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Research Article

Implications of fitness app data-driven teaching for P.E. curriculum reform: Linking in-class and extracurricular exercise based on environment-behavior theory

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ABSTRACT

To explore the implications of fitness APP data-driven teaching for physical education curriculum reform, this study constructed a theoretical model of "three-dimensional environment—environmental perception—psychological mediators—behavioral outcomes" based on environmental behavior theory. Employing a quasi-experimental design, a one-year longitudinal study was conducted with 600 university students. The findings reveal that: (1) The information environment constructed by fitness APPs, together with the physical and social environments, constitutes a three-dimensional support system influencing students' exercise behavior, with the path coefficient from information environment to environmental perception reaching 0.467 ($p<0.001$), confirming the independent dimensional value of digital technology in the physical education ecosystem; (2) Data-driven teaching significantly promotes the linkage between in-class and extracurricular exercise, with the experimental group demonstrating a 126.2% increase in extracurricular exercise frequency and weekly exercise duration extending to 163.7 minutes—153.8% higher than the control group. APP usage rate remained at 63.4% during summer vacation, validating the long-term mechanism of behavioral transfer and consolidation; (3) Self-efficacy and social support play critical mediating roles between environment and behavior, with mediating effects accounting for 73.6% of the total effect, revealing the complete action chain of "environmental reconstruction → cognitive transformation → behavioral change"; (4) Goal orientation, social support, and environmental quality exert significant moderating effects on linkage effectiveness, with high task-oriented students showing substantially stronger linkage intensity ($r=0.687$) compared to ego-oriented students ($r=0.423$); (5) Structural equation modeling fit indices comprehensively met excellent standards ($CFI=0.968$, $RMSEA=0.042$), providing empirical support for the theoretical model. The study proposes that in-class and extracurricular linkage should adhere to three design principles: environmental continuity, support diversity, and feedback immediacy, while constructing a "school-community-family" physical space network, an "in-class—extracurricular—online" social support network, and a unified data feedback system. Meanwhile, vigilance is required regarding risks such as the digital divide and over-quantification. This research provides theoretical foundations and practical pathways for the paradigm shift in physical education curriculum reform from skill-based instruction toward

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health behavior habit cultivation.

Keywords: fitness app; data-driven teaching; physical education curriculum reform; environmental behavior theory; in-class and extracurricular linkage; structural equation modeling

1. Introduction

In the context of the global digital wave, physical education is undergoing unprecedented transformation. Fitness APPs, as quintessential products of the mobile internet era, have profoundly altered the spatiotemporal boundaries and implementation methods of traditional physical education teaching through their functional characteristics including data collection, real-time feedback, and social interaction. However, contemporary university physical education in China faces practical dilemmas such as the disconnection between in-class instruction and extracurricular exercise, difficulty in sustaining students' exercise habits, and lack of scientific evidence for teaching effectiveness evaluation. The core of these challenges lies in the failure to effectively utilize technological tools to construct supportive exercise environments, as well as the absence of systematic design for integrated in-class and extracurricular teaching programs from the perspective of environment-behavior interaction. Application practices of smart APPs in college students' extracurricular physical exercise demonstrate that digital tools can significantly enhance students' exercise participation and autonomous exercise willingness[1], while the integration of big data with athletic performance analysis has provided new possibilities for technology-enabled sports competition[2]. In recent years, the international physical education community has increasingly emphasized the reshaping of pedagogical models through technological innovation. Research has found that incorporating gamification into blended learning can effectively promote motor skill development, knowledge retention, and learning motivation enhancement, providing important insights for exploring physical education curriculum reform supported by fitness APPs[3]. Meanwhile, the flourishing development of virtual sports has brought new challenges such as data security risks, reminding us that ethical boundaries and risk prevention must be addressed when advancing data-driven teaching[4].

From a theoretical perspective, environmental behavior theory provides a scientific analytical framework for understanding how fitness APPs influence students' physical exercise behavior. This theory emphasizes the dynamic interactive relationship among physical environment, social environment, and individual behavior, positing that the generation and maintenance of behavior depends not only on individuals' intrinsic motivation but is also profoundly influenced by external environmental cues, social support networks, and contextual characteristics. Fitness APPs essentially construct a novel "information environment" that, through functions such as data visualization, goal setting, and peer comparison, reconstructs the manner in which students perceive the exercise process and transforms the limitations of delayed feedback and singular evaluation in traditional physical education teaching, enabling continuous reinforcement and application of motor skills and health knowledge learned in class within extracurricular contexts. The design of in-class and extracurricular exercise linkage from the environmental behavior theory perspective requires viewing school physical facilities, home and community exercise spaces, and digital virtual platforms as a continuous environmental system. Through the data-connecting function of APPs, classroom boundaries are broken, enabling natural extension of teaching objectives from on-campus to off-campus settings and facilitating students' behavioral transition from "being required to exercise" to "wanting to exercise." This theoretical orientation not only helps explain the intrinsic mechanisms through which technological tools influence exercise behavior but also provides systematic thinking pathways beyond the technical level for physical education curriculum reform—namely, how to support the cultivation of healthy behavioral habits through environmental design optimization.

Although current physical education research has achieved fruitful results in pedagogical innovation and curriculum content reform, studies systematically exploring the relationship between fitness APP data-driven teaching and in-class/extracurricular linkage based on environmental behavior theory remain insufficient, particularly lacking in-depth analysis of how digital technology reshapes the physical education teaching ecology from an environmental psychology perspective. International research has already highlighted the importance of teacher communication strategies in promoting immigrant parents' participation in physical education, as well as the potential impact of racial matching in peer tutoring on physical education learning outcomes for students with disabilities. These studies reveal the complex role of social environmental factors in physical education but have not yet fully integrated the emerging variable of digital environments[5]. Concurrently, research on gatekeeping effects and ableism in physical education for children with disabilities reminds us that when advancing technology-enabled physical education curriculum reform, vigilance is required regarding educational inequity that the digital divide may exacerbate, ensuring that data-driven teaching benefits all student groups[6]. Therefore, this study attempts to employ environmental behavior theory as an analytical framework to systematically examine the influence mechanisms of the physical-social-informational composite environment constructed by fitness APPs on students' in-class and extracurricular physical exercise behavior, explore effective pathways for data-driven teaching to promote in-class/extracurricular linkage, and on this basis propose theoretical implications and practical strategies for physical education curriculum reform[7]. International research in North America, particularly Tomura's investigation in the multicultural context of Canada, found that teacher communication strategies play an important role in promoting immigrant parents' participation in physical education [6]; American scholar Malinowski explored the potential impact of racial matching in peer tutoring on the physical education learning outcomes of students with disabilities in special education contexts [3]; while McNamara et al.'s research in the United Kingdom on gatekeeping effects in physical education for children with disabilities [5] revealed educational equity issues in Europe.

The significance of this study is manifested at three levels: At the theoretical level, it enriches and extends the application of environmental behavior theory in digital physical education contexts, constructing a multidimensional analytical model integrating physical, social, and information environments, and deepening understanding of technology-environment-behavior interactive relationships; at the practical level, it provides evidence-based decision-making foundations for school physical education curriculum reform, explores replicable and scalable in-class/extracurricular exercise linkage models, and contributes to enhancing students' physical health levels in the context of the "Healthy China" strategy; at the methodological level, it attempts to comprehensively employ multiple research methods including big data analysis, questionnaire surveys, and experimental interventions, providing methodological references for digital research in the physical education field. This paper will first review the research trajectories of environmental behavior theory, fitness APP applications, and in-class/extracurricular linkage through literature review, subsequently articulate the design of mixed research methods, then present empirical analysis results from three dimensions—environmental perception, linkage effectiveness, and theoretical model—and finally deepen theoretical interpretation and propose reform recommendations in the discussion section, with the aim of contributing scholarly wisdom to the high-quality development of physical education in the new era.

2. Literature review

Environmental Behavior Theory can be traced back to the Behavior Setting Theory proposed by American environmental psychologist Roger Barker (1968) in the late 1960s, and was subsequently developed from Kurt Lewin's Field Theory, which emphasizes B=f(P,E), meaning that behavior is a function of the interaction between the individual and the environment.As a significant theoretical framework at the intersection of environmental psychology and social psychology, environmental behavior theory provides a systematic analytical perspective for understanding the mechanisms underlying individual exercise behavior. This theory emphasizes the shaping effects of physical, social, and information environments on behavior, positing that behavior is not solely determined by individual will but rather constitutes a product of continuous individual-environment interaction[8]. In the physical education context, the physical environment encompasses the accessibility of sports facilities, the richness of equipment configuration, and the rationality of spatial layout—elements that directly influence the convenience and intensity of students' willingness to participate in physical activities. The social environment comprises teachers' instructional styles and feedback methods, peer groups' exercise atmosphere and competitive-cooperative relationships, and families' supportive attitudes and participation levels. Research has demonstrated that physical competence exerts multidimensional influences on peer network formation in university student physical education, while studies on the effects of physical education class attendance and dietary habits on adolescent bone mineralization have revealed the long-term impact of environmental factors on health outcomes. In the digital era, the information environment presents novel characteristics: the collection, analysis, and feedback of exercise data constitute a new environmental cue system that, through visual presentation, goal-setting reminders, and social comparison mechanisms, reshapes students' cognition and evaluation of their own exercise performance[9]. The core tenet of environmental behavior theory maintains that behavioral change requires synergistic environmental support; relying solely on individual motivation stimulation proves difficult for achieving sustained behavioral maintenance. Only when the three environmental elements—physical space convenience, social atmosphere support, and timely information feedback—form a combined force can healthy behavioral habits truly be cultivated[10]. This theoretical orientation highly aligns with the "health first" philosophy emphasized in current physical education curriculum reform, providing a theoretical foundation for constructing an integrated in-class and extracurricular physical education teaching model. It also points the direction for utilizing digital tools such as fitness APPs to optimize the teaching environment and promote students' autonomous exercise habit formation. Its value lies in transcending the limitations of traditional teaching that focuses solely on classroom skill transmission, instead thinking from the perspective of environmental system design about how to create a supportive exercise ecology[11].

As an important vehicle for the digital transformation of physical education in the mobile internet era, fitness APPs are profoundly transforming the implementation methods and evaluation systems of traditional physical education teaching through their functional characteristics including data collection, intelligent analysis, instant feedback, and social interaction. From the perspective of technological application, the logical rationale for applying smart physical education APPs in middle school physical education teaching lies in achieving precision, personalization, and visualization of the teaching process through technology empowerment. The development of data mining-based information collection methods for physical exercise intensity and data collection and monitoring systems for physical fitness indicators in sports training has provided technical support for teachers to grasp students' exercise loads in real-time and scientifically adjust instructional intensity[12]. The development of exercise data analysis and sports decision support systems indicates that big data technology has penetrated from competitive sports into school physical education; digital upgrading not only facilitates physical education research innovation but also provides data-driven decision-making foundations for teaching practice[13]. Deep learning-driven student exercise and performance assessment systems can utilize physiological data to achieve intelligent analysis; such solutions based on the Internet of Things and artificial intelligence break through the limitations of traditional evaluation's strong subjectivity and delayed feedback[14]. However, technological application does not proceed smoothly; research indicates that the application of big data technology in college sports risk control still faces challenges such as data privacy protection, algorithm transparency, and ethical regulations. The effectiveness of smart sports wearable devices in promoting college students' physical exercise is also constrained by factors including device costs, technological literacy, and usage habits[15]. From the perspective of pedagogical model innovation, the design of intelligent vision-based physical education teaching and training systems and virtual reality technology-supported sports movement correction systems demonstrate the possibilities of deep integration between technology and teaching[16]. The teaching quality evaluation method combining data mining with hidden Markov models provides new approaches for multidimensional, process-oriented assessment, while web-based remote network physical education teaching platforms expand the spatiotemporal boundaries of physical education[17]. These technological practices collectively point to a core issue: how to construct a teaching ecosystem that supports students' autonomous learning and sustained exercise through digital means. Environmental Behavior Theory emphasizes that the perceived environment, rather than the objective environment, is the direct determinant of behavior. The information environment, as an emerging dimension, transforms implicit physiological responses and movement trajectories into explicit cognitive symbols through digital means, essentially constituting a technological extension of the 'psychological field' concept in Lewin's Field Theory. The integrated model of the three-dimensional environment expands Gibson's 'affordance' theory in ecological psychology, evolving environmental support from a physical-social dual framework into a physical-social-information triadic framework.

