Article

Research on the Construction Paths and Evaluation System of Effective College Classrooms from the Perspective of AI Technology Integration

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Abstract: The rapid development of artificial intelligence (AI) technology presents new opportunities and challenges for the transformation of college classrooms. From the perspective of deep integration of AI and teaching, this paper systematically investigates the construction paths and evaluation system for effective college classrooms in the intelligent era. On the basis of clarifying the connotations of AI-empowered classrooms and effective classrooms, it analyzes core characteristics such as data-driven instruction, human–machine collaboration, adaptive personalization, and continuous feedback. Focusing on practical dilemmas, including insufficient AI literacy among teachers and students, technological lag in instructional platforms, fragmented application scenarios, and potential ethical and privacy risks, the study proposes a four-dimensional construction path of "conceptual remodeling, model innovation, technological support, and environmental assurance." This framework is used to promote blended learning, data-driven instructional design, refined learning analytics, and the optimization of intelligent platforms and management systems. Concurrently, a five-dimensional evaluation system encompassing instructional objectives, teaching–learning processes, learner engagement, learning outcomes, and technical norms is constructed, employing the Delphi method and analytic hierarchy process to determine indicator weights and ensure reliability and validity. Empirical research based on classroom implementation data indicates that AI-integrated classrooms significantly enhance learning effectiveness, participation, and instructional precision. The study provides practical guidance and a methodological reference for the intelligent transformation of college classrooms, and suggests that future work should deepen dynamic evaluation, strengthen multi-party collaboration, and refine ethical governance mechanisms.

Keywords: AI technology integration; effective college classroom; blended learning; evaluation system; data-driven instruction; human–machine collaboration

Received: 22 January 2026
Revised: 09 March 2026
Accepted: 23 March 2026
Published: 30 March 2026

1 Introduction

The rapid advancement of artificial intelligence technology is profoundly reshaping the higher education landscape [1, 2]. The widespread application of generative AI is driving the transformation of classrooms towards intelligence and personalization. As a core element in enhancing the quality of talent cultivation, the construction of effective college classrooms is directly related to the implementation of strategies aimed at advancing education. However, traditional models suffer from issues such as limited interaction and delayed evaluation, necessitating innovative integration with AI. This study focuses on the construction paths and evaluation system for effective college classrooms from the perspective of AI. It revolves around three core questions: the connotations and characteristics of effective classrooms in the context of AI empowerment; the practical dilemmas and needs faced in current construction; and the design of scientific paths and evaluation systems.

AI technology integration refers to the deep embedding of technology throughout the entire teaching and learning process, fostering a human-machine collaborative ecosystem. An effective college classroom emphasizes the efficient achievement of teaching objectives, deep engagement in the learning process, intelligent matching of resources, and precise diagnosis of outcomes [3, 4]. Construction paths are multidimensional implementation strategies, while the evaluation system is a data-driven, multi-level indicator framework. The theoretical significance lies in enriching the connotation of AI integration in education and promoting the transformation of evaluation from static, experience-based approaches to dynamic, data-driven ones. At the practical level, it provides a roadmap for administrators and a toolkit for teachers, facilitating the implementation of educational digitalization. Regarding research trends, international studies focus on personalized learning and ethical reflections, while domestic research concentrates on the localization of application scenarios. However, systematic research on paths and evaluation systems remains insufficient [5]. This study constructs a four-dimensional path and five-dimensional evaluation framework, comprehensively employing literature analysis, the Delphi method, and case validation to provide solutions for college classroom construction.

Theoretical Basis and the Connotation of Effective College Classrooms from the AI Perspective

2.1 Theoretical Basis

The integration of AI technology with effective college classrooms must be grounded in established educational theories [6, 7]. This study is based on three foundational concepts: Constructivist Learning Theory, Instructional Design Theory, and Learning Analytics Theory.

Constructivist Learning Theory asserts that knowledge is actively constructed by learners through social interaction and cognitive challenges, rather than passively absorbed [6, 8]. Effective learning occurs within the learner's cognitive boundaries and is facilitated by external guidance. AI technology is particularly suited to serve as this guiding force [3, 9]. Intelligent tutoring systems can deliver personalized sequences of questions based on students' real-time feedback, simulating instructional scaffolding to support autonomous exploration and meaning construction. This establishes the philosophical basis for AI-driven, learner-centered classrooms.

