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Design and Development of an AI-Assisted Personalized Case Teaching Model Based on Fuzzy Delphi and ISM Approaches

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Abstract

This study design and developed an AI-Assisted Personalized Case Teaching Model (AI-PCT) that integrates the Fuzzy Delphi Method (FDM) and Interpretive Structural Modeling (ISM) to explore how artificial intelligence (AI) can enhance case-based learning in higher education. A panel of 15 experts identified and validated 22 key elements across five domains: pedagogical support, assessment and feedback, technical functionality, teacher and institutional control, and user experience. The ISM analysis revealed a five-level hierarchical structure, illustrating the progression from technological foundations to learner experience outcomes. The findings highlight that AI integration must balance personalization, authenticity, and ethical oversight, ensuring that AI serves as a cognitive partner rather than a substitute for educators. The AI-PCT model contributes both a validated theoretical framework and a practical pathway for embedding AI into business and management education. This model bridges the gap between theory and practice and facilitates the transition to student-centered classrooms.

Keywords: Artificial Intelligence (AI), Case-Based Teaching, Fuzzy Delphi Method (FDM), Interpretive Structural Modeling (ISM), Design and Develop

Introduction

The implementation of Artificial Intelligence (AI) in higher education has recently prompted widespread discourse, progressively becoming a central concern in the digital revolution of education(Chu et al., 2022; Crompton & Burke, 2023; Vaz de Carvalho & Bauters, 2021). With the rapid advancement of technologies such as machine learning, natural language processing (NLP), and big data analytics, AI has demonstrated unprecedented potential in adaptive learning(Huang et al., 2021) , administrative efficiency(Crompton & Burke, 2024), and personalized feedback(Nyamwange, 2025). In particular, the remarkable progress of AI-powered chatbots in recent years has exhibited exceptional utility and intelligence in text generation, content understanding, and contextual analysis(Sajja et al., 2024). This has advanced the notion of "AI-empowered teaching" from theoretical investigation to practical application.

However, in comparison to the swift progression of technology, the clearly defined implementation pathway for AI in higher education teaching environments remains unclear. Despite substantial research investigating the potential benefits of AI in enhance teaching diversity(Alqahtani & Wafula, 2025; Kakoulli et al., 2025) and intelligent question-answering(Jun et al., 2025), most studies remain at a conceptual level, lacking practical teaching implementation models and validation frameworks. The practical use of AI in classrooms, its integration with teachers' design of instruction, and the achievement of intelligent teaching while preserving pedagogical authenticity and educational ethics are critical difficulties that the academic community needs to address.

Consequently, there is an immediate necessity to develop a cohesive model based on pedagogical theory and augmented by AI technology, offering a demonstrable, adaptable, and scalable systematic framework for the integration of AI in higher education classrooms. The study aims to develop an AI- assist personalized case teaching model (AI-PCT) that balances educational principles with technical viability using expert consensus procedures and systematic modeling methodologies.

In the varied investigation into AI applications in education, case-based teaching (CBT) serves as an important path for incorporating AI into the classroom, highlighting actual circumstances, active discussion, and decision-making argumentation(Wang et al., 2024). CBT is an educational framework focused on realistic issue scenarios, student engagement, and interactive decision-making, highlighting "learning by doing" and "learning through discussion"(Giacalone, 2016; Guo et al., 2022). Originating from Harvard Business School and extensively utilized in MBA programs, the essence of CBT is to replicate real-world business scenarios to enhance students' critical thinking, problem-solving capabilities, and collaborative skills(Herreid, 2011). Nevertheless, traditional CBT class remains to face several challenges in implementation.

Firstly, the large class enrollment limit teachers from acquiring a profound understanding of each student's opinions and cognitive processes(Monks & Schmidt, 2011). Teamwork frequently demonstrates free-riding behavior, and the formative assessment system is insufficient(Harding, 2018). Secondly, classroom interaction mainly consists of teacher-centered teaching. Students possess a constrained capacity to understand and apply theoretical knowledge, impeding genuine assimilation of information(Semerci & Batdi, 2015). Furthermore, student participation is low. Most students show an absence in confidence or theoretical grounding, leading to inadequate active engagement and critical analysis during case discussions(Harmat & Herbert, 2020).