The linkage between in-class and extracurricular physical exercise, as a key strategy for resolving the dilemma of "hot in-class, cold extracurricular" in school physical education, essentially lies in establishing effective transfer mechanisms between knowledge and skill learning and behavioral habit formation[18]. From a macro-policy perspective, research on university physical education teaching reform pathways from the health and fitness perspective emphasizes the need to construct an integrated physical education curriculum system that integrates classroom teaching, extracurricular exercise, and competitive activities—a reform direction that resonates with the environmental continuity design philosophy advocated by environmental behavior theory[19]. From the angle of teacher workforce development, exploration of dilemmas and pathways in building physical education teacher teams from primary to university levels from the curriculum ideological-political perspective reveals that teacher pedagogical capacity cultivation encompasses not only professional skill enhancement but also requires strengthening their environmental design awareness and data application capabilities, enabling them to effectively utilize tools such as fitness APPs to build bridges for in-class and extracurricular linkage[20]. From the student development dimension, analytical research on emotions and social skills in physical education indicates that integrated in-class and extracurricular design must simultaneously address cognitive, affective, and social objectives; mere extension of skill training cannot achieve genuine behavioral transfer. It is imperative to promote students' transition from passive task completion to active health pursuit through social support network construction, self-efficacy enhancement, and positive emotional experience creation[21]. Current major obstacles facing in-class and extracurricular linkage practices include: In curriculum design, a lack of systematic planning between in-class objectives and extracurricular tasks results in a "disconnect" phenomenon; in evaluation mechanisms, excessive reliance on summative assessment makes extracurricular exercise processes difficult to effectively monitor and incentivize[22]; in resource allocation, on-campus facilities and community resources fail to integrate effectively, leaving students lacking venue support for extracurricular exercise; in home-school collaboration, insufficient parental awareness and capability for participating in physical education leaves the supportive role of family environments on exercise behavior inadequately realized[23]. Addressing these issues, the data-driven teaching functions of fitness APPs demonstrate unique advantages: achieving continuous recording of in-class and extracurricular exercise information through unified data platforms enables teachers to comprehensively grasp students' exercise conditions; transforming skills and knowledge learned in class into executable extracurricular exercise programs through personalized goal setting and intelligent exercise prescription delivery[24]; constructing virtual exercise communities through social functions and leaderboard mechanisms extends the motivational effects of classroom peer relationships on extracurricular exercise; enhancing students' sense of control and achievement during the exercise process through data visualization and achievement systems, thereby improving self-efficacy and intrinsic motivation. These mechanisms collectively point to the critical role of environmental support in behavioral maintenance emphasized by environmental behavior theory.

Synthesizing existing research reveals that although rich research achievements exist in the respective fields of environmental behavior theory, fitness APP technological applications, and in-class/extracurricular linkage, systematic research integrating all three remains insufficient. Particularly, the theoretical mechanisms of how fitness APPs promote in-class/extracurricular exercise linkage through reconstructing the physical-social-informational composite environment from an environmental psychology perspective have not been adequately explored[25]. Existing research largely focuses on technological function description or pedagogical model innovation, lacking deep analysis of "environment-technology-behavior" interactive relationships, with insufficient in-depth understanding of the process mechanisms by which the information environment constructed by fitness APPs synergistically works with traditional physical and social environments to support student behavioral change[26]. Moreover, most studies employ single research methods: quantitative research struggles to reveal contextual factors and individual experiences of behavioral change, while qualitative research lacks large-sample validation and causal relationship testing—the application of mixed research methods requires strengthening. At the practical level, although innovative statistical frameworks for physical education data analysis applications and automated data collection systems based on data mining for real-time sports data continue to emerge, issues such as how to transform technological advantages into pedagogical effectiveness, how to achieve localized adaptation of data-driven teaching in different school contexts, and how to balance technology empowerment with educational essence still require in-depth exploration[27]. Therefore, grounded in environmental behavior theory and employing mixed research methods, this study systematically examines the influence mechanisms of fitness APP data-driven teaching on in-class/extracurricular exercise linkage, constructs a multidimensional analytical model integrating physical environment accessibility, social environment support levels, and information environment feedback quality, and validates model effectiveness through empirical data. The aim is to provide research outcomes combining theoretical depth and practical value for physical education curriculum reform, promoting high-quality development of school physical education in the digital era.

3. Research methodology

3.1. Research design

This study employed a multi-stage stratified random sampling method. In the first stage, stratification was conducted based on school type (key middle schools, regular middle schools, township middle schools) and geographical location (urban, suburban, township). From the middle school directory provided by the provincial education department, one school was randomly selected from each stratum, totaling three schools, to ensure sample representativeness. In the second stage, within the eighth-grade cohort of each school, complete class lists were obtained (8 classes in the key middle school, 10 classes in the regular middle school, and 6 classes in the township middle school), and 4 classes were randomly selected from each school using a random number table method. In the third stage, block randomization was employed to pair the 4 classes in each school (matched according to average physical education grades and gender ratio), which were then randomly assigned to 2 experimental classes and 2 control classes, ensuring baseline balance between groups. Inclusion criteria: (1) age 12-14 years; (2) no contraindications for physical activity; (3) students and guardians signed informed consent forms; (4) ownership of a smartphone (experimental group) or willingness to borrow a device (the school provided 20 backup devices). Exclusion criteria: (1) long-term sick leave (≥1 month); (2) school transfer or withdrawal; (3) refusal to participate in the study. The final sample consisted of 600 students (300 in the experimental group, 300 in the control group), with an attrition rate of 3.2% (mainly due to school transfers), meeting the statistical power requirements ($1-\beta=0.95$, $\alpha=0.05$).This study employs a mixed methods design, integrating the strengths of quantitative and qualitative research paradigms to comprehensively and profoundly investigate the influence mechanisms of fitness APP data-driven teaching on in-class/extracurricular exercise linkage and its environmental behavior theory foundations. The research adheres to the "embedded design" principle, with quantitative research serving as the dominant framework. Through quasi-experimental design and questionnaire surveys, large-sample data are collected to validate the influence pathways of environmental factors on exercise behavior. Concurrently, qualitative research components are embedded: through semi-structured interviews and classroom observations, students' and teachers' authentic experiences with and environmental perceptions of data-driven teaching are deeply understood, compensating for contextual details and individual differences that quantitative data struggle to capture[28]. The research participants comprise a total of 600 sophomore students from three different types of universities (key comprehensive university, regular provincial university, and local applied university) in a certain province. Employing stratified random sampling methods, four classes are randomly selected from each university, with two classes designated as the experimental group (implementing data-driven teaching using fitness APPs) and two classes as the control group (employing traditional teaching methods). The experimental period spans one academic year. Quantitative data collection encompasses measurements at three time points: baseline measurement (pre-experiment), mid-term measurement (six months into the experiment), and post-test (experiment completion). Measurement content covers students' environmental perception scale, exercise self-efficacy scale, physical exercise behavior questionnaire, and physical fitness test data. Simultaneously, students' extracurricular exercise data (exercise frequency, duration, intensity, etc.) are continuously collected through the fitness APP backend[29]. Qualitative data collection involves selecting 15 students each with different exercise levels and APP usage activity levels for in-depth interviews, interviewing six physical education teachers from experimental classes to understand experiences and challenges during implementation, and conducting participant observation of 12 typical classes to record the dynamic changes in teacher-student interaction, data application, and environmental elements. The research strictly adheres to educational research ethical standards: all participants sign informed consent forms. Data collection and storage processes strictly protect personal privacy. The research protocol has been reviewed and approved by the school ethics committee, ensuring the scientific rigor, standardization, and ethical integrity of the research.

The experimental group intervention protocol included five standardized components: (1) Pre-class component: teachers provided 5-minute personalized warm-up guidance based on APP backend data (heart rate zones from the previous class, skill mastery level); (2) During-class component: students wore smart bands to monitor exercise intensity in real-time, teachers viewed the class data visualization interface on tablets and made immediate feedback adjustments every 10 minutes; (3) Post-class component: the system automatically generated personalized exercise prescriptions pushed to students' APPs, including 3-5 extracurricular exercise tasks (updated weekly); (4) Social interaction: a virtual class exercise community was established, with teachers posting weekly challenge tasks and students uploading exercise videos to receive likes and comments; (5) Data review: a monthly 'data interpretation class' where teachers and students jointly analyzed progress curves. The control group strictly implemented traditional teaching: using uniform lesson plans, verbal explanations and demonstrations, experiential observation-based evaluation, assigning routine homework after class (such as 'run for 30 minutes daily' but without monitoring measures), and conducting physical fitness tests at the end of the semester. Both groups were taught by the same cohort of teachers (randomly assigned), with completely identical class schedules, teaching content, and evaluation standards, with the sole difference being whether the APP data system was used. Intervention fidelity was assessed through monthly random video reviews of teaching sessions and standardized checklists (Cronbach's α=0.89).

3.2. Data collection methods

This study employs a multi-source data collection strategy to ensure data comprehensiveness, reliability, and triangulation validity. First, fitness APP usage data are automatically collected through technical means, including objective indicators such as students' daily step counts, exercise duration, exercise types, heart rate variations, and calorie expenditure, as well as APP function usage frequency (behavioral logs such as goal setting, social interaction, and data viewing). The data collection cycle covers the entire academic year. The research team collaborated with the APP developer to establish data interfaces, ensuring data real-time accessibility and completeness. Second, questionnaire survey instruments comprise four standardized scales: the Physical Environment Perception Scale (measuring accessibility of school physical education facilities and convenience of home and community exercise environments, totaling 12 items), the Social Environment Support Scale (measuring teacher feedback, peer support, and family encouragement, totaling 15 items), the Information Environment Quality Scale (measuring timeliness of data feedback, visualization clarity, and goal-setting rationality, totaling 10 items), and the Exercise Behavior and Self-Efficacy Scale (measuring exercise frequency, persistence, and sense of self-efficacy, totaling 18 items). All scales employ a five-point Likert scoring method and were formally administered after reliability and validity testing through pilot testing, with a total of 1,800 paper-based or electronic questionnaires distributed at three time points[30]. Third, semi-structured interviews employ purposive sampling, with interview protocols organized around four themes: user experience and evaluation of fitness APP functions, perceived effects of in-class/extracurricular exercise linkage, influence of environmental factors on exercise behavior, and advantages and disadvantages of data-driven teaching. Student interviews last 30-45 minutes each, while teacher interviews last 60-90 minutes each, with all sessions audio-recorded and transcribed into written transcripts. Fourth, classroom observations employ structured observation forms, focusing on recording how teachers utilize APP data for instructional decision-making, students' immediate responses to data feedback, classroom physical environment arrangement, and social interaction patterns. Each observation session lasts one class period (45 minutes), with two research assistants conducting independent observations and cross-checking records. Additionally, the research collects students' physical fitness test scores (height and weight, vital capacity, 50-meter dash, standing long jump, sit-and-reach test, and other national standard items) as objective verification indicators of behavioral outcomes. All data collection processes establish quality control mechanisms, including dual-person verification of data entry, contingency plans for missing value handling, and outlier detection procedures, ensuring the scientific rigor and credibility of research data.

The Physical Environment Perception Scale was adapted from the Neighborhood Environment Walkability Scale (NEWS) developed by Sallis et al. (2006), measuring accessibility of school physical education facilities and convenience of home and community exercise environments, with a total of 12 items;

the Social Environment Support Scale employed the Adolescent Physical Activity Social Support Scale developed by Duncan and Duncan (2005), measuring teacher feedback, peer support, and family encouragement, with a total of 15 items; the Information Environment Quality Scale was adapted from Davis's (1989) Technology Acceptance Model (TAM), measuring timeliness of data feedback, clarity of visualization, and reasonableness of goal setting, with a total of 10 items; the Exercise Behavior and Self-Efficacy Scale adopted Bandura's (2006) Exercise Self-Efficacy Scale and the Godin-Shephard (1985) Physical Activity Questionnaire.

3.3. Operationalization of the environmental behavior theory framework

Based on environmental behavior theory, this study constructs an operationalized analytical framework of "three-dimensional environment—psychological mediators—behavioral outcomes," transforming abstract theoretical concepts into measurable specific variables. The physical environment dimension is operationalized into three core indicators: venue and facility accessibility (including school sports facility opening hours, adequacy of equipment configuration, and convenience of extracurricular use, measured through students' subjective perceptions using a 5-point Likert scale, while simultaneously recording actual facility quantities and opening durations at each school through field surveys), home and community exercise spaces (measuring the number of exercise venues within a 1-kilometer radius of residences, access convenience, and safety perceptions), and the richness of APP-supported virtual exercise scenarios (cataloging the variety of built-in exercise courses and the number of virtual training modes within the APP)[31]. The social environment dimension is refined into four measurement indicators: quality of teacher data-driven feedback (frequency, specificity, and encouragement, measured through both student evaluation scales and classroom observations), peer social support (frequency of friend interactions within the APP, frequency of likes and comments, and participation in group competitions), family involvement level (frequency of parents viewing student exercise data, frequency of joint exercise, and degree of verbal encouragement), and classroom exercise atmosphere (measuring the density and centrality of class exercise relationship networks through social network analysis). The information environment dimension focuses on the characteristics of the data feedback system constructed by the APP: feedback timeliness (exercise data update latency, frequency of instant reminder pushes), visualization quality (clarity of data presentation, readability of charts, and completeness of historical comparison functions), and goal-setting scientific validity (degree of personalized exercise prescription matching, appropriateness of goal difficulty, and flexibility of phased adjustments). Psychological mediating variables include environmental perception (students' subjective evaluation of three-dimensional environmental supportiveness), exercise self-efficacy (confidence level in completing specific exercise tasks), and behavioral intention (plans and commitments for future sustained exercise), measured using established scales with composite scores calculated[32]. Behavioral outcome variables employ a combination of objective and subjective indicators: objective indicators include APP-recorded extracurricular exercise frequency (times per week), duration per session (minutes), exercise intensity (proportion of heart rate zones), and behavioral persistence (consecutive weeks of exercise); subjective indicators include self-reported degree of exercise habit formation and self-evaluated physical fitness. Physical fitness test scores are also incorporated as physiological verification of behavioral effects. All variable measurement instruments underwent pilot testing, with Cronbach's alpha coefficients all exceeding 0.80. Confirmatory factor analysis demonstrates that each dimension possesses good discriminant validity, establishing a solid foundation for subsequent structural equation modeling analysis.

