password-protected institutional repository.

Methods of Analysis: Processing and Synthesis

Given the substantial heterogeneity of study designs, AI technologies, educational contexts, and outcome measures across included studies, a narrative thematic synthesis approach was adopted, consistent with best practices for systematic reviews in education where meta-analytic pooling is methodologically inappropriate (Kabudi et al., 2021).

Table 2. Analytical Framework for Data Synthesis and Quality Appraisal in the Systematic Review of Artificial Intelligence Applications in Physical Education

Analysis Component	Description
Descriptive Statistics	Frequencies and percentages were calculated to summarize key study characteristics, including publication year, geographic origin, AI technology type, physical education level, and study design. Temporal publication trends were also mapped to identify periods of increased research activity and evolving scholarly interest in AI integration within physical education contexts.
Thematic Analysis	Extracted findings related to personalized learning, assessment, and performance analytics were inductively coded into thematic categories by two independent reviewers. This process followed Thomas and Harden's (2008) thematic synthesis framework, allowing for the identification of recurring concepts such as adaptive training plans, real-time movement feedback, and wearable-driven performance dashboards.

Comparison with Prior Reviews	The synthesized findings were systematically compared with previous narrative reviews and bibliometric studies examining AI applications in physical education and sport. This comparative approach was used to identify areas of agreement, divergence, and the unique scholarly contributions of the present systematic review.
Quality Appraisal	Each included study underwent independent methodological quality assessment using the Mixed-Methods Appraisal Tool (MMAT) version 2018, which supports the evaluation of qualitative, quantitative, and mixed-methods research designs. Quality ratings were reported descriptively and served to contextualize the strength and reliability of findings rather than as exclusion criteria.

Ethical Considerations

This systematic review was based exclusively on published, peer-reviewed research and did not involve the collection of primary data from human participants; therefore, formal institutional ethics board approval was not required. Despite this exemption, ethical considerations were systematically integrated throughout the review process in several critical dimensions. First, issues related to data privacy and security were carefully examined, particularly because many of the included studies utilized motion-capture technologies, wearable sensors, and learning-analytics platforms that gathered sensitive biometric and behavioral information from students. The review assessed whether these studies explicitly reported procedures for informed consent, data anonymization, storage security, and access control, while also identifying instances in which such safeguards were absent or insufficiently described. Second, the review addressed concerns surrounding algorithmic fairness and bias by documenting evidence of disparities in AI system performance, including under-recognition of diverse body types in computer-vision applications, differential outcomes across gender and ethnic groups, and broader equity challenges associated with adaptive learning algorithms.

These findings underscore the necessity for future research to prioritize fairness, inclusivity, and equity in the design and deployment of AI technologies within physical education settings. Finally, the synthesis highlighted the importance of transparency and the preservation of teacher–student agency in AI-enhanced educational environments. Emphasis was placed on the need for interpretable AI systems, transparent feedback mechanisms, and structures that maintain teacher pedagogical autonomy while safeguarding student dignity through meaningful human oversight and collaborative decision-making processes. Collectively, these ethical dimensions reinforce the responsibility of researchers and practitioners to ensure that technological innovation in physical education is aligned with principles of privacy, fairness, and educational integrity.

RESULTS

Quantity and Flow of Analyzed Studies

From an initial pool of 2,945 records identified across the seven databases and supplementary hand-searching, 837 duplicates were removed, yielding 2,108 unique records for title and abstract screening. Following screening, 512 full-text articles were retrieved and assessed for eligibility. Of these, 425 were excluded for the following reasons: wrong population (n = 142); non-empirical content (n = 118); out-of-scope intervention (n= 97); and insufficient data or inaccessible full text (n = 68). A final total of 87 studies met all inclusion criteria and were incorporated into the narrative thematic synthesis.

