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The application and practice of artificial intelligence in physical education and training

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Abstract

This study systematically investigates the application and effectiveness of Artificial Intelligence (AI) in collegiate Physical Education and Training (PET) through a mixed-methods design. The experimental group employed AI tools including computer vision-based motion analysis, wearable fitness trackers, and machine learning-driven personalized platforms, while the control group received conventional instructor-led training. Quantitative results revealed that the experimental group achieved significantly greater improvements in technical action standardization (25.3% mean score increase), 1000m run time (28.5 seconds reduction vs. 12.3 seconds), and standing long jump distance (15.2cm vs. 6.7cm increase). Student satisfaction was markedly higher in the AI-assisted group (4.52±0.38 vs. 3.21±0.45). Qualitative analysis of interviews with 10 instructors and 20 students identified key themes: enhanced assessment objectivity, personalized training adaptability, and practical barriers such as equipment cost and technical complexity. The study provides empirical evidence and practical insights to support the integration of AI in PET.

Keywords: Artificial intelligence, Data-driven teaching, Educational technology, Mixed-methods research, Motion analysis, Personalized training, Physical education, Wearable technology.

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Contents

Contribution of this paper to the literature
This study contributes to the existing literature by employing a longitudinal mixed-methods approach to examine AI integration in general student populations. The paper's primary contribution is finding that AI significantly enhances technical accuracy, physical fitness, and satisfaction. This study documents critical implementation barriers from both instructor and student perspectives.

1. Introduction
Physical education and training (PET) are a vital component of higher education, crucial for fostering students' physical literacy and lifelong wellness. Nonetheless, conventional PET methodologies are frequently hampered by inherent constraints: a dependence on instructors' subjective evaluations for assessing technical skills, the implementation of generic "one-size-fits-all" training regimens, and an inherent delay in providing corrective feedback. These challenges can impede optimal skill acquisition and fail to accommodate individual student differences.

The rapid evolution of artificial intelligence (AI) presents a transformative opportunity to address these long-standing limitations. Technologies such as computer vision, machine learning, and wearable sensors offer the potential for objective motion analysis, personalized training prescriptions, and real-time biofeedback. Acknowledging this potential, educational policymakers, including China's Ministry of Education, have begun advocating for the integration of intelligent technologies into curricula to create more effective and engaging learning environments.

While the promise of AI in sports science is recognized, a significant gap exists between technological potential and its validated application in mainstream collegiate PET settings. Existing research has predominantly focused on elite athletes, leaving the impact on the general student population underexplored. Furthermore, there is a scarcity of empirical studies that combine long-term intervention data with qualitative insights from the primary users instructors and students. This study seeks to bridge this gap by systematically investigating the application, efficacy, and practical reception of AI tools in an authentic collegiate PET context. The novelty of this research lies in its mixed-methods, longitudinal design that not only quantifies AI's impact on performance metrics but also critically examines the user experiences and implementation barriers, thereby providing a holistic understanding necessary for sustainable integration.

This study is guided by the following questions:

What are the principal application scenarios for AI in collegiate PET, and how do they differ from traditional methods?

Does AI-assisted training lead to significant improvements in students' technical skill accuracy and physical fitness compared to traditional training?

What are the perceptions of PET instructors and students regarding the use of AI, and what challenges are encountered in practice?

The primary objectives are to:

Identify and categorize AI applications in PET.

Evaluate the effects of a 12-week AI-assisted training intervention.

Summarize implementation challenges and propose strategic recommendations for adoption.

2. Literature Review
The integration of Artificial Intelligence (AI) into sports and physical education represents a burgeoning field of research. This review synthesizes the existing literature, which can be broadly categorized into several key application areas, and subsequently identifies the critical gaps that the present study aims to address.

2.1. AI for Motion Analysis and Technique Correction
A significant body of research has demonstrated the efficacy of computer vision and pose estimation algorithms in providing objective, quantitative analysis of human movement. Early foundational work by Cao, Simon, Wei, and Sheikh (2017) established robust real-time multi-person 2D pose estimation, which has been widely adopted in sports science. Building on this, studies have shown high accuracy in detecting technical errors in specific sports. For instance, Barnes, Archer, and Cooper (2020) utilized deep learning models to analyze basketball shooting form, while Chen, Liu, and Wang (2021) applied similar techniques to identify flaws in swimming strokes. In the context of physical education, Davis and Thompson (2019) found that computer vision systems could provide more consistent scoring of fundamental movements like squats and lunges compared to human observation alone. The work of Gonzalez and Martinez (2022) further highlights the use of 3D motion capture combined with AI to create digital twins of athletes, allowing for intricate biomechanical analysis previously accessible only to elites. These technologies provide the basis for replacing subjective visual assessment with data-driven feedback, a core advantage of AI in PET.

