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Review Article

AI-Enhanced Sports Training in Physical Education: Global Research Trends, Pedagogical Methods, and Ethical Frameworks (2002-2025)

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Abstract

Background. Artificial intelligence (AI) is rapidly entering physical education and sports training, providing new avenues for motion observation, learning diagnosis, and feedback. However, the pedagogical orientation and classroom feasibility of related research remain obscured by narratives focused primarily on technological performance.

Objectives. This study reviews and characterizes the knowledge base, thematic structure, and evolutionary trajectory of global AI-enabled physical education research from 2002 to 2025. It highlights implications for physical education decision-making and ethical governance, emphasizing the principle of "assisting teachers rather than replacing them."

Materials and Methods. A Web of Science Core Collection search conducted in April 2025 yielded 729 peer-reviewed English-language journal articles. Co-citation networks, keyword co-occurrence analysis, and BERT-based semantic clustering were used to identify core literature, thematic clusters, and stages of development. These results were integrated with an interpretive synthesis from a physical education perspective.

Results. Research has evolved from early motion quantification and data-driven analysis to deep learning-based motion recognition and generative AI-supported instructional feedback, demonstrating a shift toward "instructional-ethical governance." However, the evidence primarily focuses on universities and elite training programs. Empirical evidence in K–12 classrooms remains limited, and replicable implementation processes are lacking, creating a "laboratory–classroom" transition gap. Furthermore, issues such as curriculum articulation, learning stages, feedback timing, classroom risk management, and privacy and fairness remain insufficiently addressed.

Conclusions. In physical education, AI is best positioned as a teacher-led decision-support tool that enhances observation, formative assessment, and diagnostic feedback. Teachers should retain responsibility for key instructional judgments, prioritizing athletic development while ensuring safety and fairness. This study recommends using teaching effectiveness as the primary evaluation benchmark to promote explainable, controllable, and compliant classroom implementation pathways.

Keywords: artificial intelligence in physical education, bibliometric analysis, physical education pedagogy, motor learning, teacher education.

Introduction

The integration of artificial intelligence (AI) and sports science is reshaping research and practice in physical education (PE) and sports training (Lee & Lee, 2021; Zhang et al., 2023). In physical education classroom settings, AI tools are increasingly embedded in teachers' teaching loops, enabling more systematic observation of movement quality, diagnosing learning difficulties and common errors, and providing task-related feedback at appropriate teaching moments, thereby strengthening skill acquisition and the implementation of formative assessment (Lin et al., 2023). Meanwhile, deep learning demonstrates strong capabilities in movement recognition and biomechanical pattern analysis, enhancing teachers' diagnostic sensitivity. In addition, generative AI may support low-risk tasks such as lesson preparation, feedback expression optimization, and tiered task design under teacher supervision (Chen & Hou, 2022; Rahim et al., 2022). It is important to emphasize that, in physical education, AI should not be positioned as an "autonomous teacher" but rather as a teacher-led decision-support tool, one that assists professional judgment, maintains instructional control, and ensures that technology use remains consistent with curriculum goals, learners' progress, and classroom safety requirements.

However, existing research still exhibits a certain tendency toward "technology fragmentation." First, research on computer vision-based error correction often focuses on model accuracy and system development, paying insufficient attention to translating model outputs into understandable, operable motion cues and executable feedback in physical education classes (Zhao, 2022). Second, injury- or risk-related research emphasizes algorithmic prediction but provides little evidence of "classroom applicability" (Jiang et al., 2024). Third, adoption studies based on frameworks such as TAM primarily explain willingness to use but lack sufficient connection to the teaching process, classroom organization costs, formative assessment practices, and the conditions that enable teachers to sustain tool use in authentic teaching contexts (Kong & Song, 2015; Ma et al., 2025). While some studies have summarized the scale and regional distribution of output (Abulibdeh et al., 2024; Leal Filho et al., 2024), descriptive indicators alone are insufficient to address core issues in physical education. Much of the evidence remains focused on experimental settings or higher education and elite training environments, resulting in a significant "laboratory-classroom" transition gap in K-12 physical education classes under constraints related to class size, venue limitations, student heterogeneity, and risk exposure (Ba & Liu, 2022).

Accordingly, this study examines literature from 2002 to 2025, integrating co-citation analysis, keyword co-occurrence, BERT-based semantic clustering, and interpretive synthesis to characterize the knowledge base, thematic structure, and evolutionary trajectory of AI in physical education. From the perspective of physical education theory and methodology, this study identifies three interrelated challenges: (i) insufficient integration of algorithm development with instructional design; (ii) lagging ethical governance and limited classroom interpretability; and (iii) an overrepresentation of university and elite populations in the research samples, limiting transferability to diverse K-12 physical education classrooms. In response, this paper proposes a "teacher-in-the-loop" teaching paradigm in which AI provides evidence and prompts, while teachers retain ultimate responsibility for instructional judgment, task regulation, and risk management, thereby promoting a shift in research and practice from a "technology-centric" narrative to a feasible, "teaching-centric" classroom pathway.