These practical issues highlight the importance to develop an AI-assisted personalized case-based teaching model. It must offer specific guidance for educational pathways, feedback systems, and assessment techniques while maintaining the authenticity, contextual relevance, and pedagogical integrity characteristic of CBT. The deeper integration of AI technology with CBT can provide substantial assistance in dynamic case development, real-time feedback, and formative analysis, thereby creating a strong practical foundation for intelligent instruction.

In terms of the acceptance and attitudes of teachers and students towards the application of AI in classrooms, existing studies have shown that both groups generally hold a positive stance(Gawe & Gudyanga, 2025; Ofosu-Ampong, 2024). They recognize that AI can effectively alleviate the burden of teaching and learning and exhibit significant advantages particularly in processing large volumes of text and generating personalized content(Zou, 2025). Teachers expect AI to help enhance the immediacy and accuracy of in-class feedback, while students anticipate obtaining more targeted learning support(Varghese & Selvaraj, 2024). This indicates that the application of AI at the classroom level not only possesses technical feasibility but also has a foundation of practical demand and educational recognition.

However, current research still lacks a systematic instructional model and in-class integration framework for effectively embedding AI into case-based teaching. In particular, there is an absence of a validated framework grounded in expert consensus that simultaneously accounts for both pedagogical logic and technological structure. This gap matters for contemporary social science debates on human and AI collaboration, teacher agency, and equity in algorithmic-mediated classrooms: without a validated, consensus-based framework that aligns pedagogical logic with technological structure, evidence from recent studies cannot accumulate into scalable practice.

To address this gap, the present study adopts a combined methodological design integrating the Fuzzy Delphi Method (FDM) and Interpretive Structural Modeling (ISM) to construct and validate an AI-PCT model based on expert consensus. The FDM was employed to identify and refine the key pedagogical and technological elements, ensuring the scientific rigor and internal consistency of the model. The ISM was then applied to uncover the hierarchical relationships and interdependencies among these elements, thereby establishing a systematic structural model that provides a theoretical foundation for subsequent empirical research and classroom implementation.

The objectives of this study are: To identify and determine the components and elements of the AI-PCT model through expert consensus. To analyze the logical hierarchy and interrelationships among the model's dimensions using Interpretive Structural Modeling (ISM). And to explore how AI can enhance personalized teaching effectiveness while maintaining the teacher's instructional autonomy and authority.

Theoretical Foundations

This study employs the TPACK model and PDCA cycle theory as its core theoretical foundations to construct a theoretical framework for the model, ensuring the systematic and practice-oriented nature of the model design.

TPACK Model: A Knowledge Framework for Integrating Technology into Teaching

Koehler and Mishra (2005) initially introduced the concept of Technological Pedagogical Content Knowledge (TPACK), which categorizes a teacher's pedagogical knowledge into subject matter content (teaching content), pedagogy (teaching methods), and technology (teaching techniques), with effective teaching emerging from the interplay of these three knowledge domains.

TPACK comprises seven essential components. There are three fundamental components: Pedagogical Knowledge (PK), Content Knowledge (CK), and Technological Knowledge (TK); three integrative elements that intersect with the fundamental components: Technological Content Knowledge (TCK), Technological Pedagogical Knowledge (TPK), and Pedagogical Content Knowledge (PCK); and a composite element that encompasses the three fundamental components: Technological Pedagogical Content Knowledge (TPACK). Within this framework, each component possesses a distinct and significant role, while also being intricately interconnected, engaging with one another to create a complex and comprehensive knowledge structure, as illustrated in Figure 1. TPACK is not merely a static knowledge framework but a dynamic, contextualized teaching competency that emphasizes educators' ability to flexibly draw upon and integrate three types of knowledge across diverse teaching situations to achieve technology-enhanced instructional innovation.