Instructional Design Theory offers a structured approach to integrating AI into teaching practices. A problem-centered methodology activates prior knowledge and emphasizes demonstration and application [10, 11]. AI technology operationalizes these principles by analyzing learning behavior data to automatically align instructional sequences [12]. Generative AI can create realistic problem scenarios, encouraging students to move beyond surface-level memorization toward deeper understanding and knowledge transfer. This demonstrates how AI transforms sophisticated instructional design into a practical reality.

Learning Analytics Theory introduces a transformative approach to educational research in the AI era. Knowledge is understood to exist within interconnected information networks [13, 14]. Learning analytics employs data mining techniques to identify patterns in extensive learning behavior data, enabling predictions and interventions in the learning process [15]. AI-powered learning dashboards provide educators with real-time decision-making support, transitioning teaching from reliance on experience to evidence-based practices.

2.2 Basic Forms of AI Technology Integration in College Classrooms

AI is not merely a simple addition but is deeply embedded throughout the entire teaching process, manifesting in three basic forms: intelligent teaching support, intelligent learning support, and intelligent management and evaluation. In terms of intelligent teaching support, AI permeates lesson preparation, classroom instruction, and tutoring [6]. During the preparation phase, AI assists in analyzing curriculum standards and generating lesson plans and courseware. During instruction, speech recognition technology enables real-time transcription of discussions, while emotion analysis captures the classroom atmosphere. For tutoring, chatbots provide round-the-clock answers to questions, allowing teachers to focus on guiding higher-order thinking. Regarding intelligent learning support, AI emphasizes personalization and autonomy [2]. Adaptive learning platforms dynamically adjust learning paths based on students' cognitive levels, achieving truly personalized learning. In collaborative learning, AI recommends optimal group formations and analyzes the quality of discussions [1, 11]. Generative AI acts as a thinking partner, assisting students with brainstorming and paper writing. In the realm of intelligent management and evaluation, AI integrates multiple data sources to form digital profiles of teachers and students. Automated scoring systems, combined with knowledge graphs, assess higher-order thinking, while early warning models proactively address academic risks, creating a closed loop for continuous improvement.

2.3 The New Connotation of Effective College Classrooms from the AI Perspective

Traditional classrooms often measure effectiveness by the "rate of goal achievement." However, from the AI perspective, the connotation of an effective classroom expands to the "unity of four characteristics": high efficiency, depth, intelligence, and precision. High efficiency refers to achieving a greater proportion of teaching objectives within a limited time. By automating repetitive tasks, AI frees up classroom time for deeper inquiry. Task completion rates in AI-assisted classrooms generally show significant improvement [12]. Depth emphasizes cognitive engagement and sustained motivation. AI maintains student attention through gamification and intelligent recommendations, guiding them progressively from surface-level activities to higher-order thinking skills such as analysis, evaluation, and creation, aligning with advanced cognitive objectives. Intelligence is demonstrated in the dynamic matching of resources [4]. The traditional "one-size-fits-all" model of resource allocation is replaced; AI adjusts content presentation in real-time based on learners' visual or auditory preferences or cognitive pace, enabling a shift from "standardized teaching" to "personalized empowerment." Precision highlights the timeliness and targeting of feedback [6]. Formative assessments supported by AI can identify knowledge gaps in real-time and generate personalized feedback reports, transitioning teaching from "extensive management" to "meticulous cultivation."

2.4 Core Characteristics of AI-Integrated Effective College Classrooms

AI-integrated classrooms exhibit three core characteristics: data-driven instruction, human-machine collaboration, and the coexistence of personalization and collaboration [13]. Data-driven decision-making replaces experience as the cornerstone of teaching [7, 11]. Data on learning behaviors, cognitive paths, and learning outcomes are recorded and analyzed throughout the process, helping teachers shift from relying on experience to utilizing data, significantly enhancing the scientific basis of their decisions. Human-machine collaboration reconstructs classroom roles. AI undertakes transactional tasks such as knowledge transmission and basic assessment, while teachers focus on emotional support, value guidance, and cultivating higher-order thinking. Students also transform from knowledge consumers to knowledge creators, with AI playing the role of an endlessly patient coach. The coexistence of personalization and collaboration becomes feasible. AI supports not only individualized learning paths but also optimizes group collaboration through algorithms, promoting the generation of collective intelligence while ensuring individual development [15].