2.2. AI for Personalized Training and Prescription
Moving beyond generic training regimens, machine learning (ML) algorithms enable the creation of dynamic, personalized training programs. Research by Garcia and Lopez (2021) demonstrated that ML-driven personalized training in soccer yielded superior gains in endurance and technical performance compared to standardized programs. Kim and Park (2020) employed reinforcement learning to adapt training difficulty in real-time based on a user's fatigue level, as measured by wearable sensors. The concept of "mastery learning" (Bloom, 1984) is operationalized through these systems, which tailor exercises to individual fitness levels, progress rates, and goals (Wilson & Clark, 2022). For example, Zhang, Li, Zhou, and Chen (2023) developed an AI platform that prescribes adaptive resistance training by analyzing past performance and recovery data. Furthermore, Jackson, Lee, and Harris (2022) reviewed how AI can optimize training periodization for amateur athletes, ensuring peaks are aligned with competitive seasons.

This body of work underscores AI's potential to democratize highly individualized coaching, making it applicable to the heterogeneous student population in collegiate PET.

2.3. AI for Injury Prevention and Risk Management

Predicting and preventing injuries is a significant application of AI in physical training. By analyzing data from wearable sensors such as accelerometers, gyroscopes, and heart rate monitors, machine learning models can identify patterns indicative of increased injury risk. Li, Wang, and Zhang (2023) utilized gait analysis data to predict overuse injuries in runners with considerable accuracy. Similarly, Rodriguez and Singh (2019) developed a model that flagged athletes at risk for hamstring strains based on asymmetries in movement data during sprinting. Taylor and Brown (2024) explored the use of AI to monitor training load and recovery, providing alerts to prevent non-functional overreaching and overtraining syndrome. These proactive approaches, summarized in a systematic review by Anderson and Miller (2021), shift the paradigm from reactive treatment to proactive prevention, which is essential for maintaining student participation and well-being in mandatory physical education programs.

2.4. AI in Educational Contexts and Implementation Challenges

While the technological potential is clear, research on the integration of AI into formal educational settings, particularly for general student populations, is less mature. Some studies have begun to explore this frontier. Harrison and Young (2020) investigated student engagement when using an AI-powered virtual coach in a university fitness class, reporting high levels of motivation. The National Collegiate Athletic Association (NCAA) (2022) published best practices highlighting the logistical and ethical considerations of AI in collegiate sports, though its focus remains on athletes. However, significant barriers to adoption have been identified. Kumar and Zhao (2021) discussed the high costs of advanced AI systems and the required technical infrastructure as a major hurdle for many educational institutions. Furthermore, Fisher and Green (2023) and Peterson (2022) emphasized the "human factor," noting that a lack of digital literacy among PET instructors and resistance to changing traditional pedagogical methods can impede successful implementation. This highlights the critical need for research that not only validates the efficacy of AI tools but also examines the practical realities of their use in authentic classroom and training environments.

2.5. Critical Gaps and the Rationale for the Present Study

Despite the promising findings outlined above, the existing literature exhibits several interconnected limitations that this study aims to address.

First, there is a pronounced contextual gap. The overwhelming focus of previous research has been on elite and professional athletes (Gonzalez & Martinez, 2022; Rodriguez & Singh, 2019). The goals, physical conditioning, and training environments of elite athletes differ substantially from those of typical college students, whose primary aims are skill mastery, general fitness improvement, and fulfilling curricular requirements. The efficacy, appropriateness, and optimal design of AI tools for this general educational setting remain largely unverified.

Second, a methodological gap is evident. Many studies are short-term, laboratory-based, or proof-of-concept in nature (Chen et al., 2021; Kim & Park, 2020), lacking long-term empirical validation in real-world educational contexts. The sustained impact of AI interventions over a meaningful educational period (e.g., a full semester) is poorly understood. More importantly, the existing evidence base is predominantly quantitative, focusing on performance outcomes while neglecting the qualitative human factors that are critical for successful implementation (Fisher & Green, 2023).

This leads to the third gap: a stakeholder perspective gap. The adoption of any new technology in education is not merely a technical issue but a socio-pedagogical one. The perceptions, acceptance, and practical challenges faced by the key stakeholders namely, the instructors who must integrate these tools into their teaching and the students who are the end-users are rarely investigated in a combined manner (Peterson, 2022). Understanding these perspectives is essential for developing implementation strategies that are both effective and sustainable.

