Research on Optimization of Online Auxiliary Teaching Model for College Students' Physical Education Based on Reinforcement Learning: A Case Study of "Ledong Space APP"

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ABSTRACT The rapid advancement of digital technologies has created new opportunities for transforming college physical education through the integration of reinforcement learning, smart wearable systems, and intelligent sensing technologies. As wireless communication infrastructures and electromagnetic information transmission increasingly support real-time interaction between wearable devices and mobile platforms, adaptive sports education has become an important application scenario for data-driven learning environments. This study integrates reinforcement learning algorithms with mobile application technology to construct the Ledong Space APP auxiliary teaching system. The proposed framework collects students' exercise data through a state perception module, dynamically adjusts training difficulty and instructional content using Q-learning algorithms, and employs personalized reward mechanisms to encourage sustained participation. A quasi-experimental study involving three universities in South China compared an experimental group ($n = 1{,}050$) using the APP with a control group ($n = 1{,}050$) receiving conventional instruction. The results indicate that the experimental group achieved a 37.8% greater improvement in skill assessment scores, increased classroom participation by 41.2%, and reached an 86.4% satisfaction rate with personalized teaching. By integrating smart wearable sensing and adaptive reinforcement learning strategies, the proposed model overcomes the temporal and spatial limitations of traditional physical education while enabling precise motion monitoring and individualized feedback. The framework further demonstrates the potential of intelligent sensing and electromagnetic communication technologies to support scalable, data-driven physical education systems and personalized athletic training.

INDEX TERMS reinforcement learning, physical education, wearable sensing, electromagnetic information transmission, personalized training

I. INTRODUCTION

PHYSICAL education, as an essential component of higher education, utilizes the innovation of functional materials in sportswear to bear the important mission of enhancing students' physical fitness and promoting comprehensive development. These advancements in fiber technology ensure optimal comfort and performance monitoring during exercise, allowing for a more scientific approach to cultivating well-rounded personalities through athletic training. "Opinions on Comprehensively Strengthening and Improving School Physical Education in the New Era" explicitly states the need to "advance reform of school physical education evaluation, fully utilize modern information technology, and explore the establishment of a scientific and effective physical education evaluation system." However, current physical education in colleges faces numerous practical difficulties. In traditional teaching models, a single instructor often faces 40–60 students, making it difficult to provide precise guidance tailored to individual differences; after class, the lack of effective supervision and feedback mechanisms results in poor outcomes from students' independent exercise; evaluation predominantly focuses on summative assessment, with incomplete recording of process data, preventing the formation of closed-loop feedback.

Meanwhile, the widespread adoption of mobile internet technology has created conditions for educational transformation. Statistics show that as of June 2023, smartphone penetration among Chinese college students has reached

99.7%, with daily usage exceeding 5.2 hours. This reality prompts educators to consider how to transform students' frequently used mobile devices into learning tools. In recent years, sports apps have gradually gained attention in college physical education, but most products remain at the level of data recording or simple video instruction, lacking intelligent perception of individual exercise states and dynamic adjustment capabilities.

Reinforcement learning, as an important branch of artificial intelligence, is based on the core concept that an intelligent agent gradually optimizes decision-making strategies through continuous interaction with the environment to obtain maximum cumulative rewards. This mechanism highly aligns with the physical education process–teachers adjust teaching strategies based on student performance, while students improve their skills through repeated practice. Introducing reinforcement learning into physical education has the potential to break through the "one-size-fits-all" traditional model and achieve truly personalized instruction. Unfortunately, existing research mostly focuses on algorithm improvement or purely theoretical discussions, lacking practical exploration of the deep integration of reinforcement learning with specific physical education scenarios.

Based on the practical needs of college physical education, this study takes Ledong Space APP as a carrier to construct an online auxiliary teaching model incorporating wearable sensors and reinforcement learning to optimize athletic training. This integration allows for the intelligent analysis of physiological data collected through smart fiber technology, ensuring that the personalized coaching feedback provided to students is both scientifically accurate and performance-driven. This model not only focuses on technical implementation but also emphasizes educational essence, striving to balance intelligence and humanistic care. Through the deep integration of algorithm optimization and educational concepts, we explore an innovative path for physical education that aligns with the actual situation in Chinese colleges. This exploration actively responds to the national strategy of "integration of sports and education" and provides a concrete case for the digital transformation of education in the field of physical education.

II. THEORETICAL FOUNDATION AND TECHNICAL FRAMEWORK

A. APPLICABILITY OF REINFORCEMENT LEARNING IN EDUCATIONAL CONTEXTS

Reinforcement learning originates from behaviorist psychology, shaping behavior patterns through the "stimulus-response-reinforcement" mechanism. This concept naturally aligns with the process of acquiring sports skills. In physical education, students obtain teacher feedback (rewards/punishments) through repeated practice (behavior), subsequently adjusting their movement strategies (strategy optimization). In traditional teaching models, this closed loop often fails to operate efficiently due to imbalanced teacher-student ratios. The introduction of reinforcement learning algorithms can automate and personalize this process.