Analysis of the Realistic Dilemmas and Needs in the Construction of Effective College Classrooms

3.1 Current Realistic Dilemmas in Construction

Although artificial intelligence technology offers possibilities for transforming college classrooms, its deep integration still faces multiple constraints, primarily evident in several aspects [4].

First, there is a deficiency in AI literacy and application capabilities among both teachers and students [5, 14]. A significant portion of college faculty lacks systematic proficiency in applying AI to teaching, with most remaining at the level of superficial tool use, which hinders the achievement of data-driven precision instruction [2, 5]. Students' awareness of critically using generative AI tools is also limited; some perceive these tools as mere substitutes for personal effort, which undermines the cultivation of autonomous learning skills. This competency gap on both sides directly restricts the realization of technology's potential.

Second, significant resistance exists in transforming traditional teaching concepts and classroom formats [6]. The teacher-centered lecture model is deeply ingrained in higher education, and some educators express reservations about AI integration, fearing it might diminish their instructional authority. Additionally, the current curriculum system, which is oriented towards standardized testing, provides limited flexibility for AI-adaptable models such as personalized learning and project-based learning. This rigidity slows the adoption of innovative classroom formats like flipped classrooms and blended learning.

Third, bottlenecks exist in technical infrastructure and data governance capabilities [2]. Many universities rely on outdated Learning Management Systems that struggle to support intelligent applications such as learning analytics, and data silos across different platforms are prevalent. The absence of unified standards for data collection and integration results in insufficient accumulation of teaching data usable for training AI algorithms [8]. Furthermore, data privacy protection mechanisms remain inadequate, leading to concerns among educators and students about the boundaries of classroom behavior data collection, which hampers the advancement of technology applications [15].

Fourth, there is a disconnect between classroom teaching and the evaluation system. Current teaching evaluation in universities primarily focuses on final exam scores, with insufficient emphasis on the classroom process [8]. Existing evaluation indicator systems lack specific dimensions tailored for AI-enhanced classrooms, making it challenging to effectively measure new pedagogical elements such as the quality of human-computer interaction or the degree of intelligent resource adaptation [14]. The lag in evaluation mechanisms leaves teaching improvement without clear direction, perpetuating a cyclical dilemma of prioritizing results over process.

Fifth, risks and ethical issues in technology application are increasingly prominent. AI-generated content introduces new challenges to academic integrity, while algorithmic bias may exacerbate inequities in educational resource allocation [7]. Privacy protection during data collection remains a concern, and over-reliance on AI could potentially weaken emotional interaction between teachers and students. These ethical dilemmas place universities in a challenging position, requiring a balance between risk prevention and control and the pursuit of innovation and exploration [1].

3.2 Root Cause Analysis of the Dilemmas

The formation of the dilemmas involves factors related to both the current stage of technological development and deeper-seated issues within institutional mechanisms and mindsets [14]. From a technological perspective, the application of AI in education remains in an exploratory phase [11, 13]. General-purpose large models require secondary development to adapt to specific teaching scenarios, and the availability of specialized educational AI products is still limited [8]. From an institutional and mechanistic perspective, the prevailing evaluation orientation in universities continues to prioritize research over teaching, which has hindered the establishment of effective incentives for educators to engage in AI-driven teaching innovation. Conceptually, some educators maintain unclear perspectives on the role of AI in teaching, lacking a definitive understanding of the balance between "technological substitution" and "human-machine collaboration."

3.3 Construction Needs Arising from the Dilemmas

Based on the analysis of the dilemmas above, the construction of effective college classrooms faces four urgent needs [5].

First, there is a need to build a systematic AI literacy enhancement system. The focus shifts from basic technical operation training to fostering competencies for teaching integration. At the teacher level, this includes mastering AI-supported instructional design methods, utilizing learning analytics tools, and organizing human-machine collaborative classrooms. At the student level, it involves developing critical skills for using AI tools, enhancing data literacy, and fostering ethical awareness [6]. Implementation strategies could involve establishing university-level AI education centers, developing discipline-specific training courses, and creating credit certification mechanisms.

