Construction and Application of a Blended Teaching Model for the "Internal Control" Course Empowered by Artificial Intelligence

Qingjiao Rong[1,*], Huili Zhao[1]

[1]School of Accounting, Xijing University, Xi'an, Shaanxi, China

*Corresponding author: 957268471@qq.com

Keywords: Artificial Intelligence, Blended Teaching, Internal Control Education, Virtual Simulation, Personalized Learning

Abstract: This study proposes an AI-enhanced blended learning model for Internal Control education to address three pedagogical challenges: (1) overreliance on abstract frameworks that hinder practical application; (2) a disconnect between theory and practice; (3) homogenized instruction that neglects individual disparities. The model integrates intelligent diagnostics, dynamic content generation, and virtual simulations across pre-class, in-class, and post-class phases. Key innovations include a "diagnosis-update-simulation" framework converting theories (e.g., risk matrices) into immersive scenarios (e.g., supply chain disruptions), and a three-tier analytics system for personalized interventions. AI synchronizes curricula with real-time regulations (e.g., Data Security Law) and industry risks, while virtual labs enable decision-making practice with real-time feedback. Theoretically, the model extends blended learning into practice-intensive fields through AI adaptability. Practically, it offers a blueprint for curriculum modernization. Future work will validate scalability and expand simulations to organizational-level dynamics.

1. Introduction

The global digital transformation has fundamentally altered enterprise operations, creating unprecedented demands for internal control education. Traditional pedagogical approaches, heavily reliant on abstract frameworks like COSO and ISO 31000, fail to address three critical challenges in the digital era: (1) Overly theoretical concepts hinder practical application; (2) A persistent gap exists between classroom instruction and real-world scenarios, with over 60% of graduates reporting inadequate preparation for tasks like risk assessment and audit execution [1]; (3) Homogeneous teaching methods neglect individual learning disparities, leading to polarized outcomes.

To address these challenges, this study proposes an AI-enhanced blended learning model that integrates intelligent diagnostics, dynamic content generation, and virtual simulations. The model bridges the theory-practice divide by converting abstract principles into actionable competencies while enabling personalized learning pathways.

This research contributes to internal control education in three dimensions: (1) Theoretical innovation through a novel diagnosis-update-simulation framework, extending blended learning to practice-intensive domains; (2) Practical relevance via curriculum alignment with industry realities, such as real-time integration of regulatory updates (e.g., Data Security Law) and emerging risks (e.g., cybersecurity breaches); (3) Future-oriented design by outlining a roadmap for empirical validation and scalable implementation.

By leveraging AI as both an adaptive enabler and a catalyst for practical application, this study redefines internal control education as a dynamic, practice-driven discipline. It provides a scalable framework to modernize curricula, equipping students with technical proficiency and strategic agility for evolving business environments.

  DOI: 10.25236/iceesr.2025.061

2. Literature Review and Theoretical Foundations

2.1 Current Research on Blended Learning

Blended learning integrates online and offline instruction, overcoming traditional constraints through asynchronous and synchronous interactions[2]. This model balances autonomy and collaboration, combining online resources (e.g., video lectures) with offline activities (e.g., case analysis) to form a learning cycle. AI advancements further enhance this model through tools such as adaptive platforms that personalize learning paths and virtual labs that improve efficiency via 3D simulations [3, 4].

2.2 Core Functions of AI-Enabled Education

AI's role in education has evolved from a supplementary tool to a transformative force reshaping instructional paradigms. Its core functionalities can be categorized into three dimensions:

- Intelligent Diagnosis and Learning Analytics. AI constructs learner profiles using multidimensional data (e.g., engagement, assessment scores). IBM Watson's NLP identifies cognitive gaps; in a statistics course, it detected 62% misconceptions on "hypothesis testing," prompting interventions that raised mastery to 89% [5];
- Dynamic Content Generation and Updating. AI synchronizes content with industry trends. GPT-4 converts regulations (e.g., Data Security Law) into structured materials, such as case studies for supply chain disruptions [6];
- Virtual Simulation and Immersive Practice. Platforms like PwC's "Halo" simulate audit procedures, providing AI feedback. Users achieved 34% higher decision-making accuracy [7].

