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Article

# Generative AI–Enabled Reconstruction of University General Physical Education: Application Scenarios, Mechanisms, and Risk Boundaries

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**Abstract:** The rapid development of generative artificial intelligence (GenAI) is moving higher education beyond the digitization of resources toward interactive, personalized, and intelligent learning support. Although GenAI has been widely discussed in language learning, writing, engineering, and medical education, university general physical education (PE) has distinctive characteristics, including embodied practice, motor-skill acquisition, real-time interaction, and safety risks. These features make it inappropriate to transfer generic "AI-assisted teaching" models directly into PE. Drawing on conceptual analysis and an integrative narrative review, this article examines how GenAI can be incorporated into university general PE without weakening embodied practice, teacher professional judgment, or student agency. It synthesizes literature on GenAI in higher education, artificial intelligence in PE, social cognitive theory, self-regulated learning, and human-centered AI, and shifts the central question from what the technology can do to what role it should play in PE. The article identifies appropriate uses in pre-class diagnosis and preparation, low-risk in-class knowledge support, differentiated task design, post-class reflection, and support for autonomous physical activity. On this basis, a Teacher – GenAI – Student collaborative model is proposed. The model assigns professional judgment, safety control, and formal evaluation to teachers; low-risk cognitive support such as explanation, goal decomposition, task generation, and structured reflection to GenAI; and embodied practice and learning decisions to students. Four potential mechanisms—differentiated support, PE learning self-efficacy, learning engagement, and self-regulation—are further identified, together with governance boundaries concerning hallucinations, physical safety, privacy, algorithmic bias, cognitive offloading, and teacher AI literacy. The article contributes a stage-specific framework that positions GenAI as a scaffold around physical practice rather than as a substitute for it. Its educational value lies in extending support across time and space while preserving teacher professionalism and students' long-term capacity for autonomous physical activity.

**Keywords:** University general physical education; Generative artificial intelligence; Teaching model; Human–AI collaboration; PE learning self-efficacy; Self-regulated learning

## 1. Introduction

University general PE is not merely a class in which students are asked to be physically active. It is a comprehensive educational setting that combines knowledge acquisition, motor-skill development, physical fitness, health-behavior formation, and social-emotional learning. Unlike courses centered primarily on textual or symbolic processing, many learning outcomes in PE must ultimately be expressed through the body. A student may be able to recite the key points of a movement yet remain unable to execute it consistently; likewise, understanding principles of exercise load does not necessarily translate into a sustained exercise habit. A fundamental challenge of PE is therefore how to move students from knowing, to doing, and eventually to being willing and able to continue doing. This process requires teacher demonstration, real-time correction, and safety management, but also repeated student practice through which bodily experience, mastery experiences, and self-regulatory capacities can develop.

Traditional whole-class instruction ensures organizational efficiency, but it cannot fully address heterogeneous learning needs. Students in the same PE class may differ substantially in fitness, prior sport experience, rate of motor learning, interest, confidence, and out-of-class activity habits. Within limited class time, teachers must organize the group, demonstrate skills, manage practice stations, ensure safety, and conduct assessment. It is therefore difficult to provide sustained, high-frequency individualized explanation and after-class guidance to every student. Yet the long-term value of PE depends heavily on what happens beyond the lesson: whether students can organize practice, identify their own problems, record and adjust their exercise behavior, and continue to be physically active after the course. Conventional teaching offers comparatively limited support in these “teacher-not-present” periods.

GenAI creates new possibilities for this support structure. Unlike static digital resources, GenAI can sustain dialogue around a learner’s questions and generate explanations, examples, tasks, feedback, and prompts for reflection. Reviews of higher education show that GenAI has been used for personalized feedback, content generation, problem solving, self-directed learning, and instructional design (Crompton & Burke, 2024; Qian, 2025). Reviewing 139 classroom studies, Wang et al. (2025) found greater use in engineering, health and medical education, and language learning, while teaching applications in areas such as sport science remained comparatively limited. At the same time, the meta-analysis by Chen and Cheung (2025) suggested that GenAI can have positive effects on university learning outcomes overall, but the magnitude and direction of effects vary by context, and benefits for metacognitive outcomes are not consistently observed. GenAI should therefore not be treated as a universal enhancement that becomes effective simply by being introduced into a course.