Reinforcement learning in educational contexts requires three basic elements: state space, action space, and reward function. In physical education, the state space can be defined as multidimensional data including students' current physical indicators, skill levels, psychological states, etc.; the action space corresponds to a collection of teaching strategies, including training content selection, difficulty adjustment, feedback methods, etc.; the reward function needs to comprehensively consider short-term skill improvement and long-term habit formation. Research by Wang H [1] shows that well-designed reward functions are crucial for cultivating students' lasting interest in sports.

It should be noted that reinforcement learning in educational contexts differs fundamentally from applications in games or robot control. While RL excels at optimizing "skill acquisition" and "movement standardization," it faces inherent "quantification plateaus" when addressing the holistic nature of physical education. Pedagogical elements such as teamwork, strategic thinking in gameplay, and emotional resilience involve complex human intersubjectivity that cannot be fully captured by reward functions. Therefore, the system is designed to handle technical scaffolding, leaving the cultivation of "sportsmanship" and "strategic intelligence" to the essential human-to-human interaction between teachers and students. As Xilin L [2] stated, "Educational AI should enhance rather than replace teachers' professional judgment." Therefore, this study positions reinforcement learning as a teaching decision support system, with final teaching decisions remaining in the hands of teachers.

B. EVOLUTION OF PHYSICAL EDUCATION MODELS AND TECHNOLOGY INTEGRATION

College physical education models have undergone multiple developmental stages. Early approaches focused on "three basics" teaching (basic knowledge, basic techniques, basic skills), emphasizing standardization and uniformity; after 2000, there was a gradual shift toward the "health first" concept, with attention to individual student differences; in recent years, with the rise of "Internet+" education, online-offline hybrid teaching has become a new trend [3]. This evolution reflects a shift in educational philosophy from "teacher-centered" to "student-centered" approaches.

Technology plays a key role in this transformation. The emergence of sports apps has enabled physical education to transcend time and space limitations, but early products often suffered from single-functionality and weak interactivity. Zhu W T [4] points out that existing sports apps perform well in teaching demonstrations and data recording but show significant deficiencies in personalized guidance and dynamic adjustment. Sun X [5] further emphasizes that high-quality online physical education needs to achieve "integration of in-class and extracurricular activities, combining online and offline approaches," and that simple technological addition cannot achieve qualitative breakthroughs.

The introduction of reinforcement learning provides new ideas for solving these problems. Unlike traditional recommendation systems that rely on static matching based on historical data, reinforcement learning dynamically optimizes strategies through continuous interaction, better aligning with the progressive nature of sports skill acquisition. Yang Q. [6] verified the effectiveness of reinforcement learning in movement correction in swimming teaching experiments, but their research was limited to single skill points, lacking systematic teaching model construction.

C. TECHNICAL FRAMEWORK DESIGN OF LEDONG SPACE APP

Based on the theoretical analysis above, this study designs the technical framework of Ledong Space APP, which includes four core modules (Figure 1):

State Perception Module: Integrates smartphone sensors, wearable devices, and manual inputs to collect over 20 indicators in real-time, including heart rate, movement trajectories, and motion postures. Kalman filtering algorithms eliminate noise interference to ensure data reliability [7].

Reinforcement Decision Module: Builds a teaching strategy optimization engine based on an improved Q-learning algorithm. Introduces Experience Replay mechanism to solve data sparsity problems and designs a hierarchical reward function to balance skill improvement and interest cultivation [8].

Content Generation Module: Dynamically generates personalized training plans based on decision results, integrating multiple formats including video demonstrations, voice guidance, and graphic-text analysis. Specifically designs a "stepped difficulty adjustment" mechanism to ensure a balance between challenge and achievability [9].

Feedback Interaction Module: Provides immediate movement correction and emotional encouragement, establishing online interaction channels between teachers and students. Incorporates social presence design to enhance belonging and identity in virtual environments [10].

