# Digital Transformation of Engineering Courses Empowered by Large Language Models

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**Abstract:** This study explores the role of educational large language models in the digital transformation of engineering courses. A four-in-one transformation framework is constructed, covering teaching content, teaching modes, practical components, and teaching evaluation. The core course, *Facility Planning* in the Industrial Engineering program, is selected for instructional experimentation. In terms of teaching content, a knowledge graph is generated through a large language model, and industry-oriented frontier cases are dynamically produced. In teaching modes, the instructional workflow before, during, and after class is reshaped through an AI-supported dual-teacher collaboration mechanism. In the practical component, a facility-planning system integrating the DeepSeek model and the Systematic Layout Planning (SLP) method is developed. Natural-language interaction enables the full workflow from data analysis to solution optimization, supporting intelligent design training that follows the sequence of input, analysis, generation, and optimization. In teaching evaluation, a comprehensive system is adopted by combining process-based data with multi-dimensional capability assessment. Empirical results from one semester indicate significant improvements in students' engagement, abilities to solve complex engineering problems, and systems thinking. Meanwhile, the teacher's role gradually shifts from knowledge transmitter to learning facilitator and context designer. The proposed framework and its implementation path may serve as a reference for digital reform in other engineering courses. Future work extends to domain-specific model development, cross-course application, and the construction of shared resource ecosystems.

**Keywords:** Educational Large Language Models; Engineering Courses; Digital Transformation; *Facility Planning*; Instructional Reform

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## 1 Introduction

With the rapid development of generative artificial intelligence (AIGC) technology and the advancement of digital education strategies worldwide, higher education is undergoing a profound paradigmatic revolution [1, 2]. For engineering education, which shoulders the mission of cultivating outstanding engineers, digital transformation has evolved from an option to a necessity. Traditional engineering teaching has exposed many common challenges

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in meeting the demands of the new industrial revolution: the update of teaching content lags behind the pace of industrial technological iteration; the teacher-centered teaching model struggles to stimulate students' innovative thinking and ability to solve complex engineering problems; practical sessions are severely constrained by high-cost, high-risk physical equipment and the complex operational threshold of professional simulation software [3]. In addition, the traditional summative evaluation system is difficult to accurately capture and assess students' cognitive development and ability growth in solving ill-structured problems. Against this backdrop, educational large language models [4], capable of deep natural language understanding, professional logical reasoning, and multimodal content generation, have provided a key technical driving force and historic opportunity to address the aforementioned dilemmas and drive engineering courses toward in-depth digital and intelligent transformation.

In the early exploration of digital engineering teaching, researchers at home and abroad have attempted various paths. Massive Open Online Courses (MOOCs) have achieved remarkable results in promoting the sharing and popularization of educational resources [5]. However, their inherent one-way transmission model lacks strong interactivity, making it difficult to realize personalized in-depth tutoring and heuristic discussions [6]. Although virtual simulation experiments can simulate high-risk or high-cost industrial scenarios, their interaction processes are mostly preset scripts with low intelligence, failing to respond to students' dynamic and open design exploration needs, and the development cost of high-quality simulations is prohibitively high. Small Private Online Courses (SPOCs) have improved teacher-student interaction to a certain extent [7], but their core teaching paradigm remains an online migration of traditional classrooms, failing to fundamentally reshape the teaching structure and ecosystem. A systematic evaluation of learning experiences in online engineering education points out that fully online models, especially in experimental sessions, although helpful for enhancing conceptual understanding, have significant deficiencies in cultivating students' hands-on skills, promoting peer collaboration, and enabling real engineering decision-making [8]. Overall, most of these existing digital tools focus on shallow to mid-level reforms such as resource digitalization and process online, lacking the momentum to achieve in-depth paradigmatic intelligence reforms characterized by student-centeredness, high adaptability, and intelligence.

