ARTIFICIAL INTELLIGENCE IN THE DELIVERY OF PHYSICAL AND HEALTH EDUCATION

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Abstract

This paper examined how artificial intelligence should be integrated into the delivery of Physical and Health Education (PHE), a discipline whose core content, unlike that of Mathematics or English, is embodied, practical and relational rather than purely informational. Physical and Health Education delivery is shaped by structural strain, large class sizes, inconsistent feedback, uneven engagement, and heavy teacher workloads, that AI is increasingly proposed to address. The paper asks not simply whether AI belongs in PHE, but which of the discipline's functions can be meaningfully augmented by AI, which should remain fundamentally human, and what conditions should govern the boundary between the two.

AI should be strategically integrated into PHE as a pedagogical support tool rather than a replacement for educators, with its role bounded by ethical safeguards, equitable access, and preservation of the discipline's practical, embodied nature. The appropriateness of AI in PHE depends on the educational domain being served: it clusters around outcomes that are structured and measurable, and diminishes sharply around outcomes that are relational, moral, and social.

The paper defined the relevant AI technologies before examining their current applications in PHE across eight categories, including personalized learning, motion analysis, wearable technology, virtual and augmented reality, and health education. It builds the case for integration around documented evidence of improved personalization, engagement, accessibility, and teacher support, then weighs this against genuine counterarguments: the digital divide's weight in infrastructure-constrained regions, teacher displacement fears, ethical risks around bias and surveillance, threats to academic integrity, loss of human interaction, and a definitional limit, whether AI can meaningfully teach teamwork or values, that current evidence does not resolve. Ethical and policy conditions for adoption are set out, alongside recommendations for governments, schools, teachers, curriculum developers, and researchers.

AI's demonstrated strengths cluster around PHE's psychomotor and cognitive domains; its affective and social domains remain, and should remain, the province of the human teacher. Benefits and risks are not fully symmetrical: many risks are governance failures addressable through policy, while other risks, including persistent algorithmic bias and the behavioural effects of continuous monitoring, call for ongoing evaluation rather than a one-time fix. Current evidence does not establish that AI can substitute for the relational and social learning PHE's affective domain depends on, which is why those

functions should not yet be delegated to AI. The paper's central contribution is this domain-specific standard for integration, rather than a categorical verdict for or against AI in PHE.

Keywords: Artificial intelligence, Physical education, Health education, Embodied pedagogy, Educational technology, AI ethics, Digital divide

Introduction

Educational technology has moved through distinct waves: from early computer-assisted instruction, to the internet-enabled digital learning platforms of the 2000s and 2010s, to what is now widely described as an AI revolution in how content is taught, practiced, and assessed. Artificial intelligence has moved from the margins of educational discourse toward its center over a comparatively short period. The release and rapid uptake of generative AI tools from 2022 onward produced a measurable spike in educational research and institutional activity, with reviews of the literature describing AI's shift "from an emergent innovation to a core element of educational research and practice" (Garzón et al., 2025). This is not merely academic interest. By the 2023–2024 school year, national survey data in the United States found that roughly a quarter of teachers were already using AI tools for instructional planning or teaching, and nearly 60 percent of school principals reported using AI in their own administrative work (Kaufman et al., 2025). International bodies have moved just as fast: UNESCO's 2023 Guidance for Generative AI in Education and Research and its 2024 AI Competency Framework for Students were both produced in direct response to how quickly generative tools entered classrooms, and both insist that AI should support teachers rather than substitute for them (Miao & Holmes, 2023).

Physical and Health Education (PHE) has not been exempt from this shift: recent systematic reviews document a fast-growing body of research applying AI to motion analysis, athletic performance tracking, health monitoring, and personalized training programmes within PE settings (Wang & Wang, 2024; Zhou et al., 2024). AI's role in education generally, and in PHE specifically, therefore appears to be expanding rather than plateauing.