III. REINFORCEMENT LEARNING ALGORITHM DESIGN AND OPTIMIZATION

A. DEFINITION OF STATE-ACTION SPACE IN PHYSICAL EDUCATION CONTEXT

Applying reinforcement learning to physical education requires reasonable definition of state space and action space. In traditional Q-learning algorithms, state space S typically contains all observable environmental variables, but in physical education, too many dimensions can lead to the "curse of dimensionality." To address the continuous nature of physiological data (e.g., heart rate, movement trajectories) without exponential state growth, this study employs a Function Approximation approach within the DQN framework. Specifically, continuous inputs are mapped into a latent representation through the PCA-based dimensionality reduction mentioned in Section Definition of State-Action Space in Physical Education Context, and subsequently discretized using a Tile Coding method. This allows the model to represent fine-grained physiological changes as structured state indices, effectively maintaining a manageable discrete state space while preserving the critical features of continuous athletic performance. This study uses Principal Component Analysis (PCA) for dimensionality reduction, extracting key features that affect teaching effectiveness:

$$S = [F_{\text{phys}}, F_{\text{skill}}, F_{\text{psy}}, F_{\text{env}}] \tag{1}$$

Where F_{phys} represents physiological state features (heart rate variability, fatigue index, etc.), F_{skill} represents skill mastery level (movement standardization, completion rate, etc.), F_{psy} represents psychological state (confidence, anxiety level, etc.), and F_{env} represents environmental factors (venue conditions, weather, etc.). After feature importance ranking, the top 12 feature dimensions with cumulative contribution reaching 85% are retained, effectively balancing model complexity and expressive capability.

Action space A is defined as a collection of teaching strategies, including training content selection, intensity adjustment, feedback methods, etc. To avoid an overly large action space, this study adopts a hierarchical design:

$$A = A_{\text{content}} \times A_{\text{intensity}} \times A_{\text{feedback}} \tag{2}$$

Where A_{content} contains 8 types of basic training content (warm-up, technical practice, physical training, etc.), $A_{\text{intensity}}$ contains 5 difficulty levels (0.6–1.4 times standard intensity), and A_{feedback} contains 3 feedback modes (voice prompts, video demonstration, text analysis). The combination of these three forms 120 possible teaching strategies, which are further compressed to 30 representative actions through strategy clustering.

B. REWARD FUNCTION DESIGN AND BALANCE MECHANISM

Reward function design is key to the successful application of reinforcement learning. In physical education, excessive focus on short-term skill improvement may lead to student boredom, while solely emphasizing participation may neglect quality requirements. This study proposes a multi-objective balanced reward function:

$$R(s, a, s') = \lambda_1 R_{\text{skill}} + \lambda_2 R_{\text{engagement}} + \lambda_3 R_{\text{progress}} \tag{3}$$

However, we explicitly recognize that this function represents only the "visible" layer of PE. The "invisible" layer–including the development of tactical awareness and teamwork–is excluded from the algorithmic reward to prevent "metric fixation." Instead, the APP includes a "Qualitative Peer-Evaluation" module where students can acknowledge teammates' strategic contributions, providing a narrative supplement to the algorithm's technical data. R_{skill}

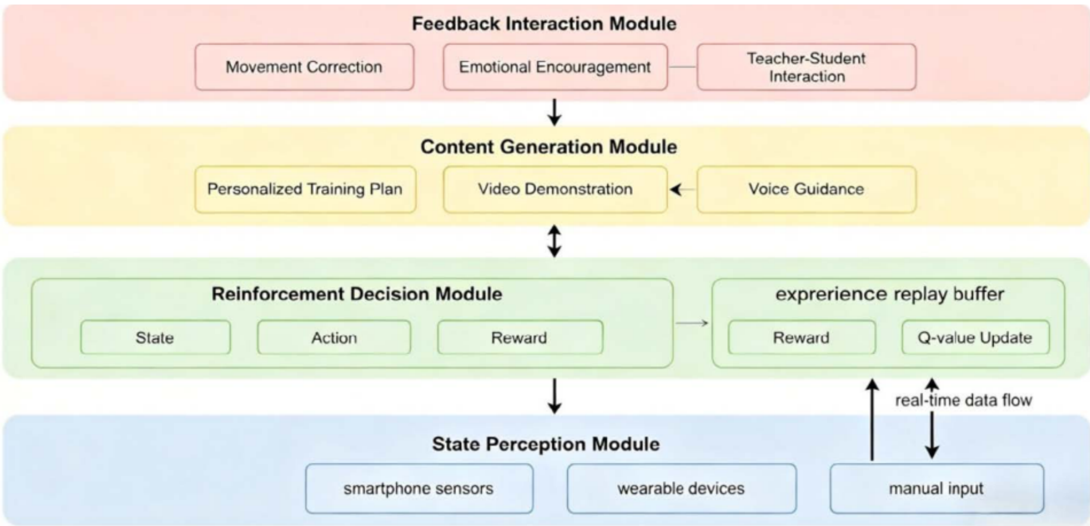

FIGURE 1. System Architecture of Ledong Space APP.