At the same time, research on the application of educational large language models has become a frontier hotspot in the global educational technology field [9]. Current explorations are mainly concentrated in general educational scenarios. For example, large language models are used to provide personalized learning path recommendations for massive online courses [10]; automated essay grading and feedback are realized in humanities and language disciplines [11]; and assistance in program code generation and debugging is provided in introductory computer science courses [12, 13]. These applications fully demonstrate the great potential of large language models in general language processing, logical reasoning, and content generation. However, when the perspective shifts to core professional courses in engineering that require the integration of complex spatial logic, rigorous engineering reasoning, and systematic design thinking, the in-depth application research of large language models is still in the exploratory stage [14]. For instance, in courses such as mechanical engineering design, although large language models can broaden the diversity of concept generation, they still face reliability challenges in specific tasks involving detailed modeling [15]. The vast majority of existing studies only regard large language models as a function-enhanced auxiliary tool, rather than using them as the core engine to systematically reconstruct the teaching content, interaction models, practical environments, and evaluation systems of engineering courses, thereby forming a complete intelligent teaching ecosystem.

In summary, there is a clear gap in existing research: on the one hand, mainstream digital teaching tools for engineering have inherent limitations in intelligence level and natural interaction capabilities [3]. Meanwhile, educational large language models lack framework design and empirical verification for in-depth integration and systematic application in highly specialized and contextualized core engineering courses. This research gap is the foothold of this study. Therefore, this study aims to systematically construct an overall framework for the digital transformation of engineering courses with large language models as the core driving engine. It selects *Facility Planning*, a core course in industrial engineering that features close integration of theory and practice and prominent pain points in traditional teaching, for in-depth empirical research. Adopting a mixed research paradigm combining the design science research method and the case study method, this study focuses on constructing and verifying a four-in-one transformation model covering teaching content, teaching modes, practical sessions, and teaching evaluation. It is expected to provide a practically verified, replicable, and promotable solution for the in-depth reform of similar engineering courses.

## 2 Theoretical Foundations

Educational large language models represent the in-depth application of generative artificial intelligence (AI) in the field of education, and their essence has transcended the initial stage of being an auxiliary question-answering tool, evolving into the intelligent hub of a new type of teaching ecosystem [16]. Compared with early adaptive learning systems or intelligent tutoring systems, contemporary large language models possess powerful capabilities in natural language understanding, professional domain reasoning, and multimodal content generation, enabling them to assume multiple roles such as cognitive partners, dynamic content generators, and interactive interfaces [17]. This transformation redefines the interactive relationship between teachers, students, and technology, elevating large language models from a single tool positioning to the foundation of an intelligent environment that can understand teaching contexts and support personalized inquiry-based learning.

The digital transformation of engineering courses is a multi-level evolutionary process, whose core connotation goes far beyond simple technical superimposition or resource electronation. This transformation encompasses a systematic change from shallow resource digitalization to mid-level process digitalization, and ultimately to in-depth paradigm intelligence. The resource digitalization stage focuses on converting static content such as textbooks and courseware into digital formats; the process digitalization stage migrates links like teaching management and assignment submission to online platforms; while paradigm intelligence represents a fundamental reshaping of teaching concepts. By creating an intelligent environment that can perceive learning status, adaptively adjust paths, and provide real-time feedback, a paradigm shift from teacher-centered knowledge transmission to student-centered competence development is achieved.

Constructivist learning theory and situated cognition theory together provide a solid theoretical foundation for this transformation. Constructivist learning theory emphasizes that learners actively construct their knowledge systems through interaction with the environment rather than passively receiving information, which directly supports the design of student-centered inquiry-based learning where large language models act as scaffolding tools to empower students' knowledge construction processes. Meanwhile, situated cognition theory further points out that learning and cognition are inherently situated, highly dependent on the specific activities and environments in which they occur. The facility planning system based on DeepSeek and the Systematic Layout Planning (SLP) method constructed in this study provides a low-cost, high-fidelity contextualized learning environment for engineering education. By deeply integrating professional algorithms through natural language interaction, the system enables students to cultivate full-process professional capabilities from data analysis to scheme decision-making through practical iterations in near-real engineering planning scenarios, thereby achieving effective knowledge transfer and application.

## 3 Integrated Framework

The transformation framework constructed in this study is core-driven by educational large language models and systematically reshapes four key dimensions of engineering courses: teaching content, teaching modes, practical sessions, and teaching evaluation. This framework positions educational large language models as the intelligent hub of the entire teaching ecosystem, and through their powerful capabilities in natural language understanding, professional reasoning, and content generation, they connect all teaching links to form an organic whole characterized by collaborative evolution and mutual enhancement.

