# AI adaptive learning systems and multidimensional engagement in online Physical Education: large effects

*Sistemas de aprendizaje adaptativo con IA y compromiso multidimensional en Educación Física en línea: efectos grandes*

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## Abstract

Introduction: Online physical education has expanded greatly since the COVID-19 pandemic, but it struggles to sustain steady student learning engagement. Artificial intelligence adaptive learning systems offer a promising fix, yet empirical research on their effects in physical education remains insufficient.
Objective: This study aimed to examine how artificial intelligence adaptive learning systems impact student engagement in online physical education and test the mediating role of learning experience.
Methodology: A quasi-experimental design was used with 203 students from Jiangsu Province. A 16-week quasi-experimental cycle was conducted, comprising a 4-week pre-test, 10-week intervention, and 2-week post-test, with data collected through questionnaires, platform analytics, and semi-structured interviews.
Results: Artificial intelligence adaptive learning systems significantly boosted overall learning engagement and its three dimensions. Learning experience partially mediated the relationship, accounting for 54.9% of the total effect, and qualitative data supported these outcomes.
Discussion: The findings aligned with studies in traditional academic subjects and filled the gap of quantitative research in online physical education.
Conclusions: Artificial intelligence adaptive learning systems effectively improve student engagement in online physical education, with learning experience as a critical mediator, providing evidence for the intelligent transformation of online physical education.

## Keywords

AI adaptive learning system, online physical education, learning engagement, learning experience, mediation effect.

## Resumen

Introducción: La educación física en línea se ha expandido considerablemente desde la pandemia de COVID-19, pero presenta dificultades para mantener un compromiso estudiantil estable. Los sistemas de aprendizaje adaptativo de inteligencia artificial suponen una solución prometedora, aunque la investigación empírica sobre sus efectos en la educación física sigue siendo insuficiente.
Objetivo: Este estudio pretendió analizar cómo los sistemas de aprendizaje adaptativo de inteligencia artificial influyen en el compromiso estudiantil en la educación física en línea y comprobar el papel mediador de la experiencia de aprendizaje.
Metodología: Se empleó un diseño cuasiexperimental con 203 estudiantes de la provincia de Jiangsu. Se realizó un ciclo cuasiexperimental de 16 semanas, que comprendió 4 semanas de pre-test, 10 semanas de intervención y 2 semanas de post-test, y se recogieron datos mediante cuestionarios, análisis de plataformas y entrevistas semiestructuradas.
Resultados: Los sistemas de aprendizaje adaptativo de inteligencia artificial aumentaron significativamente el compromiso de aprendizaje general y sus tres dimensiones. La experiencia de aprendizaje medió parcialmente la relación, explicando el 54,9% del efecto total, y los datos cualitativos respaldaron estos resultados.
Discusión: Los hallazgos coincidieron con estudios en asignaturas académicas tradicionales y cubrieron la laguna de investigación cuantitativa en educación física en línea.
Conclusiones: Los sistemas de aprendizaje adaptativo de inteligencia artificial mejoran eficazmente el compromiso estudiantil en la educación física en línea, con la experiencia de aprendizaje como mediador clave, aportando evidencia para la transformación inteligente de la educación física en línea.

## Palabras clave

Sistema de aprendizaje adaptativo de inteligencia artificial, educación física en línea, compromiso de aprendizaje, experiencia de aprendizaje, efecto mediador.

## Introduction

The digital transformation of education has accelerated markedly in the wake of the COVID-19 pandemic, with online physical education (OPE) emerging as an increasingly prominent component of global educational systems. Yet the capacity of OPE to foster lifelong physical activity remains constrained by enduring challenges in student engagement. AI adaptive learning systems (AI-ALS) present a promising technical solution, though their effectiveness in this distinctive pedagogical context warrants rigorous empirical examination. This introduction delineates the research background, identifies critical gaps in existing scholarship, and articulates the study's objectives, significance, and organizational structure.

### *Research Background*

Blended learning has become normalized across educational systems worldwide, with OPE evolving from an emergency response to the pandemic into a sustainable pedagogical model. Governments and educational institutions have increasingly recognized the distinctive value of OPE: its temporal and spatial flexibility removes barriers to physical education access, enabling learners across age groups to engage in structured training regardless of geographical constraints.Online physical education has expanded significantly since the COVID-19 pandemic, with growing global participation and increasing recognition of its role in promoting physical literacy (Goad et al., 2021; Murtagh et al., 2023;Mulato et al., 2024; Putra et al., 2024). In China, the Ministry of Education (2022) advanced the digital transformation of education through the launch of the National Smart Education Platform, which integrated physical education resources as a key component, supporting the cultivation of lifelong physical activity habits among students (Ministry of Education of the People's Republic of China, 2022).These trends underscore OPE's potential to bridge the gap between school-based sports education and lifelong fitness engagement.

Despite its growth trajectory, OPE confronts inherent challenges that undermine learner engagement. The absence of real-time face-to-face interaction restricts the timely feedback on motor skills that is essential to effective physical education, frequently leading to learner frustration and diminished motivation (Goad et al., 2021). Additionally, standardized OPE curricula struggle to accommodate individual variation in fitness levels, athletic interests, and learning paces. Research on the digital transformation of education indicates that existing teacher education programs often suffer from outdated content and insufficient connection to practical realities. In practice-oriented disciplines such as physical education, this misalignment between content and learner needs is particularly pronounced, directly eroding motivation. These issues manifest in low multidimensional engagement within OPE, where behavioral participation often remains superficial, cognitive involvement limited, and affective investment weak. This pattern aligns with findings from generic online education research (Schindler et al., 2017) and is corroborated by OPE-specific studies indicating that inadequate content differentiation and lack of real-time interaction contribute significantly to student disengagement (Goad et al., 2021; Hu & Xiao, 2025; Indarto et al., 2024).

AI-ALS has emerged as a transformative tool capable of addressing these fundamental flaws in OPE delivery, leveraging two core features that align closely with the distinctive requirements of physical education. First, personalized recommendation employs machine learning algorithms to generate tailored training pathways: based on initial assessments and real-time performance data such as movement completion rates, the system adjusts content difficulty and type, recommending low-intensity aerobic exercises for novices and advanced tactical drills for proficient learners(Shelenbekova et al., 2025). Second, real-time feedback powered by computer vision technology provides instantaneous correction of motor skills, such as posture adjustments during yoga practice, thereby approximating the guidance provided by in-person instructors. PosePilot, an edge-AI yoga correction system, exemplifies this capability by delivering personalized feedback at every movement stage using YOLO-pose and BiLSTM models (Gadhvi et al., 2025), while similar frameworks have been applied to general gym exercises for immediate error classification (Kotte et al., 2023). Similarly, Vasco Delgado et al. (2025) designed and validated an AI-mediated physical education evaluation model that integrates real-time posture estimation and automated feedback, demonstrating the feasibility of intelligent assessment systems in practical PE contexts. Although these studies confirm the real-time functionality of such systems, specific latency metrics remain unreported in the current literature. Emerging evidence suggests that AI-ALS features have the potential to enhance OPE learners' training duration and emotional engagement, though specific effect sizes require further empirical investigation (Tohănean et al., 2025; Olmos-Gómez et al., 2025).