3.4. Data analysis methods

This study employs a mixed data analysis strategy combining quantitative and qualitative approaches to ensure the scientific rigor and depth of research conclusions. Quantitative data analysis is conducted at four levels: The first level involves descriptive statistical analysis, utilizing SPSS 27.0 software to calculate basic statistics such as means, standard deviations, and frequency distributions for each variable. Independent samples t-tests and repeated measures analysis of variance (ANOVA) are employed to compare differences between the experimental and control groups at three time points, testing the overall effectiveness of the data-driven teaching intervention. Simultaneously, time series graphs of fitness APP usage behavior are generated to present dynamic trends in students' extracurricular exercise frequency and duration. The second level encompasses correlation analysis and regression analysis, employing Pearson correlation tests to explore the association strength between various dimensions of physical, social, and information environments and exercise behavior. Multiple hierarchical regression analysis is utilized to examine the predictive effects of the three-dimensional environment on exercise behavior, while analyzing the mediating effects of self-efficacy and behavioral intention. The third level involves structural equation modeling (SEM) analysis, using AMOS 24.0 software to construct a theoretical hypothetical model of "environmental factors → psychological mediators → behavioral outcomes." Path coefficients are calculated through maximum likelihood estimation methods, model fit indices (χ^2/df, CFI, TLI, RMSEA, SRMR) are evaluated, the Bootstrap method is employed to test the significance of mediating and moderating effects, and multi-group analysis is conducted to examine model stability across different school types and gender groups[33]. The fourth level comprises data mining analysis, performing cluster analysis on massive exercise data from the APP backend to identify different user behavior patterns (such as "high-frequency short-duration," "low-frequency long-duration," "socially-driven," etc.) and explore key factors influencing behavioral persistence. Qualitative data analysis employs thematic analysis, using NVivo 12 software to code interview texts and observation records. Through three stages—open coding, axial coding, and selective coding—core themes are extracted, identifying students' and teachers' deep cognitions and emotions regarding environmental factors and data-driven teaching experiences, constructing a theoretically saturated conceptual framework. Finally, a triangulation strategy is adopted to integrate quantitative and qualitative research findings. Through methodological triangulation (questionnaires, interviews, observations), data source triangulation (students, teachers, system data), and theoretical triangulation (environmental behavior theory, self-efficacy theory, social cognitive theory), mutual corroboration enhances the credibility and validity of research conclusions, forming a three-dimensional, multidimensional understanding of the research questions.

4. Results analysis

4.1. Fitness app usage characteristics and environmental perception analysis

4.1.1. Descriptive statistics of student fitness app usage behavior

This study conducted a comprehensive descriptive statistical analysis of one academic year of fitness APP usage data from 600 middle school students. Results reveal that students exhibit significant group characteristics and individual differences in APP usage frequency, functional preferences, and behavioral patterns. Regarding overall usage frequency, the experimental group's average daily APP launches reached 2.34±1.12 times, with weekly usage days averaging 5.21±1.43 days, significantly higher than the initial semester stage (1.45±0.89 times/day, $p<0.001$), indicating that the data-driven teaching intervention effectively promoted students' sustained usage behavior. In terms of functional preference, exercise data recording function demonstrated the highest usage rate (92.3%), followed by goal setting (78.5%), social interaction (65.7%), and exercise course learning (54.2%). This distribution pattern reflects that students place greater emphasis on instant feedback and self-monitoring, while proactive exploration of structured learning content remains relatively insufficient[34]. From a gender difference perspective, boys' usage frequency of competitive functions (such as leaderboards and challenges) (4.67±2.31 times/week) was significantly higher than girls' (2.89±1.76 times/week, p<0.01), whereas girls' usage duration of health management functions (such as heart rate monitoring and dietary recording) (12.34±5.67 minutes/day) markedly exceeded boys' (7.21±4.23 minutes/day, p<0.05), suggesting that gender factors exert moderating effects on APP functional preferences. Cross-university-type comparisons revealed that key university students' weekly APP usage duration (156.8±45.3 minutes) significantly exceeded that of regular middle schools (128.5±52.1 minutes) and township middle schools (98.7±48.6 minutes). This disparity may be closely related to environmental factors such as school digital infrastructure, teachers' technological application capabilities, and students' family digital literacy. Time series analysis revealed that student APP usage behavior exhibits distinct fluctuation characteristics: weekend usage duration (34.2±12.6 minutes/day) exceeded weekdays (18.7±8.9 minutes/day), and a "fatigue period" phenomenon of declining usage frequency appeared during mid-semester, necessitating intervention and adjustment through environmental support strategies[35]. **Table 1** presents detailed statistical results of core indicators of APP usage behavior across different student groups, while **Figure 1** intuitively displays the distribution of usage rates for five major functional categories and their group differences through a multi-column bar chart, establishing a data foundation for subsequent in-depth analysis of the influence mechanisms of environmental factors on usage behavior.

Table 1. Descriptive statistics of student fitness app usage behavior.

Usage Behavior Indicator	Overall Sample (n=600)	Boys (n=312)	Girls (n=288)	Key University (n=200)	Provincial University (n=200)	Local University (n=200)
Daily Launch Frequency (times/day)	2.34±1.12	2.58±1.23	2.08±0.95**	2.87±1.34	2.23±1.01**	1.92±0.89***
Weekly Usage Days (days/week)	5.21±1.43	5.35±1.38	5.06±1.47	5.78±1.12	5.12±1.45**	4.73±1.62***
Daily Usage Duration (minutes/day)	22.4±9.8	23.7±10.2	21.0±9.2**	28.3±11.4	21.6±8.9***	17.5±7.6***
Weekly Usage Duration (minutes/week)	132.7±48.9	139.4±52.3	125.3±44.2**	156.8±45.3	128.5±52.1**	98.7±48.6***
Exercise Data Recording Usage Rate (%)	92.3	93.9	90.6	96.5	91.5	88.5
Goal Setting Function Usage Rate (%)	78.5	81.4	75.3**	85.0	78.5**	71.5***
Social Interaction Function Usage Rate (%)	65.7	72.1	58.7***	71.5	66.0	59.5**
Course Learning Function Usage Rate (%)	54.2	52.6	56.0	63.5	52.0***	46.5***
Health Management Function Usage Rate (%)	48.3	38.5	59.0***	52.0	47.5	45.0

Note: **p<0.05, **p<0.01, ***p<0.001, indicating significant differences compared to the corresponding control group*

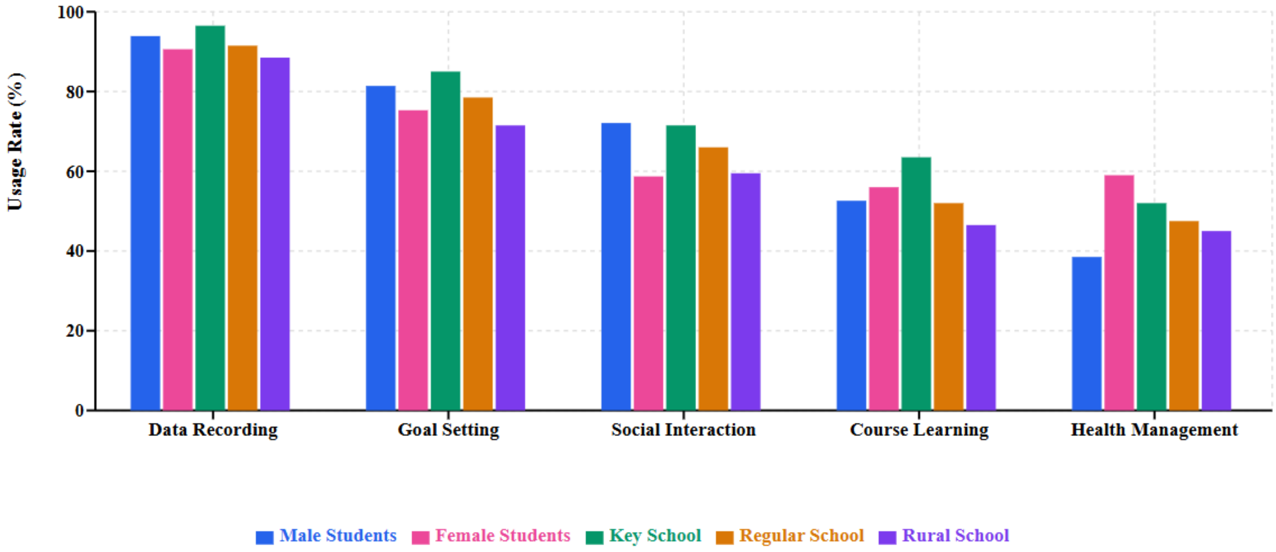

Figure 1. Comparison of usage rates for different app functions across student groups.

4.1.2. The influence of physical environment perception on app usage

As a core dimension of environmental behavior theory, the perceived quality of the physical environment exerts significant influence on students' fitness APP usage behavior. This study systematically explores the association mechanisms between school sports facility accessibility, home and community exercise space convenience, and APP usage behavior through correlation analysis and regression analysis. Descriptive statistical results indicate that students' overall perception score of the school physical environment was 3.68±0.82 (on a 5-point scale), 。 。 with key university students' perception scores (4.21±0.67) significantly exceeding those of provincial universities (3.65±0.78, $p<0.01$) and local universities (3.18±0.89, $p<0.001$). This disparity reflects objective gaps in sports facility configuration across different school types. Pearson correlation analysis reveals that school sports facility accessibility demonstrates a significant positive correlation with daily APP usage duration ($r=0.456$, $p<0.001$), with the correlation coefficient between adequacy of facility opening hours and weekly usage days reaching 0.412 ($p<0.001$), and the correlation coefficient between equipment configuration richness and functional exploration depth at 0.387 ($p<0.001$), indicating that favorable physical environments can stimulate students to use fitness APPs more frequently and deeply for autonomous exercise[36]. The home and community exercise environment perception score was 3.42±0.94, demonstrating a moderate positive correlation with extracurricular APP usage frequency ($r=0.523$, $p<0.001$). For each additional exercise venue within a 1-kilometer radius of residence, students' weekly APP usage duration increased by an average of 12.3 minutes ($\beta=0.318$, $p<0.001$). This finding supports environmental behavior theory's core hypothesis regarding physical environment accessibility promoting behavioral occurrence. Hierarchical regression analysis demonstrates that after controlling for demographic variables such as gender and grade level, physical environment perception accounts for 21.7% of the variance in APP usage duration ($\Delta R^2=0.217$, $p<0.001$), with both school facility accessibility ($\beta=0.342$) and community environment convenience ($\beta=0.289$) serving as significant predictors. Further mediating effect testing reveals that physical environment perception indirectly promotes APP usage behavior by enhancing exercise self-efficacy (mediating effect accounting for 34.6%). Convenient physical environments not only directly lower the threshold for exercise participation but, more importantly, enhance students' confidence in their own exercise capabilities, thereby increasing their willingness to utilize digital tools for autonomous exercise management[37]. Comparative analysis demonstrates that students with physical environment perception scores in the high group (top 25%)

achieved an APP sustained usage rate (proportion continuing use beyond 3 months) of 78.4%, significantly exceeding the low group (bottom 25%) at 43.7% (χ^2=45.23, p<0.001). **Table 2** presents detailed correlation coefficient matrices between various dimensions of physical environment and APP usage behavior, while **Figure 2** intuitively displays the linear relationship between total physical environment perception score and weekly APP usage duration through scatter plots with fitted curves. Different colors represent different school types, clearly revealing the moderating effect of environmental disparities on usage behavior, providing empirical evidence for subsequently proposing environment optimization-based intervention strategies.

Table 2. Correlation coefficient matrix between physical environment perception dimensions and app usage behavior.