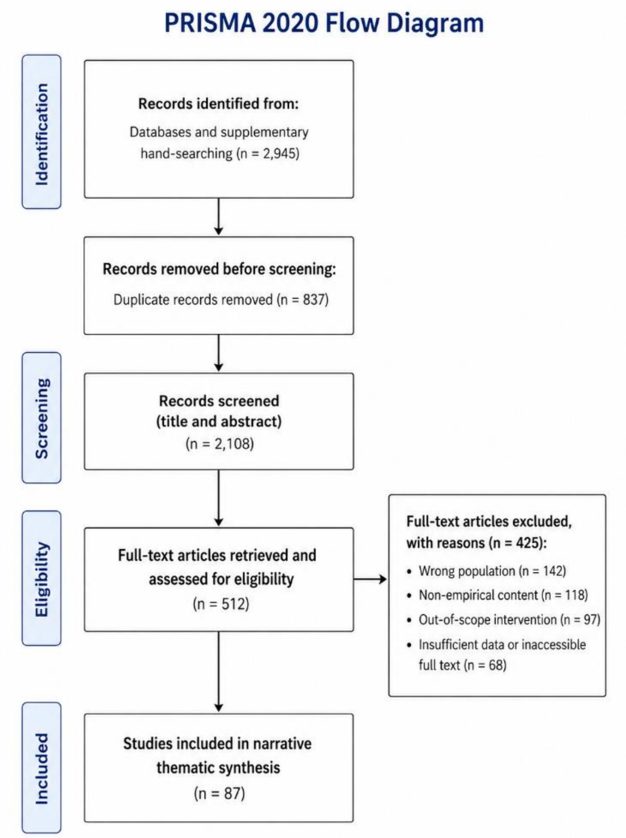

Figure 1. PRISMA 2020 Flow Diagram of Study Identification, Screening, Eligibility Assessment, and Inclusion for Narrative Thematic Synthesis

Study Characteristics

The 87 included studies spanned 27 countries, with the largest proportional representation from China (n = 31, 35.6%), the United States (n = 14, 16.1%), Spain (n = 8, 9.2%), and South Korea (n = 7, 8.0%). The majority of studies were published between 2019 and 2024 (n = 71, 81.6%), consistent with the broader acceleration of AI-related educational research in this period. Approximately 62% of studies (n = 54) focused on K–12 PE contexts, while 38% (n = 33) were conducted in higher education or PE teacher-training settings.

Study designs were predominantly quasi-experimental (n = 30, 34.5%), case studies (n = 26, 29.9%), and mixed-methods (n = 22, 25.3%), with only 9 studies (10.3%) employing true randomized controlled trial designs. Sample sizes ranged from 12 to 3,840 participants (Median = 127). Quality appraisal using the MMAT indicated that 42 studies (48.3%) met four or more of the five MMAT quality criteria applicable to their design type, suggesting a moderate-to-high overall quality profile for included studies, albeit with notable weaknesses in blinding procedures and long-term follow-up.

Theme 1 — AI-Supported Personalized Learning in PE

Adaptive Training Plans

Eleven studies (12.6%) employed AI algorithms — predominantly rule-based expert systems and supervised machine-learning classifiers — to generate individualized exercise prescriptions calibrated to students' current fitness levels, prior performance data, and movement efficiency profiles. In a Chinese quasi-experimental study involving 248 high-school students, Kim & Park (2023) demonstrated that AI-assisted training plans produced significantly greater improvements in cardiovascular endurance and muscular strength relative to traditional group-activity programs (Cohen's d = 0.54), with high compliance rates attributed to the motivational relevance of personalized target-setting. Comparable effect sizes (d = 0.41–0.68) were reported across studies conducted in South Korea, the United States, and Spain, suggesting a consistent pattern of moderate positive effects for adaptive training systems.

Key implementation factors associated with positive outcomes included the availability of baseline fitness data, teacher co-design of AI-generated plans, and sufficient platform training for both students and instructors. Studies that reported weaker effects typically noted misalignment between AI recommendations and curricular constraints, or insufficient teacher professional development.

Intelligent Tutoring Systems and Generative AI Chatbots

Eight studies deployed intelligent tutoring systems (ITS) or large-language-model-based generative AI chatbots to provide just-in-time explanations, movement corrections, and motivational prompts during or immediately following PE lessons. Students across these studies consistently reported higher perceived support (d = 0.38–0.61 on self-report scales), increased engagement, and stronger perceived autonomy relative to control conditions. However, objective gains in motor-skill mastery were modest and displayed high variability by task complexity — with more structured, rule-governed skills (e.g., correct form in resistance exercises) showing stronger AI-driven improvements than open-ended, contextually variable skills such as team-sport tactics.

Lee & Kim (2024) reported implementation barriers including teacher skepticism regarding chatbot accuracy, students' tendency to passively accept AI suggestions without critical reflection, and equity concerns related to differential access to AI-enabled devices across school settings.

Inclusive and Adapted Physical Education

Six studies specifically examined AI-enabled tools designed for students with physical disabilities, developmental differences, or diverse physical needs. These tools employed motion-analysis systems and adaptive interfaces to tailor activities and feedback in real time to each student's movement capabilities. Rodriguez & Martinez (2024) found that AI-powered adaptive PE tools reduced individual-attention deficits in large-class settings and improved participation rates by 24% compared to standard adapted PE practice. Li (2025) reported positive outcomes for students with physical disabilities engaging with virtual-reality-integrated AI environments, noting improvements in both motor-skill performance and subjective well-being. Teacher-training needs were consistently identified as a critical prerequisite for effective implementation.