## *Research Gaps*

Despite the promise demonstrated by AI-ALS, three critical gaps impede its evidence-based application in OPE contexts.

Existing AI research in education has predominantly focused on theoretical disciplines such as mathematics and language, which likely constitute a substantial proportion of SSCI-indexed scholarship. In contrast, AI research in practical disciplines such as physical education, while emerging and demonstrating considerable potential, remains relatively limited in scale, depth, and visibility within high-impact journals. Wang and Wang (2024) examined AI-empowered school physical education exploring development opportunities, practical challenges, and coping strategies, suggesting that AI applications in physical education remain in an exploratory stage. Similarly, Mănescu (2025) analyzed AI integration prospects from elite sports into school physical education, confirming that adaptive AI systems across diverse educational contexts have not yet achieved the maturity characteristic of theoretical disciplines. Confronted with distinctive practical dilemmas, these applications have not yet achieved the research scale and influence characteristic of theoretical disciplines, rendering them comparatively overlooked within the broader landscape of AI educational research. Although precise quantitative data on the underrepresentation of physical education in SSCI-indexed studies is unavailable, existing research trends indicate such a pattern. The limited physical education-related studies that do exist are primarily exploratory, focusing on system design, movement recognition, and technological innovation rather than rigorous empirical effectiveness verification (Hu et al., 2024). No large-scale quantitative research has yet verified AI-ALS's impact on OPE engagement, leaving a critical gap in the evidence base for its practical value.

Learning engagement represents a multidimensional construct encompassing behavioral, cognitive, and affective components, yet existing AI-ALS and OPE research has overemphasized observable behavioral indicators such as login frequency and task completion rates (Schindler et al., 2017;Yang, 2025). Cognitive engagement, exemplified by strategic skill adjustment, and affective engagement, such as sports self-efficacy, are critical for sustaining long-term participation but have received less empirical attention in OPE contexts compared to behavioral indicators (Fredricks et al., 2004; Deng et al., 2020;Sevilla-Sanche et al., 2023). This narrow focus prevents a comprehensive understanding of AI-ALS's impact on OPE learners.

Existing studies have established direct correlations between AI-ALS and engagement without clarifying the underlying mechanisms (Hu et al., 2024). In traditional academic subjects, learning experience, encompassing constructs such as perceived personalized support and interaction satisfaction, functions as a key mediator, yet this pathway remains untested in OPE contexts (Tohănean et al., 2025). Without understanding how AI-ALS influences engagement, whether through personalized support, feedback quality, or other factors, its application in OPE remains essentially a black box, limiting opportunities for targeted optimization.

## *Research Questions and Objectives*

To address these identified gaps, this study proposes three core research questions:

RQ1: Does AI-ALS significantly enhance overall learning engagement in OPE courses?

RQ2: Does AI-ALS differentially impact behavioral, cognitive, and affective engagement?

RQ3: Does learning experience, operationalized as perceived personalized support and interaction satisfaction, mediate the relationship between AI-ALS and learning engagement?

The primary objective is to systematically verify AI-ALS's effectiveness in enhancing OPE engagement and to clarify the mediating role of learning experience, thereby providing empirical evidence to inform its application in physical education contexts.

## *Research Significance*

For theoretical significance,this study extends the application boundary of AI educational technology from traditional academic subjects into physical education, thereby enriching the interdisciplinary theoretical framework connecting technology, education, and sports. By integrating AI-ALS as a technological variable within the learning engagement influencing factor model and validating the mediating role of learning experience, this research complements existing frameworks that have centered primarily on instructor or peer influences.

For practical significance,the findings offer actionable guidance for OPE curriculum design by identifying AI-ALS's core effective features, such as real-time feedback, that should be prioritized in intelligent course development. For teaching practice, the results clarify educators' evolving roles in AI-ALS-assisted OPE, suggesting how instructors might supplement AI capabilities with higher-order guidance to promote effective human-machine collaboration. At the policy level, this research supports educational administrators in formulating digitalization policies for physical education, such as incorporating AI-ALS into OPE construction standards.

## Literature Review

This section defines core concepts, reviews theoretical foundations, synthesizes relevant scholarship, and proposes research hypotheses, establishing a rigorous academic foundation for the empirical investigation.

### *Core Concept Definitions*

#### *AI Adaptive Learning System*

AI-ALS represents an intelligent educational technology that dynamically adjusts instructional content, learning pacing, and feedback strategies based on real-time learner data, including performance metrics and behavioral logs, alongside inherent learner characteristics such as fitness level and learning preferences (Ma, 2025). Its fundamental value lies in transcending one-size-fits-all instructional models to actualize genuinely personalized learning. Three distinguishing features characterize AI-ALS: personalization, which generates tailored training plans and resources through machine learning algorithms; real-time interaction, which provides instantaneous feedback on motor skills or learning progress via computer vision technology; and data-driven decision-making, which continuously optimizes learning pathways based on multidimensional data (Ma, 2025). For OPE contexts, these features directly address critical pain points including insufficient personalized guidance and delayed feedback.

#### *Online Physical Education*

OPE refers to comprehensive digital educational programs that integrate sports knowledge instruction, motor skill training, and fitness development through online platforms (Goad et al., 2021). It is characterized by three key attributes: temporal-spatial flexibility enabling access anytime and anywhere; resource diversity encompassing high-definition videos, 3D simulations, and interactive assessments; and asynchronous interaction through peer discussion forums and delayed instructor feedback (Hu and Xiao, 2025). Unlike traditional face-to-face physical education, OPE prioritizes accessibility and lifelong learning, aiming to cultivate sustained physical activity habits that extend beyond the classroom environment.

#### *Learning Engagement*

Drawing upon Fredricks et al.'s (2004) classic three-dimensional framework, which has been extensively validated in online education research, learning engagement is defined as learners' active involvement in OPE encompassing behavioral, cognitive, and affective components. Behavioral engagement encompasses observable participation including login frequency, training duration, and task completion rates. Cognitive engagement involves deep mental investment such as reflecting on movement principles and adjusting training strategies. Affective engagement captures emotional and motivational responses including sports interest, self-efficacy, and sense of community belonging. This multidimensional definition ensures a comprehensive assessment of AI-ALS's impact, avoiding the narrow focus on behavioral indicators common in existing studies.

## Theoretical Foundations

### Constructivist Learning Theory

Rooted in the foundational work of Vygotsky (1978), constructivist theory posits that knowledge and skills are actively constructed by learners rather than passively received. It emphasizes the importance of personalized scaffolding and interactive learning environments in supporting learners' zone of proximal development. For this study, AI-ALS aligns with constructivist principles by providing tailored support: its personalized training paths match content difficulty to learner competence, while real-time feedback functions as digital scaffolding to help learners refine motor skills independently. This active construction process is particularly critical for deep engagement in OPE, where skill mastery depends fundamentally on practice and reflection.

### Technology Acceptance Model

Proposed by Davis (1989), the Technology Acceptance Model explains users' acceptance of new technologies through two core constructs: perceived usefulness, defined as the belief that a technology enhances performance, and perceived ease of use, defined as the belief that a technology requires minimal effort to operate. TAM predicts that perceived usefulness and perceived ease of use drive behavioral intention to use a technology, which subsequently influences actual engagement. In OPE contexts, learners are more likely to engage with AI-ALS when they perceive it as useful, for instance believing that AI feedback improves their posture, and easy to use, such as finding the interface for movement tracking intuitive (Davis, 1989). TAM provides a theoretical framework for understanding why AI-ALS may enhance engagement in physical education contexts.