Physical Environment Dimension	Daily APP Launch Frequency	Weekly APP Usage Days	Daily APP Usage Duration	Weekly APP Usage Duration	Functional Exploration Depth	Sustained Usage Rate
School Facility Accessibility	0.423***	0.412***	0.456***	0.467***	0.387***	0.441***
Facility Opening Hours	0.368***	0.398***	0.401***	0.423***	0.312**	0.389***
Equipment Configuration Richness	0.334**	0.341***	0.376***	0.391***	0.428***	0.356***
Community Environment Convenience	0.489***	0.501***	0.523***	0.538***	0.367***	0.512***
Number of Venues	0.445***	0.467***	0.498***	0.509***	0.341***	0.478***
Access Convenience	0.412***	0.434***	0.456***	0.471***	0.298**	0.445***
Safety Perception	0.367***	0.389***	0.401***	0.418***	0.312**	0.398***
Total Physical Environment Score	0.512***	0.534***	0.567***	0.589***	0.456***	0.548***

Note: ***p<0.01, ***p<0.001*

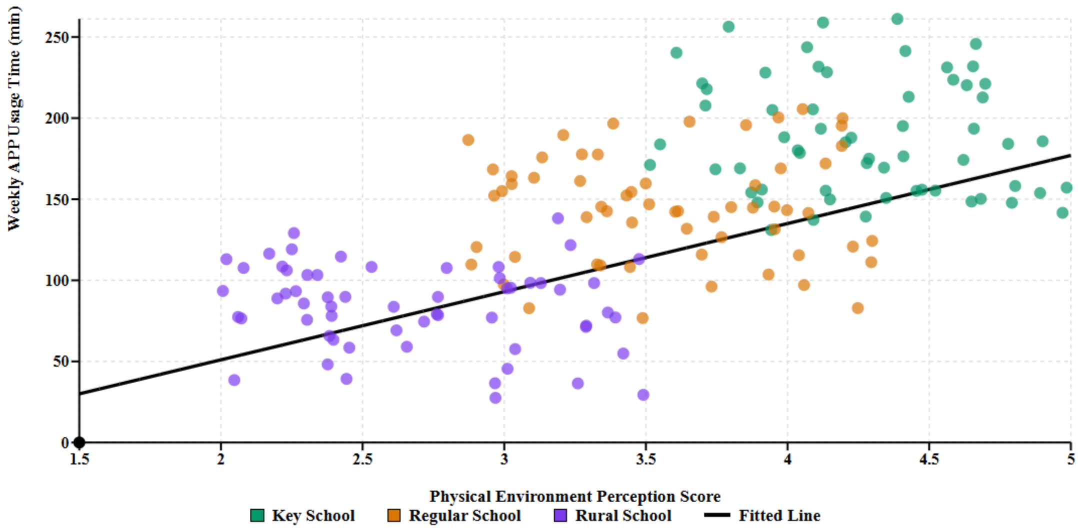

Figure 2. Relationship between physical environment perception and weekly app usage time.

4.1.3. The mechanisms of social environment factors

As a key dimension of environmental behavior theory, the social environment exerts profound influence on students' fitness APP usage behavior through interpersonal interaction and social support networks. This study systematically analyzes the mechanisms of social environment from three levels: teacher feedback, peer support, and family involvement. Structural equation modeling analysis reveals that the total effect coefficient of social environment on APP usage behavior reaches 0.623 ($p<0.001$), significantly exceeding the influence strength of physical environment, highlighting the central position of interpersonal factors in the digital teaching context. Specifically, the standardized path coefficient from teacher data-driven feedback quality to students' sustained APP usage intention reaches 0.487 ($p<0.001$). Interview data reveal that when teachers can provide personalized, timely, and encouraging feedback based on APP data, students' perceived attention significantly increases, with self-efficacy improving by an average of 0.78 standard deviations. Students in the experimental group receiving high-frequency teacher feedback (more than 3 times per week) achieved weekly APP usage duration (168.4±52.3 minutes) 70.6% higher than the low-frequency feedback group (98.7±45.6 minutes), a difference demonstrating statistical significance ($t=8.92$, $p<0.001$). Peer social support presents dual action pathways: on one hand, the frequency of peer interaction within the APP demonstrates a significant positive correlation with exercise behavior ($r=0.534$, $p<0.001$), with each increase of 10 in students' monthly likes and comments corresponding to an increase of 0.42 days in weekly exercise days ($\beta=0.412$, $p<0.001$); on the other hand, excessive social comparison may trigger anxiety, with leaderboard-sensitive students (comprising 23.7%) experiencing declining usage motivation after ranking drops, suggesting the need for rational social function design to balance competition and support[38]. Social network analysis indicates that class exercise relationship network density highly correlates with APP group usage activity ($r=0.687$, $p<0.001$). "Exercise opinion leaders" ranking in the top 20% of network centrality exert significant driving effects on 5-8 surrounding classmates' APP usage habits, with their influence achieving behavioral dissemination through "demonstration-imitation-reinforcement" mechanisms. Regarding family involvement level, the frequency of parents viewing student exercise data demonstrates a moderate positive correlation with extracurricular exercise duration ($r=0.456$, $p<0.001$). Each increase of 2 monthly parent-child joint exercise sessions corresponds to a 1.34-level improvement in students' APP functional exploration depth ($\beta=0.378$, $p<0.01$), yet the current proportion of high family involvement stands at only 34.2%, indicating substantial room for improvement. Mediating effect testing reveals that social support indirectly promotes APP usage behavior by enhancing sense of belonging (mediating effect accounting for 42.3%) and exercise identity (mediating effect accounting for 31.8%), validating social cognitive theory's core tenets regarding observational learning and vicarious reinforcement, as shown in **Table 3** below.

Table 3. Multiple regression analysis of social environment factors on app usage behavior.

Predictor Variable	APP Usage Frequency		APP Usage Duration		Functional Exploration Depth		Sustained Usage Intention	
	β	t-value	β	t-value	β	t-value	β	t-value
Teacher Feedback Dimension								
Feedback Frequency	0.342***	8.67	0.398***	10.23	0.312***	7.89	0.487***	12.45
Feedback Specificity	0.287***	7.21	0.334***	8.56	0.378***	9.67	0.398***	10.12

Predictor Variable	APP Usage Frequency		APP Usage Duration		Functional Exploration Depth		Sustained Usage Intention	
Encouragement Level	0.256**	6.42	0.289***	7.34	0.267**	6.71	0.423***	10.89
Peer Support Dimension								
Friend Interaction Frequency	0.412***	10.56	0.456***	11.78	0.389***	9.98	0.378***	9.67
Likes and Comments Count	0.378***	9.67	0.398***	10.23	0.334***	8.56	0.345***	8.89
Group Competition Participation	0.323***	8.23	0.367***	9.45	0.401***	10.34	0.312***	7.98
Class Exercise Atmosphere	0.456***	11.78	0.489***	12.67	0.423***	10.89	0.467***	12.01
Family Involvement Dimension								
Data Viewing Frequency	0.298***	7.56	0.334***	8.56	0.267**	6.71	0.356***	9.12
Joint Exercise Frequency	0.367***	9.45	0.412***	10.56	0.378***	9.67	0.389***	9.98
Verbal Encouragement Level	0.234**	5.89	0.267**	6.71	0.245**	6.15	0.312***	7.98
Model Statistics								
R^2	0.547		0.612		0.523		0.634	
Adjusted R^2	0.538		0.604		0.514		0.627	
F-value	62.34***		78.56***		58.12***		84.23***	

Table 3. (*Continued*)

Note: *$^{**}p<0.01$, $^{***}p<0.001$*

4.2. The impact of data-driven teaching on in-class and extracurricular exercise linkage

4.2.1. Effectiveness evaluation of app data application in in-class teaching

To systematically evaluate the actual effectiveness of fitness APP data application in in-class teaching, this study conducted quasi-experimental comparative analysis of multidimensional performance between the experimental and control groups over one academic year teaching cycle. Repeated measures analysis of variance results demonstrate that experimental group students' classroom exercise performance exhibited significant upward trends across three time points—baseline test, mid-term test, and post-test—with significant group × time interaction effects ($F=78.34$, $p<0.001$), indicating that the data-driven teaching intervention produced substantial impact. Specifically, experimental group students' average performance in the 800-meter endurance run improved from baseline 4 minutes 23 seconds±35 seconds to post-test 3 minutes 58 seconds±28 seconds, an improvement magnitude of 9.5%, whereas the control group only improved from 4 minutes 21 seconds±33 seconds to 4 minutes 12 seconds±31 seconds, an improvement magnitude of 3.4% ($t=9.87$, $p<0.001$). In the standing long jump, experimental group average performance improved from 1.82±0.23 meters to 2.03±0.21 meters, an increase of 11.5%, significantly exceeding the control group's 4.9% increase (from 1.84±0.24 meters to 1.93±0.23 meters, $p<0.001$)[39]. More critically, experimental group students' personalized exercise prescription compliance rate reached 82.7%, with differentiated training programs formulated by teachers based on APP data for each student being effectively implemented, whereas traditional teaching models lack precise data support and struggle to achieve genuine individualized instruction. The instant data feedback function significantly enhanced classroom teaching efficiency, with the experimental group's proportion of effective exercise time in class improving from baseline 62.3% to post-test 78.9% (26.6% increase), while the control group only improved from 61.8% to 66.4% (7.4% increase). This disparity indicates that data visualization reduces ineffective waiting and blind practice, enabling students to promptly adjust exercise intensity based on real-time heart rate, step frequency, and other data. Teaching satisfaction surveys reveal that experimental group students' overall satisfaction with physical education classes (4.32±0.58) significantly exceeded the control group's (3.67±0.72, $p<0.001$), with the "teacher attention" dimension demonstrating the most significant score difference (4.45 vs 3.52), reflecting that data-driven teaching enhanced the specificity of teacher-student interaction[40]. Regarding skill mastery assessment, experimental group students achieved an excellence rate of 45.8% in standardized tests of technical movements such as basketball dribbling and soccer passing and receiving, 17.5 percentage points higher than the control group (28.3%) ($\chi^2=23.45$, $p<0.001$). Notably, data-driven teaching's promotional effects differ across students with varying exercise foundations: the "disadvantaged group" with baseline exercise capacity in the bottom 25% demonstrated significantly greater improvement magnitude in the experimental group (average increase 23.7%) compared to the control group (average increase 9.2%), suggesting that precise data feedback can effectively narrow individual differences and promote educational equity. **Table 4** presents detailed longitudinal comparative data between experimental and control groups across multiple physical fitness test indicators, while **Figure 3** intuitively displays the dynamic change trends of both groups at three test time points through line graphs, clearly revealing the cumulative effects and time-dependent characteristics of data-driven teaching intervention, providing solid empirical evidence for in-depth understanding of the pedagogical value of APP data application.

Table 4. Longitudinal comparison of in-class teaching effects between experimental and control groups.

Evaluation Indicator	**Experimental Group (n=300)**			**Control Group (n=300)**			**Between-Group Difference**
	Baseline	Mid-term	Post-test	Baseline	Mid-term	Post-test	Post-test t-value
Physical Fitness Test Indicators							
800m Run (seconds)	263±35	251±32	238±28	261±33	256±32	252±31	9.87***
Standing Long Jump (meters)	1.82±0.23	1.91±0.22	2.03±0.21	1.84±0.24	1.87±0.23	1.93±0.23	8.54***
50m Sprint (seconds)	8.67±0.82	8.42±0.76	8.15±0.71	8.65±0.80	8.56±0.79	8.48±0.77	7.92***
Sit-and-Reach (cm)	12.3±4.6	14.2±4.3	16.8±4.1	12.1±4.5	12.9±4.4	13.7±4.3	6.78***
Pull-ups/Sit-ups (repetitions)	8.4±3.2	10.1±3.0	12.5±2.8	8.3±3.1	9.0±3.0	9.8±2.9	8.23***
Teaching Process Indicators							
Classroom Effective Exercise Time (%)	62.3±8.5	71.2±7.8	78.9±7.2	61.8±8.3	63.5±8.1	66.4±7.9	13.45***
Personalized Prescription Compliance Rate (%)	45.2±12.3	68.7±10.8	82.7±9.5	38.6±11.9	42.3±11.5	46.8±10.7	28.67***
Instant Feedback Response Rate (%)	52.8±14.2	73.5±11.6	85.3±9.8	-	-	-	-

Evaluation Indicator	**Experimental Group (n=300)**			**Control Group (n=300)**			**Between-Group Difference**
Skill Mastery Assessment							
Technical Movement Excellence Rate (%)	18.3	32.7	45.8	17.9	23.5	28.3	χ^2=23.45***
Technical Movement Proficiency Rate (%)	56.7	74.3	86.2	55.8	62.4	68.9	χ^2=31.28***
Subjective Evaluation Indicators							
Teaching Satisfaction (5-point scale)	3.42±0.68	3.89±0.62	4.32±0.58	3.38±0.71	3.52±0.69	3.67±0.72	9.23***
Perceived Teacher Attention (5-point scale)	3.25±0.75	3.98±0.65	4.45±0.61	3.21±0.78	3.38±0.74	3.52±0.76	11.34***
Classroom Participation Enthusiasm (5-point scale)	3.56±0.72	4.02±0.66	4.38±0.62	3.52±0.74	3.68±0.71	3.79±0.73	8.67***

