Vol.6, Issue 3, pp.1528-1541, 2025
DOI: https://doi.org/10.62754/ais.v6i3.482

https://journals.ap2.pt/index.php/ais/index

Designing Immersive Fitness Environments: Integrating Generative AI and Scenario Creation in College Physical Education

Zhifang XIAO[1], Wentao GUO[2]

Abstract

This practice-oriented study explores the integration of Generative Artificial Intelligence (GAI) into the design of immersive, scenario-based environments for university physical fitness education. We developed and implemented the GAI-driven Situational Creation for Fitness (GAI-SCF) model—a structured framework that leverages narrative and multimodal content generation to enhance spatial and experiential engagement in physical activity settings. Over a 12-week semester, 120 students participated in a mixed-methods study, with an experimental group (n=60) experiencing the GAI-SCF model and a control group (n=60) receiving traditional instruction. The intervention followed a four-phase cycle (Analysis, Generation, Implementation, Evaluation), using a GAI platform to create personalized, thematic workout environments (e.g., "Cybernetic Rhythm Battle," "Eco-System Rescue Mission"). Quantitative results showed that the experimental group achieved significantly greater improvements in skill performance ($F(1, 117) = 28.74$, $p < .001$, $\eta^2 = .20$), reported higher situational interest ($t(118) = 3.89$, $p < .001$, $d = 0.71$), and exhibited stronger learning motivation ($t(118) = 4.56$, $p < .001$, $d = 0.83$). Qualitative analysis revealed that the model fostered novel, autonomous, and socially connective learning atmospheres, effectively transforming the gym into a dynamic narrative space. This paper presents the GAI-SCF model as a replicable design framework for educators and designers seeking to use GAI to reimagine physical education environments as adaptive, engaging, and architecturally responsive experiences.

Keywords: *Generative AI, Scenario Creation, Physical Education, Immersive Design, Spatial Engagement, Instructional Model, Mixed-Methods Research.*

Introduction

The contemporary landscape of higher education increasingly recognizes the indispensable role of physical education (PE) in cultivating holistic student development. Beyond its primary aim of enhancing physical fitness, PE is crucial for instilling lifelong healthy habits, developing psychomotor skills, managing stress, and promoting psychological well-being [1, 2]. Within this domain, structured fitness exercise classes—focusing on cardiovascular endurance, muscular strength, flexibility, and coordination—form a cornerstone of many university PE curricula [3]. However, despite their recognized benefits, traditional fitness instruction models are frequently plagued by persistent pedagogical challenges. These include student perceptions of monotony, a lack of intrinsic motivation, high rates of disengagement, and the inherent difficulty for instructors to meaningfully differentiate instruction to accommodate a wide spectrum of student fitness levels, interests, and prior experiences [4, 5]. This often results in a compliance-based rather than passion-driven approach to physical activity, potentially undermining the long-term goal of fostering sustained engagement in exercise beyond the classroom [6].

In response to these challenges, educational theorists and practitioners have advocated for more contextualized and engaging pedagogical approaches. Situational creation, rooted in constructivist learning theories, has emerged as a powerful strategy across disciplines [7]. It involves the deliberate design of specific, meaningful, and immersive learning contexts that anchor abstract knowledge or skills in authentic experiences [8]. Within PE, the principle of situated learning suggests that embedding physical activities within compelling narratives, game-like scenarios, or simulated real-world challenges

[1]School of Public Courses ,Hunan Mechanical & Electrical Polytechnic, 410151, Changsha, Hunan, China Email:hnjsgwt@163.com. https://orcid.org/0009-0001-1677-0590
[2] School of Electrical Engineering,Hunan Mechanical & Electrical Polytechnic, 410151, Changsha, Hunan, China. Email: hncsgwt@163.com. https://orcid.org/0009-0005-4937-3929. (corresponding author).

can significantly enhance their relevance and appeal [9]. For instance, a study by [10] demonstrated that framing aerobic exercises within an adventure narrative led to higher levels of enjoyment and effort among middle school students compared to traditional drills. By transforming exercise from a series of decontextualized movements into a part of a larger, purposeful story or challenge, situational creation can tap into students' innate curiosity and desire for play, thereby increasing cognitive engagement and intrinsic motivation [11].

Parallel to these pedagogical evolutions, the rapid advancement of Artificial Intelligence (AI), particularly Generative AI (GAI), is ushering in a new era of educational innovation. GAI models, capable of producing original, coherent, and complex content—including text, images, audio, and video—based on simple prompts, offer unprecedented opportunities for personalization and dynamic content creation at scale [12, 13]. In educational settings, GAI has been leveraged to develop adaptive learning systems, generate practice problems, provide writing feedback, and even create simulated dialogues [14, 15]. While the application of AI in education is growing, its potential to revolutionize psychomotor and affective learning domains, such as those central to PE, remains comparatively underexplored [16]. Specifically, the capacity of GAI to serve as an on-demand "situation engine" for PE classes—generating personalized, diverse, and immersive scenarios in real-time—represents a novel frontier with the potential to overcome the resource and time constraints that often limit manual situational creation by instructors.