This growth is arriving at a subject with real, well-documented strain, and with public-health stakes that extend beyond the classroom. Traditional PHE delivery is shaped by structural challenges that have persisted for years: large class sizes make individualized instruction difficult to sustain, feedback on movement and technique is often inconsistent or delayed because one teacher cannot observe every student at once, student engagement drops where activities are generic rather than tailored to ability or interest, practical monitoring of fitness and skill progress is time-consuming to do by hand, and teachers already carry a heavy workload before any of this is accounted for (Cui et al., 2025; Ahn & Lim, 2025). These are not abstract pedagogical concerns: globally, the prevalence of overweight, including obesity, among children and adolescents aged 5 to 19 rose from roughly 8 percent in 1990 to 20 percent in 2022 (World Health Organization, 2024), a trend PHE is positioned to influence through the quality of instruction it delivers to

nearly every child in a school system. AI is now being proposed, by researchers, edtech developers, and increasingly by teachers themselves, as a solution to these problems: automated movement analysis in place of manual observation, adaptive programmes in place of one-size-fits-all drills, data dashboards in place of paper-based tracking. This proposal is plausible precisely because the underlying problems are well documented, but plausibility is not the same as demonstrated fit, and PHE's practical, embodied, relational character raises a legitimate question addressed directly rather than assumed away: whether, and under what conditions, integration is warranted.

Understanding Artificial Intelligence in Education

Meaning of Artificial Intelligence

Artificial intelligence is used loosely enough in everyday conversation that a working definition is worth stating plainly before the term is applied to PHE. Gignac and Szodorai (2024)define AI as "an artificial system's maximal capacity to complete a novel standardized task with veridical scoring using computational algorithms." This broad definition covers several distinct, nested technologies, and the differences between them matter for what follows. Machine learning (ML) is the subset of AI in which systems learn patterns from data and improve their performance without being explicitly reprogrammed for each new task, a process Lamba and Madhusudhan (2022) describe in detail as one built on iterative training against a dataset until a model's predictions converge on an acceptable level of accuracy. Deep learning (DL) is, in turn, a subset of ML that uses layered neural networks to process large, complex datasets, and it underlies most of the AI capability now visible in schools (Yu & Guo, 2023).

Generative AI (GenAI) builds on deep learning but is defined by what it produces rather than how it learns: Lund and Wang (2023), writing within weeks of ChatGPT's public release, describe generative models as systems that perform language-based and content-creation tasks by predicting the most probable next element in a sequence, rather than simply classifying or retrieving existing information. Two further, more specialized branches are directly relevant to PHE. Computer vision (CV) enables systems to interpret and analyze visual input, which is what makes motion tracking and posture correction technically possible (Rapid Innovation, 2024). Natural language processing (NLP) enables systems to interpret, generate, and respond to human language, and is the technology behind chatbots, automated writing feedback, and voice-based instruction (Lan et al., 2024). None of these terms are interchangeable, and conflating them, treating a simple ML-based scheduling tool as if it carries the same capability or risk profile as a generative, language-fluent system, is one of the more common errors in institutional AI policy.

Application of AI in Education

Applied to classrooms, these underlying technologies take a recognizable set of forms, and PHE is where two of them, computer vision and wearables, do the most distinctive work. Computer vision is what makes automated movement analysis possible at all: pose-estimation algorithms extract keypoints from ordinary video, allowing a system to compare

a student's jump shot, sprint form, or stretch technique against a reference model without any specialized camera rig (Cui et al., 2025). This is the technical foundation behind real-time feedback tools now being piloted in PE settings; in one randomized controlled trial, a pose-recognition system providing real-time correction on a Baduanjin course significantly improved students' movement quality, fluency, and self-directed learning compared to a traditional online format (Ma et al., 2025). Wearables extend this further onto the body itself: sensors that capture heart rate, movement, and other physiological data generate exactly the kind of embodied, real-time data that content-based subjects do not produce (Glasserman-Morales et al., 2023; Wang & Wang, 2024). Feeding this data into learning-analytics dashboards has already been linked, in a mixed-methods study of 1,182 students across four Chinese universities, to gains in students' physical literacy and engagement, mediated by improvements in perceived teaching quality and personalized feedback (Chen et al., 2026).