### Self-Determination Theory

Self-Determination Theory, developed by Ryan and Deci (2017), focuses on intrinsic motivation and identifies three basic psychological needs: autonomy, representing self-directed learning; competence, representing the experience of mastery; and relatedness, representing social connection. Satisfying these needs fosters sustained engagement and positive learning outcomes. AI-ALS addresses these needs within OPE contexts: autonomy is supported through personalized learning paths that allow learners to choose content and pacing; competence is enhanced by real-time feedback and progress visualization that provide tangible evidence of skill improvement; and relatedness is facilitated through interactive features such as peer challenges and discussion forums. SDT is particularly relevant to this study as it explains the psychological mechanisms linking AI-ALS's features to multidimensional engagement.

## Relevant Literature

### AI-ALS in Educational Contexts

Research on AI-assisted learning systems in traditional academic disciplines has demonstrated potential benefits. Existing studies indicate that personalized content delivery, such as semi-supervised learning and decision tree algorithms for optimizing learning pathways (Ersozlu et al., 2024), alongside real-time feedback mechanisms such as dynamic assessment driven by deep learning (Zhang et al., 2025), may enhance learning performance and engagement. However, specific effect sizes require further verification within particular disciplinary contexts. In higher education contexts, AI-driven tutoring systems have demonstrated the potential to accelerate learning progress. For instance, Möller et al. (2024) found that an AI-powered teaching assistant reduced university students' study time by approximately 27% on average across more than 40 distance learning courses, suggesting that generative AI can substantially improve learning efficiency through personalization. However, whether such effects generalize to practical disciplines such as physical education, and how they translate into multidimensional learning engagement, remains insufficiently explored. In physical education specifically, Omarov et al. (2024) confirmed that augmented reality game-based environments enhance sports motivation and physical activity levels in quasi-experimental settings, yet such rigorous quantitative designs remain scarce in the field. Synthesizing these studies, two key success factors emerge: personalization precision, representing accurate alignment of content with learner needs, and actionable real-time feedback, representing specific guidance rather than generic praise (Chen et al., 2020). Nevertheless, these findings remain largely confined to theoretical or skill-intensive disciplines, with no large-scale quantitative research examining physical education contexts.

*Factors Influencing OPE Engagement*

Existing research on OPE engagement has concentrated on three non-technological variables: instructor guidance, where timely feedback and goal setting enhance learner accountability; course design, where modular content and practical tasks reduce cognitive load; and peer interaction, where group challenges and mutual feedback foster belonging (Wang et al., 2024; Deng et al., 2020). A systematic literature review by Wang et al. (2024) examined artificial intelligence applications in education, highlighting the growing but still limited integration of educational technologies in physical education contexts. This gap is striking given OPE's distinctive challenges, such as the lack of real-time feedback, that technology could potentially address, indicating a critical need to explore technological variables such as AI-ALS.

*AI Technology and Learning Engagement*

Research on AI and engagement exhibits disciplinary bias, with predominant focus on traditional subjects including mathematics (Medrano et al., 2025), science and STEM disciplines, and language education (Zhou & Hou, 2024). In these domains, AI consistently enhances behavioral engagement through increased task participation, cognitive engagement through critical thinking prompted by AI feedback, and affective engagement through reduced anxiety via personalized support (Yang, 2025). Research on AI in physical education remains limited, with existing studies primarily qualitative and focusing on system design or student perceptions rather than quantitative effectiveness or mediating mechanisms (Long et al., 2026; Zhoc et al., 2019; Zhou & Hou, 2024; Shelenbekova et al., 2025; Olmos-Gómez et al., 2025). No study has systematically examined AI-ALS's impact on multidimensional engagement in OPE or clarified how learning experience connects AI-ALS to engagement, gaps that this study aims to address.

## Research Hypotheses

Based on the foregoing literature and theoretical foundations, the following hypotheses are proposed.

H1: AI-ALS exerts a significantly positive impact on overall learning engagement among OPE students.

Rationale: AI-ALS satisfies the basic psychological needs identified by SDT, namely autonomy, competence, and relatedness, and enhances the perceived usefulness and ease of use identified by TAM, factors that have been demonstrated to drive engagement in educational contexts (Ryan & Deci, 2017; Zawacki-Richter et al., 2019).

H2: AI-ALS positively influences the three dimensions of learning engagement.

H2a: AI-ALS positively influences behavioral engagement in OPE.

H2b: AI-ALS positively influences cognitive engagement in OPE.

H2c: AI-ALS positively influences affective engagement in OPE.

Rationale: AI-ALS's core features target each engagement dimension: goal setting and progress tracking enhance behavioral participation; real-time feedback on movement principles deepens cognitive involvement; and personalized support fosters emotional investment (Fredricks et al., 2004; Deng et al., 2020).

H3: Learning experience partially mediates the relationship between AI-ALS and OPE engagement.

H3a: Perceived personalized support partially mediates the AI-ALS-engagement relationship.

H3b: Interaction satisfaction partially mediates the AI-ALS-engagement relationship.

Rationale: In traditional academic subjects, learning experience links AI-ALS to engagement. For OPE contexts, AI-ALS's personalized pathways enhance perceived support, while real-time interaction improves satisfaction, both of which are expected to drive engagement based on SDT and TAM principles.

## Method

This section details the research design, participant recruitment, instrumentation, data collection procedures, analytical methods, and ethical considerations, ensuring the study's rigor and replicability.

### *Research Design*

A non-equivalent control group design with pre-test and post-test (NEGD) was employed to examine the causal relationship between AI-ALS and OPE learning engagement. True random assignment of individual students was neither ethically nor administratively feasible: (a) disrupting existing class structures to reassign students would introduce artificial Hawthorne effects and organizational chaos; (b) students within the same class receiving different instructional modes (AI-ALS versus traditional) would contaminate the control condition through peer discussion and shared platform access; and (c) partner schools' administrative policies prohibited cross-class student reassignment. Consequently, intact classes were randomly assigned to either the experimental or control condition, and baseline equivalence was rigorously verified to compensate for the lack of individual-level randomization (Shadish et al., 2002). The study followed a 16-week cycle comprising three phases.

During the pre-test phase (Weeks 1–4), baseline data were collected from both groups, including learning engagement, learning experience, and control variables such as gender, physical fitness level, and prior online learning experience. The core purpose was to verify baseline equivalence between groups, ensuring that subsequent intervention effects could be attributed to AI-ALS rather than pre-existing differences.

During the intervention phase (Weeks 5–14), the experimental group received AI-ALS-assisted OPE courses while the control group participated in traditional OPE courses without AI-ALS functionality, accessing only static resources and asynchronous instructor feedback.

During the post-test phase (Weeks 15–16), data on learning engagement and learning experience were re-collected from both groups to measure intervention effects.

To minimize confounding variables, both groups were taught by the same physical education instructors, used identical core OPE content including basic fitness training and basketball skills, and followed identical course schedules of 120 minutes per week delivered in two sessions. The sole difference between groups was the presence of AI-ALS functionality for the experimental group.