Literature review

From Technical Precision to Pedagogical Application

The integration of artificial intelligence and sports science is driving physical education teaching and training analysis from "experience-based judgment" to "data-supported diagnosis" (Lee & Lee, 2021; Zhang et al., 2023). Deep learning-based motion recognition and motion pattern analysis can be used to identify common errors, present key motion cues, and provide formative feedback for skill learning (Cheng et al., 2022; Wang et al., 2023). In instructional practice, AI can also assist teachers in identifying fatigue and risk signals, thereby improving the monitorability of classroom safety management (Yu & Mi, 2023). However, "effective under experimental conditions" does not equate to "usable in classroom settings." As venue constraints, lighting variability, and student heterogeneity increase, model performance may decline, thereby weakening the stability and credibility of feedback (Kong, 2024). Furthermore, if the training data are biased toward elite samples, the resulting conclusions and rules are difficult to adapt directly to the learning characteristics and developmental levels of non-elite students (Peng & Xu, 2022). While generative AI and reinforcement learning promise to improve the effectiveness of personalized suggestions and practice retention (Chang et al., 2023), the extent to which teachers' professional knowledge is embedded in feedback rules and instructional decisions remains low (Filius et al., 2018). Therefore, AI should be positioned as a tool for "teacher diagnosis and decision support," rather than as an automated instructor that replaces the teacher.

Resource Differences and Data Representativeness

Global research shows that the development of artificial intelligence in physical education exhibits significant regional and resource imbalances. Some regions focus more on technology application research, whereas ethical governance issues are more prominent in others (Maphosa & Maphosa, 2023). Moreover, differences in research output across regions can lead to geographic and demographic homogenization of data sources, amplifying the risk of model bias and undermining fair evaluation for students with different body types, genders, and cultural movement styles (Yang et al., 2024; Pham et al., 2025). Furthermore, insufficient interdisciplinary integration remains a common problem. Some studies prioritize technological feasibility while neglecting to adequately discuss curriculum objectives, learning patterns, and instructional organization. While generative AI has promoted international collaboration and knowledge diffusion to some extent in recent years, resource disparities may still limit the accessibility and sustained use of AI-supported teaching in low-resource schools, thereby exacerbating the digital divide in physical education. Therefore, future research should be guided by the accessibility and representativeness of K-12 physical education classrooms, and should establish validation standards and data specifications that cover diverse student groups and instructional scenarios.

Teaching Ethics, Algorithmic Bias, and Student Safety

Existing AI ethical frameworks are mostly derived from general educational contexts and are insufficient to fully cover the characteristics of physical education classrooms, which involve "higher physical risks and greater sensitivity to continuous observation (Chen, K. et al., 2022)." In practice, some systems fall short in privacy protection and explainability, making it difficult for teachers to explain to students why a judgment occurred or why a warning or correction was triggered, thereby weakening the transparency and acceptability of the teaching feedback chain. Algorithmic bias can also translate directly into classroom equity issues. If model training data are biased toward a particular group, the system may produce higher error rates for female students or students with different body types, thereby affecting evaluation and learning opportunities. Although privacy-protection technologies are considered a potential solution, governance elements such as exit mechanisms, informed consent, and data ownership are often unclear in educational settings. Therefore, the "teacher-in-the-loop" principle must be adhered to in physical education. AI provides evidence and prompts, while teachers bear ultimate responsibility for instructional discretion and safety supervision.

Summary of Literature Gaps

In summary, existing research in physical education has at least four key gaps. First, the "laboratory-classroom transformation gap" is significant in K-12 education, with limited real-world classroom validation and few operational implementation procedures. Second, insufficient resource and data representativeness can perpetuate assessment biases and widen the digital divide (Pham et al., 2025; Yang et al., 2024). Third, ethical governance surrounding student safety, privacy, and explainability remains underdeveloped. Fourth, interdisciplinary integration is insufficient, and motor-learning principles and curriculum design have not been fully incorporated into model objectives and feedback rules (Filius et al., 2018). Therefore, research needs to shift from "algorithm optimization" to "teaching optimization" by using motor-learning principles and curriculum objectives as benchmarks, clarifying the decision-support boundaries of AI, and ensuring teachers' ultimate control over instructional processes and classroom risks.

Materials and Methods

Dataset Construction

This study conducted a topic search in the Web of Science Core Collection (SCI-EXPANDED & SSCI) covering 2002–2025 (through April 2025). The search query consisted of two parts: (i) AI-related terms (e.g., artificial intelligence, AI, machine learning, deep learning, neural networks), and (ii) physical education and sports teaching–related terms (e.g., physical education, sports training, teaching, curriculum, assessment, feedback, classroom management). The query also covered PETE and college physical education curriculum contexts to include studies with "teaching transfer significance" for K–12. The inclusion criteria were: (1) peer-reviewed English journal articles; (2) studies whose context involved physical education teaching, curriculum implementation, learning assessment and feedback, classroom management, or training management closely related to physical education; and (3) studies that clearly discussed teaching objectives, learning processes, feedback mechanisms, classroom implementation, or educational governance. The exclusion criteria were: papers that discussed only algorithm performance and hardware deployment without pedagogical relevance to physical education, and papers that were not sufficiently aligned with physical education contexts. Following PRISMA deduplication and screening (see Figure 1), two researchers independently completed the initial and secondary screening. Discrepancies were resolved through discussion, resulting in a final sample of 729 papers. The included papers have been cited a total of 11,691 times (11,467 excluding self-citations).