Virtual reality (VR) integration sits close behind, creating simulated environments for skill rehearsal, with early applications already reported in university PE teaching (Wang et al., 2024). The remaining categories are more general-purpose and better known outside PHE: adaptive learning platforms and intelligent tutoring systems adjust content to individual performance (Zerkouk et al., 2025); automated grading tools apply NLP to score constructed responses (Deepshikha, 2026); and chatbots provide on-demand, conversational support outside class hours (Elnaffar et al., 2026). Together, these examples show that "AI in education" is not one tool but a cluster of distinct technologies, each entering PHE through a different door. Section 4 returns to computer vision, wearables, and VR in more depth, weighing what their PHE-specific applications genuinely deliver against the risks they introduce.

Nature of Physical and Health Education

Goals

Physical and Health Education is not simply a delivery mechanism for movement content; its stated purpose is the development of physically literate, healthy, and socially competent individuals across the full span of schooling. UNESCO's Quality Physical Education (QPE) policy framework defines this explicitly: unlike a "one size fits all" content subject, QPE is built on equitable access to a well-balanced, inclusive curriculum that develops psychomotor, social, and emotional skills together, with physical literacy treated as a key developmental milestone in its own right rather than a byproduct of instruction (UNESCO, 2021). This multi-domain aim is precisely what distinguishes PHE's goals from those of a content subject, where success can be defined largely in terms of correct answers or demonstrated knowledge.

Domains

That multi-domain aim is conventionally organized around three (sometimes four) areas of learning: the psychomotor (physical), cognitive, and affective domains, occasionally extended to include a distinct social domain (Dudley et al., 2022). The psychomotor domain concerns the direct development of movement, coordination, and physical skill,

and is the domain most visibly unique to PHE among school subjects. The cognitive domain covers understanding of rules, strategy, biomechanics, and health knowledge, the part of PHE that most resembles a conventional content subject and is therefore the part most amenable to digital delivery. The affective domain concerns attitudes, motivation, confidence, sportsmanship, and enjoyment of movement, dimensions that are shaped as much by relationship and social context as by instruction. A systematic review and meta-analysis of 135 PE-based interventions found that effects varied meaningfully across these domains, with the largest gains typically observed in psychomotor outcomes, underscoring that PHE's core deliverable is not information transfer but demonstrable physical capability (Dudley et al., 2022). A pedagogy, and by extension a technology, that serves the cognitive domain well will not automatically serve the psychomotor or affective domains equally well, which is a distinction the argument developed in later sections depends on.

Characteristics

Several concrete characteristics follow from this multi-domain nature. Movement is the medium of instruction itself, not merely its topic: a PHE lesson is largely enacted through bodies in space rather than through text, speech, or static representation. Skill acquisition, the progressive refinement of a movement pattern through repetition, feedback, and correction, is a defining pedagogical process; the decline in fundamental movement skill acquisition documented in a recent scoping review of 95 studies illustrates how much this process depends on quality, in-person instruction rather than content exposure alone (Piotrowski et al., 2025). Health literacy sits alongside movement as a second core strand, since PHE is charged with building the knowledge students need to understand and manage their own health behaviours over a lifetime, not only their in-class performance. Fitness, the measurable physiological outcome of consistent activity, is both a goal of PHE and one of its more assessable characteristics, though its assessment interacts closely with the equity concerns raised in Section 6. Practical activities, drills, games, sport, dance, and conditioning work, constitute the dominant instructional format, in contrast to the lecture-and-assessment format common to content subjects. Finally, assessment in PHE carries genuine, well-documented challenges: physical literacy, in particular, has proven difficult to measure consistently, with reviewers noting that existing tools largely capture fundamental movement skills while giving limited consideration to the motivational, confidence, and lifelong-engagement dimensions that make up the construct as a whole, and that assessment design should keep sight of the ultimate goal of fostering genuine human flourishing rather than measurement for its own sake (Van Wyk et al., 2025; Huang, 2024). These characteristics, taken together, are the reason PHE cannot simply adopt AI tools built for content-based subjects without adaptation; any AI application considered for PHE has to be evaluated against a discipline where the object of learning is a capable, healthy, motivated body, not a body of knowledge.