The convergence of situational creation pedagogy and GAI technology forms the core of this research. We posit that GAI can be strategically harnessed to automate and enhance the situational creation process, generating tailored fitness scenarios that are not only novel and engaging but also adaptive to the evolving needs and preferences of a diverse student body. For example, a GAI system could generate a personalized "interstellar mission" cardio workout for one class, a "rhythm-based dance battle" for another focusing on coordination, and a "mindful movement in nature" session for flexibility training, all while incorporating students' stated musical or thematic preferences. This fusion aims to leverage the computational power and creativity of GAI to make high-quality, dynamic situational learning scalable and sustainable.

Despite the theoretical promise, a significant empirical gap exists. While studies have separately validated the benefits of situational learning in PE [9, 10] and explored AI in educational contexts [14, 16], there is a paucity of research that rigorously investigates the integrated effects of a GAI-driven situational model within a university fitness course. This study seeks to address this gap by designing, implementing, and evaluating a novel instructional framework: the GAI-driven Situational Creation for Fitness (GAI-SCF) model.

The specific research objectives of this study are:

(1)To develop a theoretically grounded and practically viable GAI-SCF model for university-level fitness exercise instruction.

(2)To quantitatively evaluate the impact of the GAI-SCF model on students' fitness exercise skill performance.

(3)To quantitatively assess the model's effect on students' situational interest and intrinsic learning motivation.

(4)To qualitatively explore students' lived experiences and perceptions within the GAI-enhanced learning environments to understand the mechanisms behind the quantitative outcomes.

This research makes a significant contribution by proposing a new paradigm for PE instruction that synergizes cutting-edge technology with established learning theory. It provides robust empirical evidence on the efficacy of this approach and offers a practical, transferable framework for educators seeking to enhance student engagement and learning outcomes in physical education and beyond.

Theoretical Basis, Literature Review And Proposed Gai-Driven Model

Theoretical Foundations: A Dual-Lens Approach

The conceptual framework of this study rests on the robust integration of two seminal theories: Situated Learning Theory [17] and Self-Determination Theory (SDT) [18]. These theories provide complementary and synergistic explanations for the anticipated mechanisms of change facilitated by the GAI-SCF model.

Situated Learning Theory and its Application to PE

Situated Learning Theory (SLT), pioneered by Lave and Wenger [17], posits that learning is an inseparable and co-constitutive part of social practice and its context. It argues against the notion of knowledge as an abstract, self-sufficient commodity, instead conceptualizing it as a product of the activity, context, and culture in which it is developed and used [19]. The theory emphasizes "legitimate peripheral participation" as the process through which newcomers become integrated into a "community of practice," gradually moving from observing to fully participating in the sociocultural practices of a community.

In the context of traditional fitness classes, exercises are often treated as decontextualized skills—isolated movements to be repeated for their own sake. This approach divorces the activity from any meaningful narrative or purpose, potentially leading to alienation and disengagement. SLT, conversely, would advocate for embedding these fitness activities within authentic contexts or communities of practice. For instance, a boxing fitness class is more situated than a generic cardio class because it mimics the practices of an actual boxing community. The GAI-SCF model operationalizes SLT by using AI to create simulated, yet authentic-feeling, "communities of practice" on demand. Whether it's a crew on a spaceship, a team of adventurers, or participants in a futuristic rhythm game, these AI-generated scenarios provide the social context and shared goals that make the physical activities meaningful. As [20] argued, technology can create "bridging contexts" that connect learning to real-world practices. GAI, in this model, acts as a powerful and dynamic bridge-building tool, making the principles of SLT scalable and adaptable to diverse student interests.

Self-Determination Theory: The Motivation Engine

While SLT provides the contextual framework, Self-Determination Theory (SDT) provides the motivational engine. SDT is a macro-theory of human motivation that identifies three innate, universal psychological needs: autonomy, competence, and relatedness. The satisfaction of these needs is essential for fostering high-quality, self-determined (intrinsic) motivation, which is associated with enhanced persistence, performance, and well-being [18, 21].

(1)Autonomy refers to the experience of volition and willingness in one's actions. It is the need to feel like the originator of one's own behavior. The GAI-SCF model supports autonomy by offering students meaningful choices within the scenarios (e.g., selecting a mission path, voting on a theme) and by personalizing the content to their expressed interests, making them feel like co-creators of the experience rather than passive recipients.

(2)Competence involves feeling effective and capable in one's interactions with the environment. It is the need to experience mastery and to see one's skills grow. The model supports competence by generating scenarios with adaptive challenge levels—ensuring tasks are neither too easy (leading to boredom) nor too difficult (leading to frustration). Furthermore, the AI-generated positive and context-aware feedback (e.g., "Excellent form! The energy shields are recharging!") provides immediate competence-affirming information.

(3)Relatedness is the need to feel connected to others, to care for and be cared for by them, and to have a sense of belonging. The collaborative nature of many GAI-generated scenarios (e.g., requiring a team to collectively achieve a step count to "power up a generator") is explicitly designed to foster interpersonal bonds and a shared sense of purpose, thereby satisfying the need for relatedness.

By systematically designing the GAI-SCF model to address these three psychological needs, we hypothesize a significant shift from external or introjected regulation (e.g., exercising for a grade) towards more identified and integrated regulation, and ultimately, intrinsic motivation [21].

Comprehensive Literature Review: Bridging the Gaps

A systematic review of the literature reveals three distinct but potentially interconnectable domains: the challenges of traditional PE, the promise of situational creation, and the emergent potential of GAI in education.