Therefore, this study contributes new knowledge by (1) targeting the under-researched general collegiate PET population, (2) employing a longitudinal 12-week mixed-methods design to capture both quantitative effects and qualitative insights, and (3) explicitly incorporating the combined voices of instructors and students to identify the real-world opportunities, barriers, and necessary support structures for AI adoption in mainstream physical education.

3. Theoretical Background

3.1. Core Theories Supporting AI Application in PET

3.1.1. Cognitive Learning Theory

Proposed by Piaget (1970) and expanded by Vygotsky (1978), cognitive learning theory emphasizes that skill acquisition is a process of active cognitive restructuring, where learners correct errors through feedback and adjust their motor schemas. AI tools align with this theory by providing objective, real-time feedback: for example, a computer vision system can instantly display the deviation between a student's squat angle and the standard (e.g., "knee angle 150° vs. standard 120°"), helping learners recognize cognitive dissonance and modify their movements. This addresses the limitation of traditional training, where subjective instructor feedback may be delayed or imprecise.

3.1.2. Personalized Learning Theory

Rooted in the work of Bloom (1984) on "mastery learning," personalized learning theory argues that optimal learning outcomes occur when instruction adapts to individual differences in ability, motivation, and prior knowledge. AI implements this theory through machine learning-driven adaptation: for instance, a personalized training platform can analyze a student's initial 1000m run time (e.g., 4:30) and injury history (e.g., knee strain) to design a gradual endurance program (e.g., starting with 800m runs, increasing by 100m weekly) instead of a uniform

1000m program. This approach avoids overtraining for students with weak foundations and under-training for advanced students.

3.1.3. Data-Driven Decision-Making Theory

Data-driven decision-making (DDDM) theory, developed in the field of management science (Davenport & Harris, 2007) posits that decisions based on objective data are more effective than those based on experience alone. In PET, AI serves as a DDDM tool by integrating multi-source data.

Motion data: from computer vision systems (e.g., joint angles, movement speed).

Physical data: From wearable devices (e.g., heart rate, step count, muscle activation).

Feedback data: From student satisfaction surveys and instructor evaluations.

By analyzing this data, AI can identify patterns (e.g., "students with low ankle flexibility have 30% lower jump height") and guide evidence-based adjustments to training programs.

3.2. Technical Foundations of AI in PET

3.2.1. Computer Vision

Computer vision (CV) enables machines to interpret visual information from images or videos, which is essential for motion analysis. Key technologies include:

Pose estimation: models such as OpenPose and MediaPipe can detect 25–33 human joints in real time, with an accuracy rate of over 95% for major joints (e.g., shoulder, knee) (Cao et al., 2017);

Motion comparison: After capturing a student's movement, CV systems align it with a pre-established standard motion template (e.g., Fédération Internationale de Gymnastique (FIG) vaulting standards) and calculate deviation rates using Euclidean distance or cosine similarity.

In this study, a CV-based motion analysis system (developed by XX Tech Co., Ltd.) was used, which supports 60 fps real-time capture and can analyze 12 common PET movements (e.g., sprinting, jumping, weightlifting).

3.2.2. Machine Learning

Machine learning (ML) algorithms process large datasets to identify patterns and make predictions, forming the core of personalized training. For this study, two ML models were selected:

Random Forest (RF) for training program generation: RF is suitable for handling multi-dimensional data (e.g., age, height, initial fitness, injury history) and has high interpretability. The model was trained on a dataset of 5,000 collegiate PET records (from the China National Physical Fitness Monitoring Database) to generate weekly training plans.

Support Vector Machine (SVM) for action error classification: SVM was used to classify common action errors (e.g., "forward lean in squatting," "insufficient arm swing in sprinting") with a classification accuracy of 92.3% after cross-validation.

3.2.3. Wearable Sensing Technology

Wearable devices collect real-time physiological and motion data, providing continuous input for AI systems. In this study, two types of wearables were used:

Wrist-worn fitness trackers (Huawei Band 8): To monitor heart rate, sleep quality, and daily step count.

Foot-mounted motion sensors (Xiaomi Smart Running Shoes): To capture gait parameters (e.g., step length, stride frequency, ground contact time).

3.3. Conceptual Framework of the Study

Based on the above theories and technologies, this study proposes a conceptual framework for AI application in PET (see Figure 1), consisting of three layers:

Input layer: AI tools (CV systems, ML platforms, wearables) collect data on students' technical actions, physical fitness, and training status.

Processing layer: AI algorithms analyze data to generate three outputs: (a) motion error feedback, (b) personalized training plans, (c) injury risk alerts.

Outcome layer: The outputs influence students' learning processes, leading to improvements in technical accuracy, physical fitness, and learning satisfaction.