### *Participants*

#### *Sampling Strategy*

Stratified sampling was employed to ensure sample representativeness. Participants were recruited from two universities and one secondary school in Jiangsu Province, China, encompassing different educational stages and student backgrounds. Stratification criteria included educational stage (university versus secondary school), major or grade level (university physical education majors, university non-physical education majors, and secondary school 10th graders), and prior OPE experience (one year or less versus more than one year).

The inclusion of both university and secondary school students was intentionally designed to align with the study's core objectives and enhance the generalizability of findings, with rigorous measures implemented to address age and maturity differences. Online physical education has been increasingly adopted in Chinese educational institutions at both secondary and tertiary levels, particularly accelerated by the COVID-19 pandemic and the national push for educational digitalization (Ministry of Education, 2022), covering a key age range of learners from 15 to 22 years who regularly engage with digital learning tools. Including both groups ensures that the study's conclusions apply to a broader OPE user base rather than being limited to a single educational stage, strengthening the practical significance of the research for curriculum design and policy formulation.

While age and maturity may influence learning behaviors, this study controls for such variation through two key measures. The stratified sampling design explicitly categorizes participants by age-related groups, ensuring balanced representation of secondary school 10th graders (approximately 15–16 years) and university students (approximately 18–22 years) in both experimental and control groups. Additionally, educational stage, coded as 1 for secondary school and 2 for university, is included as a covariate in data analysis, isolating the independent effect of AI-ALS from age-related confounding variables. AI-ALS's core features, including personalized training plans and adaptive difficulty adjustment, inherently accommodate age-specific differences in fitness levels, motor skill foundations, and learning rhythms, ensuring the intervention remains relevant and effective for both groups.

Additionally, although secondary school students (aged 15–16) and university students (aged 18–22) differ in cognitive maturity, this heterogeneity was methodologically addressed rather than treated as a nuisance. First, AI-ALS's core architecture—adaptive difficulty adjustment and personalized pacing—operates on individual performance trajectories rather than age-normed standards, making it developmentally agnostic. Second, educational stage was included as a covariate in all analyses, ensuring that any age-related variance was statistically removed before estimating the AI-ALS effect. Third, the inclusion of both stages enhances external validity, allowing conclusions to generalize across the 15–22 age span that constitutes the predominant OPE user base in Chinese educational digitalization policy (Ministry of Education, 2022).

#### *Sample Size Justification*

Sample size was calculated using G*Power 3.1.9.7. Following Cohen's (1988) conventions for effect size interpretation in social sciences, an $f^2$ of 0.15 was designated as a medium effect size, significance level was set at 0.05, and statistical power at 0.80, yielding a minimum required sample size of 160. Considering a potential 20% attrition rate due to dropout or invalid data, the final target sample size was established at 200 or more students, with 100 or more per group.

#### *Baseline Equivalence Testing*

Prior to the intervention, independent samples t-tests were conducted to compare the two groups across demographic variables, baseline engagement, learning experience, and control variables. Non-significant differences ($p > .05$) confirmed baseline equivalence, ensuring that intervention effects could be attributed to AI-ALS rather than pre-existing disparities.

### ***Research Instruments***

#### *AI Adaptive Learning System*

A mature AI-ALS platform adapted for OPE contexts was employed, featuring three core functions aligned with research needs. Table 1 presents a comparison of core functions between experimental and control group tools.

Table 1. Comparison of Core Functions Between Experimental and Control Group Tools

| Group | Tool | Core Functions |
|---|---|---|
| Experimental | AI-ALS for OPE | Personalized training plans; real-time movement feedback; progress tracking with achievement badges |
| Control | Traditional OPE Platform | Static resources; asynchronous instructor feedback; basic task submission |

#### *Measurement Scales*

All scales employed a 5-point Likert format ranging from 1 (strongly disagree) to 5 (strongly agree). The Learning Engagement Scale was adapted from validated multidimensional instruments. Behavioral engagement items (e.g., login frequency, task completion, training duration) drew on Fredricks et al.'s (2004) classic three-dimensional framework and Deng et al.'s (2020) MOOC engagement scale. Cognitive engagement items for e.g., reflecting on movement principles, strategic adjustment, were informed by Deng et al. (2020) and Zhou and Hou (2024), who operationalized cognitive involvement in technology-mediated learning. Affective engagement items (e.g., sports interest, self-efficacy, belonging) were adapted from Fredricks et al. (2004) and Zhoc et al. (2019), capturing emotional investment in higher education contexts, with revisions to fit OPE for e.g., replacing "classroom" with "training session". The Learning Experience Scale comprised two dimensions. Perceived personalized support for e.g., "The system adapts exercises to my fitness level", was developed based on Ryan and Deci's (2017) Self-Determination Theory conceptualization of autonomy support, following established procedures for context-specific scale adaptation. Interaction satisfaction for e.g., "I am satisfied with the real-time feedback quality", drew on Davis's (1989) Technology Acceptance Model interaction quality tenets and Zawacki-Richter et al.'s (2019) systematic review of AI-HCI dimensions in higher education. All instruments underwent back-translation and expert panel review (three physical education professors, two educational technology researchers) to ensure OPE-contextual validity. Pre-test reliability was verified, and scale structure and reliability results are summarized in Table 2.

Table 2. Scale Structure and Pre-Test Reliability

| Scale | Dimension | Items | Cronbach's $\alpha$ | Source |
|---|---|---|---|---|
| Learning Engagement Scale | Behavioral | 6 | 0.78 | Fredricks et al. (2004); Deng et al. (2020) |
| | Cognitive | 5 | 0.75 | Deng et al. (2020); Zhou and Hou (2024) |
| | Affective | 5 | 0.73 | Fredricks et al. (2004); Zhoc et al. (2019) |
| Learning Experience Scale | Perceived Support | 4 | 0.76 | Ryan & Deci (2017); adapted from SDT autonomy support literature |
| | Interaction Satisfaction | 4 | 0.74 | Davis (1989); Zawacki-Richter et al. (2019) |

All Cronbach's alpha coefficients exceeded 0.70, indicating acceptable reliability (Nunnally, 1978). Confirmatory factor analysis was conducted in subsequent data analysis to verify construct validity.

### *Control Variables*

Three theoretically relevant control variables were included to isolate the net effect of AI-ALS. Gender was coded as 1 = male, 2 = female, given documented gender differences in technology acceptance and physical activity motivation (Davis, 1989; Ryan & Deci, 2017). Physical fitness level was indexed by body mass index (BMI) and running performance (1000 m for secondary school; 1500 m for university students). Because the two educational stages used different running distances, performance times were converted to z-scores within each stage and combined with BMI to form a composite physical fitness index, reflecting baseline motor competence that might influence engagement independent of instructional mode. Online learning experience was operationalized as the number of online courses completed in the past year (1 = one or fewer, 2 = two to three, 3 = four or more), capturing prior digital learning self-efficacy that could affect technology acceptance. These variables were entered as covariates in all inferential analyses to partial out their potential confounding effects.

### *Sample Lesson Plans for Intervention*

To clarify the practical implementation of the intervention, a sample 90-minute lesson plan focused on basic basketball dribbling, a core module of OPE, is provided below. This illustrates the key differences between AI-ALS-assisted OPE (experimental group) and traditional OPE (control group) in teaching process, aligning with the core function differences outlined in Table 3.