Research in PE is also expanding from conventional artificial intelligence toward generative systems. Zhou et al. (2024) showed that early AI applications in PE largely focused on movement analysis, skill assessment, training monitoring, and data-driven feedback. With the emergence of large language models, Albaloul et al. (2024), Trendowski (2025), and Lee and Kim (2025) began to discuss the use of GenAI in lesson planning, differentiated activities, assessment, and teacher professional practice. Zhu et al. (2026) further argued that GenAI research in physical and health education remains strongly technology- and performance-oriented and that greater attention is needed to curriculum design, teacher mediation, embodied participation, and ethical governance. The important question is thus shifting from whether AI can enter PE to how it can be integrated in ways that remain consistent with the nature of physical learning.

Against this background, this article addresses three interrelated questions. First, which instructional tasks in university general PE are appropriate for GenAI, and which should remain outside its scope? Second, through what psychological and learning mechanisms might GenAI influence PE learning beyond simply improving the convenience of tool use? Third, how can a collaborative model be constructed in which teachers, AI, and students have clearly differentiated responsibilities? In response, the article develops a stage-specific Teacher–GenAI–Student framework organized around pre-class preparation, in-class embodied practice, and post-class reflection, while also proposing an "embodied practice first" principle and explicit risk boundaries. The central position is that the intelligent transformation of general PE should never be achieved by reducing embodied practice, weakening professional teacher judgment, or increasing students' dependence on technology. The educational value of GenAI must therefore be determined by curriculum goals, disciplinary characteristics, learner development, and safety requirements rather than by technological novelty.

## 2 GenAI and University General Physical Education: Research Foundations and Theoretical Explanation

GenAI in higher education has broadly evolved from an efficiency tool to a learning partner and, increasingly, an environmental factor within instructional systems. Early discussions focused mainly on text generation, writing assistance, information organization, and automated feedback. More recent work has explored problem solving, personalized tutoring, and reflective learning. In their review of 44 peer-reviewed studies, Crompton and Burke (2024) identified 24-hour support, explanation of difficult concepts, personalized materials, feedback, and self-assessment as common student uses, while also highlighting hallucinations, bias, privacy, and misuse. Qian (2025) similarly found rapid diversification of GenAI across disciplines and instructional processes, but noted that classroom integration explicitly grounded in learning theory remains comparatively limited.

The educational effects of GenAI are not identical to its usability. Synthesizing 57 studies, Chen and Cheung (2025) reported positive overall effects on academic performance, affective-motivational outcomes, higher-order thinking, and language learning, but no robust advantage for metacognitive outcomes. This finding is directly relevant to PE. If students outsource task decomposition, problem diagnosis, and reflection to AI, the technology may improve immediate task efficiency without strengthening long-term self-regulation. From the perspective of student agency, Yang et al. (2024) argued that GenAI can support deep learning but can also facilitate superficial task completion, depending on whether learners retain agency in goal setting, judgment, and knowledge construction. PE applications should therefore prioritize transfer of capability rather than short-term convenience.

Within PE, the research tradition surrounding AI differs from that in many other areas of educational technology. Zhou et al. (2024) found that AI applications in PE have historically concentrated on movement recognition, performance evaluation, training planning, and analysis of exercise data, reflecting a strong measurement and performance-optimization orientation. GenAI introduced a different type of tool: one based on natural-language interaction and available without sophisticated sensors. Albaloul et al. (2024) proposed that ChatGPT can support lesson planning, instruction, and assessment, while emphasizing the need for teacher review. Trendowski (2025) described specific uses in curriculum design, activity modification, differentiated instruction, assessment, and motivation. Lee and Kim (2025) connected GenAI with an evolving conception of teacher professionalism, arguing that teachers require the capacity to judge when and how a technology is pedagogically appropriate.

Recent work has begun to articulate more clearly the distinctive nature of PE. Zhu et al. (2026) argued that physical and health education includes not only performance, but also health knowledge, reflection, and social participation. GenAI can potentially connect these dimensions, but teacher judgment and embodied observation must remain central. This suggests that the greatest value of GenAI may occur not during motor execution itself, but in cognitive preparation before movement, reflection after movement, and autonomous learning beyond the lesson. PE does not need AI to occupy every minute; it needs intelligent support to be placed where conventional teaching is weakest and where risks remain manageable.

Three major gaps emerge from the literature. First, much existing work explains what AI can do, but offers less clarity about why those functions would improve PE learning. Second, the boundary between technological support and embodied practice is often under-specified, creating a risk that verbal knowledge may be treated as a substitute for movement experience. Third, responsibility across teachers, students, and AI is not always clear. This is particularly problematic when issues of exercise load, injury risk, or health information are involved, because advice generated by a general-purpose model may be mistaken for a professional prescription. The theoretical framework developed below addresses these gaps.