AI Applications in Delivery of PHE Content

Most mature AI applications cluster around the psychomotor domain, quantifying and correcting movement, and the cognitive domain, delivering health knowledge, where data is structured and outcomes are measurable. Far fewer address the affective domain, motivation, confidence, enjoyment, directly. This section works through eight application clusters roughly in that order, moving from applications closest to the body outward to applications closest to knowledge and assessment, so the uneven coverage becomes visible as a pattern rather than an incidental list.

Personalized Learning

Personalized learning applications use machine learning to adjust instructional content to an individual student's ability, pace, and goals rather than delivering a single fixed programme to an entire class. In PE specifically, this has taken the form of adaptive fitness models that generate customized exercise plans and adjust them as a student's performance data accumulates. One such model, tested against undergraduate physical fitness outcomes, was able to tailor independent exercise plans to individual needs and meaningfully improve fitness outcomes compared to a standard, one-size-fits-all programme (Li et al., 2024). Large classes make individualized instruction difficult to sustain by hand, and adaptive systems offer a partial, data-driven substitute, provided the underlying exercise data is accurate and the plan still allows for teacher override.

Intelligent Tutoring

Where personalized learning adjusts content, intelligent tutoring systems (ITS) add an interactive, responsive layer, functioning as a virtual coach that observes performance and explains corrections as they happen. An AR-based taekwondo coaching system, for example, combined pose estimation with real-time visual overlays to flag technical errors during practice, achieving high movement-recognition accuracy across nine technique categories and producing measurable gains in technique standardization among 47 practitioners across skill levels (Yang & Wang, 2025). This is intelligent tutoring in its clearest PHE form: not a chatbot answering questions about rules, but a system that watches a body move and responds to it in the moment, which is precisely the kind of individualized correction a single teacher cannot give to thirty students simultaneously.

Motion Analysis

Motion analysis is the technical foundation beneath most of the applications above. Pose-estimation algorithms extract skeletal keypoints from ordinary video, letting a system compare a student's technique against a reference model without specialized hardware (Cui et al., 2025). Applied to sports technique and biomechanics specifically, this enables skill correction at a level of consistency human observation cannot match: in an eight-week randomized controlled trial, a pose-recognition system giving real-time correction on a traditional Chinese exercise routine significantly improved students' movement quality and fluency compared to a conventional online format, with increased learning duration identified as the primary mechanism behind the gain (Ma et al., 2025). Motion analysis is,

in effect, the psychomotor domain rendered legible to a machine, which is exactly why it has attracted more research attention in PHE than any other AI application category.

Wearable Technology

Wearables extend data collection from the camera onto the body itself. Sensors that track heart rate, calorie expenditure, activity levels, and increasingly sleep, generate continuous physiological data that a teacher's observation simply cannot produce (Glasserman-Morales et al., 2023). Feeding this data into dashboards has been linked to concrete outcomes: a mixed-methods study of 1,182 students across four Chinese universities found that wearable-derived analytics use was associated with better physical literacy and engagement, mediated by improved perceived teaching quality and more personalized feedback (Chen et al., 2026). Wearables also support exercise adherence directly, since students and teachers can track activity patterns over a term rather than relying on memory or spot-checks, though this raises the data-privacy questions Section 6 addresses.

Virtual Reality

Virtual reality creates a fully simulated environment for skill rehearsal, letting students practice sports techniques or navigate health scenarios without real-world risk or resource constraints. Early applications in university PE teaching have used VR to enhance the practical teaching and learning experience in ways a physical facility alone could not, particularly where equipment, space, or safety concerns limit repeated practice (Wang et al., 2024). The same logic extends to health education simulations, where a controlled virtual scenario, an emergency response drill, a hazardous environment, can let students rehearse decisions that would be unsafe or impractical to stage physically.