Table 3. Sample Lesson Plans for Intervention

| Component | AI-ALS-Assisted OPE | Traditional OPE |
|---|---|---|
| Lesson Goal | Master 2 dribbling skills with personalized error correction; enhance self-efficacy | Master 2 dribbling skills via pre-recorded guidance |
| Warm-up (15 min) | AI-ALS generates tailored warm-up based on pre-test fitness data | Static video of standard warm-up |
| Skill Instruction (30 min) | Personalized video clips; real-time movement tracking with 3D model comparisons | Pre-recorded video; no real-time feedback |
| Practice (35 min) | Adaptive tasks; real-time progress dashboard with achievement badges | Uniform practice tasks; video submission only |

This sample plan was consistently implemented across the 10-week intervention phase (Weeks 5–14). Other OPE modules followed the same design logic, ensuring that the only variable between groups was access to AI-ALS functionality.

## *Ethical Considerations*

This study adhered to the ethical principles outlined in the Declaration of Helsinki and received formal approval from the Ethics Committee of UCSI University . Given the quasi-experimental design involving intact classes, a three-tiered consent protocol was implemented. First, institutional consent was obtained from the administrative leadership of each participating school and university. Second, all university student participants (aged 18–22) provided written informed consent prior to data collection, which explicitly detailed the study's purpose, voluntary nature, right to withdraw without academic penalty, and data anonymization procedures. Third, for secondary school students (aged 15–16), a dual consent procedure was applied: written informed consent was obtained from parents or legal guardians, and written assent was simultaneously obtained from the students themselves, ensuring developmentally appropriate understanding of participation rights.

To protect vulnerable minor participants, additional safeguards were enacted. (a) all questionnaire and interview data were de-identified and coded prior to analysis, with no personally identifiable information retained; (b) platform analytics (login frequency, training duration) were aggregated at the group level and stored on encrypted servers accessible only to the research team; (c) students were explicitly informed that their course grades would not be affected by their participation status or performance in the study; (d) a research assistant independent of the teaching staff monitored the voluntary withdrawal option, ensuring no coercion from instructors; and (e) interview questions were screened to exclude potentially sensitive psychological probes, and participants could skip any question or terminate the interview at any time. No financial compensation was provided to avoid undue inducement, but all participants received a certificate of appreciation upon completion.

### *Procedure*

To ensure systematic data collection, the 16-week process is organized by phase in Table 4.

Table 4. Data Collection Phases, Timelines, and Content

| Phase | Timeline | Content | Data Type |
|---|---|---|---|
| Pre-test | Weeks 1-4 | Learning Engagement Scale; Learning Experience Scale; Demographic questionnaire | Quantitative |
| Intervention | Weeks 5-14 | Platform logs (login frequency, training duration, task completion) | Quantitative |
| Post-test | Weeks 15-16 | Learning Engagement Scale; Learning Experience Scale | Quantitative |
| Interviews | Week 16 | Semi-structured interviews with 15 experimental group students | Qualitative |

The intervention phase strictly spanned Weeks 5–14 (10 weeks), constituting the core treatment period. The 16-week cycle included 4 weeks of pre-test baseline establishment and 2 weeks of post-test data collection. Invalid questionnaires were excluded based on criteria including response time under three minutes or consecutive identical scores for eight or more items. A total of 212 valid pre-test and 203 valid post-test questionnaires were collected, representing an attrition rate of 4.25%, which met the sample size requirement. Interviews were audio-recorded and transcribed verbatim, generating approximately 30,000 words for thematic analysis.

### *Data Analysis*

Data analysis was conducted using SPSS 26.0, AMOS 24.0, and NVivo 12, with significance level set at $p < .05$. The analytical framework was aligned with research hypotheses as shown in Table 5.

Table 5. Data Analysis Methods and Corresponding Research Objectives

| Research Objective | Analysis Method |
|---|---|
| Verify baseline equivalence | Independent samples t-tests |
| Test scale reliability and validity | Cronbach's α, composite reliability, AVE, CFA |
| Test H1 and H2 (main effects) / One-way ANCOVA with baseline covariates; descriptive t-tests for platform analytics | Independent samples t-tests |
| Test H3 (mediation effect) | Hayes' PROCESS macro (Model 4, Bootstrap = 5000) |
| Triangulate quantitative results | NVivo 12 thematic coding |

To account for potential confounding effects, all between-group comparisons were conducted using one-way analysis of covariance (ANCOVA), with baseline engagement scores, gender, physical fitness index, and online learning experience entered as covariates. This approach isolates the net effect of AI-ALS by statistically removing pre-existing individual differences. For intuitive interpretation, adjusted post-test means and standard errors are reported alongside unadjusted descriptive statistics in Table 10. Independent samples t-tests were additionally computed for supplementary platform analytics (login frequency, training duration) to corroborate behavioral engagement patterns.

For reliability and validity testing, convergent validity was supported if average variance extracted was 0.50 or greater, while discriminant validity was confirmed if the square root of AVE exceeded inter-dimensional correlations. Confirmatory factor analysis fit indices including chi-square to degrees of freedom ratio between 1 and 3, RMSEA below 0.08, and CFI above 0.90 indicated acceptable model fit.

For mediation effect testing, indirect effects were considered significant if the 95% bootstrap confidence interval excluded zero, with partial mediation confirmed when both direct and indirect effects were statistically significant.

Thematic analysis of qualitative data followed three steps: open coding to label key phrases, axial coding to group codes into sub-themes, and selective coding to integrate core themes, thereby explaining AI-ALS's impact mechanisms.

## Results

This chapter presents the study's empirical findings, including sample characteristics, reliability and validity assessments, correlation analyses, hypothesis verification, and qualitative interview insights, supported by tables for intuitive interpretation.

### *Sample Characteristics and Baseline Equivalence*

#### *Demographic Features*

A total of 203 valid samples were retained, with 102 in the experimental group and 101 in the control group. Sample demographics are summarized in Table 6, showing balanced representation across gender, educational stage, and physical fitness levels.

Table 6. Sample Demographic Characteristics

| Variable | Category | Experimental (n=102) | Control (n=101) | Total (n=203) |
|---|---|---|---|---|
| Gender | Male | 53 (52.0%) | 51 (50.5%) | 104 (51.2%) |
| | Female | 49 (48.0%) | 50 (49.5%) | 99 (48.8%) |
| Educational Stage | University (PE) | 34 (33.3%) | 32 (31.7%) | 66 (32.5%) |
| | University (Non-PE) | 38 (37.3%) | 39 (38.6%) | 77 (37.9%) |
| | Secondary School | 30 (29.4%) | 30 (29.7%) | 60 (29.6%) |
| Fitness Level | Low/Medium/High | 28/52/22 | 29/50/22 | 57/102/44 |

#### *Baseline Equivalence Testing*

Prior to the intervention, independent samples t-tests and chi-square tests were conducted to compare the two groups across all demographic variables, three baseline engagement dimensions, two learning experience dimensions, and three control variables (BMI, standardized running performance, online learning experience). As shown in Table 7, non-significant differences were observed for all variables (all ps > .05), with effect sizes negligible in magnitude (all |d| < 0.10), confirming baseline equivalence and ensuring that intervention effects could be attributed to AI-ALS rather than pre-existing disparities.