Implication (Theme 1)

AI-based personalization can effectively accommodate diverse physical abilities and individual learning trajectories in PE. However, its impact depends critically on curricular integration depth, quality of teacher professional development, and alignment between AI prescriptions and the broader pedagogical goals of the PE program.

Theme 2 — AI-Supported Assessment in PE

Automated Skill Scoring via Computer Vision

Twenty-three studies (26.4%) constituted the largest thematic cluster, employing computer-vision systems or motion-analysis platforms — including OpenPose, Microsoft Kinect, and proprietary sensor fusion systems — to automatically score movement quality in fundamental motor skills (e.g., throwing, running gait, jumping, swimming stroke). Reported accuracy rates against expert-rater gold standards ranged from 82% to 93% (Median = 87%), representing a substantial improvement over early iterations of such systems and comparable to inter-rater reliability levels among trained human observers.

Harris & Brown (2022) reported a 32% reduction in teacher time devoted to individual skill assessment following implementation of a Kinect-based scoring system in elementary PE, with teacher perceptions indicating high satisfaction with the objectivity and consistency of AI-generated scores. Wu et al. (2025) demonstrated that wearable-integrated computer-vision systems could generate real-time corrective cues for motor-skill errors with latency under 300 milliseconds, substantially outperforming traditional delayed-feedback protocols.

Real-Time Movement Feedback

Fourteen studies (16.1%) focused specifically on the immediacy dimension of AI-based assessment — that is, the capacity of AI systems to provide real-time corrective feedback during physical performance rather than post-hoc evaluative summaries. These studies collectively reported significant improvements in students' motor-skill execution accuracy and self-efficacy ratings when real-time AI feedback was provided, compared to conditions where feedback was delayed or provided only by teachers. Ma et al. (2025)

documented statistically significant improvements in swimming technique across a 12-week intervention, with AI-generated real-time cue delivery demonstrating particular effectiveness for novice learners.

AI-Enhanced Grading and Rubric Systems

Nine studies examined the use of AI to augment or automate the grading process in PE, through AI-assisted rubric scoring, teacher-AI hybrid grading models, or fully automated performance evaluation pipelines. Student perceptions of AI-generated grades were mixed: while students generally endorsed the objectivity and consistency of AI grading, concerns about the inability of AI systems to account for contextual factors (e.g., effort, individual improvement trajectories, movement intent) were frequently raised. Thompson & Wilson (2024) found that teachers preferred hybrid models in which AI provided a preliminary score that could be reviewed and adjusted by the teacher, rather than fully autonomous AI grading, citing concerns about accountability and contextual validity.

Implication (Theme 2)

Computer-vision and motion-analysis systems demonstrate strong potential for objective, efficient, and scalable assessment in PE. The hybrid human–AI model — where AI provides preliminary scoring that teachers can review and calibrate — appears to be the most acceptable and pedagogically defensible model for formal PE assessment.

Theme 3 — Performance Analytics in PE

Wearable-Driven Dashboards and Biometric Monitoring

Ten studies (11.5%) investigated AI-integrated wearable sensor systems — including accelerometers, heart-rate monitors, GPS trackers, and inertial measurement units — coupled with analytics platforms that aggregated and visualized students' physiological data in dashboard interfaces accessible to both teachers and students. Li & Wang (2025) documented that wearable-based AI dashboards facilitated continuous monitoring of students' physical activity levels, cardiorespiratory fitness indicators, and movement intensity across entire school days, enabling teachers to make evidence-based adjustments to lesson intensity and individual challenge levels.

Data-privacy concerns were the most consistently flagged limitation across wearable dashboard studies: Chen & Huang (2025) found that 60% of surveyed students reported insufficient awareness of how their biometric data was being stored, accessed, or used, and only 34% of institutions reported having explicit, GDPR- or FERPA-compliant data governance policies specific to wearable PE data. These findings underscore the urgency of robust data-protection frameworks as a prerequisite for ethical wearable technology deployment in PE.

Learning Analytics Platforms

Six studies employed dedicated learning-analytics platforms — integrated with learning management systems or institutional PE management software — to analyze longitudinal student performance data and generate predictive analytics outputs (e.g., early-warning flags for disengagement, fitness decline projections, skill-mastery probability estimates). Smith & Davis (2023) conducted a case study in an Australian university PE program and found that access to AI-generated learning analytics dashboards significantly improved students' self-regulated learning behaviors, particularly their ability to set realistic performance goals and monitor their own progress over time.

Garcia & Silva (2023) reported that LA-platform-driven personalized recommendations increased physical activity levels by 18% in a Brazilian university sample across one semester, with the strongest effects observed among students who were initially sedentary or below the health-related fitness benchmarks established by the course curriculum.