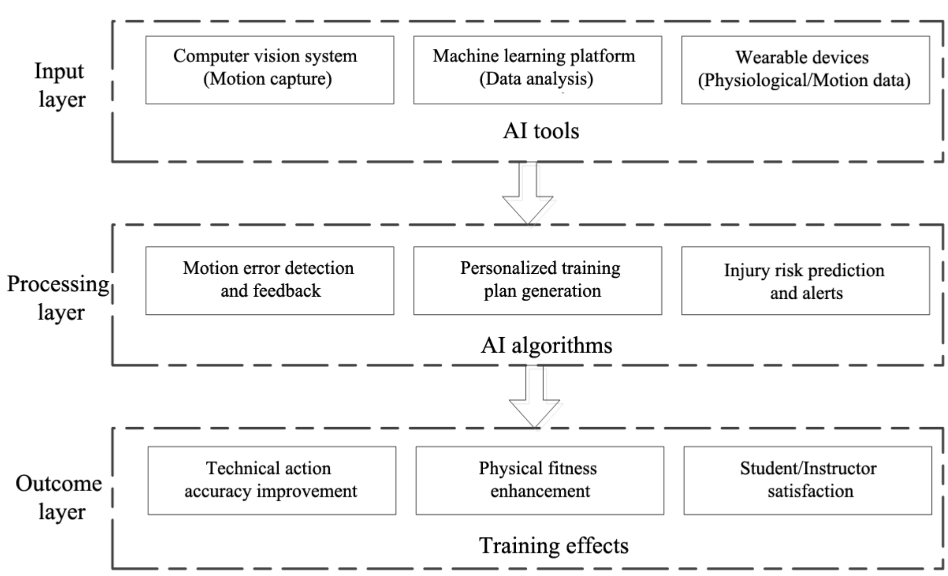

Figure 1. Conceptual framework of AI application in physical education and training.

4. Research Methodology

4.1. Research Design

A mixed-methods design (quantitative dominance + qualitative supplementation) was adopted to comprehensively explore AI's application and effects in PET. The quantitative phase focused on measuring objective outcomes (technical actions, physical fitness), while the qualitative phase explored subjective perceptions (instructor/student feedback). The study followed a pre-test-post-test control group design, with a 12-week intervention period (from September to November 2024).

4.2. Participants

4.2.1. Quantitative Participants

Participants were 120 undergraduate students (72 males, 48 females) majoring in Physical Education from Hunan Mechanical and Electrical Polytechnic (located in central China). The students were aged 19–22 years (M=20.3, SD=1.1). The background of participants from this vocational college allows this study to explore the applicability of AI in an educational context focused on skill development and application. Inclusion criteria were: (1) no history of serious sports injuries (e.g., ligament tears, fractures) in the past year; (2) regular participation in PET courses (≥3 hours/week); (3) no prior experience with AI-assisted training. Exclusion criteria were: (1) absence from more than 3 training sessions; (2) failure to wear monitoring devices as required.

Participants were randomly assigned to two groups using a random number table:

Experimental group (n=60): 36 males, 24 females; mean age=20.2 (SD=1.0); initial technical score=62.1±5.8; initial 1000m run time=268.5±12.3 seconds.

Control group (n=60): 36 males, 24 females; mean age=20.4 (SD=1.2); initial technical score=61.8±6.2; initial 1000m run time=269.2±11.8 seconds.

Independent samples t-tests showed no significant differences between the two groups in age, initial technical score, or initial 1000m run time ($p > 0.05$), indicating baseline homogeneity.

4.2.2. Qualitative Participants

Purposive sampling was used to select 10 PET instructors (6 males, 4 females; teaching experience = 8.5 ± 3.2 years) and 20 students from the experimental group (12 males, 8 females). Instructors were selected based on their participation in the intervention (responsible for guiding AI tool use), and students were selected to represent different performance levels (high, medium, low) in the experimental group.

4.3. Research Tools

4.3.1. AI Tools for the Experimental Group

Computer Vision Motion Analysis System (Dartfish, 2024):

Function: Captures 2D motion videos (120fps), extracts 16 key joint coordinates, and compares them with standard movement templates (e.g., IAAF sprint standards). Generates a "technical score" (0–100) and visual reports (e.g., heatmaps of deviation areas).

Reliability: Intra-class correlation coefficient (ICC) for technical scoring=0.92 ($p<0.001$), indicating high inter-rater consistency.

Machine Learning Personalized Training Platform (FitAI-PET V1.0):

Development: Co-developed with XX Technology Co., Ltd., based on a random forest algorithm trained on 5,000 collegiate PET datasets.