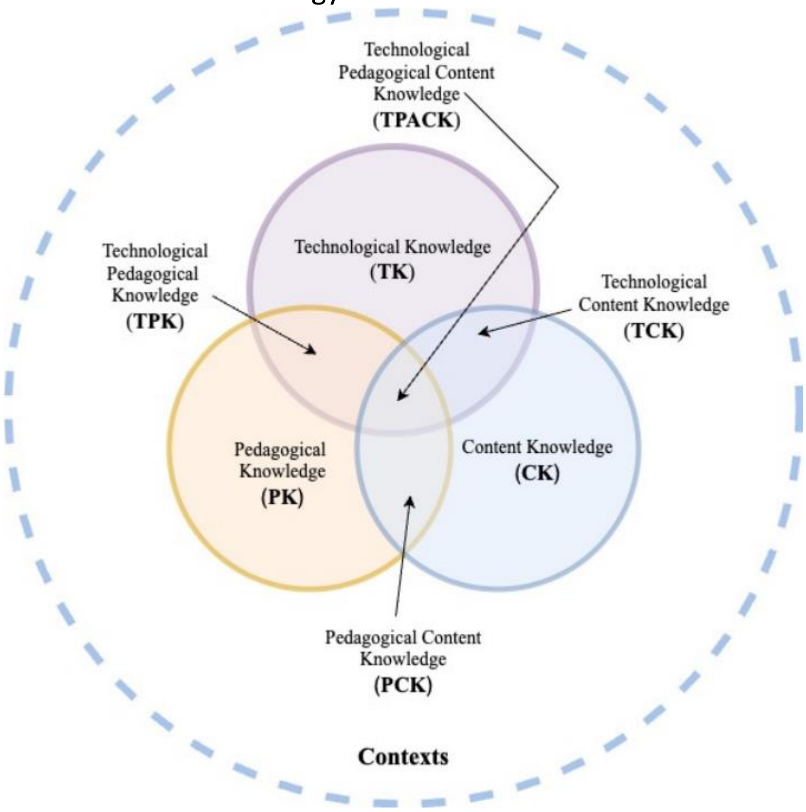

Figure 1: The TPACK framework and its knowledge components (Koehler and Mishra, 2009)

In the context of AI-enhanced education, the TPACK framework offers a theoretical basis for teachers to develop intelligent and personalized teaching activities. Recent research indicate that the incorporation of AI technology has broadened the scope of TPACK, resulting in the AI-TPACK extended model, which underscores the necessity for teachers to cultivate AI ability, pedagogical integration skills, and content flexibility(Ning et al., 2024). This study employs the TPACK framework as its theoretical foundation to facilitate the appropriate integration of AI technology into CBT. The objective is to guarantee that technology fulfills pedagogical goals and accommodates students' individualized learning requirements, hence improving the intelligence and flexibility of the entire educational system.

PDCA Cycle: A Mechanism for Continuous Improvement in Teaching Model Optimization

The PDCA cycle (Plan–Do–Check–Act) originated from the field of quality management and serves as an iterative model for continuous improvement. It has been widely applied in instructional design and teaching optimization (Moen & Norman, 2009). Four key components constitute the implementation process in case-based teaching: Plan (identification of needs and advance preparation) - Do (implementation and teaching) - Check (post-course evaluation and timely reflection) - Act (improve teaching and refine case) (Moen & Norman, 2009; Qu, 2024). Figure 2 demonstrates the integration of this framework exhibit with CBT and the iterative nature of continuous improvement.

This cyclical process promotes systematic reflection and data-driven enhancement in teaching practices, supporting sustained instructional quality and innovation.