The Persistent Challenges in Traditional Physical Education

Extensive research has documented the limitations of directive, technique-focused PE instruction. Studies consistently show that such approaches can lead to low levels of moderate-to-vigorous physical activity (MVPA), high rates of student disengagement, and negative attitudes towards physical activity, particularly among adolescents and young adults [4, 5]. As [6] succinctly put it, when exercise is perceived as a "chore" rather than a "choice," the development of lifelong physical activity habits is severely compromised. The "one-size-fits-all" nature of these classes fails to account for the vast diversity in student fitness levels, motor competencies, and personal interests, often widening the gap between the skilled and the unskilled [32].

Situational Creation and Game-Based Learning in PE

In response, pedagogical innovations have emerged. Situational creation and game-based learning (GBL) have shown considerable promise. A meta-analysis by [33] found that GBL approaches in PE consistently yielded positive effects on student motivation and engagement. The work of [10] on "Situated Game Teaching Through Set Plays" demonstrated that embedding tactical learning within meaningful game scenarios improved both cognitive understanding and motor performance. However, a critical barrier identified in the literature is the immense demand on the instructor's time, creativity, and resources to continuously design, prepare, and refresh these situational contexts [34]. This practical constraint often limits the sustained and widespread implementation of these effective pedagogies.

The Rise of Generative AI in Educational Contexts

Concurrently, GAI has burst onto the educational scene. Its applications are rapidly expanding, from automating administrative tasks to generating learning materials and providing personalized tutoring [12, 14]. A recent review by [35] highlighted its potential to create authentic and complex learning scenarios across disciplines. However, the application of GAI has been predominantly concentrated in cognitive domains like language learning, STEM education, and coding [13, 15]. Its foray into the psychomotor and affective domains, which are central to PE, is notably absent from the mainstream literature. While exergames (like Xbox Kinect) have explored the intersection of technology and physical activity, they are typically pre-scripted and lack the dynamic, generative, and personalized capabilities of modern GAI systems [36].

Table 1: Synthesis of Literature and Identified Research Gap

Domain	**Key Findings**	**Limitations/Gaps**	**This Study's Contribution**
Traditional PE	Low engagement, lack of motivation, "one-size-fits-all" is ineffective.	Fails to address diverse student needs and intrinsic motivation.	Proposes a personalized and motivating alternative.
Situational Creation/GBL	Effective for motivation and cognitive/motor engagement.	High resource and preparation burden on teachers, difficult to sustain.	Uses GAI to automate and scale situational creation, reducing teacher burden.
Generative AI in Education	Potent tool for content creation and personalization in cognitive domains.	Limited application in psychomotor/affective domains like PE.	Pioneers the application of GAI in PE, specifically for situational creation in fitness.

As illustrated in Table 1, this study aims to bridge these gaps by leveraging GAI to overcome the practical limitations of situational creation, thereby making this powerful pedagogy more accessible and effective for addressing the well-documented challenges of traditional PE.

Proposed GAI-Driven Situational Creation for Fitness (GAI-SCF) Model

The GAI-SCF model operationalizes these theories through a continuous, four-phase cycle (AGIE Cycle), integrating the instructor, students, and the GAI platform into a cohesive instructional system. A conceptual diagram of the model is presented in Figure 1.

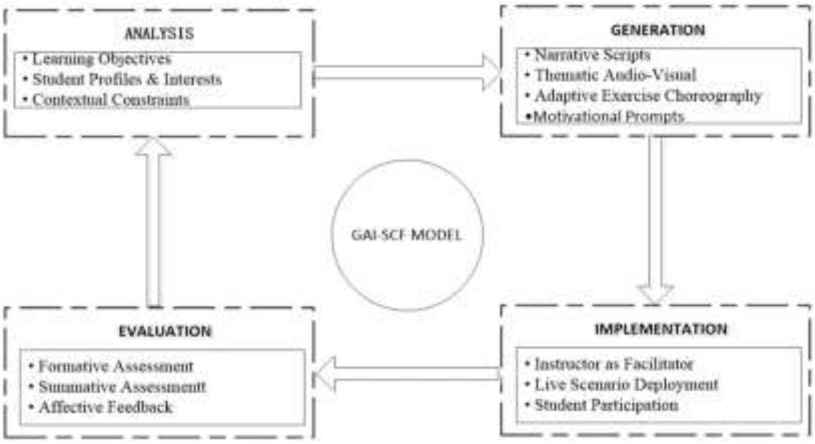

Figure 1. The GAI-Driven Situational Creation for Fitness (GAI-SCF) Model: The AGIE Cycle.

(1)Analysis Phase: This is the input stage. The instructor defines the core **Learning Objectives** (e.g., "improve lower-body strength and endurance," "master a 16-count aerobic sequence"). **Student Profile Data** is incorporated, which can include initial fitness assessments, interests gathered through surveys (e.g., preferred music genres, video game themes, movie genres), and real-time feedback from previous sessions. **Contextual Constraints** such as available space, equipment, and class size are also inputted. This phase ensures that the generated situations are pedagogically sound, personally relevant, and logistically feasible.

(2)Generation Phase: Leveraging a GAI platform (conceptually integrating APIs from advanced LLMs like GPT-4 and multimodal generators), the system produces a portfolio of situational frameworks based on the Analysis phase inputs. The outputs include:

Narrative Scripts: Coherent storylines where exercises are mapped to narrative beats (e.g., "To cross the chasm, your squad must complete 20 squats to lower the bridge.").