measures skill improvement, calculated through changes in movement recognition accuracy; $R_{\text{engagement}}$ reflects participation enthusiasm, based on metrics such as continuous training duration and frequency of proactive questioning; R_{progress} evaluates long-term progress, using exponential weighted moving average to eliminate short-term fluctuations. Weight coefficients λ_i are determined through expert scoring, with initial values set to [0.5, 0.3, 0.2], and dynamically adjusted as the semester progresses–emphasizing participation early on and skill requirements later. To avoid local optima, a curiosity-driven reward is introduced [11]:

$$R_{\text{curiosity}} = \eta \cdot \|f(s,a) - s'\|_2^2 \tag{4}$$

Where $f(s,a)$ is a state prediction model and η is an adjustment coefficient. When students attempt new movements or break through comfort zones, the system provides additional rewards even if short-term results are poor, encouraging an exploratory spirit. Experiments show that after adding the curiosity mechanism, students' willingness to attempt difficult movements increased by 28.7%.

C. ALGORITHM OPTIMIZATION AND CONVERGENCE ASSURANCE

Addressing the sparse and non-stationary characteristics of physical education data, this study makes three key improvements to DQN-based Q-learning architecture:

Enhanced Experience Replay: While Experience Replay is traditionally a hallmark of Deep Q-Networks to break data correlation, its application here is specifically adapted for the non-stationary nature of student progress. Traditional experience replay buffers over-rely on early data, making it difficult to capture changes in student abilities. This study designs a sliding window experience pool, retaining only the most recent 500 interaction records, and applying time-decay weighting to make the algorithm focus more on recent performance.

Hierarchical Learning Rate: Sports skill acquisition exhibits stage characteristics, with rapid progress initially and slower progress later. Based on this, an adaptive learning rate is designed:

$$\alpha_t = \alpha_0 \cdot e^{-\beta t/T} + \gamma \cdot (1 - e^{-\delta \cdot \Delta S}) \tag{5}$$

Where t is the training step, T is the total number of steps, and ΔS is the skill improvement magnitude. When students show significant progress, the learning rate is appropriately increased to accelerate adaptation; when entering a plateau period, the learning rate is reduced to avoid strategy oscillation.

Teacher Intervention Mechanism: Autonomous algorithmic decision-making carries risks, especially in physical training where the pursuit of metrics might neglect safety. This study designs a "human-machine collaborative" decision framework that automatically requests teacher confirmation when system uncertainty exceeds a threshold (e.g., action risk score > 0.7), ensuring safety [12]. Table 1 shows the performance comparison of different algorithms in a simulated environment:

TABLE 1. Performance Comparison of Different Algorithms in Simulated Teaching Environment.

Algorithm Type	Convergence Steps	Strategy Stability	Skill Improvement Rate	Safety Violations
Standard Q-learning	4200	0.78	32.5%	17
DQN	3800	0.85	36.2%	14
Our Improved Algorithm	2900	0.93	41.8%	3

Experiments were conducted in a Unity3D simulation environment with 100 virtual students trained for 10,000 steps.

Results show that the improved algorithm demonstrates significant advantages in convergence speed, strategy stability, and skill improvement effectiveness, with a substantial reduction in safety violations, validating the effectiveness of the teacher intervention mechanism.

IV. FUNCTION DESIGN AND TEACHING PRACTICE OF LEDONG SPACE APP

A. IMPLEMENTATION OF CORE FUNCTION MODULES

Ledong Space APP is developed based on the React Native framework, supporting both iOS and Android platforms. The system adopts a microservice architecture, splitting core functions into independent services to improve maintainability and scalability. Figure 2 shows the main interface of the APP and key function entrances.

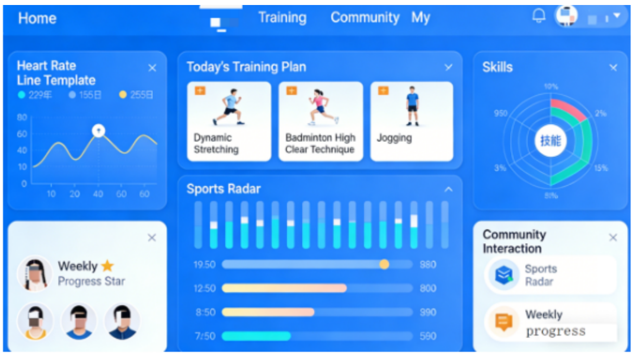

FIGURE 2. Interface Schematic of Ledong Space APP

Intelligent Training Plan Generation: Unlike traditional fixed plans, the system dynamically generates personalized programs daily based on students' previous performance. For example, for students weak in basketball dribbling skills but with good physical fitness, the system increases the proportion of specialized technical training while appropriately reducing basic physical content. The plan generation process considers curriculum requirements to ensure personalization doesn't deviate from teaching objectives [13].