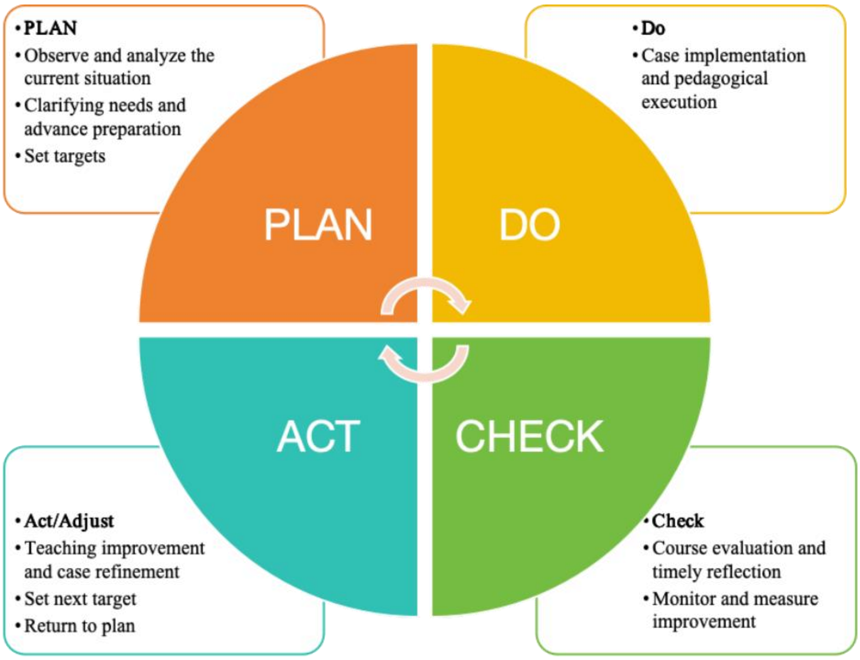

Figure 2: The PDCA Cycle in Case-based Teaching

In CBT process, the PDCA cycle provides a structural foundation for the systematization of instructional processes and the establishment of an effective feedback mechanism. Prior research has indicated that integrating the PDCA framework into CBT can effectively enhance the relevance of case design, the flexibility of instructional implementation, and the timeliness of evaluation and feedback (Qu, 2024). In this study, the PDCA cycle serves as the methodological foundation for the development and validation of the AI-PCT model, encompassing the entire process of design, implementation, evaluation, and iterative optimization. This approach ensures that the model maintains dynamic adaptability and continuous alignment with educational practice, supporting sustainable improvement in teaching quality and learning outcomes.

Methodology

This study employs a research methodology that integrates the Fuzzy Delphi Method (FDM) with Interpretive Structural Modeling (ISM), which comprises two primary phases: design and develop.

At the first phase, consensus from model design experts was gathered through the FDM method to screen and confirm the instructional, technical, and feedback elements incorporated into the model. Expert questionnaires employed a 5-point Likert scale combined with Triangular Fuzzy Numbers (TFN) for fuzzy scoring. High-consensus elements were identified by setting a consensus threshold ($d \leq 0.2$). Defuzzification formulas calculated the weight of each element, ultimately determining the core components of the model.

This study invited 15 experts to participate, covering multiple fields including educational technology, AI applications in education, business administration teaching, instructional design, and user experience.
The expert information is as follows:

Table 1
FDM Experts' Demographics

ID	Field of Expertise	Years of Experience	Current Position	Institution Type
E01	AI in Education	12	Professor	University
E02	MBA Education	18	Program Director	University
E03	Case-Based Teaching	20	Senior Lecturer	University
E04	User Experience (UX) Design	10	Industry Consultant	Tech Firm
E05	University Administration	22	Dean	University
E06	AI in Education	15	Associate Professor	University
E07	MBA Education	14	Professor	University
E08	Natural Language Processing	8	AI Researcher	Tech Firm
E09	Case-Based Teaching	16	Associate Professor	University
E10	University Administration	19	IT Director	University
E11	AI in Education	9	Assistant Professor	University
E12	MBA Education	11	Senior Lecturer	University
E13	Case-Based Teaching	25	Emeritus Professor	University
E14	UX Design	13	Head of Design	EdTech Company
E15	University Administration	17	Vice Dean	University

In the second phase, the Interpretive Structural Modeling (ISM) method was employed to analyze the logical relationships among the elements identified through the FDM process and to construct a hierarchical structural model representing the integration pathway of AI into CBT. Building upon the validated elements, ISM was used to examine the interrelationships and hierarchical structure among these components. This method is particularly suitable for analyzing complex systems with nonlinear relationships, as it transforms qualitative expert judgments into a structured, systematic model, thereby enhancing the model's coherence and practical applicability.

To ensure interaction quality and reduce expert fatigue, seven experts were selected from the original FDM panel to participate in the ISM modeling process. Through the construction of the Structural Self-Interaction Matrix (SSIM), Reachability Matrix, and Level Partition Diagram, the final hierarchical structure of the AI-PCT model was generated. This structure clarifies the logical sequence and causal pathways among pedagogical and technological elements, providing essential structural support for the design of the model's instructional process.

Analysis and Results

The Fuzzy Delphi Method (FDM) was applied to synthesize expert opinions on the significance of each indicator within the proposed AI-PCT model. The initial experts' questionnaire contained five components and 29 elements, derived from previous literature and stakeholder interviews. After the process of FDM, 22 elements met the inclusion thresholds and were retained for the model structure.

The decision criteria followed standard FDM thresholds: $d \leq 0.2$, expert agreement ≥ 75%, and fuzzy mean ≥ 0.5. The variation in fuzzy means between rounds remained below 0.1 for all items, confirming consensus stability.

Table 2 presents the summary of the final retained elements across the five primary components: Pedagogical Support, Assessment and Feedback, Technical Functionality, Teacher and Institutional Control, and User Experience.