### 3.1 Overall Framework Design

In the overall architecture, educational large language models act as the empowering hub. They connect downward to the underlying course knowledge base and professional algorithm library. Upward, they support four major application dimensions: teaching content generation, teaching mode innovation, practical environment construction, and teaching evaluation reform. These four dimensions are not isolated. Instead, the seamless flow of data streams and intelligent services is achieved through the large language models. For instance, data generated in practical sessions provides a basis for evaluation. Evaluation results are fed back to the content generation system, facilitating the dynamic adjustment of teaching content. This thereby forms a continuously optimized intelligent teaching closed loop. The four-in-one overall framework for the digital transformation of engineering courses is shown in Figure 1.

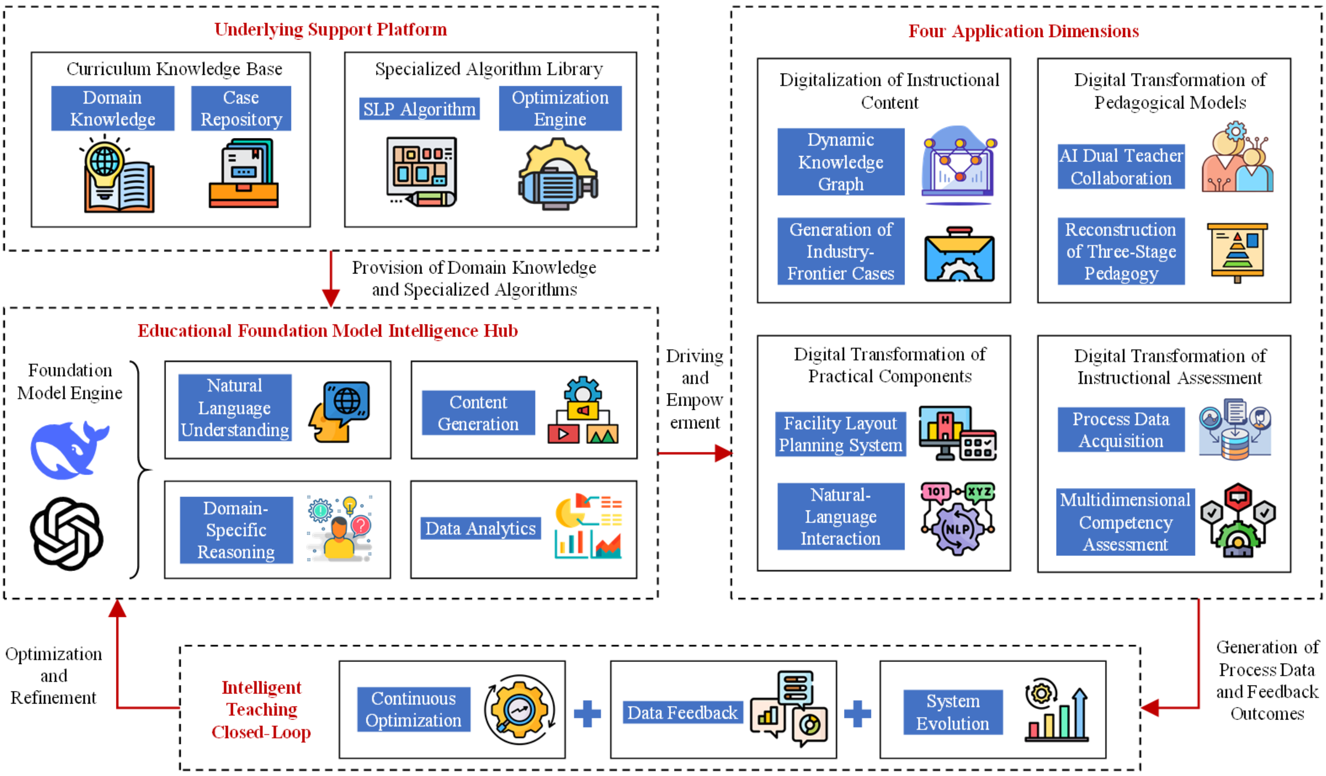



Figure 1 The four-in-one overall framework for the digital transformation of engineering courses