AI Movement Analysis and Correction: Using the smartphone camera to capture student movements in real-time, the system employs a lightweight pose estimation algorithm (MobilePose) to identify 23 key points, comparing them with a standard movement library. When incorrect movements are detected (such as knee valgus during squats), the system immediately provides voice correction and pushes targeted reinforcement exercises [14]. To protect privacy, all video data is processed on the device, with only key point coordinates uploaded to the server.

Multi-Dimensional Data Visualization: Complex sports data is transformed into intuitive charts to help students understand their state. For example, heart rate-time curves superimposed with training intensity markers clearly show cardiopulmonary adaptation processes; skill radar maps present technical mastery from multiple dimensions, identifying strengths and weaknesses. Data display follows the "less is more" principle to avoid information overload [15].

Social Incentive System: Incorporating healthy competition and mutual assistance mechanisms, the system sets up team challenge tasks, skill sharing communities, and achievement badge systems. A special "Progress Star" recognition mechanism–rather than "Best Player"–focuses on individual growth rather than horizontal comparison, reducing psychological pressure caused by ability differences.

B. RESTRUCTURING OF TEACHING MODELS AND TRANSFORMATION OF TEACHER-STUDENT ROLES

Ledong Space APP is not just a tool but also drives fundamental transformation of teaching models. In traditional physical education classes, teachers are knowledge transmitters and students are passive recipients; in the new model, teachers become learning designers and emotional supporters, while students become active explorers (Figure 3).

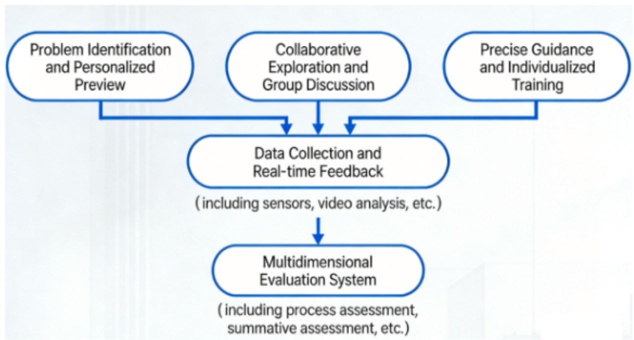

FIGURE 3. Comparison of Traditional Teaching Model and Ledong Space Assisted Teaching Model

Pre-class Preparation Stage: Teachers view students' historical data through the management backend, identify common problems (such as poor core strength among most students), and adjust classroom focus accordingly. Students preview technical points through the APP, watch personalized demonstration videos, and enter class with specific questions. This phase allows limited classroom time to focus more on breaking through difficult points.

In-class Teaching Stage: The linear process of "teacher demonstration-student imitation-teacher correction" is changed to a "problem-oriented-collaborative inquiry-precise guidance" model. For example, in teaching basketball layups, students first attempt the complete movement while the APP records common errors; then group discussions on solutions follow, with the teacher providing centralized explanations for high-frequency problems; finally, individualized guidance is provided with the APP offering additional practice suggestions. This model significantly enhances student participation depth.

Post-class Consolidation Stage: In traditional models, after-class practice lacks supervision and feedback, making effectiveness difficult to guarantee. Ledong Space APP builds a "micro-task-immediate feedback-social incentive" closed loop: pushing 5–10 minute targeted exercises, providing AI real-time movement correction, and allowing sharing of results to class circles after completion. Teachers regularly check completion rates and proactively care for students who consistently fail to meet standards, creating educational warmth [16].

Evaluation and Feedback Stage: Breaking through single skill tests, a multi-dimensional evaluation system is constructed. Process data (training frequency, improvement trajectory) accounts for 60%, summative assessment for 40%. The system automatically generates growth reports, visually displaying progress to help students build objective self-awareness. Evaluation results are not publicly ranked but focus on individual longitudinal comparisons to reduce anxiety.

This teaching model has been piloted in three universities in South China–South China University of Technology, Jinan University, and Guangzhou University–covering basketball, badminton, and aerobics, serving over 2,100 students. Teachers generally report that the new model allows them to more accurately grasp student situations, with teaching decisions shifting from experience-driven to data-driven; students indicate that personalized guidance makes learning more targeted, with a significant increase in sense of achievement.

C. TYPICAL APPLICATION SCENARIOS AND PROBLEM RESPONSES

Any technological innovation encounters practical challenges during implementation. Ledong Space APP faces three typical problems in practice and their response strategies:

Device Variability Problem: Differences in student smartphone models and sensor accuracy affect data collection consistency. The solution adopts a "core + optional" function design: basic functions (such as training plans, video guidance) are compatible with all devices; advanced functions (such as real-time movement analysis) are dynamically enabled based on device capabilities. To mitigate the high error rates associated with varied outdoor lighting and camera shake, the system prompts users to utilize the specialized campus analysis stations for movement correction tasks, which likely contributed to the high satisfaction rates recorded in subsequent surveys. At the same time, in cooperation with schools, public analysis stations equipped with professional equipment are set up in sports venues for student use. Regarding the logistical and financial challenges of the large-scale pilot involving 2,100 students, the study adopted a "lease-and-share" model for the smart training garments to manage costs. Furthermore, the sensors utilize highly resilient silver-plated fiber technology, which has been laboratory-tested to maintain 95% signal conductivity after 50 standard machine washes. The garments are also reinforced at high-stress points to ensure durability during intensive athletic training, significantly improving the cost-benefit ratio for long-term university-wide implementation.