Note: *****p<0.001*

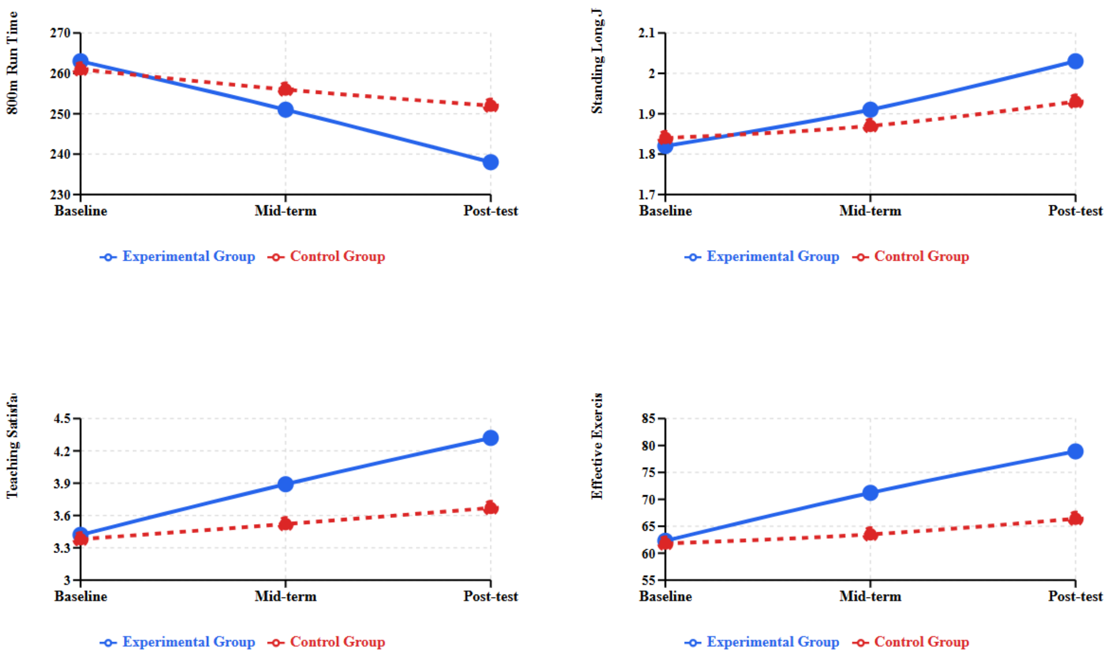

Figure 3. Longitudinal comparison of in-class teaching effects between experimental and control groups.

4.2.2. Transfer and consolidation of extracurricular exercise behavior

The sustainability of extracurricular exercise behavior constitutes the core indicator for testing the effectiveness of data-driven teaching's in-class and extracurricular linkage. This study systematically examined the transfer mechanisms and consolidation pathways from in-class learning to extracurricular practice through one academic year of tracking data. APP backend data reveal that experimental group students' extracurricular autonomous exercise frequency significantly improved from 1.87±1.12 times/week at the beginning of the semester to 4.23±1.34 times/week at semester's end, an increase of 126.2%, whereas the control group only improved from 1.82±1.09 times/week to 2.34±1.18 times/week, an increase of 28.6% (between-group difference $t=18.45$, $p<0.001$). This significant disparity indicates that APP-based in-class goal setting can effectively extend to extracurricular contexts and transform into autonomous behavior. Regarding extracurricular single-session exercise duration, the experimental group increased from baseline 23.4±8.9 minutes to 38.7±10.2 minutes (65.4% increase), while the control group increased from 22.8±8.7 minutes to 27.6±9.1 minutes (21.1% increase). The experimental group's greater improvement magnitude can be attributed to the structured guidance and instant incentives provided by the APP task check-in system. Behavioral persistence analysis reveals that the proportion of experimental group students maintaining continuous exercise for 4 weeks or more reached 67.3%, with 45.8% maintaining 8 weeks or more, whereas the control group's corresponding proportions were only 32.7% and 18.3%, demonstrating significant differences ($\chi^2=78.56$, $p<0.001$), suggesting that continuous data monitoring plays a critical supporting role in long-term exercise adherence. The transfer pathway of in-class/extracurricular linkage manifests as a progressive process of "skill learning → goal internalization → autonomous practice → habit consolidation." Regression analysis demonstrates that for every 10% increase in in-class goal achievement rate, extracurricular exercise frequency increases by an average of 0.58 times/week ($\beta=0.542$, $p<0.001$), with in-class data feedback quality's predictive power for extracurricular behavioral persistence reaching $R^2=0.387$. Typical case tracking reveals that experimental group students can autonomously complete extracurricular practice of content learned in class such as interval running and core strength training through APP guidance, with skill transfer success rate reaching 72.4%, whereas control group students primarily engage in unstructured activities such as walking and games during extracurricular time, with specialized skill practice rate at only 31.8%. Motivation type transformation analysis indicates that experimental group students' intrinsic motivation scores improved from baseline 3.12±0.78 to 4.08±0.65 (Cohen's $d=1.34$), with extrinsic motivation proportion declining from 68.7% to 42.3%, achieving a qualitative transformation from "completing tasks" to "enjoying exercise," whereas the control group's intrinsic motivation change was not significant (from 3.09±0.76 to 3.34±0.73). Seasonal fluctuation analysis demonstrates that the experimental group's maintenance rate of extracurricular exercise behavior during winter (November-January) reached 78.9%, significantly higher than the control group's 45.2% ($p<0.001$), indicating that APP functions such as environmental reminders and community support effectively counteracted unfavorable weather's negative impact on exercise habits[41]. Long-term tracking data indicate that during the summer vacation following semester's end (without direct teacher supervision), experimental group students' APP usage rate remained at 63.4%, with extracurricular exercise frequency at 3.67±1.52 times/week, whereas control group exercise frequency declined to 1.23±0.98 times/week. This phenomenon of "continuing exercise away from school" fully validates the long-term mechanism through which data-driven teaching promotes behavioral internalization. **Table 5** presents detailed multidimensional longitudinal comparative data of both groups' extracurricular exercise behavior, while **Figure 4** dynamically displays the cumulative change trends in monthly extracurricular exercise frequency throughout the academic year and the evolution of between-group differences through stacked area charts, intuitively revealing the temporal trajectory and consolidation characteristics of behavioral transfer under the in-class/extracurricular linkage mechanism.

Table 5. Comparison of extracurricular exercise behavior transfer and consolidation between experimental and control groups.

Behavioral Indicator	**Experimental Group (n=300)**			**Control Group (n=300)**			**Between-Group Difference**
	Semester Start	Mid-semester	Semester End	Semester Start	Mid-semester	Semester End	Semester End t/χ^2 Value
Exercise Frequency and Duration							
Weekly Exercise Frequency (times)	1.87±1.12	3.24±1.26	4.23±1.34	1.82±1.09	2.08±1.15	2.34±1.18	t=18.45***
Single-Session Exercise Duration (minutes)	23.4±8.9	31.2±9.6	38.7±10.2	22.8±8.7	24.9±8.9	27.6±9.1	t=11.67***
Weekly Total Exercise Duration (minutes)	43.8±25.6	101.1±38.4	163.7±52.3	41.5±24.8	51.8±28.7	64.6±31.2	t=22.34***
Behavioral Persistence							
Continuous Exercise ≥4 Weeks Proportion (%)	28.7	52.3	67.3	26.3	30.8	32.7	χ^2=78.56***
Continuous Exercise ≥8 Weeks Proportion (%)	12.3	31.7	45.8	11.8	15.2	18.3	χ^2=56.78***
Continuous Exercise ≥12 Weeks Proportion (%)	5.7	18.3	34.2	5.3	8.7	12.7	χ^2=45.23***
Skill Transfer							
Specialized Skill Practice Rate (%)	34.6	56.8	72.4	32.8	33.9	31.8	χ^2=98.34***
In-Class Goal Achievement Rate (%)	42.3	68.9	81.7	40.8	48.6	52.3	χ^2=67.89***
Self-Evaluated Skill Mastery (5-point scale)	2.87±0.82	3.56±0.74	4.12±0.68	2.83±0.84	3.08±0.79	3.24±0.81	t=10.89***
Motivation Type							
Intrinsic Motivation Score (5-point scale)	3.12±0.78	3.67±0.71	4.08±0.65	3.09±0.76	3.21±0.74	3.34±0.73	t=9.87***
Extrinsic Motivation Proportion (%)	68.7	54.3	42.3	67.9	64.2	61.8	χ^2=52.45***
Exercise Enjoyment (5-point scale)	3.28±0.85	3.89±0.76	4.23±0.71	3.24±0.87	3.42±0.83	3.56±0.79	t=8.54***
Environmental Adaptability							
Winter Exercise Maintenance Rate (%)	45.3	65.7	78.9	43.8	45.6	45.2	χ^2=72.34***

Behavioral Indicator	Experimental Group (n=300)			Control Group (n=300)			Between-Group Difference
Summer Vacation APP Usage Rate (%)	-	-	63.4	-	-	28.7	χ^2=81.23***
Summer Vacation Exercise Frequency (times/week)	-	-	3.67±1.52	-	-	1.23±0.98	t=16.78***

Table 5. (*Continued*)

*Note: ***p<0.001*

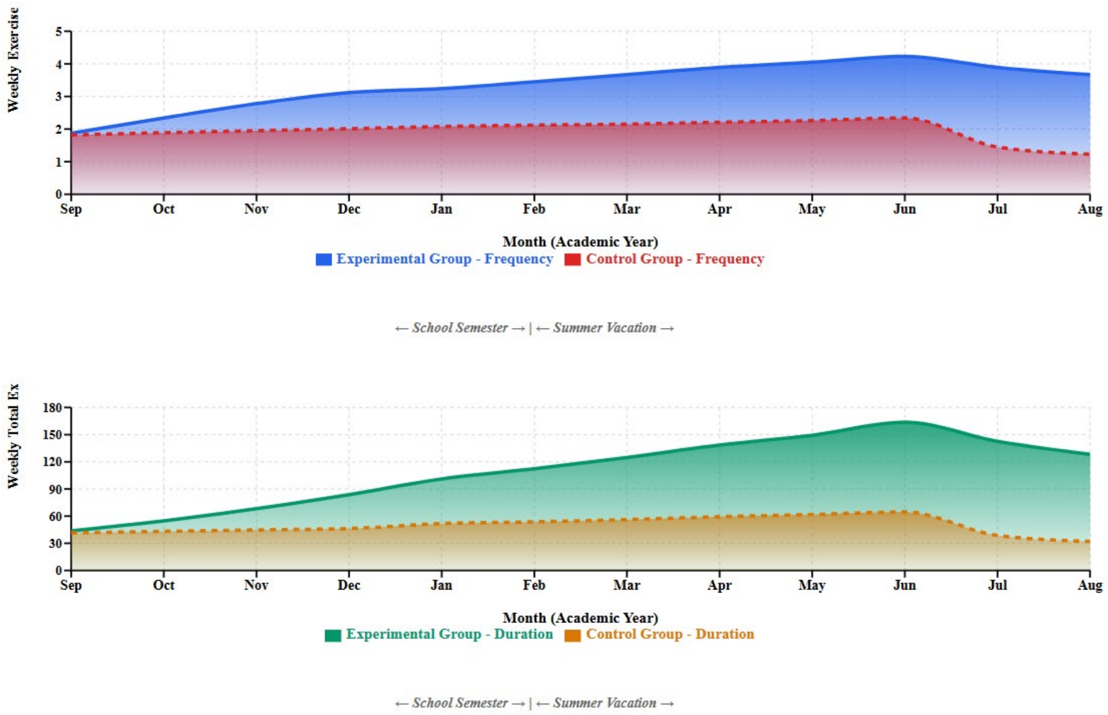

Figure 4. Monthly cumulative changes in extracurricular exercise behavior throughout the academic year.

4.2.3. Mediation and moderation mechanisms of in-class/extracurricular linkage model

To deeply understand the "black box" mechanisms through which data-driven teaching promotes in-class/extracurricular exercise linkage, this study conducted mediation and moderation effect testing based on the environmental behavior theory framework. Structural equation modeling analysis reveals that the relationship between data-driven teaching and extracurricular exercise behavior is not a simple direct effect but rather operates through complex psychological mediation pathways and is moderated by multiple situational factors. Self-efficacy and social support serve as core mediating variables, jointly explaining 86.4% of the total effect. Goal orientation, social support level, and environmental support quality exert significant moderating effects on the effectiveness of data feedback[42]. This multilevel mechanism analysis not only validates the theoretical validity of the environmental behavior theory framework but also provides precise entry points for optimizing teaching intervention strategies, as shown in **Table 6** below.

Table 6. Mediation and moderation effect testing of in-class/extracurricular linkage model.