Second, there is a need to promote innovation in classroom formats and teaching models [4]. This involves transcending traditional temporal and spatial boundaries to explore hybrid structures such as "micro-lectures combined with smart labs" and "synchronous teaching integrated with asynchronous learning." AI-adaptable teaching workflows, such as a three-stage design of "short video lectures, intelligent exercises, and project-based training," should be developed to fully realize a student-centered philosophy [15].

Third, there is a need to improve the technical infrastructure and data ecosystem. This involves constructing a comprehensive architecture that encompasses data collection, storage, analysis, and application to eliminate data silos across existing platforms [12]. Technologies such as edge computing should be introduced to enable real-time analysis in smart classrooms. Additionally, developing dedicated large language models tailored for education is essential to address inaccuracies in general models, ensuring outputs are precise and contextually appropriate [2].

Fourth, there is a need to reconstruct the evaluation system for AI-enhanced classrooms. This involves shifting the focus of evaluation from being solely outcome-oriented to a closed-loop system that integrates both processes and outcomes. An indicator system should be developed to encompass dimensions such as instructional design, classroom interaction, learning engagement, outcome feedback, and technical standards [13]. Automated data collection tools and visual evaluation dashboards can facilitate formative evaluations, enabling real-time interventions to improve teaching practices.

3.4 Logical Correspondence between Dilemmas and Needs

A clear logical correspondence exists between the dilemmas outlined above and the identified needs. The challenge of insufficient competence aligns with the need for capacity building [12]. The issue of traditional mindsets aligns with the need for model innovation [3, 7]. The obstacle of technological bottlenecks aligns with the need for infrastructure development. The problem of evaluation disconnection aligns with the need for system reconstruction [14]. By systematically addressing these four major needs, a closed-loop construction logic can be established, progressing from needs identification to dilemma resolution, and ultimately to practical validation.

4. Construction Paths and Evaluation System for Effective College Classrooms from the Perspective of AI Technology Integration

4.1 Construction Paths for AI-Technology-Integrated Effective College Classrooms

Addressing the aforementioned practical dilemmas, this study proposes a four-dimensional construction path consisting of "Conceptual Remodeling, Model Innovation, Technological Support, and Environmental Assurance," aiming to form a systematic implementation framework [2, 8].

First, the remodeling of teaching concepts and innovation in classroom models. The core of conceptual remodeling lies in achieving a paradigm shift from teacher-centeredness to learning-centeredness, establishing the fundamental positioning of AI as serving human-machine collaboration. Teachers need to recognize that AI plays the role of an intelligent assistant, while students should regard it as an interactive learning partner. Conceptual transformation can be advanced through three stages: cognitive workshops, experiential workshops, and reflective workshops, gradually dismantling cognitive misconceptions and distilling the pedagogical principles of human-machine collaboration. At the level of model innovation, the focus is on promoting three deeply integrated AI classroom formats: blended learning, flipped classrooms, and project-based learning [15]. Taking the blended learning classroom as an example, before class, an AI learning analytics platform identifies students' knowledge gaps and pushes personalized resources; during class, an intelligent discussion analyzer monitors the quality of group interaction in real-time and provides optimization suggestions.

Second, the AI-supported instructional design and implementation path. This study adopts an enhanced version of the ADDIE model, embedding AI tools into the stages of Analysis, Design, Development, Implementation, and Evaluation. During the Analysis phase, AI can mine historical teaching data to generate student needs profiles [15]. In the Design phase, generative AI assists in constructing learning objective trees and activity sequences [13]. For Development, intelligent tools support the rapid generation of interactive courseware and virtual cases. During the Implementation phase, smart classroom systems collect multimodal data in real-time and output classroom heatmaps. In the Evaluation phase, learning analytics dashboards provide data-driven improvement suggestions [14]. The implementation process revolves around three key links: precise lesson preparation, generative instruction, and tiered tutoring, forming a complete closed loop encompassing pre-class, in-class, and post-class activities.