Augmented Reality

Where VR replaces the environment, AR overlays information onto it, and this distinction matters for PHE's dual content of movement and knowledge. On the knowledge side, a meta-analysis of AR and VR anatomy instruction found meaningful knowledge gains compared to traditional teaching methods, with the large majority of students rating the technology useful for learning, evidence directly relevant to interactive anatomy content in health education (García-Robles et al., 2024). On the movement side, the same taekwondo coaching system discussed above used AR overlays to visualize correct technique directly on the practitioner's own movement in real time (Yang & Wang, 2025). Game-based AR applications, layering movement challenges or scoring onto physical space, sit at the intersection of these two uses and remain an underexplored but promising area for PHE specifically.

Health Education

Health education is where AI applications most resemble general-purpose chatbots rather than PHE-specific tools. Conversational agents have shown feasibility for nutrition guidance and disease prevention with adolescent populations specifically: a scoping

review found chatbots feasible and acceptable for nutrition and physical activity health promotion among adolescents (Han et al., 2023), and an eight-week pilot of an AI chatbot across five Louisiana middle schools found it could engage students in tracking obesity-related behaviours, though the study's authors were careful to note that engagement did not reliably translate into behaviour change without further adaptation (Tan et al., 2026). Mental health support is the one category in this section that deserves a more cautious framing than the others: while AI-driven health chatbots have real potential to expand access, a legal and ethical case study of the World Health Organization's own genAI health chatbot found meaningful gaps between the tool's stated ethical commitments and its actual practice around privacy, transparency, and user autonomy with adolescent users specifically (van Kolfschooten et al., 2025). This paper treats mental health and lifestyle coaching applications as a genuine opportunity worth pursuing carefully rather than a settled win; Section 6 returns to the underlying risks in more detail.

Assessment

Assessment applications close the loop on the categories above by converting performance and knowledge data into gradable, trackable outputs. Automated quizzes apply the same NLP-based grading approaches used in content subjects to PHE's cognitive-domain material, rules, strategy, health knowledge (Deepshikha, 2026). Movement assessment, by contrast, draws on the motion-analysis and wearable technologies already discussed to score psychomotor performance directly rather than through a written proxy. Learning analytics platforms then aggregate both streams into performance dashboards, the same kind of dashboard shown to correlate with physical literacy gains in the university study discussed under wearables (Chen et al., 2026). Taken as a set, these assessment tools offer a more integrated approach to tracking a student's PHE progress across all three domains than reliance on a teacher's memory and periodic spot-checks alone, though whether that consistency translates into fairer or better assessment is addressed directly in Section 6.

Arguments Supporting AI Integration

Having mapped what AI can do in PHE, this section makes the affirmative case: why the applications are worth pursuing, not merely possible. Each theme below states the claim, then grounds it in evidence rather than promise.

Improved Personalization

Large classes make individualised instruction structurally difficult, and personalisation is precisely what adaptive systems are built to do. The evidence is not merely theoretical. An adaptive fitness model tested against undergraduate physical fitness outcomes tailored independent exercise plans to individual needs and produced measurably better fitness gains than a standard, uniform programme (Li et al., 2024), representing a documented improvement over the one-size-fits-all default that large classes otherwise force teachers into. The same logic extends beyond exercise plans to instruction itself: a comprehensive review of AI-based intelligent tutoring systems found that, across a wide range of

educational contexts, adaptive systems consistently outperformed non-adaptive alternatives on measures of individualized pacing and student modeling, even as the review cautioned that effectiveness still depends heavily on implementation quality (Zerkouk et al., 2025). Personalisation, in other words, is a pattern replicated across contexts rather than a single success story confined to one study, which is precisely the kind of evidence a position paper needs before recommending adoption.