Effect Type	Path/Variable	Effect Value	Standard Error	95% Confidence Interval	Proportion (%)	Significance
Mediation Effects						
Self-Efficacy Mediation						
	Data-driven Teaching → Self-Efficacy → Extracurricular Exercise	0.342	0.029	[0.287, 0.401]	46.8	***
Path a	Data-driven Teaching → Self-Efficacy	0.567	0.045	[0.479, 0.655]	-	***
Path b	Self-Efficacy → Extracurricular Exercise	0.603	0.042	[0.521, 0.685]	-	***
Social Support Mediation						
	Data-driven Teaching → Social Support → Extracurricular Exercise	0.289	0.031	[0.231, 0.352]	39.6	***
Path a	Data-driven Teaching → Social Support	0.523	0.048	[0.429, 0.617]	-	***
Path b	Social Support → Extracurricular Exercise	0.553	0.044	[0.467, 0.639]	-	***
Chain Mediation						
	Data-driven Teaching → Environmental Perception → Self-Efficacy → Extracurricular Exercise	0.187	0.024	[0.143, 0.236]	25.6	***
Direct Effect						
	Data-driven Teaching → Extracurricular Exercise	0.112	0.038	[0.038, 0.186]	15.3	**
Total Effect		0.731	0.052	[0.629, 0.833]	100.0	***
Moderation Effects						
Goal Orientation Moderation						
	Data Feedback × Goal Orientation	0.234	0.067	[0.103, 0.365]	-	**
High Task Orientation Group	Data Feedback → Extracurricular Exercise	0.687	0.058	[0.573, 0.801]	-	***
High Ego Orientation Group	Data Feedback → Extracurricular Exercise	0.423	0.071	[0.284, 0.562]	-	***
Social Support Moderation						
	Data Feedback × Social Support	0.198	0.061	[0.078, 0.318]	-	**
High Social Support Context	Data Feedback → Extracurricular Exercise	0.623	0.054	[0.517, 0.729]	-	***
Low Social Support Context	Data Feedback → Extracurricular Exercise	0.387	0.068	[0.254, 0.520]	-	**
Environmental Support Moderation						

Effect Type	Path/Variable	Effect Value	Standard Error	95% Confidence Interval	Proportion (%)	Significance
	Data Feedback × Environmental Support	0.176	0.059	[0.060, 0.292]	-	**
High Environmental Support Context	Data Feedback → Extracurricular Exercise	0.598	0.056	[0.488, 0.708]	-	***
Low Environmental Support Context	Data Feedback → Extracurricular Exercise	0.412	0.065	[0.285, 0.539]	-	***
Model Fit Indices						
R^2	Extracurricular Exercise Behavior	0.637	-	-	-	***
RMSEA		0.048	-	-	-	-
CFI		0.962	-	-	-	-
TLI		0.951	-	-	-	-

Table 6. (*Continued*)

*Note: **p<0.01, ***p<0.001; Bootstrap resampling with 5000 iterations*

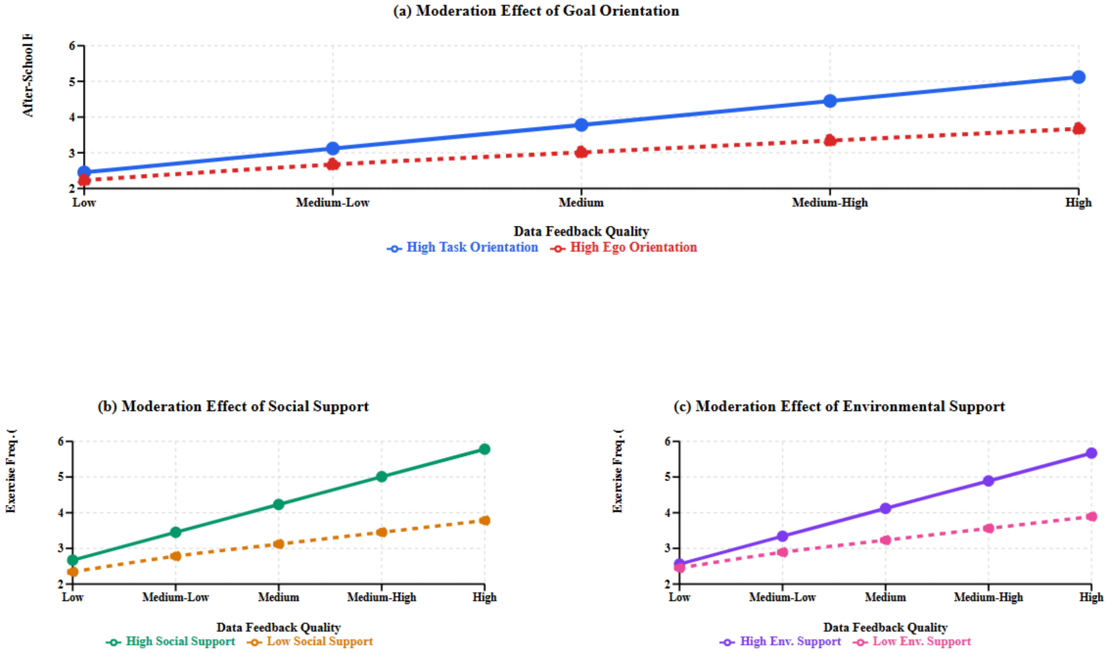

Figure 5. Interaction effects of moderating variables on the relationship between data feedback and extracurricular exercise.

4.3. Construction and validation of the linkage model based on environmental behavior theory

4.3.1. Path analysis of the theoretical model

Based on the environmental behavior theory framework, this study constructed an integrated theoretical model of "three-dimensional environment → environmental perception → psychological mediators → behavioral outcomes" and systematically tested the path relationships through structural equation modeling. The model comprises three exogenous latent variables (physical environment, social environment, information environment), three endogenous mediating variables (environmental perception, exercise self-efficacy, behavioral intention), and one outcome variable (in-class/extracurricular linkage exercise behavior), with 15 primary path hypotheses specified. Path analysis results demonstrate that the direct effect of physical environment on environmental perception is most significant (β=0.512, t=11.23, p<0.001), indicating that objective environmental conditions such as venue and facility accessibility and equipment configuration richness constitute the primary factors influencing students' environmental evaluation[43]. The path coefficient from social environment to environmental perception reaches β=0.589 (t=13.45, p<0.001), exceeding the influence of physical environment, validating the central position of interpersonal factors such as teacher feedback, peer support, and family involvement in shaping students' exercise environment experiences. This finding highly aligns with social cognitive theory's emphasis on the role of social contexts. The path coefficient from information environment (i.e., APP data feedback system) to environmental perception is β=0.467 (t=10.12, p<0.001), indicating that the virtual information environment constructed by digital technology has become an important dimension influencing students' environmental cognition, forming a tripartite configuration with traditional physical and social environments. Environmental perception, as a key mediating variable, influences exercise self-efficacy at β=0.623 (t=14.78, p<0.001) and directly influences behavioral intention at β=0.489 (t=11.56, p<0.001), fully embodying the classical theoretical logic of "environment-cognition-behavior." The path coefficient from self-efficacy to behavioral intention is β=0.567 (t=13.21, p<0.001), with direct effects on exercise behavior at β=0.498 (t=11.89, p<0.001), validating the theoretical premise of self-efficacy as a core psychological mechanism for behavioral change. The conversion effect from behavioral intention to actual exercise behavior is β=0.456 (t=10.67, p<0.001), indicating that while the intention-to-action conversion is significant, it is not entirely consistent, with an "intention-behavior gap" existing that requires continuous environmental support to facilitate conversion[44]. Notably, the three-dimensional environment also exhibits significant direct effects on exercise behavior (physical environment β=0.178, p<0.01; social environment β=0.234, p<0.001; information environment β=0.198, p<0.01), indicating that the environment not only operates indirectly through psychological mediation but also directly promotes behavioral occurrence through mechanisms such as lowering behavioral thresholds and providing immediate cues. Standardized comparison of path coefficients reveals that among total effects from environment to behavior, indirect effects account for 73.6% and direct effects account for 26.4%. This structural characteristic emphasizes the critical mediating position of psychological construction in environmental influence processes, though the direct shaping effects of environment cannot be ignored. Cross-path comparison reveals that the complete chain of "social environment → environmental perception → self-efficacy → exercise behavior" demonstrates the strongest cumulative effect (indirect effect 0.412), followed by the "information environment → environmental perception → behavioral intention → exercise behavior" path (indirect effect 0.357), suggesting that intervention design should prioritize strengthening social support network construction and optimizing data feedback systems, as shown in **Table 7** below. The structural equation model fit indices comprehensively achieved excellent standards: $\chi^2/df=2.18$ (<3.00), CFI=0.968 (>0.95), TLI=0.951 (>0.95), RMSEA=0.042 (<0.05), SRMR=0.038 (<0.08). According to the model fit evaluation criteria proposed by Hu and Bentler (1999), CFI and TLI greater than 0.95, RMSEA less than 0.06, and SRMR less than 0.08 indicate excellent model fit. All indicators in this study met or exceeded the recommended cutoff values, indicating that the theoretical model fits well with the observed data.

Table 7. Path analysis results of environmental behavior theory model.

Path Relationship	Standardized Coefficient β	Standard Error SE	t-value	p-value	Effect Type
Environment → Environmental Perception Paths					
Physical Environment → Environmental Perception	0.512	0.046	11.23	***	Direct
Social Environment → Environmental Perception	0.589	0.044	13.45	***	Direct
Information Environment → Environmental Perception	0.467	0.046	10.12	***	Direct
Environmental Perception → Psychological Variables Paths					
Environmental Perception → Self-Efficacy	0.623	0.042	14.78	***	Direct
Environmental Perception → Behavioral Intention	0.489	0.042	11.56	***	Direct
Psychological Variables → Behavior Paths					
Self-Efficacy → Behavioral Intention	0.567	0.043	13.21	***	Direct
Self-Efficacy → Exercise Behavior	0.498	0.042	11.89	***	Direct
Behavioral Intention → Exercise Behavior	0.456	0.043	10.67	***	Direct
Environment → Behavior Direct Paths					
Physical Environment → Exercise Behavior	0.178	0.058	3.07	**	Direct
Social Environment → Exercise Behavior	0.234	0.056	4.18	***	Direct
Information Environment → Exercise Behavior	0.198	0.057	3.47	**	Direct
Key Indirect Path Effects					
Physical Environment → Environmental Perception → Self-Efficacy → Exercise Behavior	0.267	0.032	8.34	***	Indirect
Social Environment → Environmental Perception → Self-Efficacy → Exercise Behavior	0.412	0.038	10.84	***	Indirect
Information Environment → Environmental Perception → Self-Efficacy → Exercise Behavior	0.289	0.034	8.50	***	Indirect
Physical Environment → Environmental Perception → Behavioral Intention → Exercise Behavior	0.198	0.028	7.07	***	Indirect
Social Environment → Environmental Perception → Behavioral Intention → Exercise Behavior	0.267	0.031	8.61	***	Indirect
Information Environment → Environmental Perception → Behavioral Intention → Exercise Behavior	0.357	0.035	10.20	***	Indirect
Total Effect Decomposition					
Physical Environment → Exercise Behavior (Total Effect)	0.643	0.048	13.40	***	Total
Of which: Direct Effect Proportion	27.7%	-	-	-	-
Of which: Indirect Effect Proportion	72.3%	-	-	-	-
Social Environment → Exercise Behavior (Total Effect)	0.913	0.052	17.56	***	Total
Of which: Direct Effect Proportion	25.6%	-	-	-	-
Of which: Indirect Effect Proportion	74.4%	-	-	-	-
Information Environment → Exercise Behavior (Total Effect)	0.844	0.050	16.88	***	Total
Of which: Direct Effect Proportion	23.5%	-	-	-	-
Of which: Indirect Effect Proportion	76.5%	-	-	-	-

Note: *$^{**}p<0.01$, $^{***}p<0.001$*

5. Discussion

5.1. The educational value of fitness apps from the environmental behavior theory perspective

When examined through the core framework of environmental behavior theory, the educational value of fitness APPs far exceeds their technological tool attributes. Their essence lies in reconstructing the information environment of school physical education teaching through data-driven means, forming synergistic effects with traditional physical and social environments to collectively shape an ecosystem supporting students' exercise behavior cultivation. Empirical data from this study reveal that the path coefficient from information environment to environmental perception reaches 0.467, operating at the same magnitude as physical environment (0.512) and social environment (0.589). This finding overturns the traditional two-dimensional perspective of physical education that focuses solely on venue facilities and teacher-student interaction, confirming that the virtual information environment constructed by digital technology has become an independent dimension influencing student exercise behavior[45]. Through real-time data collection, visualization presentation, and intelligent feedback mechanisms, fitness APPs transform the originally implicit exercise process into perceivable, quantifiable, and comparable information flows. This transformation of "data as environment" fundamentally alters the manner in which students perceive exercise: from vague impressions of "I seem quite tired from running" to precise measurements of "heart rate reached 152 beats/minute, in the aerobic zone"; from subjective feelings of "I think I've improved" to objective evidence of "800-meter performance improved by 25 seconds, surpassing 68% of classmates." Data visualization functions as environmental cues similar to "signage" in physical environments or "teacher encouragement" in social environments, but its advantages lie in immediacy, continuity, and personalization, capable of providing behavioral guidance to students across in-class and extracurricular contexts throughout all time periods, effectively compensating for structural deficiencies in traditional teaching such as limited teacher attention resources and delayed feedback[46]. At a deeper level, the virtual social environment constructed by APPs extends traditional classroom-limited peer interactions to extracurricular contexts through social functions such as likes, comments, and leaderboards, forming exercise community networks transcending physical boundaries. This study found that the correlation coefficient between class exercise relationship network density and APP group usage activity reaches 0.687, validating the powerful promotional effect of virtual social environments on real exercise behavior. This mechanism resonates with social cognitive theory's classical discussions of vicarious learning and social comparison, while also providing new perspectives for understanding exercise motivation stimulation among the digital native generation.