Table 2
The 29 elements based on Fuzzy Delphi analysis and expert consensus

Component	Element	Expert agreement	Ranking
Pedagogical Support	Pre-class preparation	ACCEPT	1
	Preview materials preparation and distribution	REJECT	-
	Provide multi-perspective problem-solving solutions	ACCEPT	4
	Visualizing and dynamically demonstrating theoretical models	ACCEPT	5
	Scenario simulation and decision	ACCEPT	3
	Dynamic case generation	ACCEPT	2
	Group case discussions	ACCEPT	2
Assessment and Feedback	Originality monitoring	ACCEPT	1
	Real-time classroom quizzes	ACCEPT	1
	Evaluation of decision simulation results	ACCEPT	2
	Visualization of individual contributions within group tasks	REJECT	-
	Team Incentive Mechanisms	ACCEPT	3
	Propose real-time suggestions	ACCEPT	3
	Post-class individualized feedback	ACCEPT	1
Technical Functionality	Natural Language Processing (NLP) Engine	ACCEPT	2
	Adaptive Learning Algorithm	REJECT	-
	Knowledge graph technology	ACCEPT	1
	System architecture and scalability	ACCEPT	3
	Data storage and processing framework	ACCEPT	2
	Speech interaction support	REJECT	-
	Device compatibility	ACCEPT	2
	Teacher's instructional authority	ACCEPT	3

Component	Element	Expert agreement	Ranking
Teacher and Institutional Control	Data security and compliance management	ACCEPT	2
	Training and teachers' capacity building	ACCEPT	1
	Institutional resource coordination	REJECT	-
User Experience	Classroom experience optimization	REJECT	-
	Classroom flow design	ACCEPT	1
	Usability and collaboration	ACCEPT	2
	Personalized and aesthetically pleasing interface design	REJECT	-

After removing several elements rejected by experts, 22 elements remained and entered the model development phase. The ISM technique was implemented to analyze the complex physical interconnections among these components and to create a clear hierarchical framework. This process played an important part in revealing the fundamental structural logic of the AI-PCT model, highlighting its foundational, interdependent, and goal-oriented elements. The resulting hierarchy acts as a strategic guide for phased development and implementation, ensuring that foundational elements are prioritized during the initial construction phase.

The ISM analysis was carried out in a structured workshop with a focus group of seven experts, selected from the original 15-member panel, to enable in-depth consensus-building discussions. The first step involved constructing the Structural Self-Interaction Matrix (SSIM). During this stage, the expert group engaged in moderated discussions to evaluate the contextual relationship between each pair of indicators by posing the question: "Does indicator i influence or enable indicator j?" The consensus for each pairwise relationship was recorded using four predefined symbols.

V: Indicator i influences indicator j.
A: Indicator j influences indicator i.
X: Indicators i and j have a bilateral influence on each other.
O: Indicators i and j are unrelated.
Then the SSIM was then converted into a binary Initial Adjacency Matrix by substituting V, A, X, and O with 1 and 0 in order to establishing ISM rules.
If the relationship is V, the (i, j) entry is 1 and the (j, i) entry is 0.
If the relationship is A, the (i, j) entry is 0 and the (j, i) entry is 1.
If the relationship is X, both (i, j) and (j, i) are 1.
If the relationship is O, both (i, j) and (j, i) are 0.

The diagonal is always 0, without considering self-loops.
The initial adjacency matrix was enhanced to meet the transitivity property, resulting in the final reachability matrix. The reachability and antecedent sets for each element were subsequently established, and items with congruent reachability and intersection sets were allocated to the same hierarchical level. The iterative procedure persisted until every piece was allocated a level. All procedures were executed online utilizing ISM software.