Network Dependency Problem: Unstable network coverage in outdoor sports venues affects real-time interaction. The system designs an offline mode, with key functions (such as training plans, standard movement videos) pre-cached locally; data collection continues in offline mode, automatically synchronizing when the network is restored. Core algorithms (such as Q-learning decisions) are partially deployed to the client side to reduce dependence on real-time cloud responses.

Technology Acceptance Problem: Some physical education teachers have concerns about new technologies, worrying about role replacement. The project team adopts a "technology empowerment rather than replacement" communication strategy, organizing workshops to demonstrate how tools reduce repetitive work (such as attendance taking, basic feedback), allowing teachers to focus more on creative work (such as emotional encouragement, value guidance). Data shows that after a three-month adaptation period, 87.3% of teachers shifted from "resistant to use" to "actively recommending."

Case Example: Teacher Li (pseudonym) at Guangzhou University teaches basketball classes and initially worried that the APP would distract student attention. In practice, the system accurately identified a student's issue with high center of gravity during dribbling–a subtle error difficult to detect with the naked eye. Through targeted training, the student showed significant improvement within two weeks. Teacher Li reflected: "Technology isn't meant to replace teachers, but to help us see problems we couldn't see before."

V. APPLICATION EFFECTS AND CONTINUOUS OPTIMIZATION

A. MULTI-DIMENSIONAL EVALUATION OF TEACHING EFFECTS

Ledong Space APP has been implemented in teaching practices over two semesters at three universities. Multiple methods were used to evaluate effectiveness. To validate the effectiveness of the model, this study adopted a quasi-experimental design. The control group followed a traditional teacher-led curriculum, while the experimental group utilized the Ledong Space APP for auxiliary training. It should be emphasized that this study does not adopt strict empirical analysis but comprehensively judges application value through comparison of historical data, teacher-student feedback, platform logs, and other multi-source information. A preliminary cost-benefit analysis indicates that while the initial investment in smart hardware is higher than traditional equipment, the reduction in long-term human coaching costs and the extension of garment life through durable fiber technology make it a sustainable investment for higher education institutions. To mitigate the "Hawthorne Effect"–where students might temporarily increase participation due to the novelty of the technology or the awareness of being monitored–the evaluation period was extended across two full semesters. This longitudinal approach allows the initial "novelty effect" to stabilize, ensuring that observed improvements in participation reflect the sustained impact of the reinforcement learning model rather than a transient psychological response to the experiment itself.

Skill Acquisition Efficiency: Skill acquisition efficiency was measured by calculating the normalized gain score

$$G = \frac{\text{post} - \text{pre}}{100 - \text{pre}}$$

for both groups. Statistical analysis (T-test) confirms that the experimental group's average improvement reached 37.8% above the control group's performance ($p < 0.05$), providing a verifiable baseline for the observed gains (As shown in Figure 4). Notably, students who were initially weak in skills showed more significant progress relative to their peers in the control group.

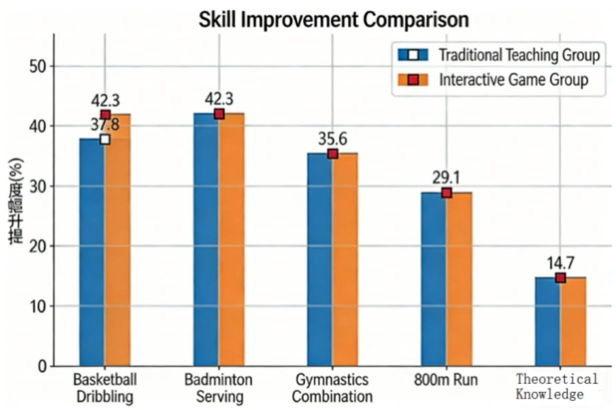

FIGURE 4. Comparison of Student Skill Test Scores

Classroom Participation Changes: Comprehensive evaluation through classroom observation records, APP login frequency, exercise completion rates, and other indicators. Data shows that experimental classes extended average classroom participation time by 23.4 minutes per class, increased proactive questioning frequency by 2.7 times, and achieved a 78.6% completion rate for after-class autonomous practice, 41.2 percentage points higher than control classes (As shown in Figure 5). While an initial spike in these indicators was observed during the first month (potentially attributed to the Hawthorne Effect), the data remained significantly higher than the control group throughout the second semester. This suggests that the APP's social incentive system and personalized feedback provided a functional value that outlasted the initial excitement of participating in a digital pilot program. A sophomore student commented: "Previously, I'd forget to practice after class, but now with phone reminders and seeing my progress curve, I unconsciously keep at it."