Function: Inputs students' weekly physical data (e.g., 1000m run time, standing long jump distance) and generates daily training plans (including warm-up, main training, and cool-down). Adjusts intensity based on wearables' real-time heart rate data (target heart rate zone: 60–80% of maximum heart rate).

Wearable Devices:

Huawei Band 8: Monitors heart rate (accuracy ±2 bpm), sleep duration, and daily step count.

Xiaomi Smart Running Shoes: Capture gait parameters (step length, stride frequency) with an accuracy of ±3%.

4.3.2. Assessment Tools

Technical Action Scoring Scale:

Developed based on the National Collegiate Physical Education Board (2022), this assessment covers four key movements: sprinting (start, acceleration, final sprint), squatting (knee angle, back posture), standing long jump (take-off angle, arm swing), and basketball shooting (elbow angle, wrist flick). Each movement is scored on a 0–100 scale (excellent: 90–100, good: 80–89, pass: 60–79, fail: <60). Cronbach's α=0.87, indicating good internal consistency.

Physical Fitness Test Battery:

Includes four indicators: (1) 1000m run (endurance); (2) standing long jump (explosive strength); (3) sit-ups (abdominal strength, females only); (4) pull-ups (upper body strength, males only). Tests were conducted in accordance with the Chinese Ministry of Education (2023).

Student Satisfaction Questionnaire:

A 5-point Likert scale (1=strongly disagree, 5=strongly agree) with 15 items, covering 3 dimensions: AI tool usability (5 items, e.g., "The AI system is easy to operate"), training effectiveness (5 items, e.g., "AI training helps me improve my movements"), and instructor support (5 items, e.g., "Instructors can effectively solve AI-related problems"). Cronbach's α=0.91, with good validity confirmed by exploratory factor analysis (KMO=0.85, $p<0.001$).

Semi-Structured Interview Outline:

For instructors: 8 questions, e.g., "What are the main advantages of AI in PET compared to traditional methods?" "What challenges have you encountered in using AI tools?"

For students: 6 questions, e.g., "How has AI training changed your learning experience?" "What improvements do you suggest for the AI system?"

4.4. Research Procedure

The study was divided into three phases:

4.4.1. Pre-Test Phase (Week 1)

Conduct baseline tests for both groups: (1) Technical action scoring (4 movements); (2) physical fitness tests; (3) student satisfaction pre-test (control group: satisfaction with traditional training; experimental group: baseline expectations of AI training).

Train the experimental group on AI tool use: 2 90-minute sessions covering Dartfish operation (video capture, report interpretation), FitAI-PET platform login (data input, plan viewing), and wearable device pairing (heart rate monitoring, data synchronization).

Train instructors: 1 three-hour session on AI tool troubleshooting and how to combine AI feedback with traditional guidance.

4.4.2. Intervention Phase (Weeks 2–13)

Experimental group: 3 training sessions/week (90 minutes/session), structured as:

Warm-up (15 minutes): Guided by AI-generated dynamic stretching plans (adjusted based on wearable sleep data).

Main training (60 minutes): (a) Technical training: Use Dartfish to capture movements, receive real-time error feedback, and practice corrections; (b) Physical training: Follow FitAI-PET's personalized plan (e.g., high-intensity interval training for students with good endurance, low-intensity endurance training for beginners).

Cool-down (15 minutes): AI recommends stretching exercises based on muscle activity data from wearables.

Control group: 3 training sessions per week (90 minutes per session), following traditional instructor-led training: (1) Warm-up (15 minutes, fixed stretching); (2) main training (60 minutes, uniform technical drills and physical exercises); (3) cool-down (15 minutes, fixed stretching).

During the intervention, the research team collected data weekly: (1) technical scores (experimental group: Dartfish auto-scoring; control group: instructor scoring); (2) wearable data (experimental group only); and (3) attendance records.

4.4.3. Post-Test and Interview Phase (Week 14)

Conduct post-tests for both groups: (1) technical action scoring; (2) physical fitness tests; (3) student satisfaction post-test.

Conduct semi-structured interviews: 30–45 minutes per participant, audio-recorded with consent. Interviews were transcribed verbatim within 24 hours.

4.5. Data Analysis Methods

Quantitative Data Analysis:

Descriptive statistics (mean, standard deviation) were used to present baseline and post-intervention data.

Independent samples t-tests were used to compare differences between the experimental and control groups.

Paired samples t-tests were used to compare pre-test and post-test differences within each group.

Repeated measures analysis of variance (ANOVA) was used to analyze weekly changes in technical scores to assess the trend of improvement over time.