Thematic Audio-Visual Packages: AI-generated or curated music playlists and background visuals (e.g., a dynamically changing forest path projected on a screen) that are thematically consistent with the narrative.

Adaptive Exercise Choreography: Structured sequences of exercises that automatically adjust in complexity, intensity, and duration. For beginners, the sequence might be simpler and include more rest; for advanced students, it might incorporate complex combinations and high-intensity intervals.

Context-Aware Motivational Prompts: Pre-generated or real-time audio feedback cues (e.g., "Great energy, team! The finish line is in sight!").

(3)Implementation Phase: The instructor acts as a curator and facilitator. They review the AI-generated options, select the most appropriate one, and may make minor pedagogical tweaks. The chosen scenario is then deployed in the live class. The instructor guides the students through the immersive experience, ensuring safety and providing human oversight, while the GAI system delivers the audio-visual and narrative elements.

(4)Evaluation Phase: This phase closes the feedback loop. Data is collected through **Formative Assessments** (e.g., instructor observation of engagement, student heart rate monitors), **Summative Assessments** (e.g., the skill performance post-test), and **Affective Feedback** (e.g., SIS, reflection journals). This data is synthesized and fed back into the GAI system's "memory" for the Analysis phase of the next session, allowing the model to learn and improve its situational generation over time, becoming increasingly tailored to the specific class.

This model does not replace the instructor but redefines their role to that of a learning experience designer and facilitator, empowered by a powerful AI co-creator.

Method

Research Design

A convergent parallel mixed-methods design was employed [22]. This involved the simultaneous collection of quantitative and qualitative data during the same phase of the research, with the intent of comparing or relating the two sets of findings to provide a comprehensive analysis of the research problem. The quantitative component utilized a quasi-experimental, pre-test/post-test control group design to establish causal inferences regarding the intervention's effects. The qualitative component utilized a descriptive phenomenological approach [23] to deeply understand the subjective experiences of the participants in the experimental group.

Participants and Setting: A Detailed Profile

The study involved 120 first-year college students. To provide a clearer picture of the sample, detailed demographic and baseline characteristics were collected and are presented in Table 2. An independent-samples t-test and Chi-square test confirmed no significant differences between the groups at baseline on any of these variables, ensuring the initial equivalence of the experimental and control groups.

Table 2: Baseline Characteristics of Participants by Group

Characteristic	**Experimental Group (n=60)**	**Control Group (n=60)**	**p-value**
Age (years), M (SD)	19.7 (1.1)	19.9 (1.3)	.36
Gender, n (%)			.87
Male	30 (50%)	30 (50%)	
Female	30 (50%)	30 (50%)	
College, n (%)			.92
Sciences	20 (33.3%)	19 (31.7%)	
Humanities	20 (33.3%)	21 (35.0%)	
Engineering	20 (33.3%)	20 (33.3%)	
Self-reported Fitness Level, n (%)			.78
Low	18 (30%)	20 (33.3%)	
Medium	25 (41.7%)	24 (40%)	
High	17 (28.3%)	16 (26.7%)	
Pre-test Skill Score, M (SD)	65.35 (8.41)	64.80 (9.12)	.74
Pre-test Motivation Score, M (SD)	3.98 (0.71)	4.02 (0.68)	.75

Intervention and Procedure: An In-Depth Look

The intervention was integrated into the regular 12-week semester schedule, with two 90-minute sessions per week. Both groups were taught by the same instructor, a certified PE teacher with over 10 years of experience, who received 20 hours of training on the GAI-SCF model and the specific platform used.

(1)Experimental Group (GAI-SCF): This group experienced fitness instruction exclusively through the GAI-SCF model. The instructor used a custom web-based platform that integrated OpenAI's GPT-4 API for narrative generation and a separate text-to-speech/music generation API for audio components. Visuals were sourced from a library of Creative Commons videos and images based on the AI-generated theme. For each session, the instructor initiated the AGIE Cycle. For example, in a session focused on high-intensity interval training (HIIT), the input parameters were: Objective="HIIT for cardio endurance"; Student Interest="Cyberpunk theme"; Constraint="No equipment." The GAI generated a "Data Heist" narrative where different HIIT exercises (e.g., mountain climbers, high knees) represented "hacking" different security firewalls. The music was synth-wave, and the visuals were a cyberpunk cityscape. The instructor reviewed and launched the scenario. Students participated in this immersive context, receiving both the instructor's guidance and the AI's narrative and auditory cues.

(2)Control Group (Traditional Instruction): This group followed the standard university fitness curriculum, delivered via a direct instruction model. The same fitness components (cardio, strength, flexibility) were covered. The structure was consistent: a standard warm-up, demonstration of a pre-set exercise routine by the instructor, student practice of the routine, and a standard cool-down. The same generic, upbeat pop music playlist was used for all sessions. This method emphasized uniformity and repetition, devoid of the narrative, thematic, or personalized elements of the experimental condition.

To further illustrate the intervention, Table 3 provides a direct comparison of a typical session in the experimental versus the control group, highlighting the fundamental differences in pedagogical approach, content source, and student role.