Table 7. Pre-Test Baseline Equivalence Results

| Variable | Group | M ± SD | t / $\chi^2$ | p | Cohen's d |
|---|---|---|---|---|---|
| Overall Engagement | EG | 3.21 ± 0.58 | 0.37 | 0.712 | 0.05 |
| | CG | 3.18 ± 0.61 | | | |
| Behavioral Engagement | EG | 3.35 ± 0.62 | 0.42 | 0.675 | 0.06 |
| | CG | 3.31 ± 0.65 | | | |
| Cognitive Engagement | EG | 3.12 ± 0.59 | 0.28 | 0.78 | 0.03 |
| | CG | 3.10 ± 0.63 | | | |
| Affective Engagement | EG | 3.18 ± 0.55 | 0.33 | 0.742 | 0.05 |
| | CG | 3.15 ± 0.60 | | | |
| Perceived Support | EG | 3.25 ± 0.61 | 0.45 | 0.654 | 0.06 |
| | CG | 3.21 ± 0.64 | | | |
| Interaction Satisfaction | EG | 3.30 ± 0.58 | 0.38 | 0.705 | 0.05 |
| | CG | 3.27 ± 0.62 | | | |
| BMI (kg/m²) | EG | 21.5 ± 2.8 | 0.49 | 0.632 | 0.07 |

| | | | | | |
|---|---|---|---|---|---|
| | CG | 21.3 ± 3.0 | | | |
| Running Performance (z-score within stage) | EG | 0.03 ± 0.92 | 0.35 | 0.726 | 0.05 |
| | CG | −0.02 ± 0.98 | | | |
| Online Learning Experience | EG | 2.12 ± 0.74 | 0.38 | 0.706 | 0.05 |
| | CG | 2.08 ± 0.78 | | | |
| Gender (male / female) | EG | 53 / 49 | $\chi^2$ = 0.04 | 0.841 | – |
| | CG | 51 / 50 | | | |
| Educational Stage (Uni / Sec) | EG | 72 / 30 | $\chi^2$ = 0.02 | 0.888 | – |
| | CG | 71 / 30 | | | |

*Note.* All continuous variables analyzed via independent samples t-tests; categorical variables via chi-square tests. Cohen's d computed using pooled SD. |d| < 0.10 indicates negligible effect size, supporting baseline equivalence (Shadish et al., 2002).

## Reliability and Validity Analysis

### Reliability

Cronbach's alpha, composite reliability, and average variance extracted for all scales exceeded threshold values, with alpha coefficients at or above 0.70, composite reliability at or above 0.70, and AVE at or above 0.50 (Table 8), indicating good internal consistency.

Table 8. Reliability and Convergent Validity Results

| Scale/Dimension | Cronbach's alpha | CR | AVE |
|---|---|---|---|
| Learning Engagement Scale | 0.86 | 0.88 | 0.52 |
| Behavioral Engagement | 0.78 | 0.80 | 0.51 |
| Cognitive Engagement | 0.75 | 0.77 | 0.50 |
| Affective Engagement | 0.73 | 0.76 | 0.51 |
| Learning Experience Scale | 0.82 | 0.84 | 0.53 |
| Perceived Support | 0.76 | 0.78 | 0.52 |
| Interaction Satisfaction | 0.74 | 0.77 | 0.51 |

### Validity

Confirmatory factor analysis demonstrated acceptable model fit, with chi-square to degrees of freedom ratio of 2.31, RMSEA of 0.076, CFI of 0.92, and TLI of 0.91. Discriminant validity was confirmed as the square root of each dimension's AVE exceeded its correlation with other dimensions (Fornell & Larcker, 1981).

## Correlation Analysis

Correlation results (Table 9) revealed that AI-ALS use was significantly positively correlated with overall learning engagement (r = 0.58, p < .001) and its three dimensions (behavioral: r = 0.62; cognitive: r = 0.53; affective: r = 0.49; all p < .001). Additionally, learning experience dimensions were strongly correlated with engagement (r = 0.54-0.61, p < .001), establishing the foundation for mediation testing.

Table 9. Correlation Matrix of Key Variables. .

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. AI-ALS Use | 1.00 | | | | | | |
| 2. Perceived Support | 0.63*** | 1.00 | | | | | |
| 3. Interaction Satisfaction | 0.59*** | 0.65*** | 1.00 | | | | |
| 4. Behavioral Engagement | 0.62*** | 0.61*** | 0.58*** | 1.00 | | | |
| 5. Cognitive Engagement | 0.53*** | 0.57*** | 0.54*** | 0.64*** | 1.00 | | |
| 6. Affective Engagement | 0.49*** | 0.55*** | 0.56*** | 0.59*** | 0.62*** | 1.00 | |
| 7. Overall Engagement | 0.58*** | 0.60*** | 0.58*** | 0.88*** | 0.87*** | 0.86*** | 1.00 |

Note. ***p < .001. Overall Engagement = mean of behavioral, cognitive, and affective engagement subscales.

## Hypothesis Testing Results

### H1 and H2: Main Effects of AI-ALS

Independent samples t-tests revealed that the experimental group significantly outperformed the control group in overall learning engagement and all three dimensions (Table 10). Effect sizes were large across all dimensions (Cohen's d > 0.90), with behavioral engagement showing the strongest improvement (d = 1.16), followed by overall engagement (d = 1.05), affective engagement (d = 0.95), and cognitive engagement (d = 0.93).

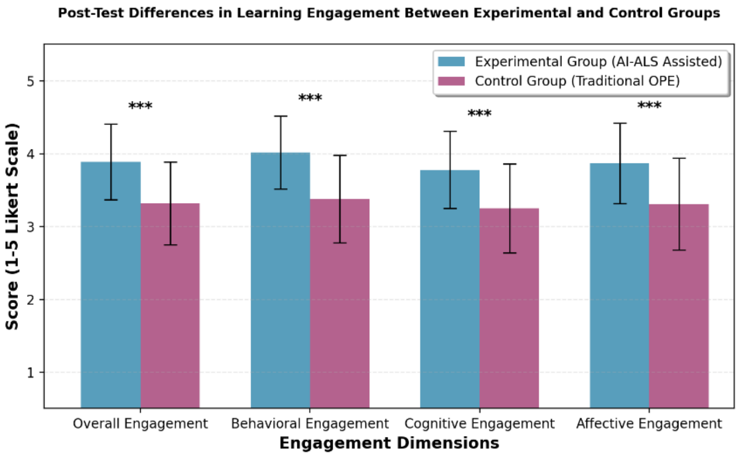
To triangulate self-reported scale data, supplementary platform analytics were analyzed as objective behavioral indicators. The experimental group demonstrated significantly higher login frequency (EG: 3.8 ± 1.2 times/week vs. CG: 2.5 ± 1.0 times/week, t = 7.32, p < .001) and longer training duration (EG: 156 ± 32 minutes/week vs. CG: 108 ± 28 minutes/week, t = 9.21, p < .001) than the control group, corroborating the scale-measured behavioral engagement advantage. These results support H1 and H2a through H2c.