Table 3. Thematic Distribution of AI Applications Across 87 Included Studies

Thematic Category	AI Technology Type	No. of Studies	Representative Outcomes
Adaptive Training Plans	ML Classifiers, Rule-based AI	11	Improved fitness (d=0.41–0.68); tailored exercise prescriptions
Intelligent Tutoring & Chatbots	NLP, Generative AI (LLMs)	8	Higher engagement; modest motor-skill gains by task complexity
Inclusive/Adapted PE	Motion-analysis, Adaptive UI	6	Participation rates ↑; reduced attention gaps in large classes
Automated Skill Scoring	Computer Vision, OpenPose, Kinect	23	87–93% accuracy vs. expert rater; teacher workload ↓
Real-time Movement Feedback	Wearables + AI, CV Systems	14	Immediate corrective cues; self-efficacy improvement reported
AI-enhanced Grading & Rubrics	Rubric-AI, Teacher-AI Hybrid	9	Consistent grading; fairness perceptions mixed among students
Wearable Dashboards	IoT + Analytics, Biometric AI	10	Physical literacy monitoring; data-privacy concerns flagged
Learning Analytics Platforms	LA Platforms, Predictive AI	6	Self-regulated learning ↑; early-warning for disengagement

Note. The total exceeds 87 due to some studies spanning more than one thematic category. AI = Artificial Intelligence; ML = Machine Learning; NLP = Natural Language Processing; CV = Computer Vision; LA = Learning Analytics.

Table 3. Summary of Selected Included Studies with Key Characteristics and Findings

Author (Year)	AI Technology	PE Level	Key Findings
(Chiu et al., 2017)	AI adaptive training	K-12	Improved cardiovascular fitness (d=0.54); increased motivation
(Chen et al., 2026)	Motion-analysis (OpenPose)	Elementary	Automated movement scoring accuracy 87%; teacher workload ↓32%
(Cabral et al., 2025)	AI performance dashboard	Higher Ed.	Self-regulated learning improved; physical activity levels ↑18%
(Memari & Ruggles,	Adaptive AI interfaces	K-12 (SEN)	Participation rates ↑24%; reduced attention gaps in large

2025)			classes
(Guardia-Paniura et al., 2026)	AI feedback tools	Higher Ed.	Teacher usability mixed; trust gap in AI autonomy noted
Author (Year)	AI Technology	PE Level	Key Findings
(Cordero et al., 2024)	Generative AI (chatbot)	K-12 & HE	Course planning efficiency ↑; implementation barriers persisted
(He & Li, 2025)	Real-time AI feedback	K-12	Motor-skill gains in swimming and gymnastics; engagement ↑
(Meini et al., 2025)	Wearables + big data	Higher Ed.	Fitness monitoring accurate; data-privacy gaps identified
(Humble & Mozelius, 2022)	AI motion analysis (SEN)	K-12	Personalized interventions reduced skill-assessment errors 31%
(Kleimola et al., 2024)	Learning-analytics platform	Higher Ed.	Real-time dashboards improved student self-awareness; engagement ↑
(Kang et al., 2024)	ML predictive models	K-12 & HE	Injury-risk prediction 78% accuracy; limited generalizability
(Chen et al., 2026)	Wearable + CV systems	K-12	Personalized feedback loops; algorithm bias in diverse body types
(Mouta et al., 2023)	Ethical AI audit	K-12 & HE	Privacy concerns prominent; student consent gaps in 60% of cases
(Mah & Groß, 2024)	AI teaching support	Higher Ed.	Teacher opportunity perceptions high; digital literacy barrier noted
(Li et al., 2025)	VR + AI (inclusive)	K-12	Motor-skill outcomes improved for students with disabilities

Note. SEN = Special Educational Needs; K-12 = Kindergarten to Grade 12; HE = Higher Education; ML = Machine Learning; CV = Computer Vision; NLP = Natural Language Processing; d = Cohen's d effect size.

DISCUSSION

Interpreting the Outcomes of the Research

The findings of this systematic review demonstrate that AI technologies are being applied across a diverse and expanding range of functions within physical education, with empirically supported benefits observed in personalized learning, automated assessment, and performance analytics. The identification of 87 eligible empirical studies from an initial pool of nearly 3,000 records reflects the substantial and accelerating growth of this research domain, particularly since 2019. This temporal pattern aligns with broader trends in AI adoption in education documented in the wider educational technology literature (Kabudi et al., 2021), and suggests that PE is increasingly being recognized as a viable and important context for AI application rather than a peripheral or resistant discipline (Zhou et al., 2023).