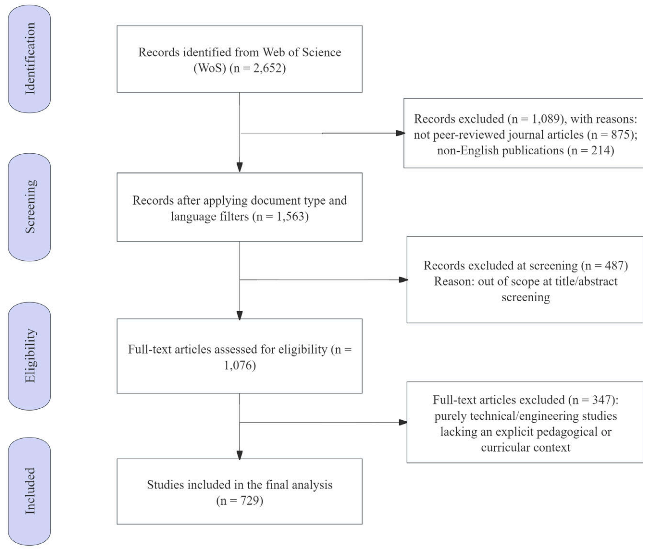

Fig. 1. PRISMA flow diagram of study selection. Records were identified from Web of Science (WoS) and screened according to predefined eligibility criteria for inclusion in the bibliometric analysis (2002-2025)

Table 1. Systematic Literature Search Strategy in Web of Science Core Collection

Parameter	Value
Database	Web of Science Core Collection (SCI-EXPANDED & SSCI), Version 2025-01
Time Span	2002-2025 (Year)
Search Field	Topic (Title, Abstract, Keywords)
AI Keywords	"Artificial Intelligence" OR "AI" OR "Deep Learning" OR "Machine Learning" OR "Neural Networks"
Application Context	"Physical Educat" OR "Higher Educat" OR "AI in physical education (teaching and training)"
Document Type	Article
Language	English

Data source: Web of Science.

Analytical Modeling

After the sample was determined, text and metadata preprocessing was performed, including keyword synonym merging and standardization, author and institution name disambiguation, and duplicate record removal. VOSviewer was then used to conduct quantitative analyses to map the knowledge base and conceptual structure of the field and to support pedagogical interpretation in physical education (Maphosa & Maphosa, 2023; van Eck & Waltman, 2010). Specifically, the analyses included: (1) co-citation analysis to identify the knowledge base and key theoretical sources; (2) keyword co-occurrence analysis to characterize thematic structure and conceptual evolution, with attention to shifts from "technical indicators and model terms" to pedagogical concepts such as "sports learning, teaching feedback, and curriculum evaluation"; (3) author and institutional collaboration network analysis to describe interdisciplinary collaboration patterns and their contributions to physical education research; and (4) performance indicator analysis to summarize the output and impact of authors, journals, institutions, and countries/regions. Furthermore, CiteSpace burst (emergence) detection was used to identify temporal shifts in keywords and themes, and developmental stages were delineated accordingly (see Fig. 2) (Chen, C., 2006). To reduce topic ambiguity caused by synonyms and variation in expression, this study integrated BERT-based semantic clustering to improve the consistency of topic classification and cross-validated the results against co-word clustering.

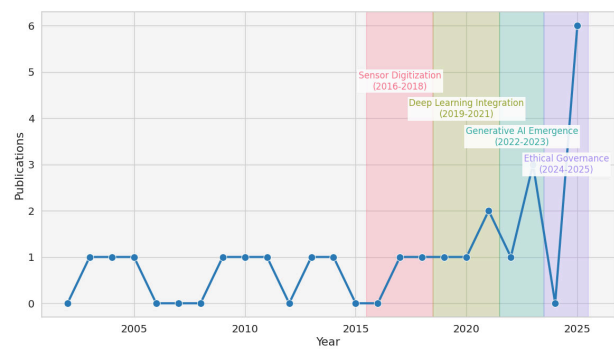

Fig. 2. Temporal evolution of research in AI in physical education (teaching and training), showing four developmental phases identified via CiteSpace burst detection.
Data source: Web of Science

Interpretive Synthesis

Building upon the bibliometric results, this study employs interpretive synthesis to transform network-structure findings into evidence demonstrating the interpretability and feasibility of physical education teaching. This was achieved through triangulation across co-citation, co-occurrence, and burst phases (Fig. 2), together with analysis of representative studies, thereby enhancing the traceability and pedagogical significance of the interpretation. At the interpretive level, a clear distinction is made between bibliometric conclusions and pedagogical interpretations. Each thematic cluster is described not only in technical terms but also reinterpreted within a physical education framework, including how it supports teachers' observation–diagnosis–feedback decision-making and whether its outputs align with principles of motor learning, curriculum objectives, and classroom management requirements. Finally, at the synthesis level, this study proposes a teacher-led boundary for human–machine collaboration. AI provides data-based evidence and prompts, while teachers retain responsibility for instructional judgment, task adjustment, and ensuring safety and fairness, thereby shifting emphasis from technological effectiveness to pedagogical effectiveness.

Results and Discussion

Publication Trends: Growth in Research on AI in physical education and Rising Demand for Digital Teaching

An analysis of 729 articles included in the Web of Science Core Collection shows a continued upward trend in AI research related to physical education (teaching and training). This field has been cited a total of 11,691 times (11,467 excluding self-citations), with an H-index of 52. The annual distribution (see Figure 3) indicates that 2002–2015 was a relatively slow "foundational period," during which research focused primarily on basic sensing and data-collection validation. Publication output accelerated significantly from 2019 onward and increased further after 2020. Specifically, 84 articles were published in 2021, rising to 188 in 2022 (2,147 citations), and peaking at 214 in 2024 (3,759 citations).

Pedagogical Interpretation. The growth reflects not only improvements in algorithms and hardware capabilities but also increasing demand for "observable, diagnosable, and feedback-oriented" digital support in physical education settings. In school physical education, teachers must monitor learning progress, assess movement quality, and manage risks under limited class time and complex conditions, and therefore rely more heavily on tools that can provide evidence and prompts. Therefore, this study emphasizes that AI should be positioned as a tool that supports teachers' observation, diagnosis, and decision-making rather than a "self-coach" that replaces instructional control, consistent with physical education curriculum goals and principles of motor learning.