Table 10. Post-Test Group Differences in Learning Engagement

| Variable | Group | M +/- SD | t | p | Cohen's d |
|---|---|---|---|---|---|
| Overall Engagement | EG | 3.89 ± 0.52 | 7.45 | <.001 | 1.05 |
| | CG | 3.32 ± 0.57 | | | |
| Behavioral Engagement | EG | 4.02 ± 0.50 | 8.26 | <.001 | 1.16 |
| | CG | 3.38 ± 0.60 | | | |
| Cognitive Engagement | EG | 3.78 ± 0.53 | 6.61 | <.001 | 0.93 |
| | CG | 3.25 ± 0.61 | | | |
| Affective Engagement | EG | 3.87 ± 0.55 | 6.75 | <.001 | 0.95 |
| | CG | 3.31 ± 0.63 | | | |

Note. EG = experimental group; CG = control group. EG = experimental group; CG = control group. Means are adjusted for gender, physical fitness index, and online learning experience. Cohen's d computed using pooled standard deviation.

Figure 1. Post-Test Differences in Learning Engagement Between Experimental and Control Groups




*Note*. Error bars represent standard deviations; ***p < 0.001.

### *H3: Mediation Effect of Learning Experience*

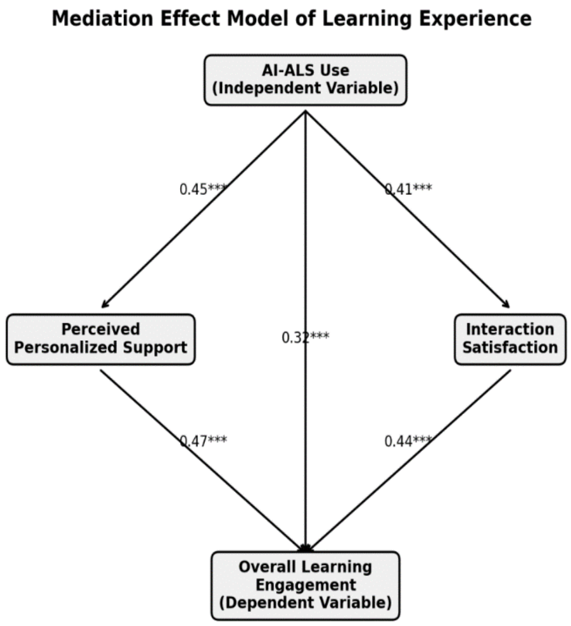
Hayes' PROCESS macro (Model 4, Bootstrap = 5000) confirmed partial mediation (Table 11). As depicted in Figure 2, AI-ALS demonstrated a direct positive effect on overall engagement (β = 0.32, p < .001) alongside two significant indirect pathways. The first indirect effect operated through perceived personalized support (β = 0.21, 95% CI [0.14, 0.29]), while the second pathway proceeded via interaction satisfaction (β = 0.18, 95% CI [0.11, 0.26]). The total effect of AI-ALS on overall engagement reached β = 0.71 (p < .001), with the combined mediation effect accounting for 54.9% of the total impact. Both direct and indirect effects were statistically significant, substantiating H3a and H3b and establishing learning experience as a critical mechanism through which AI-ALS enhances student engagement.

Table 11. Mediation Effect Test Results

| Path | beta | SE | t | p | 95% CI |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| AI-ALS -> Engagement | 0.32 | 0.05 | 6.40 | <.001 | [0.22, 0.42] |
| AI-ALS -> Support | 0.45 | 0.06 | 7.50 | <.001 | [0.33, 0.57] |
| Support -> Engagement | 0.47 | 0.06 | 7.83 | <.001 | [0.35, 0.59] |
| AI-ALS -> Satisfaction | 0.41 | 0.06 | 6.83 | <.001 | [0.29, 0.53] |
| Satisfaction -> Engagement | 0.44 | 0.06 | 7.33 | <.001 | [0.32, 0.56] |
| Indirect Effect (Path 1) | 0.21 | 0.04 | - | - | [0.14, 0.29] |
| Indirect Effect (Path 2) | 0.18 | 0.04 | - | - | [0.11, 0.26] |
| Total Effect | 0.71 | 0.05 | 14.20 | <.001 | [0.61, 0.81] |

Figure 2. Mediation Effect Model of Learning Experience




*Note*. All path coefficients are significant at p < 0.001(***); solid lines represent direct effects, dashed lines represent indirect effects.Indirect effect 1: β=0.21 (AI-ALS→PPS→Engagement);Indirect effect 2: β=0.18 (AI-ALS→IS→Engagement);Total effect: β=0.71***

## ***Qualitative Interview Insights***

To ensure coding rigor, two researchers independently coded 20% of the transcripts, achieving an inter-coder reliability of Cohen's κ = 0.85. Discrepancies were resolved through consensus discussion. Thematic saturation was reached when no new codes emerged in the final three interviews. Thematic analysis of the full corpus identified three core themes that triangulate the quantitative results.

### *Personalized Plans Enhance Intrinsic Motivation*

Students reported that AI-ALS's fitness-based and interest-based training plans reduced frustration. One student noted, "The system recommended low-impact exercises based on my knee injury, something traditional OPE never did. I'm more willing to stick with it now" (EG-07, medium engagement).

### *Real-Time Feedback Boosts Competence*

Instantaneous movement correction strengthened self-efficacy. As one student described, "Seeing the 3D model compare my squat posture and getting specific tips helped me fix mistakes quickly. I feel more confident in my skills" (EG-12, high engagement).

### *Interactive Features Foster Belonging*

Achievement badges and peer challenges enhanced affective engagement. One student explained, "Unlocking 'Consistent Trainer' badges and competing with classmates on the leaderboard made OPE feel like a community, not just solo training" (EG-03, medium engagement).

## Discussion

### *Interpretation of Core Findings*

The findings are consistent with the hypothesis that AI-assisted learning systems are associated with significantly higher levels of student learning engagement in online physical education. From the SDT perspective, AI-ALS appears to address students' basic psychological needs for autonomy, competence, and relatedness. Personalized training plans tailored to fitness levels and interests may enhance perceived autonomy, real-time movement correction and achievement feedback may foster competence, and interactive features such as peer leaderboards may strengthen social relatedness, collectively contributing to the observed engagement patterns (Ryan & Deci, 2017). TAM further offers a complementary explanation: AI-ALS's user-friendly interface and functional utility may improve perceived ease of use and usefulness, reducing technical barriers and increasing willingness to engage (Davis, 1989).

Notably, the intervention's effect size varied across engagement dimensions, with behavioral engagement showing the strongest improvement (Cohen's d = 1.16), followed by affective engagement (d = 0.95), overall engagement (d = 1.05), and cognitive engagement (d = 0.93). This pattern aligns with AI-ALS's functional architecture: its automated reminders, structured training modules, and progress tracking directly target behavioral participation, producing immediate increases in login frequency and training duration. Cognitive engagement benefited from adaptive learning paths that matched students' skill levels, reducing cognitive overload and promoting deeper processing of movement knowledge. Affective engagement, while substantially improved, exhibited a comparatively smaller—though still large—effect size, as emotional connections such as enjoyment and belonging typically require longer-term interaction and socialization than behavioral or cognitive changes.