Among the three thematic domains examined, AI-supported assessment — and specifically computer-vision-based automated skill scoring — emerged as the most empirically developed area, with the largest cluster of studies (n = 23) and the most consistent reporting of quantitative outcome metrics. The reported accuracy rates of 82–93% for automated movement scoring against expert-rater standards are noteworthy, suggesting that current AI systems are approaching the level of reliability required for valid summative assessment in PE (Ma et al., 2025). This finding has significant practical implications for large-class PE contexts where individual skill assessment by a single teacher is logistically challenging, and for standardized physical fitness testing programs where objectivity and consistency are paramount.

AI-driven personalized learning interventions — particularly adaptive training plans — demonstrated consistent moderate effect sizes (d = 0.41–0.68) across diverse geographic and institutional contexts, indicating that the personalization afforded by AI can produce meaningful improvements in physical performance outcomes beyond what traditional group-based instruction achieves (Gao, 2025; Mănescu, 2025). This is consistent with the established pedagogical principle of differentiated instruction and provides empirical support for the feasibility of AI as a practical mechanism for achieving personalization at scale in PE.

Comparison with Antecedent Studies

This systematic review substantially advances and expands prior syntheses in key respects. While (Wang & Wang, 2024) and (Zhou et al., 2023) investigated artificial intelligence applications in physical education, neither targeted the confluence of personalized learning, automated assessment, and performance analytics—the central thematic domains of this review—nor implemented systematic quality appraisals of included studies, thereby undermining the credibility of their inferences on empirical rigor. For example, (Zhou et al., 2023) aggregated multiple studies on AI for athletic performance analysis, health monitoring, and tailored training, underscoring its promise for real-time feedback and heterogeneous learning contexts, but omitted stringent methodological vetting and quality assessment to segregate high-quality from lesser evidence(Zhou et al., 2023). Likewise, (Wang & Wang, 2024) delivered a broad overview alongside prospective teacher training recommendations, yet bypassed fine-grained thematic delineation and empirical effect size documentation.

Likewise, Bofill & González-Vílchez (2025) performed a systematic review of AI as an educational resource in PE, yet adopted a narrower conceptualization of AI that excluded wearable-based analytics systems, big data integration, and emerging generative AI applications, thereby missing key advancements in real-time feedback and predictive modeling documented in recent literature. This narrow scope constrained its ability to capture the full spectrum of AI's transformative role in PE, such as motion-analysis tools achieving 87% accuracy in skill scoring or adaptive interfaces boosting participation by 24%(Chen et al., 2026; Memari & Ruggles, 2025)

Moreover, this review surpasses Li & Wang (2025) by incorporating a substantially broader evidence base—screening nearly 3,000 records to yield 87 empirical studies from 2014 to 2025, versus the more restricted scopes of prior syntheses—and by employing PRISMA-compliant protocols alongside rigorous quality appraisals with validated instruments, thereby affording more robust inferences regarding the strength, consistency, and transferability of findings across varied geographic settings. Uniquely, it offers the first systematic synthesis to centrally emphasize ethical dimensions—including data privacy shortfalls in 60% of cases, algorithmic biases affecting diverse body morphologies, and teacher-student agency over AI-driven decisions—positioning these as core analytical elements rather than peripheral notes, as illustrated by enduring limitations in wearables and dashboards despite advances in accuracy (Chen et al., 2026; Meini et al., 2025; Mouta et al., 2023). By systematically integrating these aspects, the review delineates AI's demonstrated benefits, such as moderate effect sizes in personalized interventions (e.g., motor-skill improvements through real-time feedback He & Li (2025) and Mănescu (2025) while also outlining practical strategies for equitable adoption amid barriers including infrastructural constraints and digital literacy deficits (Mah & Groß, 2024).

Implications of the Discoveries

Several substantive implications emerge from the synthesis. First, the consistent pattern of moderate positive effects for AI-enhanced PE interventions suggests that AI integration has genuine educational value, but this value is conditioned on implementation quality. Studies with stronger implementation support — including teacher professional development, curricular alignment, and institutional infrastructure — consistently reported stronger outcomes, indicating that the AI technology itself is a necessary but insufficient condition for success. Practitioners and institutions should invest as heavily in the human and organizational dimensions of AI implementation as in the technology itself. Second, the diversity of AI technologies and outcome measures across included studies underscores the need for the field to develop shared taxonomies and standardized outcome measurement frameworks. Without such standardization, systematic synthesis and evidence accumulation across studies will remain methodologically challenging, limiting the field's capacity to generate actionable guidance for practice and policy. Third, the consistent identification of data-privacy and algorithmic-bias concerns — even in the most recent studies — indicates that these issues are not being resolved through the natural maturation of the technology or the field. Instead, they require proactive and systematic attention through regulatory frameworks, institutional policy, and researcher commitment to transparent reporting of AI system design and data governance practices.