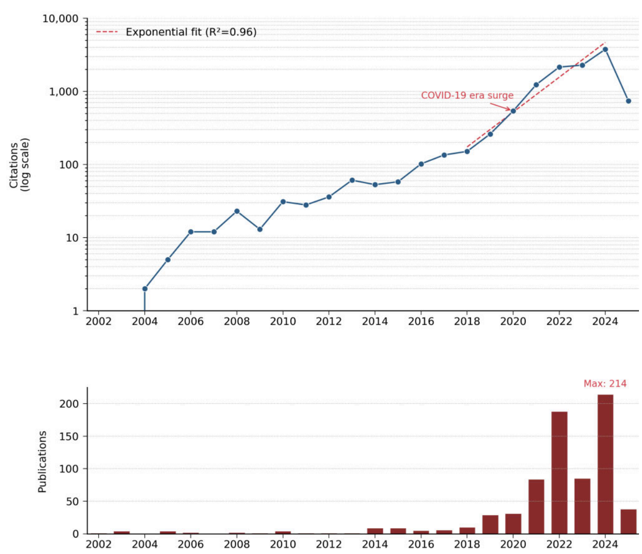

Fig. 3. Exponential growth patterns in academic output and influence (2002-2025). (A) Semi-logarithmic plot of annual citation counts with exponential trend line (2018-2024, R^2=0.98).(B)Projected publication growth (2024-2025) derived from historical CAGR of 31.2% (2016-2023). Accelerated adoption phase (2020-2022).
Data source: Web of Science

Performance Analysis: Subject Structure Characteristics and the Lack of Teaching Contextualization

This section reveals the subject structure characteristics of the field based on bibliometric performance indicators and further assesses the extent to which physical education (PE) issues are presented within the broader AI discourse, focusing on their consistency with the laws of sports learning, curriculum objectives, and instructional control.

High-impact literature

Highly cited research exhibits a "dual-track" structure. One stream emphasizes algorithm accuracy, recognition performance, and system implementation, often treating PE as a data-collection setting rather than a teaching context. The other stream focuses on classroom interaction, feedback mechanisms, and learning support, reflecting a more direct orientation toward instructional innovation. For example, Tedre et al. (2021) discuss the pedagogical trajectory of AI education from the perspective of K–12 AI literacy and classroom implementation. Rahim et al. (2022) explain the role of AI chatbots in learning support and adoption mechanisms in higher education. This structure suggests that "high-impact evidence" does not necessarily equate to evidence that is transferable to physical education instruction. Future research should shift evaluation from "technological effectiveness" to "instructional effectiveness."

Journal Impact

Journal distribution indicates that publications are concentrated in general or engineering-oriented journals rather than specialized physical education journals. For example, Sustainability (51 articles, 682 citations) and Engineering (41 articles, 907 citations) are among the most prominent outlets. The total link strength of Sustainability (TLS = 22) suggests increasing interdisciplinarity, with research beginning to align with education governance and the Sustainable Development Goals. However, from a physical education perspective, this pattern highlights a "technology-first, instruction-lagging" diffusion pathway: innovation is often driven by technological feasibility rather than by curriculum objectives, learning processes, or teacher instructional control.

Author and Institutional Contributions

Collaboration networks exhibit differentiated research emphases. For example, the Bucea-Manea-Tonis, Ilic, and Kuleto team (3 papers, 88 citations, TLS = 4) focuses on educational technology adoption and learning support, whereas the Artyukhov team (TLS = 18) concentrates on specific technological directions. At the institutional level, King Abdulaziz University leads in publication volume (16 papers), whereas Zhejiang University (7 papers) and the Royal Institute of Technology (KTH; 4 papers) show higher citation impact. These results suggest that institutions with both engineering capacity and a tradition of educational application are more likely to produce "usable and teachable" reference models.

National and Regional Distribution

At the national level, China dominates in output (290 papers, 2,055 citations), reflecting a greater emphasis on large-scale development and evaluation of "smart sports." In contrast, the United States (63 papers) and several European countries (e.g., the United Kingdom and Spain) place greater emphasis on educational governance and ethical frameworks. Notably, although South Korea and Malaysia have smaller publication volumes, they show high network connectivity (TLS = 37 and 32, respectively) and may serve as bridges between "evidence of technological scaling in East Asia" and "Western education-governance frameworks." For physical education, the value of such complementary collaboration lies not in comparing publication counts but in jointly addressing the translation gap between evidence generated in university and elite training contexts and implementation in K–12 classrooms.

Co-citation Analysis

Table 2 presents the 10 most influential papers in the co-citation network, forming the core knowledge foundation of the field. Overall, this foundation reflects a composite structure spanning "reviews of educational AI, technology-adoption theory, structural equation modeling, and generative-AI governance," indicating that research on AI in physical education draws heavily on educational technology and information-systems frameworks to explain the feasibility, effectiveness, and governance boundaries of AI use in physical education classrooms.

First, Zawacki-Richter et al. (2019), addressing the core question of "Where are the teachers?", argue that without teacher involvement in rule setting and outcome interpretation, AI systems may deviate from principles of motor learning and classroom management requirements in physical education. Relatedly, Popenici and Kerr (2017) and Chen et al. (2020) delineate functional boundaries for AI in education, providing a conceptual basis for positioning AI in physical education as a tool for "observation–diagnosis–feedback."