Social cognitive theory provides one basis for explaining how GenAI might influence PE learning. Bandura (1986) emphasized the reciprocal interaction of personal factors, behavior, and environment, with self-efficacy playing a central role in behavioral choice, effort, and persistence. In PE, self-efficacy is especially visible: faced with the same new skill, students with stronger self-efficacy are more likely to attempt the task, tolerate failure, and continue practicing, whereas students with low self-efficacy may avoid challenge. Teachers typically build confidence through demonstration, task decomposition, mastery experiences, and feedback. GenAI cannot replace these real mastery experiences, but it can reduce cognitive load around understanding, help decompose goals, and make incremental progress easier to recognize, thereby functioning as a cognitive scaffold for self-efficacy.

However, self-efficacy cannot simply be manufactured through encouraging language from AI. In social cognitive theory, authentic mastery experience remains one of the most powerful sources of efficacy information. If students receive repeated positive reinforcement from AI without corresponding improvement in physical competence, artificially inflated confidence may actually increase the risk of poor movement or unsafe decisions. AI feedback in PE should therefore be linked to observable evidence, teacher-validated goals, and course standards rather than allowing a model to declare independently that a student has “mastered” a skill.

Self-regulated learning provides a second theoretical foundation. Zimmerman (2002) described self-regulation as a cyclical process of forethought, performance, and self-reflection involving goal setting, strategy selection, self-monitoring, and adjustment. A persistent challenge in general PE is that students may complete tasks while a teacher is present yet lack the ability to organize physical activity independently after class. The conversational accessibility of GenAI creates opportunities for it to act as an after-class self-regulation scaffold—for example, by helping students translate a broad goal such as “improve endurance” into actionable learning objectives, prompting them to record perceived exertion or practice experiences, and encouraging reflection through structured questions.

Nevertheless, the finding by Chen and Cheung (2025) that GenAI does not consistently improve metacognitive outcomes warns against assuming that AI use automatically strengthens self-regulation. When plans, judgments, and review are all generated by the model, students may simply be implementing external instructions. A more appropriate design is a fading-scaffold approach: during early stages, AI can provide more structured prompts; in the middle stages, students should be required to formulate their own goals and reasons before consulting the model; and later, AI should function primarily as a checking or review tool. The desired outcome is not a student who knows how to ask AI how to exercise, but a student who can plan and monitor basic physical activity even without AI.

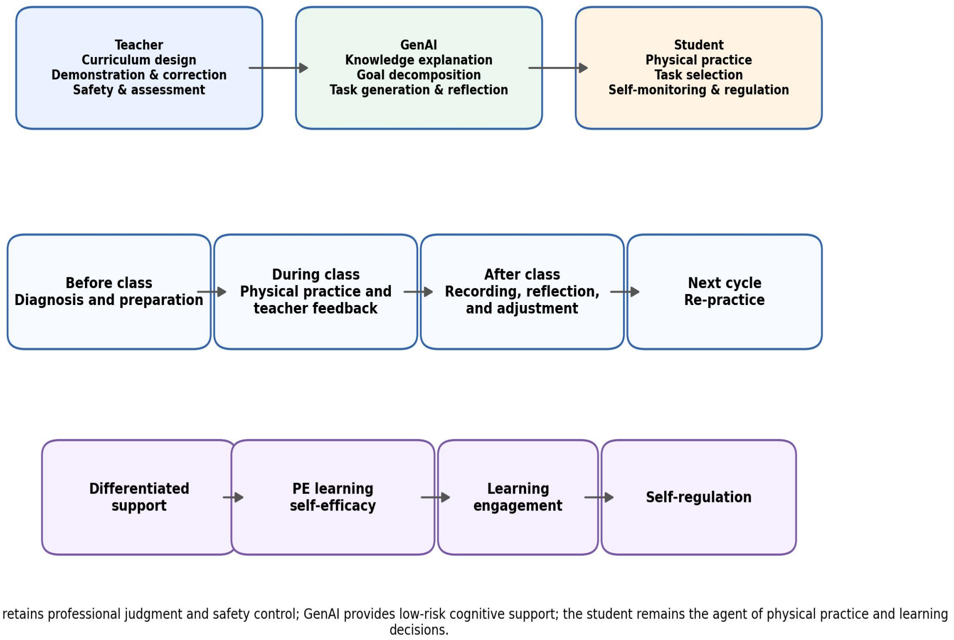
Student agency in PE must also be understood as embodied agency. Yang et al. (2024) noted that GenAI can support deep learning or foster shallow dependence depending on the agency retained by learners. In PE, agency is expressed not only in choosing and judging but also in bodily action. Students must perform movements, experience fatigue, encounter success and failure, cooperate with peers, and make on-site decisions. This article therefore advances an "embodied practice first" principle: core outcomes that can only be achieved through genuine movement experience should never be replaced by screen-based interaction. AI should provide prior understanding, process structure, and post-practice reflection in service of physical practice rather than substituting for it.