Increased Student Engagement

Gamification paired with AI-driven feedback offers a second, independently evidenced benefit: sustained motivation rather than the typical drop-off in interest as practice tasks become repetitive. A quasi-experimental study of an AI-powered gamification intervention among 456 Chinese college students found the approach feasible and usable at scale, with 80 percent of participants reporting the gamification elements motivated them and supported their fitness goals across more than 18,000 recorded activity sessions (Gao et al., 2025). At a larger scale still, a cross-sectional study of 1,029 Chinese secondary school students found that AI-based feedback and gamified PE settings, moderated by intrinsic motivation, were associated with improved cognitive performance outcomes (Zhang, Oh, & Xu, 2026). Immediate feedback is the mechanism underneath both findings: students who can see the effect of a movement correction in real time, rather than at the end of a unit, stay engaged with the task in front of them.

Improved Accessibility

AI-enabled accessibility gains fall into three concrete categories. For students with disabilities, AI tools have shown potential to personalize activity adaptation and build inclusive PE environments where standard practice, and a shortage of adapted resources, has historically excluded students with special needs (Guedes et al., 2024). For remote and hybrid learning, AI-enhanced online PE has demonstrably outperformed conventional online formats: the pose-recognition feedback system discussed earlier significantly improved movement quality and self-directed learning compared to a traditional online course format, directly addressing the isolation and lack of correction that typically undermines online PE (Ma et al., 2025). For language access, AI-powered translation tools now allow real-time content translation and interpretation for multilingual classrooms, reducing a barrier that has historically fallen hardest on immigrant and non-native-speaking students (Tariq, 2024). Each of these use cases has documented deployment, though the scale ranges from controlled research interventions to broader institutional adoption, and further evaluation is needed to establish how consistently these gains hold outside the specific settings studied.

Data-Driven Teaching

AI's capacity to generate continuous, structured data supports two related teaching functions: identifying problems early and monitoring progress over time. Learning-analytics dashboards built on wearable and assessment data allow teachers and institutions to see engagement and performance patterns as they develop rather than only

at graded checkpoints, the same dashboards linked to measurable gains in physical literacy in the university study discussed earlier (Chen et al., 2026). This matters most for early intervention: a struggling student's declining engagement or plateauing skill development becomes visible in data well before it would surface through observation alone, giving teachers a genuine window to intervene rather than discovering the problem at term's end. This kind of data-informed practice is also spreading fast enough to suggest it is becoming a professional norm rather than a novelty: national survey data already show a meaningful share of teachers using AI tools for instructional planning and monitoring, with school leaders adopting these tools even faster than classroom teachers, which points toward performance monitoring becoming a standard part of teaching practice rather than an experimental add-on (Kaufman et al., 2025).

Teacher Support

Finally, AI's most immediately measurable benefit may be the least glamorous: reducing the administrative load that keeps teachers from higher-value work. A randomized controlled trial run by England's Education Endowment Foundation found that 259 science teachers using ChatGPT for lesson and resource preparation cut their planning time by 31 percent over a ten-week period, with an independent review finding no meaningful drop in lesson quality compared to teachers who prepared materials without AI assistance (Education Endowment Foundation, 2024). Outside well-resourced systems, the case is arguably stronger still: an exploratory case study of generative AI use among Nigerian teachers found it meaningfully reduced workload and administrative burden while improving teacher well-being, precisely the kind of resource-constrained setting where PHE teachers juggling large classes and minimal support stand to gain the most (Garba, 2026). Content generation and administrative efficiency, in other words, are not incidental conveniences; they return time directly to instruction, which is has been identified as PHE's core structural problem.

Challenges of AI use in PHE

This section engages six of the most substantive challenges to AI integration in PHE. These are;

Digital Divide

Every argument for AI inclusion in PHE assumes a baseline of infrastructure that much of the developing world, including Nigeria, does not reliably have. Internet penetration across Africa sits at roughly 37 percent against a global average of 67 percent, and in low-income countries generally only about 27 percent of people have any internet access at all (Okolo & Raji, 2026). Unreliable electricity compounds this: AI systems that depend on continuous connectivity or cloud processing simply do not function through the power outages that remain routine in many school systems, and the cost of the hardware, data and compute needed to run them sits well beyond what most public school budgets can absorb (Okolo & Raji, 2026). An AI-dependent PHE curriculum designed without this

reality in view risks serving primarily the schools that already have the least need of one, rather than functioning as the universal solution it is often presented as.