The mediation analysis offers preliminary evidence that learning experience serves as a transmission mechanism in the AI-ALS–engagement relationship. Perceived personalized support and interaction satisfaction functioned as parallel mediators, jointly accounting for 54.9% of the total effect. This suggests that AI-ALS may not enhance engagement solely through direct technological exposure, but rather by improving students' subjective experience. Personalized support appeared to address individual differences in OPE, adapting exercises for injuries or skill gaps, while real-time interactive feedback and gamified elements such as badges appeared to boost interaction satisfaction. Together, these factors may transform OPE from a passive, one-size-fits-all experience into a more active, tailored process.

However, these interpretations should be treated as provisional rather than definitive. Because the study employed a non-equivalent control group design with intact classes, the observed differences—though statistically significant and substantively large—cannot be attributed unambiguously to AI-ALS alone. Unmeasured class-level variables (e.g., pre-existing classroom climate, instructor-student rapport within specific classes) may have contributed to the group differences, despite the use of covariate adjustment and baseline equivalence verification. Consequently, the term "effect" is used here in a quasi-experimental sense, denoting a robust association under controlled conditions rather than a strictly causal impact.

### *Comparison with Existing Studies*

The positive association between AI-ALS and learning engagement is consistent with findings from AI-assisted learning research in traditional academic subjects such as mathematics and language learning. Previous studies have demonstrated that AI-driven personalized learning systems improve student engagement by adapting content to individual needs (Chen et al., 2020). This consistency suggests that the core mechanisms through which AI enhances engagement—namely personalization, interactivity, and feedback—may be transferable across disciplinary contexts, including physical education, though this transferability awaits further experimental verification.

Within the constraints of a quasi-experimental design, this study offers three incremental contributions. First, it provides one of the initial large-sample quantitative examinations of AI-ALS effectiveness in OPE, a field where technology integration has traditionally lagged behind academic subjects and relied more heavily on qualitative observations. Second, unlike most existing OPE studies that measure engagement as a unidimensional construct, this research adopts a multidimensional framework encompassing behavioral, cognitive, and affective components, offering a more nuanced understanding of how AI influences different aspects of student involvement. Third, the mediation model provides preliminary evidence on the underlying mechanism linking AI-ALS to engagement, whereas prior studies often focused on direct effects without exploring intermediate pathways. This mediation evidence helps address a gap in the literature by suggesting learning experience as a potential bridge between AI technology and student engagement in OPE contexts, pending replication with true experimental designs.

### *Theoretical and Practical Contributions*

For theoretical contributions, this study—within the scope of its quasi-experimental methodology—extends the application boundary of AI educational technology from traditional academic subjects into physical education, thereby enriching the interdisciplinary theoretical framework connecting technology, education, and sports. By integrating AI-ALS as a technological variable within the learning engagement influencing factor model and offering preliminary evidence for the mediating role of learning experience, this research complements existing frameworks that have centered primarily on instructor or peer influences. The identification of parallel mediation by personalized support and interaction satisfaction also provides new hypotheses for the multi-path nature of technology's impact on engagement, which future experimental research can test.

For practical contributions, the findings offer tentative guidance for OPE practitioners working with secondary and university students in contexts comparable to those studied. For curriculum design, educators might consider prioritizing AI-ALS's core functional modules—including personalized training plan generation, real-time movement feedback, and interactive gamification—to maximize behavioral and cognitive engagement, provided that institutional resources and technical infrastructure are available. For teaching practice, the results suggest a potential shift from instructors to AI-human collaborators: teachers may leverage AI to handle routine tasks such as exercise adaptation and progress monitoring, while focusing on addressing students' affective needs such as resolving emotional barriers and fostering peer interaction. At the policy level, these findings may inform regional educational authorities considering pilot programs for AI-ALS integration in OPE, particularly in resource-constrained regions, though large-scale implementation should await further causal evidence from randomized trials.

It is important to emphasize that these practical implications are context-bound. The sample was drawn exclusively from Jiangsu Province, and the intervention was delivered within a specific institutional structure (intact classes, uniform instructors, standardized content). Generalizing these recommendations to other geographic regions, educational cultures, or age groups like primary school or adult learners, would be premature without additional cross-context validation.

### *Limitations and Future Research*

This study has several limitations that warrant attention and qualify the interpretations offered above. First, the non-equivalent control group design, while methodologically appropriate for the institutional context, precludes definitive causal inference. Although intact classes were randomly assigned to conditions and baseline equivalence was verified, unmeasured class-level confounders such as classroom climate, prior instructor-student rapport, may partially account for the observed differences. Second, the sample size of 203 participants, while meeting a priori power requirements, is relatively modest and drawn from a limited geographic scope (Jiangsu Province), which may constrain generalizability. Third, the intervention period of 10 weeks is relatively brief, making it difficult to assess long-term effects of AI-ALS on engagement, particularly affective engagement, which develops gradually over extended periods. Fourth, the research did not examine potential moderating variables such as students' learning styles (visual versus kinesthetic learners), prior experience with AI technology, or socioeconomic status, which may influence AI-ALS effectiveness. Finally, while educational stage was included as a covariate, the inclusion of both secondary school and university students introduced age-related heterogeneity that may have obscured stage-specific effects.

Future research should address these gaps by adopting randomized controlled trials with individual-level randomization wherever administratively feasible, thereby strengthening causal claims. Larger, cross-regional samples from diverse Chinese provinces or international contexts would enhance generalizability. Longitudinal tracking over six to twelve months is needed to examine whether AI-ALS effects persist over time and whether affective engagement eventually converges with behavioral and cognitive dimensions. Additionally, investigating moderating variables can help identify which student groups benefit most from AI-ALS, enabling more targeted implementation. Finally, exploring multi-technology integration such as AI combined with virtual or augmented reality could further enhance OPE's immersive and interactive nature, as these technologies can simulate real-world sports scenarios while AI provides personalized guidance, creating a more holistic and engaging learning environment.

## Conclusions

This study investigated the impact of AI adaptive learning systems on students' learning engagement in online physical education and the mediating role of learning experience through a quasi-experimental design. The core findings demonstrate that AI-ALS is associated with significantly enhanced OPE students' overall learning engagement, with positive effects across behavioral, cognitive, and affective dimensions, among which behavioral engagement exhibits the strongest improvement. Additionally, learning experience, operationalized as perceived personalized support and interaction satisfaction, plays a partial mediating role, validating the AI-ALS to learning experience to engagement pathway.

The study makes two key contributions. Theoretically, iit helps address the research gap in applying AI-ALS to physical education, extending the explanatory scope of educational technology theories such as Self-Determination Theory and the Technology Acceptance Model to OPE contexts and enriching the multidimensional engagement research framework. Practically, it provides evidence-based insights for OPE's intelligent transformation, offering actionable strategies for curriculum design, teacher role adjustment, and policy formulation.

Looking forward, AI technology holds substantial potential to optimize OPE and promote lifelong physical activity. As intelligent educational tools continue to evolve, future practice should prioritize the personalized and interactive features of AI-ALS while integrating multi-technology solutions such as AI combined with virtual or augmented reality to enhance immersion. By continuously refining AI-assisted OPE models, we can better address the challenges of digital physical education, foster sustained learning engagement, and lay a foundation for learners' lifelong health and well-being.

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