A human-centered AI perspective further clarifies the teacher's role. UNESCO guidance emphasizes human agency, privacy protection, ethical validation, and continued human control over important educational decisions (Miao & Holmes, 2023). In general PE, this principle means that teachers are not diminished by AI; rather, they assume a more complex mediating role. They must combine disciplinary expertise with judgments about which questions are suitable for AI and which require human decision-making. Teachers become curriculum designers, risk gatekeepers, reviewers of AI output, and guides for students' technology use. The focus of integration therefore shifts from whether teachers can operate a model to whether they can design appropriate human–AI task relationships.

## 3 Applications of GenAI in University General PE and a Collaborative Teaching Model

Pre-class diagnosis and knowledge preparation are among the most appropriate uses of GenAI. Differences among students are already present before they enter the lesson: some have no experience of the activity, while others may have participated in clubs or private training. Teachers can use brief standardized diagnostic tasks to understand students' existing knowledge and then allow GenAI to explain rules, movement terminology, and common errors. In a badminton course, for example, beginners might use AI to understand grip, service courts, and basic footwork concepts, whereas more experienced students might explore tactical choices or specific rules. Such diagnosis should focus on learning experience and conceptual understanding; it should not require students to submit sensitive health histories to open-access models.

**Figure 1. Teacher-GenAI-Student Collaborative Model for University General Physical Education**




Source: Developed by the authors based on the integrated theoretical and empirical literature.

As shown in Figure 1, the proposed model operates across three connected layers. The upper layer defines the differentiated responsibilities of the teacher, GenAI, and the student; the middle layer represents the temporal sequence from pre-class preparation to in-class practice, post-class reflection, and re-practice; and the lower layer summarizes the hypothesized learning pathway from differentiated support to PE learning self-efficacy, engagement, and self-regulation. The arrows indicate a pedagogical sequence rather than empirically confirmed causal effects, which should be tested in future studies.

GenAI can also support teacher preparation and differentiated task design by reducing the time needed to generate multiple task versions. The teacher first defines curricular objectives, movement standards, and safety constraints; the model is then asked to propose variations at different levels of difficulty; finally, the teacher screens and revises the suggestions. Both Trendowski (2025) and Albaloul et al. (2024) have highlighted GenAI's potential in lesson planning and activity adaptation. In large PE classes, the practical value is not to create a completely different curriculum for every student, but to provide multiple entry points toward common objectives. Differentiation must remain subordinate to shared course standards so that fairness and coherence of assessment are maintained.

During class, the main instructional resource should remain physical activity time. Students should not repeatedly stop movement to conduct prolonged conversations with AI. GenAI is better suited to limited, low-risk knowledge support, such as clarifying rules, terminology, sport culture, or written task instructions prepared by the teacher. This can reduce the amount of teacher time spent answering repetitive factual questions and allow more attention to be directed toward movement observation, safety control, and real-time interaction—functions that a language model cannot replace. The principle of teacher mediation emphasized by Zhu et al. (2026) is therefore better implemented through limited embedding rather than continuous AI presence.

After class, GenAI can support reflective learning and exercise logs. Valuable information from a PE lesson is often quickly forgotten. Students may remember only that a lesson "did not go well" without being able to specify whether the problem involved movement sequencing, force control, timing, or attention. A fixed set of AI-supported prompts can ask what was completed, what the teacher identified as the main problem, which attempt was most successful, and what should be changed next time. This use is safer than asking AI to diagnose movement independently and is more conducive to developing a language of reflection. Longitudinal logs may also help students see their progress over time and strengthen perceived control over the learning process.