2.3 Instructional Challenges in Internal Control Courses

Existing research identifies three structural contradictions that constrain the pedagogical efficacy of Internal Control courses [1]:

- Disjunction between Theoretical Abstraction and Practical Application. Abstract concepts (e.g., COSO Framework) lack intuitive understanding. Only 28% of students could create "risk matrix diagrams" ;
- Skill Development Gaps and Scenario Deficiencies. Traditional methods fail to contextualize competencies (e.g., risk identification), leaving students unprepared for emergent risks;
- Homogenized Instruction vs. Individualized Needs. Divergent student proficiency levels exacerbate polarization in learning outcomes: high-achievers perceive content as rudimentary, while underprepared learners lag behind. Data from a vocational college demonstrated a standard deviation of 31% in mastery levels of the "Five Components of Internal Control" within a single cohort.

AI-enhanced blended learning models exhibit unique advantages in addressing these challenges by transforming abstract theories into visualizable contexts, enabling multidimensional decision-making drills, and facilitating targeted interventions.

3. Construction of the AI-Enhanced Blended Learning Model

3.1 Overall Framework Design

The AI-enhanced blended learning model proposed in this study adheres to three core principles—technology-driven innovation, closed-loop process design, and competency-oriented outcomes—aligned with the instructional objectives of the Internal Control course. Through bidirectional synergy between AI-enabled technological empowerment and pedagogical process design, the model establishes a closed-loop system encompassing "resource integration → intelligent diagnosis → dynamic instruction → practice reinforcement → outcome feedback" (as illustrated in Figure 1). This framework integrates three technological modules—intelligent diagnostic systems, dynamic content updating, and virtual simulation platforms—across pre-class, in-class, and post-class phases. It aims to achieve precise resource allocation, dynamic optimization of learning pathways, and systematic cultivation of practical competencies.

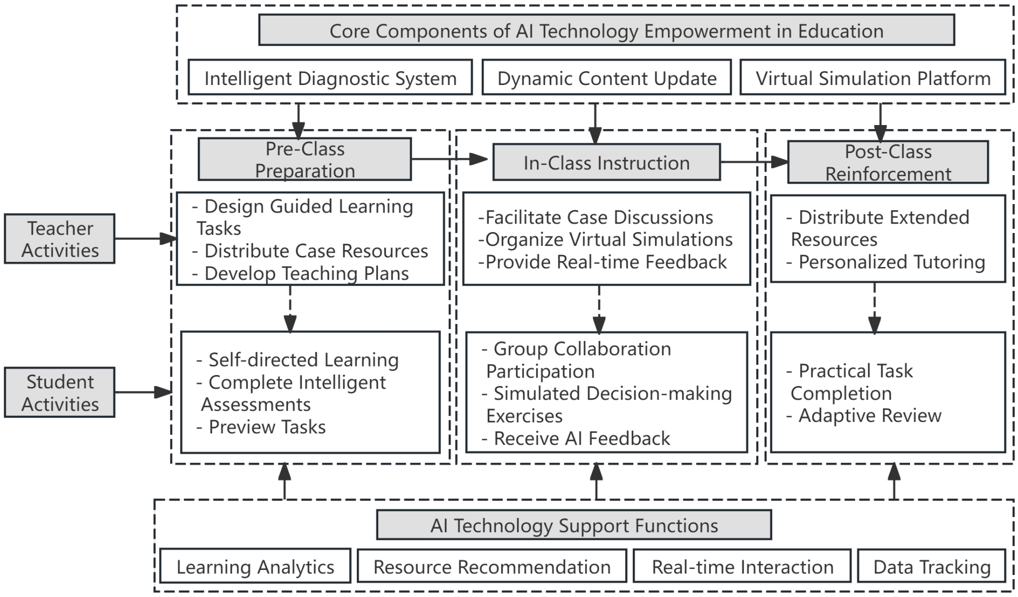

Fig.1 Framework of the AI-Enhanced Blended Learning Model for Internal Control Courses

3.1.1 Core AI-Driven Empowerment

(1) Intelligent Diagnostic System

Leveraging machine learning algorithms, the system dynamically collects student data from multiple touchpoints: pre-class preparation (e.g., video viewing duration, self-assessment accuracy), in-class interactions (e.g., question frequency, discussion participation), and post-class assignments (e.g., flowchart standardization, risk response plan feasibility). These data are synthesized to construct dynamic learner profiles. For instance, within the risk management module, the system identifies common errors in students' risk assessment models (e.g., conflating "inherent risk" and "residual risk") and generates personalized recommendations (e.g., delivering micro-lectures on "risk classification criteria").