Second, Davis's (1989) TAM and Venkatesh et al.'s (2003) UTAUT are highly cited, suggesting that the key bottleneck in physical education is not simply algorithmic accuracy but whether "ease of use, low disruption, and interpretability" can sustain teachers' continued implementation. Fornell and Larcker (1981) and Henseler et al. (2015) provide measurement and methodological foundations for adoption mechanisms and the evaluation of teaching effectiveness.

Finally, Dwivedi et al. (2023) and Kasneci et al. (2023) highlight the coexistence of teaching support and academic-integrity risks associated with generative AI. In physical education, generative AI should support instructional design, rule interpretation, and personalized feedback generation; however, its use should adhere to the "human-in-the-loop" principle to ensure classroom safety, fairness, and instructional consistency. Biggs et al.'s (2001) learning-orientation measure also suggests that research evaluation should shift from "technical performance" toward the learning process and teaching effectiveness.

Thematic Clusters in the Co-citation Network

Based on the VOSviewer co-citation network (see Figure 4), this study identified four main thematic clusters. Unlike clusters commonly reported in general educational

Table 2. Top 10 Documents Identified Through Co-Citation Analysis

Rank	Authors	Title	Citations	Total Link Strength
1	Zawacki-Richter, O et al. (2019)	Systematic review of research on artificial intelligence applications in higher education-where are the educators?	26	93
2	Chen, L et al. (2020)	Artificial intelligence in education: A review	18	83
3	Fornell, C et al. (1981)	Evaluating structural equation models with unobservable variables and measurement error	18	83
4	Davis, F. D et al. (1989)	Perceived usefulness, perceived ease of use, and user acceptance of information technology	17	92
5	Venkatesh, V et al. (2003).	User acceptance of information technology: Toward a unified view	17	90
6	Henseler, J et al. (2015)	A new criterion for assessing discriminant validity in variance-based structural equation modeling	16	84
7	Popenici, S. A et al. (2017)	Exploring the impact of artificial intelligence on teaching and learning in higher education	16	69
8	Biggs, J et al. (2001)	The revised two-factor study process questionnaire: R-SPQ-2F	16	22
9	Dwivedi, Y. K et al. (2023).	Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy	14	83
10	Kasneci, E et al. (2023).	ChatGPT for good? On opportunities and challenges of large language models for education	14	73

Data source: Web of Science.: VOSviewer analysis on co-citation.

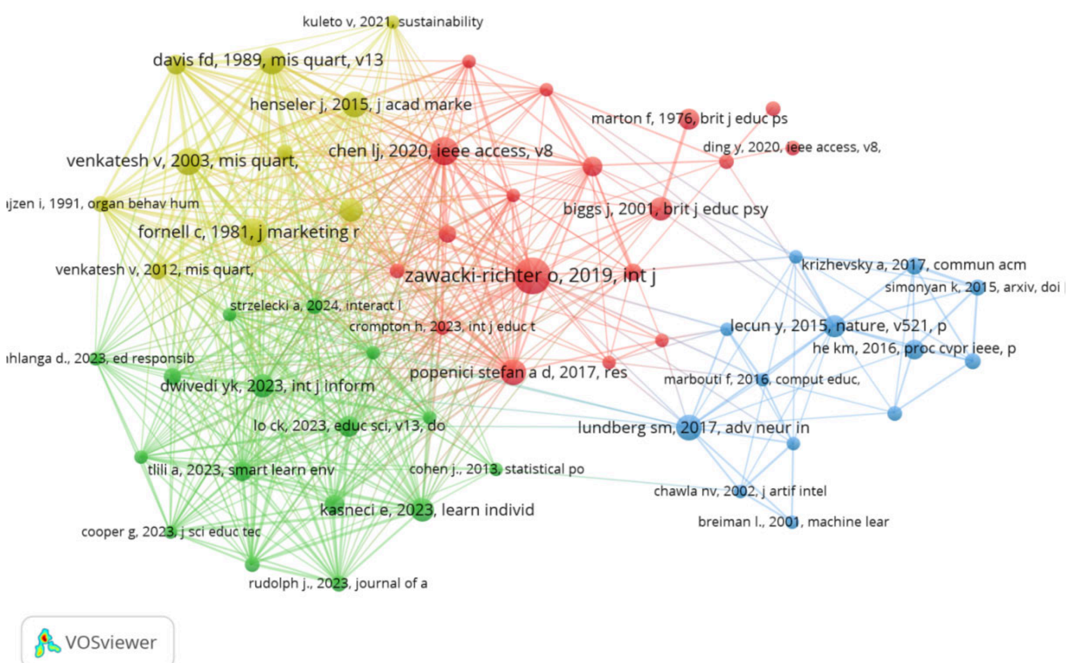

Fig. 4. Network visualization of document co-citation relationships identifying thematic research clusters (Generated using VOSviewer)

technology research, this study reinterprets them from a physical education perspective, focusing on how each cluster supports the "observation–diagnosis–feedback–regulation" teaching loop and assessing alignment with principles of motor learning, curriculum objectives, and classroom implementation requirements.

Cluster 1 (Red): Teaching Practice and Teacher Role

This cluster emphasizes that when AI enters physical education classrooms, teachers remain key actors in rule setting and meaning interpretation. Related research indicates that without teacher involvement, system outputs may become "black-box" judgments that fail to align with classroom feedback timing and safety management (Zawacki-Richter et al., 2019). This cluster also includes discussions of AI-enabled personalization and instructional management, as well as the impact of generative AI on student participation and K–12 ethics (Chen et al., 2020; Akgun & Greenhow, 2022; Chan & Hu, 2023). Therefore, in physical education, AI should remain subordinate to teachers' professional discretion, with teachers determining error-correction thresholds, feedback methods, practice prescriptions, and evaluation standards.