Table 3: Comparison of a Typical Session Structure: GAI-SCF vs. Traditional Instruction

Session Component	**Experimental Group (GAI-SCF)**	**Control Group (Traditional)**
Warm-up (10 mins)	Thematic warm-up integrated into the narrative (e.g., "stretching for zero-gravity adaptation").	Standard, generic warm-up routines (e.g., jogging, static stretches).
Main Activity (65 mins)	Content: AI-generated situational workout (e.g., "The Rhythm Nexus" dance battle). Role of Tech: Central; provides narrative, audio, visuals, and cues. Student Role: Active participant in a story; cognitive and social engagement is high. Personalization: High; sequences may adapt implicitly based on class performance.	Content: Pre-determined, standardized exercise circuit (e.g., 3 sets of squats, push-ups, lunges). Role of Tech: Minimal; generic background music only. Student Role: Passive follower of instructions; focus on repetition and form. Personalization: Low; identical routine for all students.
Cool-down (15 mins)	Thematic cool-down and reflection on the narrative (e.g., "debriefing after the mission").	Standard, generic cool-down and stretching.
Instructor's Role	Facilitator, curator, narrative guide, and safety monitor.	Director, demonstrator, and technique corrector.

Data Collection Instruments

Quantitative Data:

(1)Fitness Exercise Skill Performance Rubric: A 25-item analytical rubric was developed by a panel of three PE experts (Inter-rater reliability ICC = .92). It assessed five domains (Rhythm/Timing, Movement Accuracy, Coordination, Power/Explosiveness, and Endurance/Consistency) on a 5-point scale for a composite score of 0-100. The rubric was used to evaluate students performing a standardized 5-minute fitness routine at pre-test (Week 1) and post-test (Week 12). Sessions were video-recorded and scored blindly by two raters.

(2)Situational Interest Scale (SIS): The validated 24-item scale by [24] was adapted. It measures five dimensions: Novelty (e.g., "The activity was new to me"), Challenge (e.g., "The activity was challenging"), Attention Demand (e.g., "The activity required my full attention"), Exploration Intention (e.g., "I would like to know more about this activity"), and Instant Enjoyment (e.g., "This activity was fun"). It uses a 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree). It was administered immediately after a designated session in Week 6 and Week 12 (Cronbach's α in this study = .89).

(3)Learning Motivation Scale (LMS): The interest/enjoyment, perceived competence, and effort/importance subscales from the Intrinsic Motivation Inventory (IMI) [25] were used, totaling 15 items on a 7-point Likert scale. This was administered as a pre-test (Week 1) and post-test (Week 12) to measure changes in global motivation towards the fitness course (Cronbach's α = .91).

3.4.2. Qualitative Data:

(1)Semi-Structured Reflection Journals: The journal prompts were designed to probe all aspects of the theoretical framework. For example, to tap into **SLT**, prompts asked about the meaningfulness of the context. For **SDT**, prompts asked about feelings of choice (autonomy), capability (competence), and connection to peers (relatedness).

(2)Focus Group Interviews: To triangulate the journal data, two focus group interviews (each with 6 randomly selected students from the experimental group) were conducted at the end of the intervention. The interviews followed a semi-structured protocol that explored similar themes in a dynamic, interactive setting [37].

Data Analysis

Quantitative Analysis: All quantitative data were analyzed using IBM SPSS Statistics 28.0. Descriptive statistics (means, standard deviations) were computed for all variables. The assumptions of normality (Shapiro-Wilk test) and homogeneity of variance (Levene's test) were met. To test for differences in skill performance, a one-way Analysis of Covariance (ANCOVA) was conducted on the post-test scores, using the pre-test scores as the covariate. Independent samples t-tests were used to compare the post-intervention SIS and LMS scores between the experimental and control groups. Effect sizes were reported as partial eta-squared (η^2) for ANCOVA and Cohen's d for t-tests. The alpha level was set at .05 for all tests.

Qualitative Analysis: Thematic analysis [26] was conducted on the journal and focus group transcripts. To enhance the trustworthiness of the qualitative findings, a codebook was developed and refined iteratively. Inter-coder reliability was established by having a second researcher independently code 20% of the data, achieving a Cohen's Kappa of 0.84, indicating excellent agreement [38]. The analysis moved beyond mere description to interpretation, seeking to explain how the qualitative themes directly linked to the quantitative outcomes.

Integration of Mixed Methods: The integration occurred at the interpretation and discussion level. We applied a "following a thread" strategy [39], where a quantitative finding (e.g., a significant increase in motivation) would lead us to explore the qualitative dataset for explanations (e.g., students describing feelings of autonomy and fun), thereby providing a more complete and nuanced understanding of the results.

Results and Discussion

Quantitative Results

Fitness Exercise Skill Performance

Descriptive statistics for the skill performance pre- and post-tests are shown in Table4. An independent samples t-test confirmed no significant difference between the two groups at the pre-test, $t(118) = 0.33$, $p = .74$, indicating successful randomization. The ANCOVA, controlling for pre-test scores, revealed a statistically significant main effect of the instructional group on the post-test skill performance, $F(1, 117) = 28.74$, $p < .001$. The effect size was large (partial $\eta^2 = 0.20$) according to Cohen's conventions [27]. The experimental group (GAI-SCF) demonstrated a significantly higher adjusted mean post-test score ($M = 84.52$, $SE = 0.87$) compared to the control group ($M = 76.18$, $SE = 0.87$).