Autonomous physical activity outside class is another important application area. A major purpose of general PE is to promote physical activity beyond scheduled lessons. GenAI can help students understand general training principles, organize weekly activity goals, create low-risk practice checklists, and reflect on completion. However, it should not issue medicalized or high-intensity prescriptions based on limited self-reported information. Questions involving chest pain, persistent pain, previous disease, rehabilitation, or aggressive weight-loss goals should trigger clear referral to a teacher, campus health professional, or medical practitioner. A boundary must therefore be maintained between educational guidance and professional health decision-making.

GenAI can also contribute to teacher professional learning. As Lee and Kim (2025) observed, AI is changing the meaning of professionalism in PE. Teachers can use models to compare alternative lesson structures, generate observation checklists, anticipate questions that students may ask, and support post-lesson reflection. Yet they must also possess verification skills so that popular but unsupported claims produced by AI are not inserted directly into instruction. Teacher AI literacy should therefore include evidence awareness, risk awareness, and instructional design rather than being treated as a purely technical competence.

On this basis, this article proposes a Teacher–GenAI–Student collaborative model for university general PE. The three actors do not occupy equivalent positions. The teacher retains final authority over curricular objectives, safety, movement standards, and formal evaluation. GenAI occupies a supporting role by providing cognitive, informational, and reflective scaffolds. Students remain responsible for physical practice, information judgment, and learning decisions. This structure is consistent with the human-control principle advocated by Miao and Holmes (2023) and with the disciplinary reality that safety and on-site judgment in PE cannot be outsourced.

## 4 Mechanisms and Risk Boundaries of GenAI-Supported PE Learning

The model begins with a pre-class phase of diagnosis, goal clarification, and preparation. Teachers define course objectives and identify high-risk areas in which AI should not intervene. Students complete a knowledge and learning-experience diagnosis. Within teacher-defined boundaries, AI helps explain concepts, organize difficulties, and generate preparatory questions. In classes with substantial differences in prior experience, AI may also help create tiered pre-class tasks, but all tasks must remain aligned with the same instructional objectives. The purpose is to help students enter the lesson with questions, not to have AI “teach the lesson in advance.”

The second phase—demonstration, practice, feedback, and re-practice during class—is the point at which technology use should be lowest and the teacher’s role strongest. Teachers provide movement demonstrations and safety instructions, students build experience through genuine physical practice, and teachers correct key errors on the basis of direct observation. AI may be used for rule queries or for displaying brief, teacher-reviewed prompts, but it should not make real-time injury judgments or independently diagnose motor performance. Intelligent PE should not reduce students’ active time; AI use during class must remain subordinate to movement density and learning quality.

The third phase is post-class recording, reflection, and adjustment. Students translate teacher feedback, personal sensations, and practice results into brief exercise or learning logs. AI uses structured questions to help separate factual observations, subjective feelings, and next-step plans. Teachers may periodically review summaries in order to identify common class-level difficulties and adjust subsequent instruction. This creates a new information loop in which teachers need not monitor every student–AI conversation in real time, but can use student-organized learning evidence to understand post-class learning states.

A fourth element is re-practice combined with scaffold fading. The goal of AI support is not permanent dependence, but gradual development of students’ ability to set goals and reflect independently. Courses can therefore vary the degree of AI support across stages. Early in learning, students may be allowed more template-based assistance. In the middle stage, they should be required to make an initial judgment before consulting AI. Later, they should plan independently and use the model mainly for checking. In this way, technology can shift from answer provider to thinking checker.

Viewed as a whole, the model forms a closed cycle of diagnosis, goal setting, preparation, physical practice, teacher feedback, structured reflection, individualized adjustment, and re-practice. Its logic is not to insert GenAI into every stage, but to add intelligent scaffolding where human support is limited and risk is comparatively low, while strengthening teacher authority in embodied practice, safety, and evaluation.

One potential mechanism is differentiated support. A central tension in whole-class PE lies between common objectives and individual variation. GenAI can quickly generate explanations, questions, and practice suggestions at different levels of difficulty, reducing the marginal cost of differentiation. More concrete explanations may reduce early frustration for students with little experience, while more challenging questions and tasks may sustain engagement among advanced students. The value is not complete personalization, but reduced mismatch between task difficulty and learner readiness.

A second mechanism involves PE learning self-efficacy. According to Bandura (1986), efficacy beliefs influence behavioral choice and persistence. By decomposing goals and documenting progress, GenAI can make partial improvement more visible. A student may not yet have mastered a complete technique but can recognize improvement in preparatory position, rhythm, or rules understanding. Such visible progress can support a more stable perception of competence. Yet positive AI feedback must remain evidence-based; unconditional praise cannot replace professional evaluation.