## 3.2 Teaching Content

The digital transformation of teaching content is intended to convert it from a static and fixed knowledge system into a dynamic and evolving knowledge ecosystem. Firstly, the semantic understanding and association capabilities of educational large language models are utilized. Discrete knowledge points in the course are constructed into a structured knowledge graph through these capabilities. Logical relationships between concepts are made explicit via this graph. It supports students' non-linear knowledge exploration and associative learning. Secondly, based on well-designed professional prompts, virtual cases, exercises, and project tasks closely aligned with industry frontiers are generated in real time by large language models. This generation is conducted in accordance with teaching progress and students' interests [18]. For example, in the course *Facility Planning*, diversified scenarios can be dynamically generated. Such scenarios include the layout of an electric vehicle battery recycling production line and the zoning design of an automated warehousing system. This ensures that teaching content consistently maintains its cutting-edge nature and high contextual relevance.

## 3.3 Teaching Modes

The innovation of teaching modes is reflected in the construction of a new paradigm of AI-supported dual-teacher collaborative teaching [19]. In this paradigm, AI assumes dual roles: first, as an AI teaching assistant, repetitive tasks such as answering questions, generating teaching materials, and conducting initial homework evaluation are processed automatically, which liberates teachers' productivity; second, as an AI learning companion, one-on-one and heuristic learning companionship and support are provided for each student [20]. Based on this role definition, the teaching process is reshaped: Before class, students conduct an inquiry-based preview with AI learning companions. Academic performance early warnings are provided for teachers by an AI based on students' feedback. During class, teachers focus on organizing in-depth discussions and group collaboration. As an intelligent blackboard or debate opponent, AI generates schemes, visualizes ideas, or puts forward challenging questions in real time. After class, students are guided by AI learning companions to consolidate knowledge and iterate schemes. A new teaching closed loop featuring efficient collaboration among students, AI, and teachers is thereby formed.

## 3.4 Practical Components

The core of the transformation in practical sessions lies in the construction of a facility planning system. This system is deeply integrated with the DeepSeek large language model and the SLP method. It covers the entire workflow from basic data management to the optimal selection of final schemes. Specific functional modules include: activity unit information management, logistics from-to chart management, logistics closeness analysis, logistics relationship diagram generation, comprehensive interrelationship analysis, comprehensive relationship diagram generation, location relationship diagram design, area relationship diagram generation, layout scheme design, and scheme evaluation and optimal selection. The workflow of the facility-planning system based on DeepSeek and SLP methods is shown in Figure 2.