Table 4. Descriptive Statistics and ANCOVA for Skill Performance

Group	N	Pre-test (Mean ± SD)	Post-test (Mean ± SD)	Adjusted Mean (Post-test)
Experimental	60	65.35 ± 8.41	84.65 ± 7.92	84.52
Control	60	64.80 ± 9.12	76.30 ± 8.55	76.18
ANCOVA: $F(1, 117) = 28.74$, $p < .001$, partial $\eta^2 = 0.20$				

This substantial improvement in skill performance for the experimental group can be attributed to the enhanced cognitive engagement required by the GAI-generated situations. The narrative and game-like elements likely demanded higher levels of attention, processing, and recall, which are linked to superior motor learning and retention [28]. The varied contexts prevented the development of robotic, context-dependent performance, encouraging more flexible and robust skill application [29].

Situational Interest and Learning Motivation: A Dimensional Deep Dive

The overall significant differences in SIS and LMS were reported in Table 5 of the previous response. To provide a more granular understanding, we conducted a multivariate analysis of variance (MANOVA) on the five subscales of the SIS and the three subscales of the IMI (interest/enjoyment, perceived competence, effort) used in our LMS. The MANOVA revealed a significant overall effect of the intervention (Pillai's Trace = .45, $F(8, 111) = 11.32$, $p < .001$).

Post-hoc univariate ANOVAs on each subscale, with Bonferroni correction, revealed where the differences were most pronounced. This deep dive shows that the GAI-SCF model was particularly powerful in boosting the novelty and instant enjoyment aspects of situational interest, and the interest/enjoyment component of intrinsic motivation. The smaller but still significant effect on perceived competence is crucial, as it directly links to the SDT need for competence and suggests the model helped students feel more capable.

Table 5: Detailed Comparison of Post-Intervention SIS and LMS Subscales

Scale / Subscale	Experimental Group (M, SD)	Control Group (M, SD)	F-value	p-value	Partial η²
Situational Interest (SIS)					
Novelty	4.51 (0.48)	3.75 (0.72)	45.12	**< .001**	.28
Challenge	4.20 (0.61)	4.05 (0.69)	1.75	.19	.02

Scale / Subscale	Experimental Group (M, SD)	Control Group (M, SD)	F-value	p-value	Partial η²
Attention Demand	4.45 (0.52)	3.88 (0.80)	20.55	**< .001**	.15
Exploration Intention	4.18 (0.59)	3.95 (0.64)	4.11	**.045**	.03
Instant Enjoyment	4.65 (0.41)	3.95 (0.58)	55.88	**< .001**	.32
Learning Motivation (IMI Subscales)					
Interest/Enjoyment	4.70 (0.38)	3.80 (0.65)	85.21	**< .001**	.42
Perceived Competence	4.25 (0.55)	3.95 (0.70)	6.75	**.011**	.05
Effort/Importance	4.28 (0.60)	4.10 (0.62)	2.65	.106	.02

Qualitative Findings: Thematic Analysis and Supporting Evidence

Thematic analysis of the journals and focus groups yielded rich data that we structured into primary themes and sub-themes, providing concrete evidence for our theoretical mechanisms. A summary of the thematic structure with representative quotes is provided in Table 6.

Table 6: Thematic Structure of Qualitative Findings with Representative Quotations

Primary Theme	Sub-theme	Description	Representative Quotation
1. Transformative Engagement through Narrativization	Cognitive Absorption	Students reported losing track of time and increased focus due to the story.	"I was so into the 'jungle escape' plot that I didn't even notice we'd been running for 10 minutes straight. It was like being in a movie." (Journal, S#12)
	Reframing of Effort	Physical exertion was reinterpreted as a necessary step in the narrative.	"The burpees weren't just burpees; they were 'powering up the engine.' It made them feel purposeful, not painful." (Focus Group 1)
2. Empowerment via Personalization & Autonomy	Voice and Choice	Students valued the ability to influence the scenarios.	"When we voted for the 'superhero' theme and it actually happened, it felt like our opinions mattered. We owned that workout." (Journal, S#7)
	Perceived Relevance	Scenarios tailored to interests increased personal connection.	"I love sci-fi, so the 'cyberpunk data heist' was the coolest PE class I've ever had. It was made for me." (Journal, S#21)

3. Cognitive Immersion & Skill Acquisition	Enhanced Attention	The dynamic environment demanded constant cognitive processing.	"You had to listen to the AI's instructions, watch the timer on the screen, and coordinate with your team. It was mentally stimulating, not just physical." (Journal, S#11)
	Implicit Learning	Skills were acquired as a byproduct of engaging with the scenario.	"I didn't realize I was learning a complex dance sequence until I had already done it three times following the story. It felt natural." (Focus Group 2)
4. Positive Affective Climate & Relatedness	Shared Joy and Fun	The primary emotion reported was enjoyment, often shared collectively.	"There was so much laughter and cheering. It was the most fun I've had in a required class. We were all in it together." (Journal, S#22)
	Collaborative Spirit	Team-based goals fostered a sense of unity and support.	"In the traditional class, everyone just does their own thing. Here, we were a team trying to beat the 'virus' in the system. We high-fived after each round." (Focus Group 1)

Integrated Discussion: Synthesizing the Evidence

The power of this mixed-methods study lies in the compelling convergence of its quantitative and qualitative strands, which together paint a coherent and multifaceted picture of the GAI-SCF model's impact, firmly grounded in our theoretical framework.