A third mechanism is learning engagement. GenAI may influence behavioral, cognitive, and affective engagement simultaneously. Differentiated tasks improve the fit between ability and challenge; immediate explanation reduces withdrawal caused by misunderstanding; post-class reflection increases psychological involvement in the learning process. The meta-analysis by Chen and Cheung (2025) reported positive overall effects of GenAI on affective-motivational outcomes, providing general higher-education support for this possibility. Whether these effects translate into more meaningful physical activity in PE rather than simply greater enjoyment of AI use, however, remains an empirical question.

A fourth mechanism is self-regulation. The most important long-term contribution of GenAI may be to help students internalize the external management previously provided by teachers. Goal setting, recording, reflection, and adjustment are core components of this process (Zimmerman, 2002). But simply copying AI-generated goals does not constitute self-regulation.

Students should be asked to justify why they selected a goal, identify the evidence that suggests adjustment is needed, and decide how to respond when AI advice conflicts with teacher guidance.

GenAI may also redistribute teacher attention. For repetitive pre-class materials, factual questions, and reflection templates, AI can reduce routine workload and free teacher attention for movement observation, individual correction, emotional support, and safety management. Bond et al. (2024) emphasized the importance of examining role relations within authentic educational systems. From this perspective, the value of GenAI may lie in reallocating professional attention, not merely in directly increasing achievement.

Together, these mechanisms suggest a testable pathway: appropriately designed GenAI support increases access to differentiated learning support, which may strengthen PE learning self-efficacy and engagement; sustained goal–reflection cycles may then promote self-regulation. This pathway should be treated as a theoretical proposition rather than as an empirically established causal chain in general PE. Future research should distinguish immediate learning experience, course performance, and long-term autonomous physical activity rather than relying on a single satisfaction measure to claim effectiveness.

Risk boundaries are equally important. First, hallucinations and professional accuracy are serious concerns. Crompton and Burke (2024) noted factual inaccuracy and bias in systems such as ChatGPT. In a theory course, misinformation may mainly create conceptual error; in PE, inappropriate training advice can also create physical risk. Low-risk content such as rule explanation can be AI-supported, whereas movement standards, exercise load, and high-risk training should require teacher review. Institutions should establish course-level categories such as “AI may answer,” “must be verified,” and “AI should not answer.”

Physical safety and medical boundaries must remain explicit. A general-purpose GenAI system should not decide, on the basis of a few self-reported statements, whether an injury is serious, whether a student should continue training, or when return to activity is safe. Persistent pain, disease history, medication use, chest discomfort, severe dizziness, or similar concerns should be referred to qualified professionals. PE teachers should also avoid using AI as a means to extend educational guidance into medical diagnosis. As Zhu et al. (2026) emphasized the importance of teacher judgment and health-promotion goals, AI integration should be embedded in existing school health and safety systems rather than operating as a parallel “intelligent health advice” system.

Data privacy and minimization are also critical because health information, fitness-test results, exercise records, and identity data may be sensitive. Miao and Holmes (2023) stressed the need for privacy protection and ethical validation in education. PE course design should follow a minimum-data principle: if a learning task only requires the information that a student is a beginner, a full health examination report should not be uploaded; if only practice frequency is needed, identifiable video and location data should not be collected. The closer AI applications come to bodily and health data, the stronger the governance requirements should be.

Algorithmic bias can create another form of risk. GenAI suggestions reflect patterns within training data and may reproduce assumptions about gender, body type, athletic ability, or cultural background. When teachers use AI to produce differentiated tasks, they should examine whether suggestions presuppose that certain categories of students are naturally weaker or stronger. Genuine individualization should be based on actual performance, not inferred from identity labels.

Cognitive offloading and technological dependence are further concerns. Yang et al. (2024) showed that GenAI can scaffold deep learning but can also become a shortcut for superficial completion. A parallel risk exists in PE: students may become accustomed to asking AI what to do before every exercise session rather than learning to judge goals and bodily states independently. Fading scaffolds, explanation requirements, and human verification are therefore necessary to ensure that students' judgment becomes stronger rather than weaker through technology use.