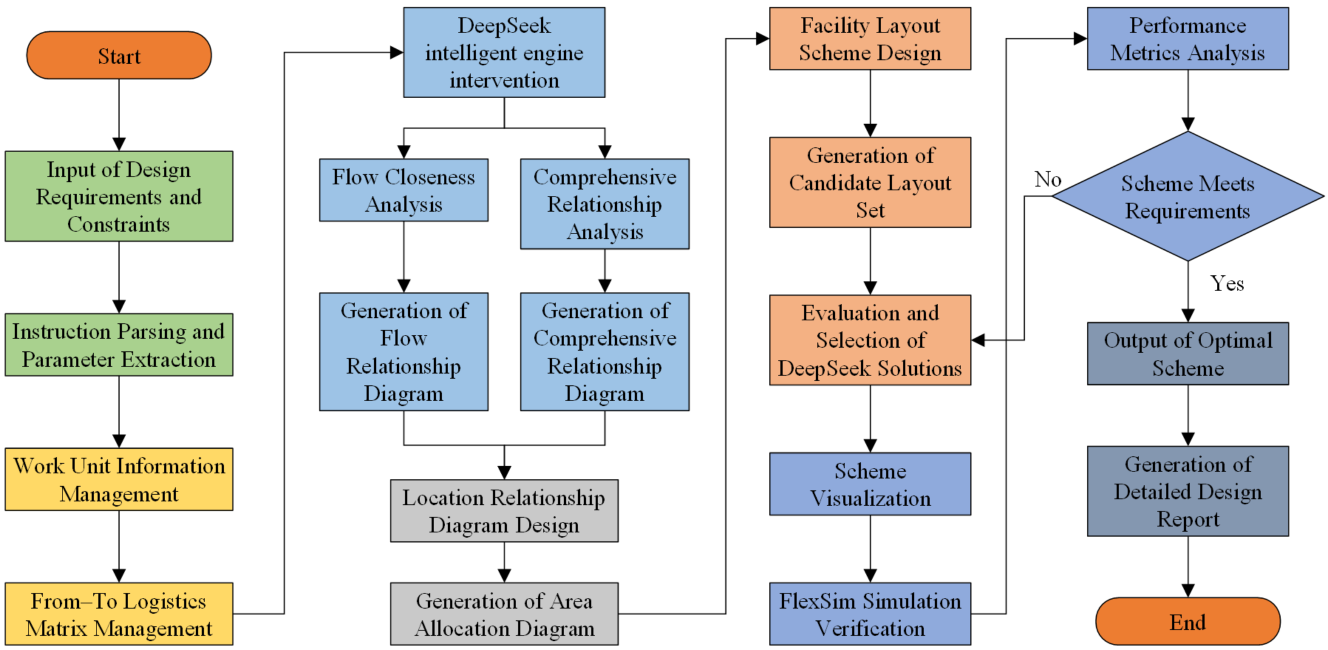


Figure 2 The workflow of the facility planning system based on DeepSeek and the SLP method

In this workflow, the DeepSeek large language model serves as an intelligent decision-making engine. It deeply empowers key links: it can assist in logistics closeness analysis and comprehensive interrelationship analysis, providing students with a professional reasoning basis. At the final stage, multi-dimensional evaluation and optimal selection of multiple alternative schemes can be conducted by it. Through a natural language interface, the system significantly lowers the professional threshold. Students can drive the system operation with natural language instructions. A complete digital design closed loop is realized, covering data input, intelligent analysis, chart generation, scheme design, simulation verification, and optimization and selection. This liberates students from tedious manual calculations and drawing tasks. They can then focus on the cultivation of systematic thinking and innovative decision-making capabilities.

## 3.5 Teaching Evaluation

The digital transformation of teaching evaluation is based on a data-driven, process-oriented, and comprehensive assessment. By leveraging the analytical capabilities of large language models, interaction data of students throughout the learning process can be continuously collected and analyzed by the system. Such data includes the quality of questions raised, the logical path of scheme iteration, and the depth of discussions with AI. Personalized reports on learning engagement and cognitive development are thereby generated.

In terms of comprehensive competency assessment, a multi-dimensional model integrating AI quantitative scoring and teacher qualitative evaluation has been established. AI can conduct rapid and consistent quantitative evaluation on multiple objective indicators of design schemes (e.g., logistics costs, space utilization rate). On this basis, teachers perform qualitative evaluation on students' innovation, systematic thinking, and professional literacy. This evaluation incorporates project reports, classroom performance, and other relevant factors. Ultimately, a comprehensive score that fully reflects students' knowledge, abilities, and literacy is formed.

# 4 Effectiveness Analysis

## 4.1 Case Design

The selection of *Facility Planning* as an empirical case is based on its representativeness. This course requires students to master theoretical methods such as SLP. Meanwhile, they must complete a comprehensive facility layout design. It embodies the characteristic of close integration between theory and practice. In traditional teaching, students are often burdened with tedious manual calculations and drawing. The exploration and optimization of multiple layout schemes remain inadequate. The teaching experiment was conducted on one class, spanning a full semester. In terms of technical implementation, a core intelligent engine was built by integrating large language model APIs. A technical support system was formed by combining knowledge graph tools and FlexSim simulation software. Data collected included: course scores, interaction logs between students and the system, course design works, questionnaires distributed at the end of the semester, and semi-structured interview records of some students.