Cluster 2 (Green): Generative AI and New Teaching Support

This cluster focuses on the coexistence of support and risks associated with generative AI, represented by ChatGPT (Dwivedi et al., 2023; Kasneci et al., 2023). It also addresses students' experiences and emotional responses (Strzelecki, 2024), as well as academic-integrity and ethical risks (Cotton et al., 2024; Tlili et al., 2023). In physical education, generative AI is better suited as a "teaching decision-support interface" to generate lesson scripts, interpret rules, and provide tiered practice suggestions. However, recommendations involving safety, load control, and risk warnings should be reviewed by teachers before implementation to reduce the risk of injury resulting from inappropriate feedback.

Cluster 3 (Blue): Learning Analytics and the Foundation of Instructional Diagnosis

This cluster provides foundational methods for motion recognition and learning-process analysis (He et al., 2016; LeCun et al., 2015) and emphasizes identifying learning differences and process risks through learning analytics (Gašević et al., 2016). From a physical education perspective, these technical capabilities should be used not only to identify "standard" movements but also to identify learning stages and developmental levels, thereby expanding the diagnostic focus from competitive performance to classroom learning evidence and supporting formative assessment and process feedback rather than single-outcome ranking.

Cluster 4 (Yellow): Adoption Mechanism and Use Intention

This cluster integrates adoption models such as TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003) with behavioral theory and measurement-validity testing methods (Ajzen, 1991; Fornell & Larcker, 1981). In physical education, the bottleneck to widespread adoption is often not "higher precision" but "fewer interruptions." Only when AI tools are sufficiently lightweight, interpretable, and controllable—and do not increase classroom-organization costs—can teachers use them consistently in real classrooms.

In summary, the four clusters collectively indicate that algorithmic capabilities enable potential applications, whereas teacher leadership, classroom safety, and ethical governance determine usability, and adoption mechanisms shape sustained implementation. Future research should use principles of motor learning and curriculum objectives as benchmarks to advance AI from "technologically effective" to "teaching-effective," thereby bridging the gap between experimental research and classroom practice.

Keyword Co-occurrence Analysis

Table 4 shows that among the 729 included articles, high-frequency keywords are dominated by general AI and educational-technology discourse. "Artificial intelligence" (127) and "higher education" (73) occupy central positions in the network, whereas "physical education" (23) ranks 12th, suggesting that when AI enters school-sport contexts, the disciplinary identity of physical education can be overshadowed by a broader "educational technology" narrative. At the same time, the total link strength of "physical education" (TLS = 40) indicates a key bridging role. When it appears in the co-occurrence network, it links concepts related to algorithms and systems, learners, teaching outcomes, and classroom applications, underscoring physical education as a node connecting technology-oriented research with pedagogical interpretation. It should be noted that variants such as "higher education" and "higher-education," as well as "artificial intelligence," "artificial-intelligence," and "AI," appear separately in Table 4 due to differences in writing style. Synonym merging and standardization were applied during preprocessing; therefore, this pattern reflects disciplinary discourse habits rather than a substantive conceptual split.

Table 4. Top 15 keywords from the keyword co-occurrence analysis.

Rank	Keyword	Occurrences	Total Link Strength
1	artificial intelligence	127	262
2	higher education	73	193
3	deep learning	65	84
4	education	52	134
5	higher - education	44	109
6	students	40	94
7	model	34	67
8	machine learning	31	67
9	artificial - intelligence	29	75
10	system	24	69
11	chatgpt	23	80
12	physical education	23	40
13	performance	22	64
14	ai	20	53
15	big data	20	52

Data source: Web of Science.: VOSviewer analysis on co-occurrence.

Figure 5 further reveals five thematic clusters. Rather than treating these clusters as "components of a digital teaching system," this study highlights their pedagogical functions and limitations within the "observation–diagnosis–feedback–regulation–evaluation" evidence chain in physical education.

Cluster 1 (Red): Generative AI and Instructional Support

This cluster centers on ChatGPT, generative AI, and related models, and primarily concerns the generation of instructional content, learning support, and classroom communication. In physical education, its value lies primarily in low-risk activities such as lesson preparation, generation of tiered tasks, explanation of rules and tactics, and formative assessment, rather than replacing key judgments and safety checks in technical-skill instruction.

Cluster 2 (Green): Data-Driven Classroom Management and Safety Governance

This cluster links themes such as "big data—risk—management—training and classroom optimization." It suggests that more mature applications of AI in physical