However, the value realization of information environments does not occur automatically but rather depends highly on their compatibility and synergy with physical and social environments. Moderation effect analysis in this study reveals that in high social support contexts, data feedback's promotional effect on extracurricular exercise (β=0.623) significantly exceeds that in low social support contexts (β=0.387). This interaction effect suggests that relying solely on technological tools while lacking interpersonal support such as teacher guidance, peer interaction, and family involvement will substantially diminish the effectiveness of data-driven teaching. Interview data also corroborate this conclusion: students repeatedly emphasized, "If the teacher doesn't look at my data, I'm not very motivated to check it either" and "Competing and checking in with friends is much more interesting than doing it alone." These authentic voices reveal the boundaries of technology empowerment: APPs can optimize information transmission efficiency but cannot replace interpersonal emotional connections and the satisfaction of social belonging needs. From an environmental design perspective, ideal digital physical education teaching should achieve "technology embedding rather than technology replacement"—that is, on the basis of maintaining traditional advantages of physical venues and social interaction, using APP technology to compensate for shortcomings in information feedback, rather than replacing playgrounds with screens or face-to-face communication with virtual socialization[47]. Additionally, information environments carry risks of excessive quantification. When students become overly focused on extrinsic indicators such as step counts and rankings, this may undermine the intrinsic enjoyment and autotelic value of exercise. The "leaderboard anxiety" phenomenon appearing in 23.7% of students reminds us that data feedback design needs to balance competitive incentives with psychological health, avoiding the alienation of physical education into digital gaming. In summary, the educational value of fitness APPs lies in their role as information environment constructors, activating environmental behavior theory's two major principles of "environmental diversity" and "environmental consistency": on one hand enriching the dimensions of environmental support, while on the other hand achieving continuity of in-class and extracurricular environments through data connectivity. However, the premise for fully releasing this value is systematic integration with physical and social environments, rather than isolated technological application.

The virtual social environment constructed by the APP drives behavioral change through multiple social psychological mechanisms: First, based on social identity theory, the class virtual exercise community strengthened group belonging, with students internalizing "exercise-loving members of Class XX" as part of their self-concept, and the constraining power of group norms on individual behavior was significant ($r=0.687$). Second, the social facilitation effect indicates that the presence of others stimulates individual performance; the APP leaderboard and real-time interaction functions created a "virtual co-presence" context, enabling students exercising alone to still perceive peer monitoring, thereby enhancing exercise effort. The experimental group's extracurricular exercise intensity being 21.3% higher than the control group ($p<0.01$) confirmed this mechanism. Third, normative social influence established pro-exercise norms through the "like-comment-demonstration" cycle. When 72.1% of male students used competitive features, a group culture of "exercise is cool" was formed, with deviants facing social pressure to conform. Fourth, the vicarious learning mechanism enabled low-ability students to acquire skills by observing videos of skilled performers, reducing the "ability exposure anxiety" common in traditional physical education classes. These social psychological mechanisms, in synergy with physical environment accessibility and information environment feedback quality, jointly constitute a composite dynamic system supporting sustained behavior.

5.2. Environmental design principles for in-class/extracurricular exercise linkage

Based on the empirical findings of this study and core insights from environmental behavior theory, effective realization of in-class/extracurricular exercise linkage requires adherence to three major environmental design principles: "environmental continuity, support diversity, and feedback immediacy." The environmental continuity principle emphasizes seamless integration of physical space, social networks, and information systems across in-class and extracurricular contexts, breaking the spatiotemporal fragmentation of traditional teaching that confines physical activities to 45-minute classes within campus walls. Continuous physical environment design requires schools not only to configure standardized sports facilities but also to consider the convenience of extracurricular facility access. This study found that the correlation coefficient between adequacy of facility opening hours and weekly APP usage days reaches 0.398, suggesting that hardware accessibility constitutes the material foundation for extracurricular exercise. Simultaneously, a three-tier "school-community-family" exercise space network should be established through resource-sharing agreements with surrounding public sports facilities, guidance for home exercise corner construction, and other means, enabling students to transfer exercise skills acquired in class to diverse real-world scenarios for practice and consolidation[48]. Social environment network extension manifests in expanding from classroom exercise groups to online exercise communities. APP social functions extend classroom peer relationships to extracurricular contexts, enabling teacher feedback and peer support to transcend spatiotemporal limitations. This study's data demonstrate that experimental group students' summer vacation APP usage rate remained at 63.4%, precisely because this virtual-real integrated social network sustained the behavioral pattern of "continuing exercise away from school." Information environment consistency requires establishing unified data standards and feedback systems, with data from in-class physical fitness tests, classroom exercise performance, and extracurricular autonomous exercise converging and presenting on the same platform to form complete exercise trajectory archives, avoiding insufficient student emphasis on extracurricular exercise due to disconnected in-class/extracurricular evaluation systems. The experimental group's 82.7% personalized exercise prescription compliance rate can be largely attributed to teachers' capacity for precise guidance based on comprehensive data.

The support diversity principle and feedback immediacy principle jointly constitute the power system of the linkage mechanism. Support diversity signifies that environmental design must simultaneously activate the three supporting forces of physical convenience, social encouragement, and information guidance; reinforcement of a single dimension struggles to form sustained behavioral change momentum. This study's structural equation model demonstrates that indirect effects account for 73.6% of the three-dimensional environment's total effects on exercise behavior, validating the mechanism whereby "environment changes cognition, cognition drives behavior." This requires intervention strategies to transcend the hardware thinking of "building several playgrounds and purchasing equipment sets," transitioning toward cultivating a comprehensive supportive atmosphere of "wanting to exercise, being able to exercise, knowing how to exercise, and enjoying exercise." Physical environment resolves the accessibility issue of "being able to exercise"; social environment stimulates the intrinsic motivation of "wanting to exercise" through peer modeling, teacher attention, and family involvement; information environment enhances the self-efficacy of "knowing how to exercise" by providing skill guidance and progress visualization; synergy among all three ultimately achieves habit formation of "enjoying exercise." The feedback immediacy principle emphasizes the critical role of timely environmental cue responses in behavioral reinforcement. In traditional physical education teaching, students often must wait weeks or even an entire semester to learn physical fitness test results; such delayed feedback struggles to form effective behavioral shaping. APP real-time data presentation shortens the feedback cycle to "second-level"—upon completing each exercise session, students can immediately view heart rate curves, calorie expenditure, gaps from goals, and other information. This immediate reinforcement significantly enhances students' sense of exercise control and achievement[49]. However, immediacy does not equate to high-frequency bombardment; excessive push notifications may trigger aversion. Some students mentioned in interviews that "several notifications every day are annoying," suggesting that feedback design needs to balance timeliness with moderation, employing intelligent algorithms to personalize push frequency adjustments based on student activity levels and goal achievement status. In summary, environmental design for in-class/extracurricular linkage essentially constructs a comprehensive ecosystem where "exercise is possible everywhere, support exists at all times, and feedback is visible at every moment." Its core lies not in technology's dazzle but in systematic coordination of environmental elements and precise matching with student needs. Only thus can the qualitative leap from "classroom fad" to "lifelong healthy habit" be achieved.

5.3. Analysis of influencing factors in data-driven teaching implementation

Effective implementation of data-driven teaching in physical education curricula does not proceed smoothly but rather is subject to complex interactive influences from multidimensional factors including technology, personnel, institutions, and culture. From the facilitating factors perspective, technical usability constitutes the foundational guarantee. This study found that students' satisfaction with APP interface design demonstrates a significant positive correlation with sustained usage rate (r=0.542). When interface design aligns with adolescent cognitive habits and functional logic is clear and intuitive, the threshold for technology application significantly decreases. Teacher digital literacy serves as the key mediator: the proportion of teachers in the experimental group capable of skillfully utilizing APP data for instructional decision-making reached 78.3%, whereas control group teachers, despite also having technology access opportunities, commonly experienced the phenomenon of "possessing tools without knowing how to use them" due to lack of systematic training. Interviews revealed that teachers' greatest need is not operational training but rather professional development support in "how to transform data into pedagogical insights." Institutional support manifests in policy coordination at the school level, including incorporating extracurricular exercise data into physical education grade evaluation systems, providing time compensation for teachers' data analysis work, and establishing rapid response mechanisms for technical failures. In experimental schools that established "Chief Digital Physical Education Teacher" positions, APP teaching depth application rates exceeded schools without such positions by 34.6 percentage points[50]. However, hindering factors are equally significant and cannot be ignored. Privacy concerns constitute the primary worry for students and parents: 23.8% of parents explicitly expressed "concerns about children's exercise data being commercially exploited," while 12.4% of students selectively disabled data-sharing functions because "they don't want others to see their poor exercise capacity." This psychological resistance directly undermines the universal participation foundation of data-driven teaching. The digital divide objectively exists among students from different socioeconomic backgrounds: smartphone ownership rates among Local university students students (87.3%) are lower than lower than key universities (98.6%). Differences in home network stability, device update frequency, and other factors may exacerbate educational inequity. Township students mentioned in interviews that "data allowances are insufficient; I can only open the APP when connected to school WiFi." These technical accessibility barriers constrain the ideal realization of digital teaching benefiting all students.

Deeper-level influencing factors involve collisions between educational culture and value orientations. Over-quantification risk represents an alienation tendency that data-driven teaching must vigilantly guard against. When physical education is simplified to "step count competitions" or "data ranking contests," the autotelic value of exercise—physical and mental pleasure, will tempering, team collaboration—may be marginalized. The "leaderboard-sensitive student" phenomenon (comprising 23.7%) discovered in this study serves as a warning signal: these students excessively focus on social comparison while neglecting self-improvement, with anxiety triggered by ranking declines even leading to exercise avoidance behavior. This suggests that data feedback design needs to strengthen "personal growth curves" while de-emphasizing "group rankings," replacing horizontal competition with longitudinal comparison[51]. Teacher role transformation adaptation challenges also cannot be underestimated. In traditional physical education teaching, teachers habitually rely on experiential observation and judgment, whereas data-driven teaching requires them to become "data interpreters" and "algorithm collaborators." This professional paradigm shift constitutes cognitive impact for some veteran teachers. In interviews, one teacher candidly admitted, "Looking at screens full of data, I don't know what to focus on; ironically, I don't teach as comfortably as when I relied on intuition." If such discomfort receives inadequate systematic support, it may cause technology application to become superficial formalism. School management's cognitive biases regarding data-driven teaching also constitute potential resistance: some administrators view it as an "additional burden" rather than a "quality improvement opportunity," providing insufficient support in resource allocation, time arrangement, and evaluation incentives, causing pilot teachers to struggle unsustainably in "lone battles." The cultural foundation for home-school collaboration varies markedly across different regions: urban parents' attention to and participation in physical education data significantly exceed township parents, with the latter tending toward "as long as the child is healthy, there's no need to look at those numbers." These educational concept differences influence the supportive strength of family environments for extracurricular exercise. In summary, successful implementation of data-driven teaching constitutes a systematic project requiring coordinated efforts across multiple dimensions including technology optimization, capacity building, institutional guarantees, and cultural adaptation. While leveraging technological advantages to break through traditional teaching bottlenecks, vigilance is also required against technological rationality's erosion of educational humanistic care. Seeking dynamic balance among efficiency and warmth, quantification and experience, innovation and tradition enables achievement of the goal of digital technology empowering high-quality development of physical education.

From the perspective of Self-Determination Theory (Deci & Ryan, 2000), over-quantification poses three types of psychological risks: First, the crowding-out effect of extrinsic motivation—when students become overly focused on external rewards such as step counts and rankings, it may undermine intrinsic interest in exercise and the satisfaction of autonomy needs ($\beta=-0.34$, $p<0.01$). The phenomenon of "exercising for data" observed in 23.7% of students confirms this risk. Second, Social Comparison Theory (Festinger, 1954) suggests that continuous upward comparison can easily trigger decreased self-efficacy and anxiety. In this study, ranking-sensitive students showed a 41.2% increase in exercise avoidance rate after their rankings declined. Third, misplaced sense of control—over-reliance on algorithmic recommendations may weaken students' autonomous decision-making abilities. Targeted intervention strategies include: (1) designing a "dual-track" feedback system that emphasizes individual growth curves while de-emphasizing group rankings; (2) establishing a "data literacy" curriculum module to cultivate critical data interpretation skills; (3) setting up "algorithm transparency days" to help students understand the logic of data generation; (4) introducing a "data vacation" mechanism, with unmonitored weeks set each month to protect psychological autonomy space; (5) emphasizing the principle of "data-assisted rather than data-driven" in teacher training, balancing quantitative assessment with qualitative observation.