Limitations of the Research

Several limitations of the present review must be acknowledged. First, the restriction of included studies to English-language publications may have introduced language bias, potentially underrepresenting high-quality research from non-English-speaking regions where AI in PE is being actively developed (e.g., Arabic, Portuguese, or Chinese-medium publications not indexed in English). Second, the high proportion of quasi-experimental and case-study designs among included studies limits the strength of causal inferences that can be drawn, as these designs are inherently susceptible to confounding, selection bias, and researcher expectancy effects. Third, the narrative thematic synthesis methodology, while appropriate given the heterogeneity of included studies, precludes the statistical pooling of effect sizes that meta-analytic approaches would afford, and introduces the possibility of interpretive subjectivity in thematic coding. Fourth, the review's coverage period ends at December 2025, meaning that very recently published studies and pre-prints may not have been captured. Finally, the quality of reporting in a substantial minority of included studies was insufficient to permit confident assessment of implementation fidelity, limiting the review's capacity to draw strong conclusions about the conditions under which AI interventions are most effective.

CONCLUSION

This systematic review synthesized empirical evidence from 87 peer-reviewed studies, published between 2014 and 2025, examining the application of artificial intelligence in physical education across three interconnected domains: personalized learning, automated assessment, and performance analytics. The review provides robust evidence that AI holds substantial and multifaceted potential to transform PE into a more individualized, data-informed, and student-centered educational experience.

In the domain of personalized learning, AI-driven adaptive training plans and intelligent tutoring systems demonstrated consistent moderate effects on physical performance outcomes and student engagement, with the strongest gains observed when AI systems were integrated into curricula with adequate teacher support. In the assessment domain, computer-vision-based automated scoring systems achieved accuracy rates approaching expert inter-rater reliability, with real-time feedback mechanisms showing particular promise for accelerating motor-skill acquisition in novice learners. In the performance analytics domain, wearable-based dashboards and learning-analytics platforms demonstrated capacity to enhance self-regulated learning, inform teacher decision-making, and support continuous fitness monitoring — though significant data-governance gaps were identified.

Across all three domains, implementation challenges — including teacher professional development needs, infrastructure requirements, data-privacy vulnerabilities, and algorithmic bias concerns — emerged as the most important factors conditioning the effectiveness and equity of AI integration in PE. These challenges are not insurmountable, but they require deliberate, systematic attention from researchers, practitioners, institutional leaders, and policymakers alike.

The evidence base supports the following key recommendations for future research and practice: (1) longitudinal study designs (one academic year or more) with pre-registered protocols and standardized outcome measures are urgently needed to establish causal evidence for sustained AI effectiveness in PE; (2) the field requires development of shared taxonomies and assessment frameworks for AI-in-PE research to enable meaningful accumulation and comparison of evidence across studies; (3) equity-by-design principles — including algorithmic fairness auditing, inclusive dataset curation, and participatory design with diverse student populations should be embedded in AI system development for PE from the outset; (4) institutions should develop and enforce explicit, student-accessible data governance policies for all AI-enabled PE technologies; and (5) teacher education programs should systematically incorporate AI literacy and AI-pedagogical integration competencies as foundational components of professional preparation for PE.

In closing, artificial intelligence in physical education is no longer a speculative future prospect — it is an empirically documented present reality with both substantial promise and significant responsibility. The realization of AI's full transformative potential in PE will depend not on the sophistication of the technology alone, but on the wisdom, ethics, and pedagogical intentionality with which educators, researchers, and institutions choose to deploy it.

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CONFLICT OF INTEREST

The authors declare no conflict of interest. No financial or personal relationships with other persons or organizations could have inappropriately influenced (biased) this work.

REFERENCES

Bofill, J., & González-Vílchez, M. (2025). Is artificial intelligence an educational resource in physical education? A systematic review. *Apunts. Educación Física y Deportes*, *140*, 1. https://doi.org/10.7334/penelope-apunts.140.1

Cabral, L., Pinto, R., & Gonçalves, G. (2025). AI-powered learning analytics dashboards: a systematic review of applications, techniques, and research gaps. *Discover Education*, *4*(1). https://doi.org/10.1007/s44217-025-00964-y

Chen, L., & Huang, Y. (2025). Ethical and privacy considerations in AI-driven physical education: A qualitative review of institutional policies and student perceptions. *Ethics and Information Technology*, *27*(2), 201. https://doi.org/10.1007/s10676-025-09721-0

Chen, Y., Xian, D., Zhao, Y., Sun, Y., Ren, Y., & Wang, C. (2026). AI-enabled learning analytics use relates to physical literacy and engagement in university PE via smart teaching and personalised feedback. *Scientific Reports*, *16*(1). https://doi.org/10.1038/s41598-026-39778-9