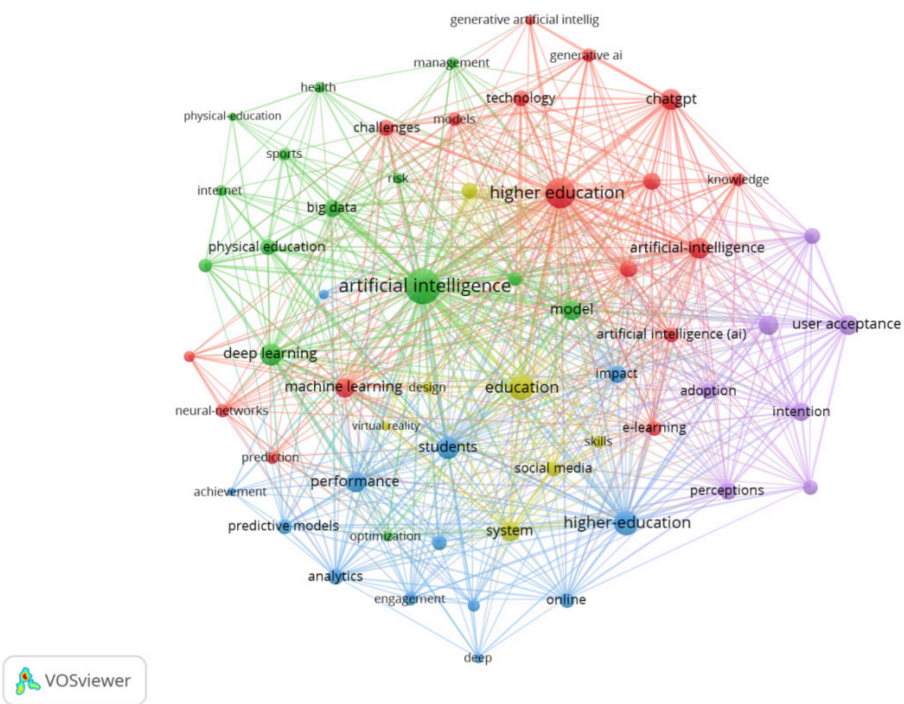

Fig. 5. Thematic clusters identified through keyword co-occurrence analysis focusing on artificial intelligence and physical education (VOSviewer).

education are not aimed at "teaching movements directly" but at assisting teachers in monitoring workload and participation, providing risk warnings, and managing classroom order, thereby improving classroom controllability and student safety. To maintain thematic consistency, this study uses the term "AI-supported monitoring and early warning" to avoid extending the discussion to technologies unrelated to the main theme.

Cluster 3 (Blue): Learning Analysis, Motivation, and Learning Outcomes.

This cluster reflects a shift from "outcome performance" to the "learning process," emphasizing the use of objective data to characterize participation, activity levels, and progress trajectories. This shift provides an evidentiary basis for reforming assessment in physical education and promotes a transition from "talent- and achievement-oriented" evaluation to "effort- and progress-oriented" formative assessment.

Cluster 4 (Purple): Technology Adoption and Teacher Usability

This cluster focuses on variables related to acceptance and use intention (e.g., TAM and UTAUT), indicating that barriers to implementation often lie in teacher workflow and classroom procedural costs rather than in recognition accuracy alone. Physical education classrooms, in particular, require low-burden, low-interruption, interpretable, and controllable tool designs; otherwise, even "high accuracy" may be difficult to integrate into routine practice.

Cluster 5 (Yellow): Immersive Learning and Skill Acquisition

This cluster points to topics such as VR and skill learning, whose significance in physical education lies in providing beginners with contextualized demonstrations and a safe environment for practice, thereby reducing the cognitive load of complex skills and improving practice quality.

Overall, the keyword structure indicates that research is expanding from "systems and models" toward "teaching applications." However, research on AI in physical education still needs to be anchored in curriculum objectives, principles of motor learning, and classroom implementation. This requires positioning AI as a teacher-led decision-support tool, emphasizing classroom feasibility and instructional effectiveness, and designing implementation pathways with safety and equity as non-negotiable constraints (see Table 4 and Figure 5).

Implications

Theoretical Significance

While deep learning-based action recognition can improve diagnostic efficiency, its implicit assumption of "standard action–deviation correction" can lead to the view that a single "ideal posture" represents the only correct answer, thereby neglecting functional variation and developmental differences in motor learning. Therefore, in physical education, AI outputs should be framed as evidence and prompts, with teachers providing pedagogical interpretation and secondary decision-making based on learners' levels, task objectives, and safety constraints. Data representativeness should not be viewed merely as a matter of technical accuracy but should be incorporated into an educational-equity framework. Overly homogeneous training data may introduce systematic errors across gender, body type, or culturally patterned movement styles, thereby undermining fairness in assessment opportunities and learning support (Pham et al., 2025). Privacy-oriented approaches (e.g., federated learning) hold promise, but their educational legitimacy depends on informed consent, data minimization, clearly defined ownership, and teacher-controlled data-use rules.

Practical Significance

Given that laboratory models often show performance degradation and contextual mismatch in real classrooms, AI should be prioritized for low-risk formative assessment in physical education, such as identifying learning-progress trends, monitoring participation and movement quality, providing risk alerts, and supporting classroom management. It should not be used directly for high-risk summative scoring or single-session ranking. To improve K–12 feasibility, system design should emphasize lightweight deployment, interpretable outputs, and teacher-adjustable thresholds and rules to ensure that "technology does not disrupt the teaching process." Teacher education, including physical education teacher education (PETE), should systematically incorporate AI literacy, bias identification, and ethical-governance competencies, enabling teachers to evaluate evidence reliability and retain ultimate responsibility for classroom safety and assessment fairness (Tedre et al., 2021; Akgun & Greenhow, 2022). At the policy level, replicable classroom-validation standards and cross-context assessment processes should be established to promote the transfer of evidence from university and elite training contexts to diverse K–12 classrooms.

Conclusion, limitations and future avenues

Conclusion

Based on 729 peer-reviewed English journal articles (2002–2025) retrieved and screened from the Web of Science Core Collection, this study systematically depicts the knowledge structure and evolution of artificial intelligence (AI) research in physical education and sports training. The results indicate that existing evidence primarily focuses on university and competitive training settings, whereas evidence on curriculum integration, classroom management, and operational implementation in K–12 classrooms remains limited, creating a substantial "research-to-classroom" translation gap (Filho et al., 2024). Furthermore, inadequate privacy protection and limited interpretability weaken teachers' control over the "observation–diagnosis–feedback–regulation" teaching loop (Abulibdeh et al., 2024). Therefore, AI in physical education should be positioned as a teacher-led decision-support tool: AI provides evidence and suggestions, whereas teachers retain responsibility for setting instructional objectives, adjusting tasks, ensuring safety, and exercising evaluative discretion to align instruction with learner differences and motor-development patterns.