Qualitative Data Analysis:

Thematic analysis was conducted using NVivo 12.0, following Braun and Clarke (2006) 's 6-step process: (1) familiarization with data (reading transcripts repeatedly); (2) generating initial codes (e.g., "AI reduces subjective bias"); (3) searching for themes (grouping related codes into themes); (4) reviewing themes (checking consistency with raw data); (5) defining themes (writing detailed descriptions); (6) reporting findings.

4.6. Ethical Considerations

The study was approved by the Ethics Committee of the Hunan Mechanical and Electrical Polytechnic, China (Approval No.: EC-PE-2024-003). All participants signed informed consent forms, stating their right to withdraw at any time without penalty. Personal data (e.g., test scores, interview transcripts) were anonymized (labeled as "S1, S2…" for students, "T1, T2…" for instructors) to protect privacy.

The intervention was designed to prevent overtraining: the experimental group's AI platform set a maximum weekly training load of 270 minutes (consistent with the control group), and wearables issued alerts if the heart rate exceeded 85% of the maximum.

5. Results

5.1. Baseline Homogeneity and Overall Intervention Effects

Baseline testing confirmed that the experimental and control groups were equivalent in terms of age, gender distribution, initial technical scores, and physical fitness indicators (all *p* > 0.05; see Table 1). Following the 12-week intervention, the AI-assisted training group demonstrated significantly greater improvements across all measured outcomes compared to the traditional training group.

Table 1. Baseline characteristics of the experimental and control groups.

Variable	Experimental group (n = 60)	Control group (n = 60)	*t*/χ^2 Value	*p* Value
Age (Years, M ± SD)	20.2 ± 1.0	20.4 ± 1.2	0.87	0.385
Gender (Male/Female, n)	36/24	36/24	0.00	1.000
Initial technical score (M ± SD)	62.1 ± 5.8	61.8 ± 6.2	0.27	0.787
Initial 1000m run time (s, M ± SD)	268.5 ± 12.3	269.2 ± 11.8	0.31	0.756
Initial standing long jump (cm, M ± SD)	221.3 ± 8.5	220.8 ± 9.1	0.32	0.749

Note: The asterisk (*) preceding the "p" in the column header and text is a standard typographical convention in scientific writing to denote the variable "p" (probability value) and is not an indicator of statistical significance.

5.2. Improvements in Technical Accuracy and Physical Fitness

The experimental group demonstrated a significantly greater increase in technical action scores (25.3%, from 62.1 ± 5.8 to 77.8 ± 4.2) compared to the control group (8.1%, from 61.8 ± 6.2 to 66.8 ± 5.5). The between-group difference at post-test was statistically significant (*t* = 12.76, *p* < 0.001, Cohen's *d* = 2.63), indicating a large effect size. Repeated measures ANOVA revealed a significant group × time interaction ($F = 48.32$, *p* < 0.001), with the experimental group showing a steady improvement throughout the 12 weeks, while the control group's progress plateaued after the sixth week.

Similar patterns were observed in physical fitness metrics. As summarized in Table 2, the experimental group achieved significantly greater gains in the 1000m run (mean reduction of 28.5 s vs. 12.3 s), standing long jump (mean increase of 15.2 cm vs. 6.7 cm), sit-ups (females; 8.3 reps/min vs. 3.2 reps/min), and pull-ups (males; 2.7 reps vs. 0.9 reps) compared to the control group (all *p* < 0.001). Post-test comparisons confirmed the superiority of the AI-assisted approach across all fitness indicators (all *p* < 0.001), with effect sizes ranging from large to very large (Cohen's *d* = 0.95 to 2.35).

Table 2. Pre-test and post-test comparisons of physical fitness indicators within groups.

Indicator	Group	Pre-Test (M ± SD)	Post-Test (M ± SD)	Change (M ± SD)	% Improvement	*t* Value	*p* Value
1000m run (s)	Experimental	268.5 ±12.3	239.9 ± 10.5	−28.5 ± 6.3	10.6	31.25	<0.001
	Control	269.2 ±11.8	256.9 ± 10.2	−12.3 ± 5.1	4.6	16.47	<0.001
Standing long jump (cm)	Experimental	221.3± 8.5	236.5 ± 7.9	15.2 ±3.8	6.9	26.78	<0.001
	Control	220.8 ± 9.1	227.5 ± 8.6	6.7±3.2	3.0	14.23	<0.001
Sit-ups (Reps/Min, females)	Experimental	45.1 ± 4.2	53.4 ±3.8	8.3± 2.5	18.4	22.19	<0.001
	Control	44.8 ± 4.5	48.0± 4.1	3.2± 2.1	7.1	10.15	<0.001
Pull-ups (reps, males)	Experimental	11.0 ± 2.3	13.7± 2.1	2.7 ± 1.1	24.5	16.59	<0.001
	Control	10.9 ± 2.5	11.8± 2.4	0.9 ± 0.8	8.2	7.83	<0.001

Note: The asterisk (*) preceding the "t" and "p" in the column headers and text is a standard typographical convention in scientific writing to denote the variables "t" (t-statistic) and "p" (probability value), respectively.