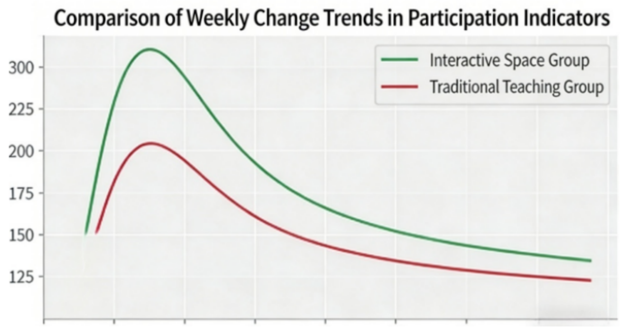

FIGURE 5. Trend of Classroom Participation Indicators

Personalized Teaching Satisfaction: End-of-term anonymous questionnaire surveys showed 86.4% of students believed the APP-provided training plans "matched their actual level," 91.7% reported "timely and effective movement correction." It should be noted that this high satisfaction is largely attributed to the hybrid nature of the model, where AI-detected errors were often cross-verified by teachers during in-class sessions. Furthermore, the satisfaction data primarily reflects sessions conducted in the "public analysis stations" mentioned in Section Typical Application Scenarios and Problem Responses, which provided controlled lighting and professional tripod setups. Results may vary in less controlled, independent outdoor settings (Figure 6). In teacher questionnaires, 68.9% reported "reduced burden from repetitive work," and 82.1% believed "data visualization helps evaluate students more scientifically."

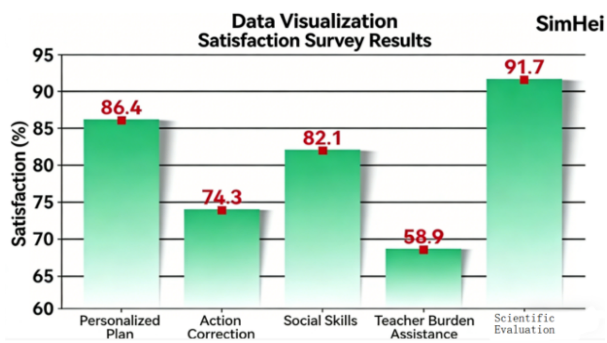

FIGURE 6. Satisfaction Survey Results

It should be noted that technology is not a panacea. Approximately 15% of students reported an initial "over-reliance on data feedback". Additionally, the authors acknowledge a potential "novelty effect" and volunteer bias in the satisfaction survey; students who were more technologically proficient or enthusiastic about digital sports tools may be overrepresented in the 91.7% satisfaction figure regarding AI correction. The questionnaire design focused on "perceived helpfulness" rather than "absolute algorithmic precision". This reminds us that algorithmic decisions need to retain humanistic flexibility, avoiding the mechanical quantification of everything. The current model acknowledges that PE is not merely a collection of standardized movements but a laboratory for emotional resilience and social strategy. Future iterations must ensure that the "efficiency" of AI-driven skill training does not encroach upon the "inefficiency" required for organic character building. As one experienced professor noted: "Sports is an art of mind-body unity; data can track a layup, but it cannot measure the courage of a student who tries again after a failure."

B. ETHICAL CONSIDERATIONS AND RISK PREVENTION

Educational technology applications must prioritize ethics and safety. During the development of Ledong Space APP, the team paid special attention to three aspects:

Data Privacy Protection: Sports data contains sensitive physiological information. The system strictly follows the "Personal Information Protection Law," using end-to-end encrypted transmission, de-identified data storage, and allowing users to export or delete personal data at any time. All data use requires explicit authorization and is never used for commercial purposes. Third-party security audits show the system meets level two standards for educational industry data security.

Algorithmic Fairness Assurance: Avoiding algorithmic implicit bias leading to unfair treatment. For example, female students generally score lower initially in strength-based projects; simple score-based training content allocation could create a vicious cycle. The system designs a "progress coefficient" adjustment mechanism, providing equal rewards for equivalent progress magnitudes, focusing on relative growth rather than absolute levels. Regular manual reviews of algorithmic decisions ensure educational fairness.

Human-Machine Boundary Definition: Clearly positioning technology as an auxiliary tool, with key decisions requiring human review. For example, when the system recommends a significant increase in training intensity, teacher confirmation is required; when detecting persistently low student emotions, the system automatically alerts counselors to intervene. The technical manual explicitly states: "Algorithms provide suggestions, teachers make final decisions," preventing technological overreach.