(2) Dynamic Content Updating

Powered by natural language processing (NLP), the AI system autonomously curates real-world internal control cases (e.g., the Enron scandal, Luckin Coffee financial fraud) and emerging regulations (e.g., revised editions of Basic Standards for Enterprise Internal Control), transforming them into structured instructional resources. Emerging risks (e.g., data breaches) are converted into interactive case studies through NLP-driven content generation.

(3) Virtual Simulation Platform

Utilizing 3D modeling and AI decision engines, the platform constructs high-fidelity enterprise internal control scenarios. In the supply chain risk module, students simulate crisis scenarios such as "raw material shortages causing production line shutdowns." They employ AI tools to analyze supplier credit data, inventory turnover rates, and other metrics to formulate risk mitigation strategies. The system provides real-time feedback on decision outcomes (e.g., "procurement costs increase by 10%, but production capacity recovery improves by 60%").

3.1.2 Instructional Process Design

The model adopts a three-phase progression—pre-class, in-class, and post-class—to establish a cohesive instructional loop:

(1) Pre-Class Preparation

Instructors leverage AI to dynamically integrate industry reports (e.g., 2024 Global Risk Management Trends) and enterprise case databases, distributing personalized pre-class task packages to students. After self-directed learning, the system conducts intelligent assessments to predict knowledge gaps, providing data-driven insights to inform in-class teaching strategies.

(2) In-Class Instruction

A dual-track approach combining flipped classrooms and virtual simulations is employed. Instructors facilitate case discussions to deepen theoretical understanding while organizing risk decision-making drills in virtual environments. AI analyzes discussion content and operational logs in real time, generating immediate feedback (e.g., "insufficient risk coverage" or "redundant approval workflows").

(3) Post-Class Reinforcement

Based on AI-generated learning reports, instructors assign tiered extension tasks: foundational groups complete skill-specific exercises (e.g., "risk identification drills"), while advanced groups engage in applied projects (e.g., "AI audit bot development"). The system continuously monitors learning outcomes to iteratively refine subsequent instructional plans.

3.2 Instructional Phase Design and AI Applications

3.2.1 Pre-Class Phase

(1) Resource Integration and Intelligent Recommendation

Instructors use AI tools to aggregate real-time industry insights from sources like Bloomberg and Wind Database. The system generates personalized pre-class packages, including video lectures, interactive quizzes, and supplementary readings. It identifies weak knowledge areas and delivers targeted remedial materials.

(2) Dynamic Adjustment of Teaching Plans

AI analyzes class-wide pre-class performance to propose instructional optimizations, such as adjusting lecture durations and allocating more time to virtual simulations. The system adapts discussion topics based on learner preferences to enhance engagement.

3.2.2 In-Class Instruction Phase

(1) Theoretical Explanation with AI Enhancement

Instructors use AI-generated knowledge graphs to visualize risk management processes, clarifying logical chains between concepts. Students employ intelligent note-taking tools to flag questions, triggering real-time semantic analysis and contextual resource delivery.

(2) Virtual Simulation Practices

Students engage in simulated scenarios like "supply chain disruption risks," role-playing as internal control teams. They use AI tools to analyze real-time data and formulate mitigation strategies. The AI evaluates solutions and generates decision reports, while instructors guide students in reflecting on trade-offs.

(3) AI-Assisted Interaction and Q&A

During debates, AI captures student perspectives and visualizes high-frequency keywords. Voice assistants parse student queries, retrieving relevant guidelines and synthesizing case-based responses.

3.2.3 Post-Class Reinforcement Phase

(1) Assignment Evaluation and Feedback Optimization

AI assesses practical tasks like designing internal control flowcharts, generating scoring reports and remedial tutorials for common errors.