Table 3
The Partitioning of Reachability Matrix

No	Reachability Set	Antecedent Set	Intersection
1	1,2,3,4,5,6,10,11,12,21,22	1,5,7,8,9,13,14,15,16,17,18,19,20,22	1,5,22
2	2,3,4,6,10,11,12,21	1,2,3,4,5,7,8,9,11,12,13,14,15,16,17,18,19,20,21,22	2,3,4,11,12,21
3	2,3,4,6,10,11,12,21	1,2,3,4,5,7,8,9,11,12,13,14,15,16,17,18,19,20,21,22	2,3,4,11,12,21
4	2,3,4,6,10,11,12,21	1,2,3,4,5,7,8,9,11,12,13,14,15,16,17,18,19,20,21,22	2,3,4,11,12,21
5	1,2,3,4,5,6,10,11,12,21,22	1,5,7,8,9,13,14,15,16,17,18,19,20,22	1,5,22
6	6,10	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22	6,10
7	1,2,3,4,5,6,7,8,9,10,11,12,18,19,21,22	7,8,9,13,14,15,16,17,18,19,20	7,8,9,18,19
8	1,2,3,4,5,6,7,8,9,10,11,12,18,19,21,22	7,8,9,13,14,15,16,17,18,19,20	7,8,9,18,19
9	1,2,3,4,5,6,7,8,9,10,11,12,18,19,21,22	7,8,9,13,14,15,16,17,18,19,20	7,8,9,18,19
10	6,10	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22	6,10
11	2,3,4,6,10,11,12,21	1,2,3,4,5,7,8,9,11,12,13,14,15,16,17,18,19,20,21,22	2,3,4,11,12,21
12	2,3,4,6,10,11,12,21	1,2,3,4,5,7,8,9,11,12,13,14,15,16,17,18,19,20,21,22	2,3,4,11,12,21
13	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22	13,14,15,16,17,20	13,14,15,16,17,20
14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22	13,14,15,16,17,20	13,14,15,16,17,20
15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22	13,14,15,16,17,20	13,14,15,16,17,20
16	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22	13,14,15,16,17,20	13,14,15,16,17,20
17	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22	13,14,15,16,17,20	13,14,15,16,17,20
18	1,2,3,4,5,6,7,8,9,10,11,12,18,19,21,22	7,8,9,13,14,15,16,17,18,19,20	7,8,9,18,19
19	1,2,3,4,5,6,7,8,9,10,11,12,18,19,21,22	7,8,9,13,14,15,16,17,18,19,20	7,8,9,18,19
20	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22	13,14,15,16,17,20	13,14,15,16,17,20
21	2,3,4,6,10,11,12,21	1,2,3,4,5,7,8,9,11,12,13,14,15,16,17,18,19,20,21,22	2,3,4,11,12,21
22	1,2,3,4,5,6,10,11,12,21,22	1,5,7,8,9,13,14,15,16,17,18,19,20,22	1,5,22

Table 4
Level Partition of Reachability Matrix

Level	Element No
5	6,10
4	2,3,4,11,12,21
3	1,5,22
2	7,8,9,18,19
1	13,14,15,16,17,20

Based on the hierarchical classification process of the final Reachability matrix, 22 validated elements were organized into a five-level hierarchical framework through iterative identification of the intersection between each indicator's accessibility set (all indicators it influences) and prerequisite set (all indicators that influence it). This framework (as shown in Figure 3) offers a distinct visual and logical depiction of the model architecture.