## 4.2 Specific Implementation

In terms of content reconstruction, the core concepts and methods of the course are constructed into a knowledge graph. The logical path from logistics relationship analysis to spatial relationship determination is clarified. Through prompt engineering, cutting-edge cases are generated. Examples include the layout planning of a new energy motor assembly workshop with an annual output of 100,000 units and the design of an unmanned distribution center serving the last mile of urban logistics. These cases are used as project tasks to drive students to apply the knowledge they have learned. In terms of teaching mode, a coherent AI-supported dual-teacher interaction process is formed. Before class, students discuss the preliminary application of SLP in the generated cases with AI through a natural language interface. During class, teachers guide each group to present the schemes co-generated with AI and stimulate inter-group debates. AI provides real-time data support or raises questions from different perspectives. After class, students continuously optimize their course design reports based on classroom discussions and iterative suggestions from AI. The workflow of AI-supported dual-teacher collaborative teaching is shown in Figure 3.

The facility planning system based on DeepSeek and the SLP method is deeply applied in practical sessions, as shown in Figure 4. In teaching projects, students first enter basic data through the system’s activity unit information management and logistics from-to chart management modules. The core layout analysis phase is then strongly supported by the DeepSeek large language model, particularly in logistics closeness analysis and comprehensive interrelationship analysis. For instance, when students have doubts about the relationship level between the assembly area and the quality inspection area, they can directly ask the system. Based on SLP principles and logistics data, DeepSeek generates analysis reasons combining qualitative and quantitative methods, assisting students in formulating more reasonable relationship levels and automatically generating logistics relationship diagrams and comprehensive relationship diagrams.

On this basis, the system guides students to complete the design of location relationship diagrams and area relationship diagrams, and automatically generates multiple feasible layout schemes. In the final scheme evaluation and optimal selection phase, DeepSeek helps students establish an evaluation index system. It conducts comparative reviews of schemes from multiple dimensions, such as logistics efficiency, space utilization rate, and scalability, supporting students in making optimal decisions. The entire process closely integrates the classic SLP teaching method with the cutting-edge intelligent decision-making capabilities of large language models. This enables students to experience full-process digital and intelligent planning from data input to scheme formulation.