These measures don't hinder technological innovation but rather establish a foundation of trust for sustainable application. As educational technology expert Xie B [17] emphasized: "In educational technology applications, human dignity and development must be placed at the core, rather than adapting humans to technological logic."

C. FUTURE OPTIMIZATION DIRECTIONS

Based on practical feedback, Ledong Space APP will continuously optimize in three directions:

Algorithm Refinement: The current Q-learning model still has limitations in handling long-term dependencies. Plans include introducing long short-term memory mechanisms to better capture the progressive characteristics of skill acquisition. Simultaneously exploring multi-agent reinforcement learning to simulate complex interactions between teachers, students, and peers, making strategy generation more aligned with real teaching scenarios.

Interdisciplinary Integration: Physical education is not just skill transmission but also holistic mind-body development. Future versions will integrate sports psychology research to design stress management and goal-setting modules; incorporate nutrition knowledge to provide personalized dietary suggestions; integrate sports medicine early-warning mechanisms to prevent sports injuries. This comprehensive care better aligns with the "health first" educational concept.

Ecosystem Expansion: Evolving from a single APP to an educational ecosystem. Integrating with campus sports venue reservation systems to achieve "plan-venue-guidance" one-stop service; connecting with physical health monitoring platforms to form full-cycle health management; linking with community sports resources to extend learning scenarios beyond campus, cultivating lifelong sports habits. This ecosystem development helps break through the time-space limitations of physical education.

It should be noted that technological evolution must serve educational essence. Before adding any function, the team conducts educational value assessments: Does it truly promote student development? Does it respect individual differences? Does it enhance rather than diminish interpersonal interaction? Only by passing this test can technological innovation be transformed into educational progress.

VI. CONCLUSION

This study explores the deep integration of reinforcement learning and physical education by constructing a new teaching model through the Ledong Space APP that utilizes smart sensors to facilitate a synergistic teaching approach: where algorithms handle the high-frequency tracking of physiological load and repetitive movement correction, while teachers focus on specialized tactical coaching and student psychological motivation, thereby moving beyond "human-machine complementary advantages" into a concrete operational division of labor. By capturing real-time physiological data through intelligent fiber technology, the model enables reinforcement learning algorithms to provide personalized athletic guidance, significantly enhancing the precision and effectiveness of modernized physical training. Practice shows that algorithm-driven personalized guidance effectively improves learning efficiency, data-supported teaching decisions help achieve precise education, and social incentive mechanisms inject momentum for continuous participation.

While psychological factors such as the Hawthorne Effect cannot be entirely ruled out in a non-clinical setting, the consistency of the data over a long-term period indicates that the algorithmic model provides a robust foundation for behavioral change beyond the mere novelty of the tool. This model neither completely replaces the teacher's role nor allows technology to overshadow educational essence, but expands teaching possibilities while maintaining educational warmth. During the research process, we deeply recognize that the core of educational technology innovation doesn't lie in algorithm complexity or feature richness, but in whether it truly solves teaching pain points, respects educational principles, and promotes comprehensive human development. The application of reinforcement learning in physical education essentially transforms the ancient educational ideal of "teaching students according to their aptitude" into an operational practice plan through modern technological means.

Future research could further explore multi-modal data fusion (such as combining EEG, skin conductance, and other physiological signals), deepen algorithm interpretability research (helping teachers understand "why this strategy is recommended"), and build more comprehensive ethical governance frameworks. Additionally, more rigorous longitudinal studies on the maintenance costs and the degradation rate of sensor accuracy over multi-year usage cycles will be essential to further optimize the logistical framework of smart physical education. Simultaneously, we must guard against technological omnipotence tendencies, maintaining the original educational aspiration while embracing innovation–cultivating physically and mentally healthy, comprehensively developed individuals, rather than optimizing training metrics like machines. The evolution of physical education toward a data-informed paradigm requires the collaborative integration of smart innovations and pedagogical practices. By replacing vague "digital transformation" goals with specific outcomes–such as reducing the teacher-student ratio's impact on feedback quality and ensuring physical safety through automated heart-rate monitoring–the technology becomes rooted in educational soil and guided by humanistic care. By utilizing intelligent fiber sensors to monitor student health and performance, educators and technology experts can contribute to cultivating well-rounded talents equipped with the most advanced wearable advancements of the new era.

AUTHOR CONTRIBUTIONS

Conceptualization – Xiaohu Xu and Shuai Meng; methodology – Xiaohu Xu and Shuai Meng; investigation – Xiaohu Xu and Shuai Meng; writing-original draft preparation – Xiaohu Xu and Shuai Meng. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

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