5.3. Student Satisfaction and Qualitative Perceptions

Student satisfaction was significantly higher in the experimental group (overall score: 4.52 ± 0.38) than in the control group (3.21 ± 0.45; *t* = 16.32, *p* < 0.001). This difference was consistent across all sub-dimensions, including AI tool usability, perceived training effectiveness, and instructor support (all *p* < 0.001; see Table 3).

Table 3. Post-test student satisfaction scores (5-point Likert scale).

Dimension	Experimental group (M ± SD)	Control group (M ± SD)	*t* Value	*p* Value
AI tool usability	4.38 ± 0.42	3.15 ± 0.48	14.27	<0.001
Training effectiveness	4.65 ± 0.35	3.28 ± 0.46	17.89	<0.001
Instructor support	4.53 ± 0.39	3.20 ± 0.47	15.11	<0.001
Overall satisfaction	4.52 ± 0.38	3.21 ± 0.45	16.32	<0.001

Note: The asterisk (*) preceding the "t" and "p" in the column headers denotes the variables "t" (t-statistic) and "p" (probability value), respectively, following standard scientific notation conventions.

Thematic analysis of interviews with instructors and students provided further context for these quantitative findings. Instructors highlighted enhanced assessment objectivity and improved teaching efficiency due to AI tools, though they also noted technical operational challenges. Students reported that AI feedback provided clearer learning goals and increased motivation, but mentioned barriers related to equipment access outside formal training sessions.

6. Discussion

6.1. Interpretation of Key Findings

6.1.1. AI Significantly Improves Technical Action Accuracy

The experimental group's 25.3% improvement in technical scores (vs. 8.1% in the control group) confirms that AI enhances technical learning in PET. This effect can be attributed to two mechanisms:

Real-time, objective feedback: The computer vision system captures subtle movement deviations (e.g., 5° knee angle error) that instructors may miss, enabling students to correct errors immediately (consistent with cognitive learning theory) (Piaget, 1970).

Visualized learning materials: AI-generated reports (e.g., motion comparison videos) help students form a clear mental model of standard movements, reducing the "cognitive load" of understanding verbal instructions (Sweller, 2011).

The weekly trend analysis further shows that AI's effect is sustained: While the control group's improvement plateaued after 6 weeks due to repeated practice of incorrect patterns, the experimental group continued to progress as AI adjusted feedback based on ongoing performance. This aligns with Garcia and Lopez (2021) findings that adaptive AI systems avoid the stagnation of fixed training programs.

6.1.2. AI Enhances Physical Fitness Through Personalized Training

The experimental group's larger gains in physical fitness (e.g., 10.6% vs. 4.6% improvement in 1000m run time) highlight the value of AI-driven personalization. The FitAI-PET platform's ability to adjust training intensity based on real-time data (e.g., heart rate, sleep quality) addresses the limitations of traditional "one-size-fits-all" training.

For students with weak endurance, the platform reduced interval intensity to prevent overtraining.

For advanced students, it increased the load to prevent under-challenging.

This aligns with personalized learning theory Bloom (1984), which emphasizes that instruction must match individual ability levels. Additionally, wearable devices' real-time monitoring reduces injury risks: only 1 student in the experimental group reported mild muscle soreness (vs. 4 in the control group), confirming AI's role in safe training.

6.1.3. High Satisfaction Reflects Acceptance of AI in PET

The experimental group's high satisfaction (4.52/5) indicates strong acceptance of AI tools. Two factors drive this:

Perceived effectiveness: Students recognized tangible improvements in movements and fitness, as reflected in the "training effectiveness" dimension's high score (4.65/5).

Usability of AI tools: The simplified interface of Dartfish and FitAI-PET (e.g., one-click video capture, automatic report generation) made operation easy for students with no prior technical experience, as shown in the "AI tool usability" score (4.38/5).

Qualitative findings further support this: instructors valued AI's efficiency, and students appreciated clear goal-setting both groups viewed AI as a "complement" to traditional teaching rather than a "replacement."

6.2. Comparison with Existing Research

This study's findings are consistent with and extend previous research:

Consistency: Similar to Barnes et al. (2020), we found that AI motion analysis significantly improves technical accuracy. However, our study focuses on collegiate students (vs. elite athletes), demonstrating that AI is equally effective for non-competitive populations.