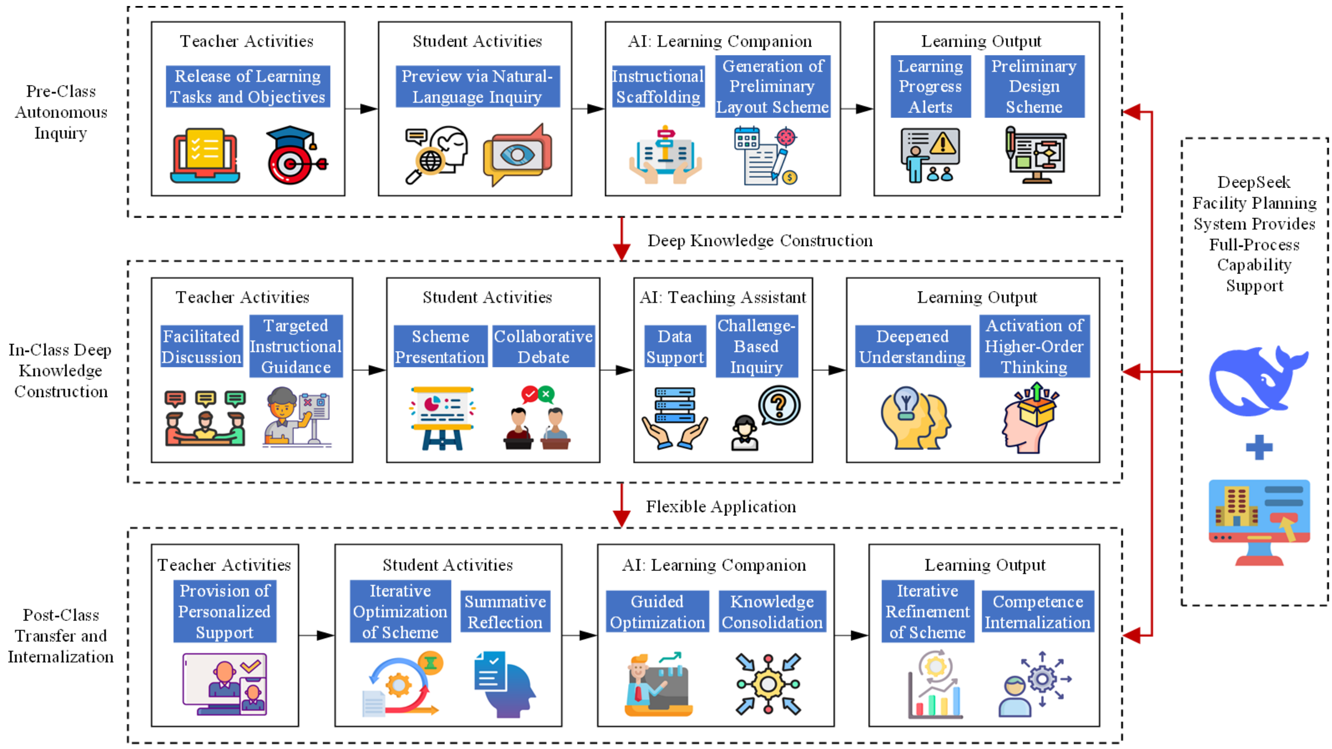
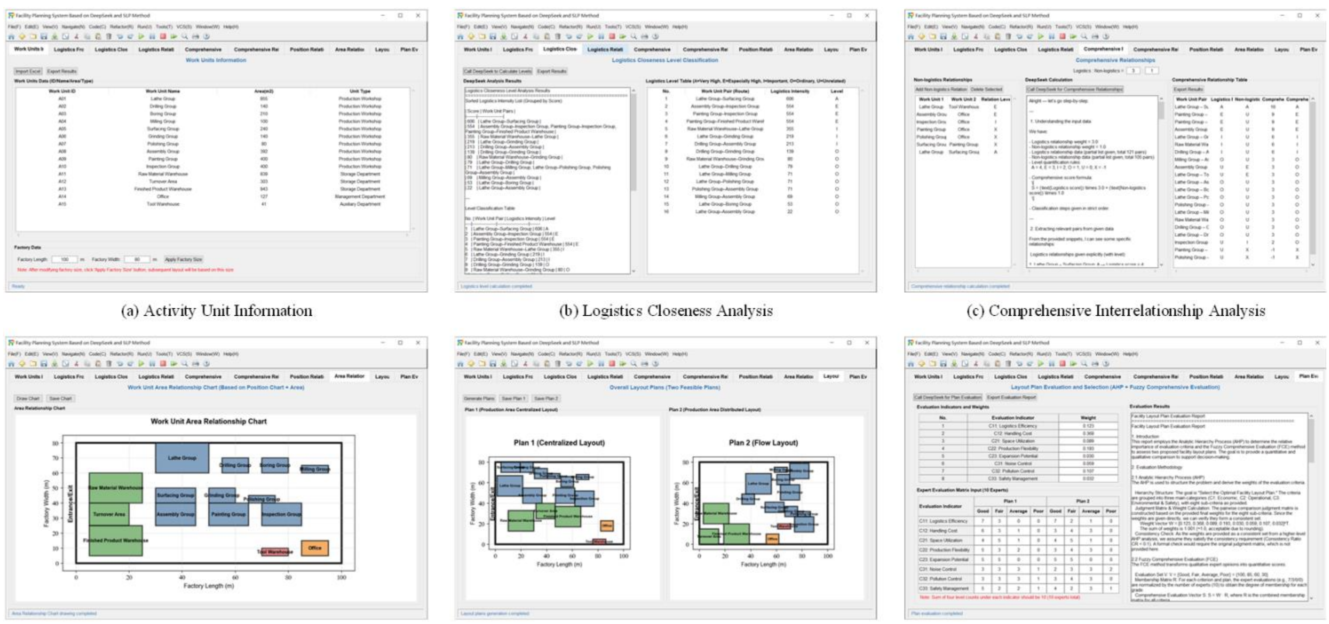



Figure 3 The workflow of AI-supported dual-teacher collaborative teaching



(a) Activity Unit Information (b) Logistics Closeness Analysis (c) Comprehensive Interrelationship Analysis

(d) Area Relationship Diagram (e) Layout Schemes (f) Comparative Analysis of Schemes

Figure 4 The usage process of the facility planning system based on DeepSeek and the SLP method

The teaching evaluation system has shifted to a full-process data-driven operation. The system automatically records students' key behaviors during course design, such as the number of scheme iterations, the adoption of AI feedback and quality of improvements, and the logical depth of questions raised, and generates process-oriented learning reports. The final performance assessment integrates quantitative analysis by AI and qualitative evaluation by teachers: AI is responsible for objective scoring of techno-economic indicators of design schemes, such as logistics intensity and area utilization rate, while teachers focus on evaluating the innovation of design thinking, the systematicity of reports, and teamwork performance, with each accounting for a certain proportion of the weight.