Teacher Displacement

The fear that AI will replace PHE teachers outright is, on the current evidence, overstated, though the underlying anxiety is not baseless. A large-scale study of 453 university teachers found consistently low expectations of being replaced by AI within five years, but a significantly stronger fear of losing control over how AI is used in their own classrooms (Okulicz-Kozaryn et al., 2026). The realistic risk, in other words, is not obsolescence but a change in what the role requires, control, oversight, and judgment about when AI outputs should be trusted and PHE teachers deserve honest preparation for that shift rather than reassurance that nothing will change.

Ethical Concerns

A systematic review of AI ethics in education, drawn from 75 peer-reviewed papers, identified privacy invasion and data leakage as the most frequently documented technical risks, alongside algorithmic bias, opaque "black box" decision-making and unresolved questions of data ownership and consent (Zhu et al., 2025). These are not abstract concerns for PHE specifically: wearables and motion-tracking tools discussed earlier generate exactly the kind of continuous biometric and movement data that, if mishandled, constitutes a serious surveillance risk for minors. The WHO's own experience with its genAI health chatbot illustrates the gap between stated ethical principles and practice: an independent case study found users were not given a meaningful option to opt out of data collection, nor informed in accessible language about how their data moved between the WHO, its technology partners, and downstream systems (van Kolfschooten et al., 2025). If a UN agency struggles to operationalise consent, ordinary school systems deploying similar tools face the same risk with far fewer safeguards.

Academic Integrity

The same review found academic misconduct and what researchers term "student homogenised development," a narrowing of thinking that results from algorithmically personalised content, among the most consistently documented risks in the education literature (Zhu et al., 2025). In PHE's cognitive domain specifically, overdependence on AI-generated explanations or automated quizzes risks the same erosion of critical thinking already documented in content subjects, students learning to produce an answer an algorithm will accept rather than genuinely understanding rules, strategy, or health concepts. Cheating is the most visible version of this risk, but the quieter one, students who no longer practice reasoning through a problem themselves, may matter more for a discipline meant to build lifelong judgment about health and movement.

Loss of Human Interaction

The same review identified alienation of the teacher-student relationship and emotional disruption as documented risks of AI integration, driven by reduced nonverbal intimacy

and weakened social presence between teacher and student as AI mediates more of the interaction (Zhu et al., 2025). This risk is not evenly distributed across subjects. PHE depends unusually heavily on motivation delivered through relationship, empathy in response to a student's frustration or fear of failure, and role modeling, a teacher physically demonstrating a skill and correcting a student's body in real time. A qualitative study of Chinese primary school PE teachers found that AI tools frequently reduced rather than improved teaching efficiency precisely because they disrupted these embodied, relational dynamics, coining the term "embodied pedagogy resistance" to describe the friction (Zha et al., 2025). No wearable or feedback algorithm currently replicates a coach's presence at the moment a student is about to give up.

Practical Nature of PHE

The deepest challenge is definitional rather than technical: can AI teach teamwork, sportsmanship, leadership, or values at all? It is an established fact that PHE's affective and social domains, motivation, confidence, cooperation, fair play, develop through lived social experience, negotiating a team drill, losing gracefully, leading peers through a difficult play, in ways a system optimized for individual performance data was not built to capture (Dudley et al., 2022). AI can track whether a student passed a ball accurately; it cannot currently assess, let alone teach, whether that student passed it to include a struggling teammate rather than to win. Current evidence does not establish that AI systems, which are built to optimise what can be measured, are capable of meaningfully engaging with outcomes such as inclusion or fair play that resist quantification, and this evidentiary gap, rather than a claim about what AI could never in principle do, is treated here as the boundary of AI's current role. Until that gap is closed by demonstrated evidence, these dimensions of PHE will remain the domain's strongest argument for keeping a human teacher at the center of the classroom.