Finally, teacher AI literacy and responsibility must be addressed institutionally. Teacher responsibility does not disappear because a recommendation came from AI. On the contrary, teachers require stronger skills in verification, explanation, and risk judgment. Lee and Kim (2025) regarded such capacities as part of professionalism in the AI era. Institutions should specify which tools are permitted, what data may not be uploaded, how erroneous recommendations should be handled, whether AI may contribute to formal assessment, and how teachers should document its use. Governance should not suppress innovation; it should make innovation accountable.

## 5 Discussion

The first major argument of this article is that the value of GenAI in general PE is highly stage-selective. In much of higher education, GenAI is imagined as an always-available learning assistant. In PE, however, core outcomes must be developed through physical practice. The most productive spaces for AI may therefore lie before and after embodied practice rather than within the movement itself. Before class, GenAI can build cognitive readiness; after class, it can help organize experience and formulate next-step plans; during class, it should remain relatively unobtrusive so that teacher feedback and real movement retain priority. This "non-uniform integration" better reflects disciplinary fit in PE.

Second, GenAI may change how personalization is achieved in university general PE. Traditional personalization usually requires additional teacher time and is difficult to sustain in large classes. AI can reduce the cost of generating explanations, task variations, and reflective prompts, but it cannot replace professional judgments about movement quality and risk. Future personalization is therefore likely to operate through a two-layer structure: teachers define common goals, professional standards, and safety boundaries, while AI provides differentiated cognitive support within that framework. Such a model can preserve fairness in a public course while responding more quickly to individual differences.

Third, the evaluation of GenAI-supported PE should not be reduced to whether students like the technology. Acceptance, satisfaction, and intention to use are common outcomes in technology studies, but they do not demonstrate improved PE learning. Discipline-relevant outcomes should include at least three categories: movement and knowledge outcomes, such as motor skill, rules understanding, and course performance; psychological and process outcomes, such as PE self-efficacy, engagement, and self-regulation; and long-term behavioral outcomes, such as out-of-class physical activity and persistence after the course ends. The heterogeneous effects identified by Chen and Cheung (2025) reinforce the need for multidimensional evaluation.

Fourth, GenAI may make teacher professionalism more visible rather than less important. Once low-level information explanation and material generation are partially automated, teachers' distinctive value becomes even more concentrated in observing bodies, judging safety, diagnosing learning difficulty, and supporting emotion and social interaction. The discussions of Albaloul et al. (2024) and Lee and Kim (2025) point in this direction. Professional development should therefore move beyond learning to operate a new tool toward understanding how technology restructures teaching relationships.

Fifth, PE should avoid technology-centered innovation. If the use of AI itself becomes an institutional indicator of innovation, courses may add unnecessary screen time merely to demonstrate technological adoption. A more educationally meaningful criterion is whether the technology can eventually be withdrawn. If students retain motor competence, self-efficacy, and autonomous planning when AI is removed, then the technology has functioned as a scaffold. If students cannot decide how to exercise without AI, the course may have created a new dependency. This criterion places intelligent transformation back under the authority of educational purpose.

The proposed model aligns with Zhu et al. (2026) in emphasizing teacher mediation, embodiment, and ethical use, but it focuses specifically on the temporal structure of university general PE: before class, during class, and after class. It also adds explicit risk stratification and scaffold fading. In this sense, the model translates broad human–AI collaboration principles into a course process that can be used as an intervention framework in future quasi-experimental or design-based research.

For sustainability, GenAI integration should move beyond individual experimentation by a few technologically enthusiastic teachers. If each teacher establishes different rules and tools, students encounter inconsistent expectations and institutions face uneven responsibility. A more sustainable approach is to develop course-team agreements about permitted tasks, standard prompts, referral rules for high-risk issues, and minimum privacy requirements, then revise them through ongoing teaching development. This can turn isolated tool use into a stable curricular practice.

Equity also requires attention. Students differ in device access, paid model subscriptions, digital literacy, and prompting skills. If a course assumes universal access to high-quality commercial AI, existing inequalities may widen. Formal learning tasks should therefore use institutionally provided tools where possible or be designed so that basic versions are sufficient. Prompt-engineering sophistication should not be mistaken for PE learning competence. The advantages of personalization only have public-course legitimacy when basic access is equitable.

Future empirical work must also distinguish the effect of the technology from the effect of redesigned instruction. A GenAI intervention may simultaneously alter teacher feedback frequency, task structure, and reflection practices. Any resulting improvement cannot automatically be attributed to the model itself. Stronger designs could compare AI-supported and human-supported versions of the same reflection process, different intensities of AI use, and retention after scaffolds are withdrawn. Such comparisons can identify the incremental value of GenAI rather than attributing every instructional improvement to artificial intelligence.