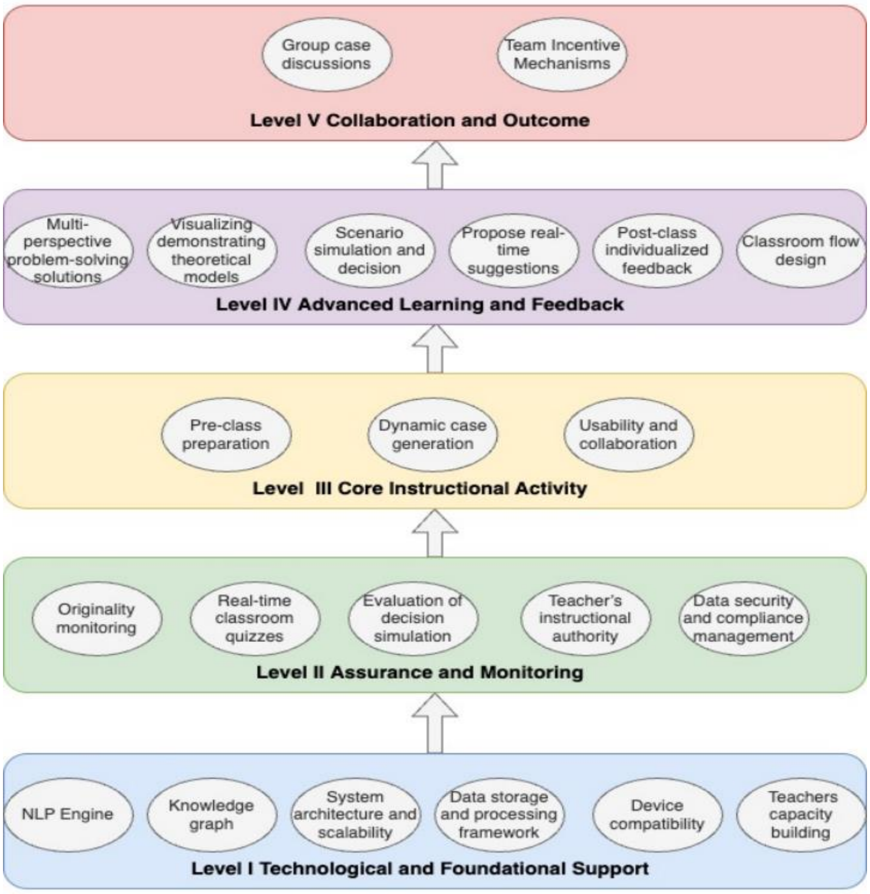

Figure 3 Hierarchical structure of the AI-PCT Model

Level I: Technological and Foundational Support
This foundational level provides the essential technological infrastructure for AI-assisted teaching, including NLP engines, knowledge graphs, system scalability, data processing, and device compatibility. It also emphasizes teacher capacity building in line with the TPACK framework. Together, these elements ensure the platform's intelligence, scalability, and security, forming a stable base for higher-level pedagogical activities.

Level II: Assurance and Monitoring
This layer ensures quality, equity, and integrity in teaching through mechanisms such as originality monitoring, real-time classroom assessment, simulation-based evaluation, teacher authority protection, and data security compliance. It maintains academic fairness and data reliability, supporting transparent instructional processes.

Level III: Core Instructional Activity
At the center of the framework, this level represents the operational hub of instructional design and implementation. It includes pre-class preparation, dynamic case generation, and collaborative learning support. By leveraging AI-generated case materials, educators can enhance student engagement, interactivity, and collaborative problem-solving.

Level IV: Advanced Learning and Feedback
This layer promotes deep learning and reflective thinking through multi-perspective problem-solving, scenario simulation, visualization, and decision-making activities. It integrates real-time recommendations and personalized feedback, ensuring continuous learning optimization and flow in the classroom.

Level V: Collaboration and Outcome
Positioned at the top of the hierarchy, this level facilitates knowledge application through group discussions and team-based case analysis. It strengthens motivation, teamwork, and learner autonomy, supporting the shift from teacher-centered to student-centered instruction.

In summary, the five-level hierarchical structure defines the “what” (key components) and the “why” (pedagogical logic), while the technological architecture delineates the “how”, the operational pathway for implementing intelligent, adaptive, and interactive CBT.

Conclusion

This study combines the FDM with the ISM technique to design and develop an AI-assisted personalized case teaching model (AI-PCT). The process through expert consensus and hierarchical structural analysis, identified 22 critical elements affecting the successful integration of AI into CBT. A five-live structural model was constructed, encompassing technology foundations, teacher implementation, and classroom objective attainment, systematically demonstrating how AI facilitates personalized, interactive, and reflective learning processes.

The results of studies suggest that the implementation of AI in CBT must constantly consider three dimensions: pedagogy, technology, and ethics. The function of AI is not to replace teachers but to act as a supporting instrument for instructional design. Combining AI technology and course optimization, it improves student involvement in collaboration and their problem-solving skills in case analysis. Teachers continue to be the principal decision makers in the classroom. This balanced integration maintains the authenticity and educational rigor of conventional CBT while improving instructional efficiency and personalization through intelligent technologies.

This study theoretically presents a structured framework, validated by experts, that effectively integrates AI capability with the teaching process, thus bridging the divide between academic discourse and classroom applications in previous studies. The AI-PCT model offers higher education instructors in business administration and related disciplines a reproducible, scalable operational framework for the integration of AI teaching technologies. This framework facilitates modifications and enhancements according to specific course objectives and situational factors.

However, this study possesses specific limitations. Presently, model validation predominantly depends on expert assessments; subsequent research may enhance the model's applicability and efficacy through quantitative empirical investigations and classroom exercises. Furthermore, future study should explore the ethical limits of AI-assisted education, data privacy protocols, and their enduring effects on learning outcomes and faculty workload.

In conclusion, the AI-PCT model offers a viable pathway for transforming traditional CBT into a data-driven, student-centered, and ethically sustainable pedagogical model. It illustrates that AI is not a replacement for human educators but a potent instrument for improving teachers' professional skills by promoting students' profound learning and decision-making abilities in intricate, real-world contexts.

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