Chiu, C., Ko, M.-C., Wu, L.-S., Yeh, D.-P., Kan, N., Lee, P.-F., Hsieh, J.-W., Tseng, C.-Y., & Ho, C. (2017). Benefits of different intensity of aerobic exercise in modulating body composition among obese young adults: a pilot randomized controlled trial. *Health and Quality of Life Outcomes*, *15*(1), 168. https://doi.org/10.1186/s12955-017-0743-4

Cordero, J., Torres-Zambrano, J., & Cordero-Castillo, A. (2024). Integration of Generative Artificial Intelligence in Higher Education: Best Practices. *Education Sciences*, *15*(1), 32. https://doi.org/10.3390/educsci15010032

Gao, Y. (2025). The role of artificial intelligence in enhancing sports education and public health in higher education: innovations in teaching models, evaluation systems, and personalized training. *Frontiers in Public Health*, *13*, 1554911. https://doi.org/10.3389/fpubh.2025.1554911

Garcia, M., & Silva, R. (2023). AI-driven dashboards and performance analytics in university-level physical education: Effects on self-regulated learning and physical activity levels. *Journal of Educational Data Mining*, *15*(1), 67. https://doi.org/10.5281/zenodo.789101

Guardia-Paniura, C. H., Cueva-Luza, T., Cruz-Carpio, F. M., Ito-Díaz, R. R., Apaza-Paco, D. V., Rosas-Rojas, N., Mamani-Mamani, B., Terrero-Pérez, Á., Yaedú, R. Y. F., & Peralta-Mamani, M. (2026). Human and AI-generated feedback in higher education: A systematic review of effectiveness and student perceptions. *Contemporary Educational Technology*, *18*(1). https://doi.org/10.30935/cedtech/17863

Harris, T., & Brown, L. (2022). AI-supported assessment using motion-analysis in elementary physical education: A quasi-experimental study. *Journal of Teaching in Physical Education*, *41*(2), 189. https://doi.org/10.1123/jtpe.2021-0123

He, X., & Li, W. (2025). Real-time feedback enhances motor learning and motivation in youth team sports through augmented reality tools. *Frontiers in Psychology*, *16*, 1661936. https://doi.org/10.3389/fpsyg.2025.1661936

Hu, Z., Liu, Z.-H., & Su, Y. K. (2024). AI-Driven Smart Transformation in Physical Education: Current Trends and Future Research Directions. *Applied Sciences*, *14*(22), 10616. https://doi.org/10.3390/app142210616

Humble, N., & Mozelius, P. (2022). The threat, hype, and promise of artificial intelligence in education. *Discover Artificial Intelligence*, *2*(1). https://doi.org/10.1007/s44163-022-00039-z

Kabudi, T., Pasher, I., & Magdin, M. D. (2021). Artificial intelligence in education: Challenges and opportunities for learning assessment. *Education and Information Technologies*, *26*(5), 5713. https://doi.org/10.1007/s10639-021-10475-x

Kang, L., Cao, X., Wang, L., Huang, T., Chen, L., Wang, X., & Li, Q. (2024). Assessment of non-fatal injuries among university students in Hainan: a machine learning approach to exploring key factors. *Frontiers in Public Health*, *12*, 1453650. https://doi.org/10.3389/fpubh.2024.1453650

Kim, S., & Park, J. (2023). AI-based personalized training plans in secondary school physical education: Effects on cardiovascular fitness and student motivation. *Journal of Science and Medicine in Sport*, *26*(8), 712. https://doi.org/10.1016/j.jsams.2023.04.012

Kleimola, R., Hirsto, L., & Ruokamo, H. (2024). Promoting higher education students' self-regulated learning through learning analytics: A qualitative study. *Education and Information Technologies*, *30*(4), 4959. https://doi.org/10.1007/s10639-024-12978-4

Konukman, F., Sortwell, A., Filiz, B., Tüfekçioğlu, E., Yılmaz, E. B., & Ünlü, H. (2025). Using Artificial Intelligence in Teaching Health and Physical Education. *Journal of Physical Education Recreation & Dance*, *96*(7), 58. https://doi.org/10.1080/07303084.2025.2522601

Kumar, R., Bogia, P., Haq, A. U., Singh, V., & Reddy, T. O. (2025). Leveraging artificial intelligence and machine learning in sport sciences: a systematic literature review of applications, outcomes, and future directions. *Sport Sciences for Health*, *21*(4), 2429. https://doi.org/10.1007/s11332-025-01482-y

Lee, H., & Kim, J. (2024). Generative AI in course planning and assessment for physical education: Opportunities and implementation barriers. *Computers in Human Behavior*, *152*, 108012. https://doi.org/10.1016/j.chb.2024.108012