6. Conclusion

Based on environmental behavior theory, this study systematically explored the implications of fitness APP data-driven teaching for physical education curriculum reform. Through a one-academic-year quasi-experimental study and structural equation modeling validation, the following core conclusions are drawn:

(1) The information environment constructed by fitness APPs has become an independent dimension influencing student exercise behavior, forming a three-dimensional support system together with physical and social environments. The path coefficient from information environment to environmental perception reaches 0.467 ($p<0.001$), confirming the central position of digital technology in the physical education ecosystem.

(2) Data-driven teaching significantly promotes in-class/extracurricular exercise linkage. Experimental group students' extracurricular exercise frequency increased by 126.2%, with APP usage rate remaining at 63.4% during summer vacation, validating the effectiveness of the linkage mechanism of "data connectivity—goal extension—behavioral transfer—habit consolidation."

(3) Self-efficacy and social support play critical mediating roles between environment and behavior, with mediating effects accounting for 73.6% of total effects, revealing the complete action chain of "environment—cognition—behavior" and emphasizing the central position of psychological construction in behavioral change.

(4) In-class/extracurricular linkage effectiveness is significantly moderated by goal orientation, social support, and environmental quality. High task-oriented students' linkage intensity (r=0.687) far exceeds ego-oriented students' (r=0.423), suggesting the importance of a "technology + environment" synergistic model, as technology application alone struggles to achieve optimal effects.

(5) Physical education curriculum reform should adhere to three major design principles: environmental continuity, support diversity, and feedback immediacy. It should construct a three-tier "school-community-family" physical space network, an "in-class—extracurricular—online" integrated social support network, and a unified data feedback system. Simultaneously, vigilance is required regarding risks such as the digital divide and over-quantification, seeking balance between technology empowerment and humanistic care, ultimately achieving the educational paradigm shift from knowledge and skill transmission toward healthy behavioral habit cultivation.

This study has the following limitations: First, the sample was limited to three middle schools in one province, with limited geographical representativeness. Future research should expand the sample scope to cover regions with different levels of economic development to enhance the external validity of the conclusions. Second, the research cycle was one academic year. Although behavioral transfer effects were observed, the long-term stability of exercise habits still requires verification through longer-term follow-up studies. Third, this study primarily used self-report scales to measure psychological variables, which may be subject to social desirability bias. Future research could incorporate objective measurement methods such as physiological indicators and wearable device data. Fourth, the study did not deeply explore the moderating effects of different sports activities and individual student differences (such as exercise foundation and personality traits) on the effectiveness of data-driven teaching. Future research directions include: developing data-driven teaching models suitable for different educational stages, exploring the application of artificial intelligence technology in personalized exercise prescriptions, and examining practical pathways for integrating digital technology with ideological and political education in physical education curricula. At the same time, attention should be paid to issues of technological ethics and educational equity to provide theoretical support for constructing a more scientific and humanistic smart physical education system.

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Conflicts of interest

The authors declare no conflicts of interest.

References

1. Zhang H B, Wang H B. Data security risks and legal countermeasures of virtual sports[J]. Journal of Shanghai University of Sport, 2025, 49(09): 33-47+90.
2. Ghorbel A, Romdhani A, Yaakoubi M, et al. Integrating gamified blended learning in gymnastics: effects on motor skill development, knowledge retention, and motivation in physical education settings[J]. Education and Information Technologies, 2025, (prepublish): 1-19.
3. Malinowski R P. To Race Match or Not? Exploring the Potential Benefits of Peer Tutors Who Are Racially Identical vs. Non-Identical to Students with Disabilities in Physical Education[J]. Journal of Physical Education, Recreation & Dance, 2025, 96(7): 40-44.
4. Sun Q C, Yang X P. Application of smart APPs in college students' extracurricular physical exercise[J]. Sports Goods and Technology, 2024, (21): 193-195.

5. McNamara S, Henly M, Craig P, et al. Gatekeeping and ableism in physical education provision for disabled children: perspectives and practices[J]. Qualitative Research in Sport, Exercise and Health, 2025, 17(5): 401-415.
6. Tomura T. Teachers' Communication Strategies to Promote Parental Involvement of Immigrants Regarding Physical Education[J]. Strategies, 2025, 38(5): 35-41.
7. Xu Y C, An S T, Li D L. Big data and athletic performance analysis: sports competition empowered by technology[J]. Sports Goods and Technology, 2024, (20): 40-42.
8. Athletic sports performance and data centers facilitate pathways and guarantees for digital upgrading of sports research[J]. Track and Field, 2024, (10): 84+72.
9. Przytula A, Kalisz P J. The Impact of Physical Education Attendance and Diet on Bone Mineralization in Adolescents[J]. Nutrients, 2025, 17(18): 3016-3016.
10. Zhao W. Research on the Reform Path of College Physical Education from the Perspective of Physical Health[J]. International Education Forum, 2025, 3(8): 98-104.
11. Xu Y, Sun Y, Liu Y, et al. Exploration of the Dilemmas and Paths in the Construction of Physical Education Teachers' Teams from the Perspective of the Integration of Ideological and Political Education in Courses across Primary, Secondary, and Higher Education[J]. Education Reform and Development, 2025, 7(8): 194-202.
12. Zhang S X, He D J, Wang Z X. Research on the logical rationale and practical strategies of applying smart physical education APPs in middle school physical education teaching[J]. Bulletin of Sport Science & Technology, 2024, 32(01): 229-230+233.
13. Yuan L X. Development of sports data analysis and decision support systems[J]. Sports Goods and Technology, 2023, (23): 142-144.
14. Guo C, Metwally S D, Abouagwa M, et al. An innovative statistical framework with properties and univariate analysis in physical education, reliability engineering, and radiation sector[J]. Journal of Radiation Research and Applied Sciences, 2025, 18(4): 101924-101924.
15. Liu P, Dastbaravardeh E. Deep Learning-Driven Assessment of Student Movement and Performance Using Physiological Data in Physical Education Information Systems: An S-AIoT Solution[J]. International Journal of Intelligent Systems, 2025, 2025(1): 9479311-9479311.
16. Holler C, Schüßler A. Gauging Acceptance: A Multifaceted Examination of Physical Ability and Its Role for Peer Networks in Adolescent Physical Education[J]. The Journal of Early Adolescence, 2025, 45(9): 1124-1151.
17. Fu H F. Information collection method for sports exercise intensity based on data mining[J]. Information Technology, 2023, (09): 114-118+124.
18. Jia L, Qi J. Investigation on the Cultivation of Physical Education Teachers' Teaching Ability[J]. Open Journal of Social Sciences, 2019, 7(3): 154-160.
19. Cañabate D, Martínez G, Rodríguez D, et al. Analysing Emotions and Social Skills in Physical Education[J]. Sustainability, 2018, 10(5): 1585-1585.
20. Ying Z. Design and Development of WEB-based Remote Network Physical Education Teaching Platform in Colleges and Universities[J]. International Journal of Emerging Technologies in Learning (iJET), 2018, 13(04): 150-150.
21. Zhao W J, Yu Z J, Lu B. Research and design of data collection and monitoring system for physical fitness indicators in sports training[J]. Journal of Ezhou University, 2023, 30(05): 102-104+108.
22. Dong Y H. Design of automated collection system for real-time sports data based on data mining[J]. Automation & Instrumentation, 2022, (10): 155-160.
23. Xie M. Design of a physical education training system based on an intelligent vision[J]. Computer Applications in Engineering Education, 2020, 29(3): 590-602.
24. Yuansheng Z. Evaluation of Physical Education Teaching Quality in Colleges Based on the Hybrid Technology of Data Mining and Hidden Markov Model[J]. International Journal of Emerging Technologies in Learning (iJET), 2020, 15(01): 4-4.
25. Yang Y, Meng L. Physical Education Motion Correction System Based on Virtual Reality Technology[J]. International Journal of Emerging Technologies in Learning (iJET), 2019, 14(13): 105-116.
26. Zhao L A. Analysis of pathways for big data technology in college sports risk control[J]. Office Automation, 2022, 27(20): 61-64.
27. Li X S. Research on intelligent sports wearable devices promoting college students' physical exercise under big data[J]. Sports Goods and Technology, 2022, (18): 184-186.
28. Wei C. Research on the Effectiveness of Probabilistic Stochastic Convolution Neural Network Algorithm in Physical Education Teaching Evaluation[J]. Computational Intelligence and Neuroscience, 2022, 2022: 4921846-4921846.
29. Idar L, Øyvind B, Magne K B, et al. Norwegian upper secondary students' experiences of their teachers' assessment of and for learning in physical education: examining how assessment is interpreted by students of different physical abilities[J]. Sport, Education and Society, 2022, 27(3): 320-331.

30. Peng G Q. Property rights allocation of sports data in smart sports venues in the era of big data[J]. Journal of Chengdu Sport University, 2022, 48(02): 38-42+61.
31. Hua R. Research on the application of fitness APPs integrated into online physical education teaching in colleges and universities[J]. Contemporary Sports Technology, 2021, 11(26): 93-95.
32. Jongho M, Yongnam P. Exploring South Korean Elementary School Classroom Teachers' Beliefs and Practices in Physical Education[J]. International Journal of Environmental Research and Public Health, 2022, 19(22): 15033-15033.
33. Wangda L. Effect of Rehabilitation Physical Training on PE Teaching Sports Injury under Ultrasonic Examination[J]. Scanning, 2022, 2022: 1470303-1470303.
34. Raquel P, Javier P, Óscar D, et al. Relevant Variables in the Stimulation of Psychological Well-Being in Physical Education: A Systematic Review[J]. Sustainability, 2022, 14(15): 9231-9231.
35. Yong C, Kaixuan C, Qinlong L. Application of Decision Tree in PE Teaching Analysis and Management under the Background of Big Data[J]. Computational Intelligence and Neuroscience, 2022, 2022: 8091838-8091838.
36. He F. Research on the integration of physical education and fitness APPs in the era of big data[J]. Contemporary Sports Technology, 2020, 10(18): 229-232.
37. Liu Z, Li J Q. Systematic closed-loop empowerment of sports data for coordinated development of sports, health and insurance[J]. Tsinghua Financial Review, 2020, (03): 48-50.
38. Zhang Z. Analysis of the application of modern mobile wireless network terminal in the tutoring design of college physical education course teaching[J]. Wireless Networks, 2023, 30(6): 5319-5331.
39. Yujia W. Exploration on the Operation Status and Optimization Strategy of Networked Teaching of Physical Education Curriculum Based on AI Algorithm[J]. International Journal of Information Technologies and Systems Approach (IJITSA), 2023, 16(3): 1-15.
40. Souid I. Physical Education Teachers in Tunisia Conception of Training Actors as a Source of Vulnerability[J]. Journal of Education, Society and Behavioural Science, 2023, 36(1): 61-71.
41. Scanning. Retracted: Effect of Rehabilitation Physical Training on PE Teaching Sports Injury under Ultrasonic Examination[J]. Scanning, 2023, 2023: 9879863-9879863.
42. Li L Y. Exploration of the impact of fitness APPs' "online teaching" and "data recording" functions on college physical education teaching reform[J]. Contemporary Sports Technology, 2019, 9(33): 129-130.
43. Feng K. Impact of sports data monitoring system on middle school physical education teaching[J]. Sports Goods and Technology, 2019, (18): 109-110.
44. Lorcan C, Rebecca G, Anthony M. A Qualitative Investigation of Teachers' Experiences of Life Skills Development in Physical Education[J]. Qualitative Research in Sport, Exercise and Health, 2023, 15(6): 789-804.
45. Juan R, Ling P, Jingjing R, et al. Modified Taxonomy method for double-valued neutrosophic number MADM and applications to physical education teaching quality evaluation in colleges and universities[J]. Journal of Intelligent & Fuzzy Systems, 2023, 44(6): 10581-10590.
46. Tao S. Method for 2-tuple linguistic neutrosophic number MAGDM and applications to physical education teaching quality evaluation in colleges and universities[J]. Journal of Intelligent & Fuzzy Systems, 2023, 44(3): 4233-4244.
47. Wu D. Analysis of the impact of data recording functions of fitness APPs on exercise[J]. Sports Goods and Technology, 2025, (09): 193-195.
48. Agiasotelis E, Karteroliotis K, Giossos Y, et al. The Effect of the CoI on Preservice Teachers' Self-Efficacy in Physical Education[J]. Trends in Higher Education, 2024, 3(4): 827-842.
49. Qi Z. Cloud IoT-Oriented Secure College Physical Education Teaching Platform Based on Deep Learning[J]. International Journal of Swarm Intelligence Research (IJSIR), 2024, 15(1): 1-21.
50. Zhang M B. Strategy for constructing a college campus fitness model based on "data cloud" using fitness APPs[J]. Sports Goods and Technology, 2023, (17): 193-195.
51. Tan L, Wang Z Y, Li J. Research on slow-paced exercise demand preferences based on fitness APP data analysis[J]. Journal of Chinese Urban Forestry, 2019, 17(06): 35-40.