From the broader educational goals of PE, GenAI also raises a tension between short-term convenience and long-term capability. Rapid access to rules, technique explanations, and practice suggestions can certainly reduce information-search costs, but movement skills still require repeated bodily practice. AI can shorten parts of cognitive preparation; it cannot shortcut the practice needed to stabilize motor learning. The relevant question is therefore whether improved preparation results in more effective practice, more accurate self-judgment, and more sustained physical activity. Public PE should be organized around increasing meaningful movement time and practice quality, not around increasing the number of human–AI interactions.

The Teacher–GenAI–Student relationship should also be dynamic rather than fixed. Early in a course, when students are unfamiliar with rules, concepts, and self-planning, teachers and AI may provide stronger scaffolds. As motor competence and self-monitoring improve, prompts should be reduced and decision-making returned to students. Such fading is central to lifelong physical activity, which ultimately requires learners to make reasonable activity choices without dependence on a course or technology. Instructional design should therefore address not only how to use AI, but when to reduce it.

Different types of PE courses will also require different degrees of GenAI involvement. Rule- and tactics-intensive ball games may benefit more from scenario analysis and post-class review. Dance, aerobics, and coordination-based activities rely heavily on visual demonstration and bodily feedback, so text-based tools may add less value. Endurance and fitness courses may lend themselves to goal tracking and reflective planning, but they also involve exercise load and individual health differences that require stronger human oversight. “GenAI-enabled PE” should thus not be a single template, but a set of principles determined jointly by activity characteristics, instructional goals, and risk level.

In practical terms, institutions can begin with low-risk, high-value applications: pre-class explanations of rules and concepts, teacher generation of tiered tasks, post-class logs, and structured reflection. AI should not initially be used as an independent movement diagnostician or exercise prescriber. Teachers should develop prompt templates, verification criteria, and clear prohibited-use statements as part of course planning.

Teacher development should cultivate a combined competence of PE expertise and AI judgment. Training should include basic model principles, hallucination recognition, evidence checking, privacy protection, prompt design, risk stratification, and assessment. Particular attention is needed for identifying exercise recommendations that sound professional but lack sufficient individual evidence.

Institutional governance should specify approved tools, data-processing principles, lines of responsibility, and referral procedures for high-risk questions. Because general PE involves bodily data and safety responsibility, it cannot simply adopt AI policies designed for writing courses. Institutions should also address digital accessibility so that students are not required to purchase premium tools in order to complete mandatory PE learning tasks.

This article remains conceptual and integrative, and the proposed mechanisms linking differentiated support, self-efficacy, engagement, and self-regulation have not yet been directly tested in university general PE. The framework is also intended as a general model rather than a one-size-fits-all prescription; its applicability may vary across activity types, class sizes, institutional resources, and students’ prior experience with AI. Future research should therefore use quasi-experimental designs, longitudinal follow-up, and comparisons across activity types to evaluate skill, psychological process, and long-term physical activity outcomes. Particularly important are studies with an AI-support phase, a reduced-support phase, and a no-AI retention phase, which can test whether students acquire transferable capabilities rather than temporary performance gains. Comparative studies should also distinguish the effect of GenAI itself from the effect of broader instructional redesign.

## 6 Conclusion

GenAI creates new opportunities for personalized and continuous support in university general PE, but the embodied nature of the subject means that technology cannot replace the human and physical core of instruction. The Teacher–GenAI–Student model proposed here assigns professional judgment and safety control to the teacher, low-risk cognitive support to GenAI, and physical practice and learning decisions to the student. The instructional cycle is organized around pre-class diagnosis and preparation, in-class physical practice and teacher feedback, and post-class recording and reflection.

The relevant criterion for judging whether GenAI truly enhances PE is not how much AI appears in a lesson, but whether it enables more meaningful physical practice, clearer feedback, more stable PE learning self-efficacy, and stronger autonomous activity skills. Only when GenAI is placed in the right tasks and constrained by professional judgment, safety ethics, and student agency can it become a constructive component of the reconstruction of university general PE.

## AUTHOR CONTRIBUTIONS

Liang Shang: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration, and Supervision.Yao Jiankang: Conceptualization, Methodology, Writing – review & editing, Validation, and Supervision.

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## CONFLICT OF INTEREST STATEMENT

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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