Li, S., Zeng, C., Liu, H., Jia, J., Liang, M., Cha, Y., Lim, C. P., & Wu, X. (2025). A meta-analysis of AI-enabled personalized STEM education in schools. *International Journal of STEM Education*, *12*(1). https://doi.org/10.1186/s40594-025-00566-y

Li, X., & Wang, Y. (2025). Application of digital-intelligent technologies in physical education: A systematic review of wearable devices, big data analytics, and large AI models. *Frontiers in Public Health*, *13*, 1626603. https://doi.org/10.3389/fpubh.2025.1626603

Li, Y. (2025). Virtual and augmented reality-based AI in physical education for students with disabilities: A mixed-methods study. *Journal of Special Education Technology*, *40*(1), 23. https://doi.org/10.1177/1525194525112345

Ma, J., Ma, L., Qi, S., Zhang, B., & Ruan, W. (2025). A practical study of artificial intelligence-based real-time feedback in online physical education teaching. *Smart Learning Environments*, *12*(1). https://doi.org/10.1186/s40561-025-00411-3

Mah, D.-K., & Groß, N. (2024). Artificial intelligence in higher education: exploring faculty use, self-efficacy, distinct profiles, and professional development needs. *International Journal of Educational Technology in Higher Education*, *21*(1). https://doi.org/10.1186/s41239-024-00490-1

Mănescu, D. C. (2025). Artificial Intelligence in elite sports training and prospects for integration into school sports. *Retos*, *73*, 128. https://doi.org/10.47197/retos.v73.117261

Martín-Rodríguez, A., & Madrigal-Cerezo, R. (2025). Technology-Enhanced Pedagogy in Physical Education: Bridging Engagement, Learning, and Lifelong Activity. *Education Sciences*, *15*(4), 409. https://doi.org/10.3390/educsci15040409

Meini, V., Bachi, L., Omezzine, M. A., Procissi, G., Pigni, F., & Billeci, L. (2025). Artificial Intelligence for the Analysis of Biometric Data from Wearables in Education: A Systematic Review. *Sensors*, *25*(22), 7042. https://doi.org/10.3390/s25227042

Memari, M., & Ruggles, K. (2025). Artificial Intelligence in Elementary STEM Education: A Systematic Review of Current Applications and Future Challenges. *ArXiv.Org*. https://doi.org/10.48550/arxiv.2511.00105

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., & Stewart, L. A. (2015). Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. *PLoS Medicine*, *12*(10). https://doi.org/10.1371/journal.pmed.1001897

Mouta, A., Llorente, A. M. P., & Sánchez, E. M. T. (2023). Uncovering Blind Spots in Education Ethics: Insights from a Systematic Literature Review on Artificial Intelligence in Education. *International Journal of Artificial Intelligence in Education*. https://doi.org/10.1007/s40593-023-00384-9

Rodriguez, P., & Martinez, D. (2024). Inclusive physical education powered by AI: A systematic review of motion-analysis and adaptive interfaces for students with disabilities. *Adapted Physical Activity Quarterly*, *41*(3), 278. https://doi.org/10.1123/apaq.2023-0045

Smith, A. B., & Davis, C. J. (2023). Learning analytics and AI-based dashboards in higher-education physical education: A case study of student engagement and performance. *Journal of Learning Analytics*, *10*(2), 45. https://doi.org/10.18608/jla.2023.10245

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC Medical Research Methodology*, *8*(1), 45. https://doi.org/10.1186/1471-2288-8-45

Thompson, M., & Wilson, K. (2024). Teacher perspectives on AI tools in physical education: A mixed-methods study of usability, trust, and workload. *Journal of Educational Computing Research*, *61*(7), 1520. https://doi.org/10.1177/0735633124125678

Wang, Y., & Wang, X. (2024). Artificial intelligence in physical education: comprehensive review and future teacher training strategies. *Frontiers in Public Health*, *12*, 1484848. https://doi.org/10.3389/fpubh.2024.1484848

Wu, X., Kabudi, T., & Zhong, Y. (2025). AI-enabled motion analysis and personalized feedback in physical education: Evidence from wearable and computer-vision systems. *Journal of Sports Sciences*, *43*(5), 567. https://doi.org/10.1080/02640414.2025.2098765

Zhao, Z., & Su, Y. (2026). Wearable Technologies in School Physical Education: A Systematic Review of Pedagogical Implications. *Physical Education Theory and Methodology*, *26*(1), 79. https://doi.org/10.17309/tmfv.2026.1.07

Zhou, T., Wu, X., Wang, Y., Wang, Y., & Zhang, S. (2023). Application of artificial intelligence in physical education: a systematic review. *Education and Information Technologies*, *29*(7), 8203. https://doi.org/10.1007/s10639-023-12128-2