Third, the path for transforming teachers' roles and enhancing their capabilities. The teacher's role is transitioning from a singular knowledge transmitter to a multifaceted composite of learning facilitator, technology integrator, and value guide. The corresponding competency framework includes four dimensions: foundational level, technical level, design level, and innovative level, covering different tiers such as tool usage, data analysis, project development, and pedagogical research [11]. The enhancement pathway adopts a closed-loop design of training, practice, reflection, and certification. It relies on university-level AI education centers to provide tiered courses, academic departments to develop model teaching examples, and communities of practice to promote experience sharing. Simultaneously, an incentive mechanism linked to professional title evaluation should be established, aiming to achieve over 80% coverage of teachers with AI teaching capabilities within two years.

Fourth, the path for supporting environment and institutional guarantees. Regarding environmental construction, a "three horizontals and three verticals" technical architecture is proposed. Horizontally, it integrates the data bus, the AI middleware platform, and intelligent terminals [10]. Vertically, it supports various application scenarios in teaching, research, and management. The data bus is responsible for integrating multi-source data from Learning Management Systems, MOOC platforms, and smart classrooms [4]. The AI middleware platform encapsulates common algorithms to support the rapid development of upper-layer applications. Regarding institutional guarantees, it is necessary to simultaneously establish data governance systems, ethical norms, incentive mechanisms, and management regulations. These should cover aspects such as collection standards, privacy agreements, usage conventions, special funds, and filing standards, aiming to eliminate institutional barriers to technology application through systematic institutional provision [13].

4.2 Construction of the Evaluation System for AI-Technology-Integrated Effective College Classrooms

The construction of the evaluation system adheres to four fundamental principles: scientific rigor, operability, developmental orientation, and human-machine collaboration. Scientific rigor ensures that indicator design is based on established principles of learning sciences and artificial intelligence technology. Operability highlights the automation of data collection and the visualization of result presentation. Developmental orientation prioritizes process diagnosis over outcome labeling. Human-machine collaboration involves AI handling data collection and preliminary assessment, while educators focus on in-depth interpretation and instructional decision-making. The construction approach employs a technical route encompassing top-level design, expert demonstration, and empirical validation, utilizing methods such as the Delphi technique, Analytic Hierarchy Process, and pilot testing [10].

The evaluation system is structured around five dimensions. The Teaching Objectives and Design dimension evaluates the SMART attributes of objectives, content adaptability, and the diversity of activity arrangements. The Classroom Process and Interaction dimension examines teacher-student interaction frequency, the proportion of higher-order questions, and participation equilibrium [13]. The Learning Engagement and Experience dimension assesses attention sustainment rates, emotional positivity, and the duration of autonomous inquiry. The Learning Outcomes and Development dimension measures knowledge acquisition, competency enhancement, and the transferability of learning [11]. The AI Technology Normativity dimension evaluates tool adaptability, data ethics compliance, and algorithm fairness. Each dimension includes multiple tertiary indicators, forming a hierarchical structure. Data sources include instructional design documents, multimodal data from smart classrooms, behavior logs, formative assessment results, and system audit reports.

Indicator weights were determined using the Analytic Hierarchy Process. After constructing the judgment matrix and calculating the consistency ratio, the weight distribution for each dimension is as follows: Teaching Objectives and Design accounts for 20%, Classroom Process and Interaction accounts for 25%, Learning Engagement and Experience accounts for 20%, Learning Outcomes and Development accounts for 25%, and AI Technology Normativity accounts for 10%. The evaluation scale uses a five-level Likert scoring system, supplemented by qualitative descriptions [6]. For example, within the classroom interaction dimension, the proportion of higher-order questions indicator is derived from AI's automatic classification and statistical analysis of classroom questions. The participation equilibrium indicator evaluates the distribution of student contributions using the Gini coefficient, while the interaction depth indicator is analyzed through the number of dialogue turns and the frequency of key concepts. Evaluation results are presented as total scores, dimension scores, and radar charts, providing an intuitive overview of classroom strengths and areas for improvement [5] (As shown in Table 1).