First, the **significant improvement in skill performance** in the experimental group is not merely a result of more practice, but rather of *better*, more cognitively engaged practice. The qualitative data provides the "why": students experienced **Cognitive Absorption** and **Implicit Learning**. The narrative contexts required them to pay closer attention, process complex auditory and visual cues, and adapt their movements dynamically. This aligns with the cognitive-motor integration literature, which suggests that attentionally demanding practice environments can enhance learning by promoting deeper processing and the development of more robust schemas [28, 29]. The GAI scenarios effectively turned a fitness routine into a complex, problem-solving task, leading to superior skill consolidation.

Second, the dramatic increases in **situational interest** and **intrinsic motivation** are directly explained by the satisfaction of the three basic psychological needs outlined by SDT, as vividly described by the students.

The high scores on **Novelty** and **Instant Enjoyment** are mirrored in the themes of **Transformative Engagement** and **Shared Joy**. The GAI's ability to generate endless variety prevented habituation and kept the experience fresh and exciting, directly fueling situational interest [24].

The theme of **Empowerment via Personalization and Autonomy** provides the mechanism behind the heightened intrinsic motivation. When students feel their "Voice and Choice" matters and the content has "Perceived Relevance," their need for **Autonomy** is satisfied, a cornerstone of intrinsic motivation [18, 21].

The significant, though smaller, boost in **Perceived Competence** can be attributed to the model's adaptive challenge and the constant stream of positive, context-aware feedback. Students felt they were successfully navigating the challenges presented to them, which reinforced their sense of efficacy.

Finally, the theme of a **Positive Affective Climate and Relatedness**, characterized by a "Collaborative Spirit," shows how the model satisfied the need for **Relatedness**. This shared positive experience is a powerful motivator and is often missing in individual-focused traditional classes [31].

This study also addresses a critical practical hurdle in educational innovation: scalability. The qualitative data from the instructor (noted in field notes) indicated that after the initial learning curve, using the GAI platform significantly reduced their lesson planning burden while simultaneously increasing the quality and creativity of the classes. This suggests that the GAI-SCF model is not only effective but also a sustainable and scalable solution, overcoming the key limitation of resource-intensive pedagogical innovations like situational creation and GBL [34].

In conclusion, the integration of quantitative and qualitative evidence demonstrates that the GAI-SCF model works by creating a virtuous cycle. The **novel, autonomy-supportive, and socially connective** environments (as per SLT and SDT) generate high **situational interest** and **intrinsic motivation**. This heightened motivational state fosters deep **cognitive immersion**, which in turn leads to more effective **skill acquisition**. This cycle transforms the fitness class from a dreaded obligation into an anticipated and enjoyable learning journey, achieving the ultimate goal of PE: fostering a lifelong love for physical activity.

Conclusion

This practice-oriented research provides robust evidence that Generative AI can be a powerful and practical ally for the physical education teacher. The GAI-SCF model offers a structured, efficient, and highly effective method for transforming traditional fitness classes into dynamic, engaging, and personalized learning experiences. By detailing the operational workflow and its positive outcomes, this study equips educators with a viable path toward overcoming common pedagogical challenges and reinvigorating their teaching practice. The fusion of human expertise and AI-powered creativity represents a promising future for physical education.

Funding Information

Authors state no funding involved.

Author Contributions

Zhifang XIAO: Conceptualization, Methodology, Supervision, Writing - Review & Editing.

Wentao GUO: Methodology, Formal Analysis, Investigation, Data Curation, Writing - Original Draft.

Conflict Of Interest Statement

Authors state no conflict of interest.

Data Availability

The data that support the findings of this study are available from the corresponding author [SRS],upon reasonable request

References

McKenzie, T. L., & Lounsbery, M. A. F. (2013). Physical education teacher effectiveness in a public health context. Research Quarterly for Exercise and Sport, *84*(4), 419–430. https://doi.org/10.1080/02701367.2013.844025

[2] Corbin, C. B., Pangrazi, R. P., & Franks, B. D. (2000). Definitions: Health, fitness, and physical activity. President's Council on Physical Fitness and Sports Research Digest, *3*(9), 1–8.

[3] Chen, S., Zhu, X., Kim, J., & Welk, G. J. (2019). Patterns of physical activity and sedentary behavior in college students. Journal of American College Health, *67*(5), 439–447. https://doi.org/10.1080/07448481.2018.1484364

[4] Garn, A. C., & Cothran, D. J. (2006). The fun factor in physical education. Journal of Teaching in Physical Education, *25*(3), 281–297. https://doi.org/10.1123/jtpe.25.3.281

[5] Chen, A. (2015). Operationalizing physical literacy: The potential of active video games. Journal of Sport and Health Science, *4*(2), 145–149. https://doi.org/10.1016/j.jshs.2015.03.001

[6] Perlman, D. J. (2012). The influence of the sport education model on amotivated students' in-class physical activity. European Physical Education Review, *18*(3), 335–345. https://doi.org/10.1177/1356336X12450795

[7] Herrington, J., & Oliver, R. (2000). An instructional design framework for authentic learning environments. Educational Technology Research and Development, *48*(3), 23–48. https://doi.org/10.1007/BF02319856