Limitations

This study used only the WoS Core Collection, which may have overlooked relevant regional or interdisciplinary journals in physical education; moreover, restricting the corpus to English inevitably introduces language bias. As a bibliometric study, this paper is well suited to revealing macro-structures, research hotspots, and evolutionary trends; however, it cannot fully capture "in-situ teaching evidence," such as classroom interactions, teacher experiences, implementation processes, and contextual constraints. These limitations could be addressed by complementary methods such as classroom experiments, design-based research, and qualitative interviews (Demartini et al., 2024).

Future directions

1. From "Technological Effectiveness" to "Teaching Effectiveness": Grounded in curriculum objectives, principles of motor learning, and formative assessment, future work should develop interpretable AI and actionable feedback rules so that outputs can inform teachers' instructional decisions rather than merely reporting model indicators (Abulibdeh et al., 2024).

2. Strengthen teacher education and ethical-audit capacity: Systematically incorporate AI literacy, bias identification, data governance, and safety-responsibility training into PETE, positioning teachers as key nodes in a human–machine collaborative loop to ensure classroom safety, assessment fairness, and instructional autonomy (Tedre et al., 2021).

3. Narrow the K–12 transition gap and resource disparities: Promote low-threshold, privacy-friendly deployment solutions and cross-school, cross-cultural validation standards; conduct replicable K–12 empirical studies and longitudinal follow-up to build a scalable evidence base for classroom implementation (Leal Filho et al., 2024).

Ethics Approval

Not applicable. This bibliometric review is based exclusively on publicly available literature sources and did not involve human participants, animals, or identifiable personal data.

Informed Consent

Not applicable, as the study did not involve human participants.

Data Availability Statement

The data underlying this study were derived from publicly available bibliographic records retrieved from the Web of Science Core Collection. The search strategy, eligibility criteria, and analysis procedures are described in the Methods section. The dataset generated and analyzed during the current study is available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Transparency Statement

AI-assisted tools were used solely for language refinement and structural editing of the manuscript, based exclusively on content developed by the authors. No AI tools were used for data collection, data analysis, interpretation of results, or generation of data, findings, or references. The authors retain full responsibility for the accuracy, integrity, and final content of the manuscript.

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Тренування у спорті та фізичному вихованні з використанням штучного інтелекту: глобальні дослідницькі тренди, педагогічні методи та етичні рамки (2002–2025)

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Авторський вклад: A – дизайн дослідження; B – збір даних; C – статаналіз; D – підготовка рукопису; E – збір коштів

Реферат. Стаття: 21 с., 4 табл., 5 рис., 45 джерел.

Обґрунтування. Штучний інтелект швидко входить у сферу фізичного виховання та спортивної підготовки, відкриваючи нові можливості для спостереження за рухами, діагностики навчання та надання зворотного зв'язку. Однак педагогічна спрямованість і можливість практичного застосування результатів відповідних досліджень у навчальному процесі часто залишаються невиразними через домінування наративів, зосереджених переважно на технологічній ефективності.

Мета дослідження. У дослідженні здійснено огляд і характеристику бази знань, тематичної структури та еволюційної траєкторії світових досліджень застосування штучного інтелекту у фізичному вихованні у 2002–2025 роках. Особливу увагу приділено їхнім наслідкам для прийняття рішень у фізичному вихованні та етичного врядування з акцентом на принципі «допомагати вчителям, а не замінювати їх».

Матеріали і методи. Пошук у базі даних Web of Science Core Collection, проведений у квітні 2025 року, дав змогу відібрати 729 рецензованих журнальних статей англійською мовою. Для визначення ключової літератури, тематичних кластерів і етапів розвитку використано аналіз мереж коцитування, аналіз співзустрічальності ключових слів та семантичну кластеризацію на основі моделі BERT. Отримані результати були інтегровані з інтерпретаційним синтезом із позицій фізичного виховання.

Результати. Дослідження еволюціонували від раннього кількісного вимірювання рухів і аналізу на основі даних до розпізнавання рухів на основі глибинного навчання та використання генеративного штучного інтелекту для підтримки навчального зворотного зв'язку, що свідчить про перехід до «інструкційно-етичного врядування».Водночас наявні докази зосереджені переважно на університетах і програмах підготовки спортсменів високого рівня. Емпіричні дані щодо використання в школах залишаються обмеженими, а відтворювані процеси впровадження практично відсутні, що створює розрив між «лабораторією та класом». Крім того, такі питання, як узгодженість навчальних програм, етапи навчання, час надання зворотного зв'язку, управління ризиками в класі, а також конфіденційність і справедливість, залишаються недостатньо опрацьованими.

Висновки. У фізичному вихованні штучний інтелект доцільно розглядати передусім як інструмент підтримки прийняття рішень під керівництвом учителя, що посилює можливості спостереження, формувального оцінювання та діагностичного зворотного зв'язку. Учителі повинні зберігати відповідальність за ключові педагогічні рішення, надаючи пріоритет розвитку рухових здібностей і забезпечуючи безпеку та справедливість. У дослідженні рекомендується використовувати ефективність навчання як основний критерій оцінювання для просування пояснюваних, керованих і нормативно сумісних шляхів застосування штучного інтелекту в навчальному процесі.

Ключові слова: штучний інтелект у фізичному вихованні, бібліометричний аналіз, педагогіка фізичного виховання, моторне навчання, підготовка вчителів.

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