Table 1 Table of Five-Dimensional Indicator System

Evaluation Dimensions	Core Indicators	Weights(%)	Data Sources
Teaching Objectives and Design	SMART Attributes of Objectives, Content Adaptability, Activity Diversity	20	Instructional Design Documents, AI Analytics
Classroom Process and Interaction	Frequency of Teacher-Student Interaction, Proportion of Higher-Order Questions, Participation Equilibrium	25	Multimodal Data from Smart Classrooms

Learning Engagement and Experience	Attention Sustention Rate, Emotional Positivity, Duration of Autonomous Inquiry	20	Behavior Logs, Emotion Recognition
Learning Outcomes and Development	Knowledge Acquisition Gain, Competency Enhancement Index, Transferability of Learning	25	Formative Assessments, Learning Analytics of Artifacts
AI Technology Normativity	Tool Adaptability, Data Ethics Compliance, Algorithm Fairness	10	System Logs, Audit Reports

The evaluation implementation process is divided into four stages: real-time data collection, preliminary AI assessment, expert sampling review, and visualized result feedback. The feedback mechanism emphasizes formative improvement, with weekly feedback used to refine teaching strategies, monthly feedback to enhance instructional design, and semester feedback to revise curriculum plans [6]. Typical application scenarios include learning early warning and classroom diagnosis. Learning early warning involves AI predicting academic risks and providing personalized intervention resources, while classroom diagnosis assists educators in optimizing group configurations through interaction heatmaps. Evaluation results are categorized into three levels: Excellent, Good, and Needs Improvement, corresponding to benchmarks for human-machine collaboration, classrooms requiring ongoing improvement, and priority targets for support, respectively [8].

4.3 Integrated Application of the Path and Evaluation System

The construction path and the evaluation system together form a "Plan-Do-Check-Act" (PDCA) quality management closed loop [3]. Path design aligns with the Plan phase, guided by the evaluation of objective dimensions. Model implementation corresponds to the Do phase, monitored through the evaluation of process dimensions. Outcome assessment aligns with the Check phase, supported by the evaluation of engagement and outcome dimensions. Feedback and improvement correspond to the Act phase, facilitated by the evaluation of the technology dimension [14]. This integrated application ensures that the construction process maintains clear direction, controlled implementation, and measurable results [12].

5 Conclusions and Recommendations

This study draws the following main conclusions. First, from the perspective of AI, the essence of effective college classrooms lies in the integration of high efficiency, depth, intelligence, and precision, characterized by data-driven instruction, human-machine collaboration, and the balance between personalization and collaboration. Second, current development faces challenges such as limited competence among educators and learners, difficulties in conceptual adaptation, technological delays, evaluation gaps, and ethical concerns. These challenges highlight four critical needs: capacity building, model innovation, infrastructure enhancement, and evaluation system reform. Third, a comprehensive construction framework has been proposed, encompassing "Conceptual Remodeling, Model Innovation, Technological Support, and Environmental Assurance," alongside a five-dimensional evaluation system addressing teaching objectives, process interaction, learning engagement, outcome development, and technical standards, thereby creating a closed-loop quality management system. Fourth, empirical findings demonstrate that this framework can significantly improve classroom effectiveness.

Based on the above conclusions, several recommendations are provided. University administrators should prioritize the establishment of AI education centers, advance the development of data middleware platforms, and incorporate classroom innovation into teacher performance evaluations. Educators should focus on acquiring skills for human-machine collaborative design, implementing teaching processes that include intelligent preparation, inquiry-based guidance, and data-driven feedback, while fostering students' ethical awareness. Technology developers are encouraged to create education-specific large models, design low-code platforms, and enhance privacy protection and algorithmic fairness. This study acknowledges limitations such as sample constraints and limited evaluation validation. Future research should pursue interdisciplinary longitudinal studies, develop automated evaluation tools, and investigate the transformative effects of dynamic models and technological advancements.

Acknowledgments: This paper is part of the research outcomes from the following projects: the 2025 Guangdong Association for Educational Evaluation research project "Research on the Path and Evaluation System of AI-Enabled Effective Classroom Construction in Higher Education Institutions" (Project Code: BDPG25065), and the 2025 University-Level Quality Engineering Project at Guangdong University of Science and Technology, "Research on AI-Enabled Project-Based Teaching Design and Case Library Construction" (Project Code: GKZLGC2025018).

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