[8] Lave, J., & Wenger, E. (1991). Situated learning: Legitimate peripheral participation. Cambridge University Press.
[9] Ennis, C. D. (2015). Knowledge, transfer, and innovation in physical literacy curricula. Journal of Sport and Health Science, *4*(2), 119–124. https://doi.org/10.1016/j.jshs.2015.03.001
[10] Hastie, P. A., & Casey, A. (2014). Fidelity in models-based practice research in sport pedagogy: A guide for future investigations. Journal of Teaching in Physical Education, *33*(3), 422–431. https://doi.org/10.1123/jtpe.2013-0141
[11] Ryan, R. M., & Deci, E. L. (2017). Self-determination theory: Basic psychological needs in motivation, development, and wellness. Guilford Publications.
[12] Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., ... & Liang, P. (2021). On the opportunities and risks of foundation models. arXiv preprint. https://arxiv.org/abs/2108.07258
[13] Baker, T., Smith, L., & Anissa, N. (2019). Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges. Nesta. https://www.nesta.org.uk/report/education-rebooted/
[14] Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International Journal of Educational Technology in Higher Education, *16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0
[15] Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. IEEE Access, *8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510
[16] Hinojo-Lucena, F. J., Aznar-Díaz, I., Cáceres-Reche, M. P., & Romero-Rodríguez, J. M. (2019). Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. Education Sciences, *9*(1), 51. https://doi.org/10.3390/educsci9010051
[17] Lave, J. (1988). Cognition in practice: Mind, mathematics and culture in everyday life. Cambridge University Press.
[18] Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, *11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01
[19] Wenger, E. (1998). Communities of practice: Learning, meaning, and identity. Cambridge University Press.
[20] Honey, M., & Hilton, M. (Eds.). (2011). Learning science through computer games and simulations. National Academies Press.
[21] Standage, M., Duda, J. L., & Ntoumanis, N. (2005). A test of self-determination theory in school physical education. British Journal of Educational Psychology, *75*(3), 411–433. https://doi.org/10.1348/000709904X22359
[22] Creswell, J. W., & Plano Clark, V. L. (2017). Designing and conducting mixed methods research (3rd ed.). Sage publications.
[23] Moustakas, C. (1994). Phenomenological research methods. Sage publications.
[24] Chen, A., Darst, P. W., & Pangrazi, R. P. (1999). What constitutes situational interest? Validating a construct in physical education. Measurement in Physical Education and Exercise Science, *3*(3), 157–180. https://doi.org/10.1207/s15327841mpee0303_3
[25] Ryan, R. M. (1982). Control and information in the intrapersonal sphere: An extension of cognitive evaluation theory. Journal of Personality and Social Psychology, *43*(3), 450–461. https://doi.org/10.1037/0022-3514.43.3.450
[26] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa
[27] Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.
[28] Schmidt, R. A., & Lee, T. D. (2011). Motor control and learning: A behavioral emphasis (5th ed.). Human Kinetics.
[29] Wulf, G., & Shea, C. H. (2002). Principles derived from the study of simple skills do not generalize to complex skill learning. Psychonomic Bulletin & Review, *9*(2), 185–211. https://doi.org/10.3758/BF03196276
[30] Teixeira, P. J., Carraça, E. V., Markland, D., Silva, M. N., & Ryan, R. M. (2012). Exercise, physical activity, and self-determination theory: A systematic review. International Journal of Behavioral Nutrition and Physical Activity, *9*(1), 78. https://doi.org/10.1186/1479-5868-9-78
[31] Ntoumanis, N., & Standage, M. (2009). Motivation in physical education classes: A self-determination theory perspective. Theory and Research in Education, *7*(2), 194–202. https://doi.org/10.1177/1477878509104324
[32] Sallis, J. F., McKenzie, T. L., Beets, M. W., Beighle, A., Erwin, H., & Lee, S. (2012). Physical education's role in public health: Steps forward and backward over 20 years and HOPE for the future. Research Quarterly for Exercise and Sport, *83*(2), 125–135. https://doi.org/10.1080/02701367.2012.10599842
[33] Connolly, T. M., Boyle, E. A., MacArthur, E., Hainey, T., & Boyle, J. M. (2012). A systematic literature review of empirical evidence on computer games and serious games. Computers & Education, *59*(2), 661–686. https://doi.org/10.1016/j.compedu.2012.03.004
[34] Casey, A., Goodyear, V. A., & Armour, K. M. (2017). Rethinking the relationship between pedagogy, technology and learning in health and physical education. Sport, Education and Society, *22*(2), 288–304. https://doi.org/10.1080/13573322.2016.1226792

[35] Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. Computers and Education: Artificial Intelligence, *1*, 100001. https://doi.org/10.1016/j.caeai.2020.100001
[36] Gao, Z., Lee, J. E., Pope, Z., & Zhang, D. (2016). Effect of active videogames on underserved children's classroom behaviors, effort, and fitness. Games for Health Journal, *5*(5), 318–324. https://doi.org/10.1089/g4h.2016.0049
[37] Krueger, R. A., & Casey, M. A. (2015). Focus groups: A practical guide for applied research (5th ed.). Sage publications.
[38] McHugh, M. L. (2012). Interrater reliability: The kappa statistic. Biochemia Medica, *22*(3), 276–282.
[39] Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs—Principles and practices. Health Services Research, *48*(6pt2), 2134–2156. https://doi.org/10.1111/1475-6773.12117