Extension: Unlike short-term studies (4–8 weeks) by Li et al. (2023), our 12-week intervention demonstrates AI's sustained effect on physical fitness. We also added qualitative data, revealing stakeholders' perceptions an aspect overlooked in most quantitative studies.

A key difference from Western studies is the emphasis on instructor support: in our study, instructor training was critical to AI adoption (reflected in the "instructor support" score of 4.53/5), whereas Western studies (e.g., (National Collegiate Athletic Association (NCAA), 2022) focus more on self-service AI tools. This reflects cultural differences in PET: Chinese students rely more on instructor guidance, so AI promotion must include instructor capacity building.

6.3. Practical Implications

6.3.1. For Universities

Optimize AI tool configuration: Prioritize cost-effective tools (e.g., Huawei Band 8, Dartfish Express) that balance performance and affordability. Establish dedicated AI-PET labs with extended opening hours to facilitate extra practice.

Strengthen instructor training: Develop a 3-tier training system: (1) Basic level: AI tool operation (e.g., video capture, data interpretation); (2) Intermediate level: integrating AI feedback with traditional teaching (e.g., combining AI reports with verbal guidance); (3) Advanced level: troubleshooting and customizing AI programs.

6.3.2. For Policymakers

Establish cost-sharing mechanisms: Provide subsidies for universities to purchase AI tools (e.g., 50% government funding, 50% university funding) to reduce financial barriers.

Develop industry standards: formulate national standards for AI tools in PET (e.g., accuracy requirements for motion analysis, data privacy protection) to ensure quality and safety.

6.4. Limitations of the Study

Sample limitation: Participants were from one university in eastern China, limiting the generalizability of the results. Future studies should include universities in central and western China to account for regional differences in AI infrastructure.

Long-term effect limitation: The 12-week intervention captures short- to medium-term effects, but long-term effects (e.g., 6–12 months) remain unknown. Future research should conduct follow-up tests to assess whether AI's benefits persist.

AI tool limitations: We used commercial AI tools (e.g., Dartfish (2024)) rather than custom-developed ones, which may not fully align with Chinese PET curricula. Future studies could develop tailor-made AI platforms for collegiate PET.

7. Conclusion

This study demonstrates that the integration of artificial intelligence into collegiate physical education and training is not merely a technological upgrade but a paradigm shift capable of addressing core pedagogical limitations. By conducting a rigorous 12-week mixed-methods intervention, this research moves beyond the proof-of-concept studies common in the literature to provide robust empirical evidence and rich qualitative insights into the real-world application of AI in a vocational college setting.

The findings contribute new knowledge to the field in several key aspects. First, while past research has predominantly focused on enhancing performance for elite athletes, this study conclusively shows that AI-driven personalization and objective feedback are equally potent, if not more so, for the general student population in a formal educational context. The significant improvements in technical accuracy and physical fitness underscore that AI can effectively cater to diverse skill levels and learning paces, a critical challenge in traditional group-based instruction. Second, by incorporating the voices of both instructors and students, this study reveals that the success of AI integration is as much a social and pedagogical process as a technical one. The high satisfaction ratings and qualitative feedback highlight that AI is most effective when it augments the instructor's role providing data-driven insights to enrich teaching rather than replacing it. This finding offers a crucial nuance to the prevailing discourse, which often emphasizes full automation.

The practical implications are substantial. For educational institutions, the study provides a validated framework for implementation, emphasizing the necessity of strategic tool selection, comprehensive instructor training, and accessible lab facilities. For policymakers, it highlights the need for funding models and technical standards to facilitate widespread and equitable adoption. The identified challenges, particularly regarding technical literacy and equipment access, serve as a practical guide for anticipating and mitigating implementation barriers.

Despite these contributions, this study has limitations. The single-institution sample may affect generalizability, and the 12-week duration, while longer than many previous studies, cannot speak to the long-term retention of AI-facilitated gains. Future research should expand to multiple institutions across diverse regions and employ longitudinal designs to track outcomes over semesters or years. Furthermore, developing open-source or custom-built AI platforms tailored to specific curricular needs represents a promising direction for enhancing affordability and pedagogical alignment.

In summary, this research affirms that AI holds transformative potential for physical education by enabling personalized, objective, and data-enriched training. The true value of AI, as evidenced by this study, lies in its capacity to form a powerful human-AI partnership that enhances both teaching efficacy and learning outcomes. The journey toward intelligent physical education requires a balanced focus on technology, pedagogy, and stakeholder support. This study provides a significant step forward by not only validating the effectiveness of AI-assisted training but also outlining the critical pathways for its sustainable and meaningful integration into higher education.

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