(2) Personalized Tutoring and Advanced Learning

AI tailors micro-courses for struggling students and provides advanced learners with applied projects like AI audit bot development. High-achievers simulate end-to-end audit workflows, with performance ranked based on detection accuracy.

3.3 AI-Driven Innovations

(1) Dynamic Content Generation Mechanism

Overcoming traditional textbook update cycles, this mechanism ensures alignment with industry advancements, addressing the "outdated case study" dilemma.

(2) Integrated Virtual-Physical Practice Loop

Virtual simulations enable "learning by doing," bridging the "theory-practice divide" inherent in conventional pedagogy.

(3) Three-Tier Learning Analytics System

Data-driven interventions operate at three levels: class-wide proficiency, group collaboration efficiency, and individual learning trajectories, ensuring precision in instructional adjustments.

4. Conclusion

This study proposes an AI-enhanced blended learning model for Internal Control education, aiming to address key pedagogical challenges. The model integrates intelligent diagnostics, dynamic content generation, and immersive virtual simulations, providing a theoretically grounded framework that bridges the gap between abstract theoretical frameworks and real-world applications while accommodating individual learning differences.

The model contributes to Internal Control education in three key ways. First, it bridges the theory-practice gap by converting abstract concepts into practical skills through a "diagnosis-update-simulation" framework, enabling students to apply theoretical principles in real-world scenarios. Second, it aligns curriculum with industry needs by dynamically updating content to reflect evolving regulations and emerging risks, ensuring students gain skills relevant to current challenges. Third, it supports personalized learning through a three-tier analytics system, addressing skill gaps at various levels and providing advanced learners with opportunities to engage in applied projects.

However, the model's practical implementation requires further validation. The effectiveness of virtual simulations depends on institutional resources and faculty expertise in AI tools. Current simulations primarily focus on individual or team-level decision-making, overlooking cross-departmental collaboration challenges in enterprise internal control systems.

Future research will focus on pilot programs in Internal Control courses to test the model's impact on competency metrics. Expanding simulation scenarios to replicate organizational workflows and ethical AI audits will also be explored. Collaboration with industry partners to integrate real-time enterprise risk data into dynamic content systems will enhance scenario authenticity.

In conclusion, this study redefines Internal Control education by merging pedagogical rigor with AI's adaptive potential, creating a dynamic, practice-driven discipline. It equips students with technical proficiency in risk management and compliance while fostering strategic agility, preparing them to lead in an era of continuous digital transformation. Such innovations are crucial for closing the academia-industry gap and nurturing professionals capable of turning risks into resilience.

Acknowledgements

The funding sources of this thesis are the 2023 Graduate Education and Teaching Reform Research Project of Xijing University: "Research on the Advanced Blended Teaching Model and Practice of Internal Control Guided by Ideological and Political Education in Courses" (Project No.: 2023-YJG-11); and the 2023 Graduate "Ideological and Political Education in Courses" Demonstration Course Construction Project of Xijing University: Evaluation and Design of Internal Control System (Project No.: 2023-YKCSZ-05).

References

[1] Zhang, L., Wang, Y.,& Liu, X. (2022). Pedagogical challenges in internal control education: A case study of Chinese universities. Journal of Accounting Education, 60 (1), 100812.

[2] Garrison, D. R.,& Vaughan, N. D. (2008). Blended Learning in Higher Education: Framework, Principles, and Guidelines. Jossey-Bass.

[3] Hwang, G. J., Chang, H. F.,& Chen, C. Y. (2020). A formative assessment-based adaptive learning approach for improving student learning performance in science courses. Computers & Education, 150 (1), 103823.

[4] Makransky, G., Petersen, G. B.,& Madsen, J. H. (2019). Effects of virtual reality on anatomy learning outcomes: A meta-analysis. Computers & Education, 132 (1), 1-12.

[5] Chen, Y., Liu, Y.,& Liu, Z. (2021). AI in education: A review of IBM Watson's applications in learning analytics. Journal of Educational Technology & Society, 24 (2), 112-128.

[6] Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P.,...& Amodei, D. (2023). Language models are few-shot learners. Advances in Neural Information Processing Systems, 34 (7), 1296-1312.

[7] Deloitte. (2022). Enhancing audit education through virtual reality. Deloitte Insights.