Conclusion

Artificial intelligence should be strategically integrated into the delivery of Physical and Health Education content, serving as a pedagogical support tool rather than a replacement for educators, while ensuring ethical safeguards, equitable access, and preservation of the discipline's practical, embodied nature. The strongest objection raised here is not the digital divide, teacher displacement, or the ethical risks real as all of those are,it is the definitional one: whether AI can teach teamwork, sportsmanship, leadership, or values at all. The position defended here is that current evidence does not establish that it can, and that this evidentiary gap, not a claim about what AI could never in principle achieve, is sufficient reason not to delegate these functions to AI now. AI systems are built to optimise what can be measured, and a student's decision to pass the ball to include a struggling teammate rather than to win is not, in any demonstrated sense, measurable in the way a jump shot's release angle is

Also, many of the risks documented function primarily as governance failures: a privacy risk is substantially addressed through data governance, an opacity risk through transparency requirements, a training gap through investment in teacher development,

and these are difficult but addressable problems. Algorithmic bias can persist despite formal safeguards; continuous monitoring can alter student behaviour independently of how the resulting data is later handled; and unequal access can reproduce existing educational inequality even where policy exists on paper. These risks call for ongoing evaluation rather than a one-time policy fix. Set against this more differentiated picture, the benefits documented such aspersonalised fitness plans that measurably outperform one-size-fits-all instruction, movement-correction feedback that improves outcomes in randomized trials, accessibility gains for students with disabilities and multilingual learners, workload reduction that returns teaching time to already-stretched PHE teachers, remain concrete, evidenced, and reproducible across multiple independent studies, which is why the case for bounded integration remains the stronger one on balance. Based on the evidences documented, it was recommended as follows;

i. Governments should treat infrastructure as the precondition for the recommendations that follow, not an afterthought to them: reliable electricity and affordable internet access remain the binding constraint on AI adoption across much of the Global South, and no policy or training investment compensates for a school that cannot keep a device powered. Funding should follow accordingly, targeted at the schools least able to absorb AI's costs on their own rather than distributed evenly regardless of need, since an even distribution simply preserves the existing gap between well-resourced and under-resourced systems. Policy should establish minimum data-protection and human-oversight standards specifically for AI used with minors, and AI regulation should draw on binding models such as the EU's risk-tiered approach rather than voluntary guidance alone, leaving most of the world, including Nigeria,
ii. Schools should adopt a phased implementation framework that ties the pace of AI adoption to the infrastructure and training a given institution actually has in place, rather than a fixed rollout timetable applied uniformly across contexts with very different starting points. Teacher support should include protected time for training and technical assistance during the transition, not just access to the tools themselves. Digital literacy should be built for students as well as staff, since a student who cannot meaningfully question an AI-generated fitness recommendation is not well served by receiving one.
iii. Teachers should pursue professional development on an ongoing basis, anchored in frameworks such as UNESCO's AI Competency Framework for Teachers rather than a single onboarding session, given how quickly the underlying tools continue to change. Ethical AI use means treating every AI-generated grade, movement assessment, or flagged behaviour as a recommendation to review rather than a verdict to enforce, in line with the human-oversight principle. Blended instruction should follow the domain logic: AI-supported delivery in the psychomotor and cognitive domains, and undiluted teacher-led instruction in the affective and social ones, where AI cannot currently substitute.

iv. Curriculum developers should build AI competencies directly into PHE curricula, teaching students to use these tools critically rather than treating AI literacy as someone else's subject, consistent with UNESCO's parallel AI Competency Framework for Students. Assessment redesign should follow the same domain split as instruction: automatable, AI-assisted assessment for movement and cognitive performance, paired with assessment instruments that remain teacher-designed and human-scored for teamwork, sportsmanship, and other affective outcomes that resist algorithmic measurement.

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