### 4.3 Result Analysis

Quantitative data in Figure 5 shows positive outcomes. The score rate of comprehensive application questions in the final exam of the experimental class is significantly higher than that of the control class, and its course design works show better overall performance in scheme diversity, technical rationality, and data comprehensiveness. Questionnaire survey results indicate that an overwhelming majority of students recognize the role of this model in enhancing their ability to solve complex engineering problems and systematic thinking.

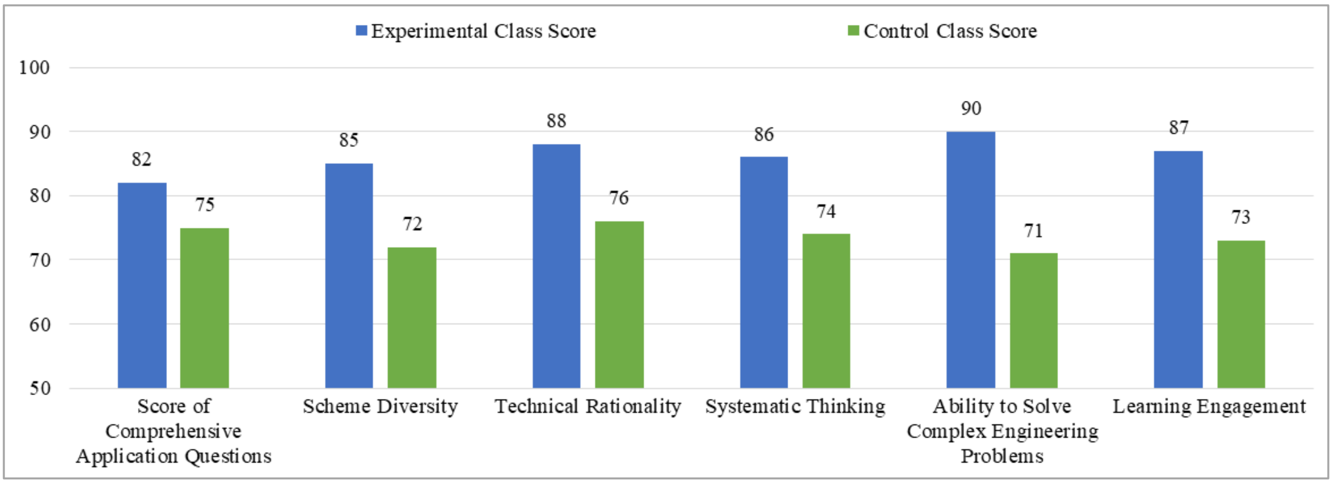



Figure 5 Comparison of teaching practice effects.

Qualitative feedback further reveals the sources of these outcomes. Students generally reflect that AI acts as a tireless collaborator, forcing them to think more rigorously and comprehensively, and believe that the process of discussing schemes with AI has greatly stimulated their interest in exploration. Teachers' reflections point out that a profound transformation has occurred in the teaching role: from a one-way knowledge transmitter to a designer of learning scenarios, a facilitator of classroom discussions, and a stimulator of higher-order thinking. The quality and depth of teacher-student interaction have achieved substantial improvement.

## 5 Conclusion and Future Directions

A digital transformation framework for engineering courses centered on large language models is systematically constructed in this study, and empirical verification is conducted in the course *Facility Planning*, which verifies the framework's effectiveness and innovative value in reshaping teaching content, teaching modes, practical sessions, and evaluation systems. It is confirmed that the four-in-one transformation path driven by educational large language models as the intelligent hub can significantly improve students' course participation, ability to solve complex engineering problems, and systematic innovative thinking, while promoting the modern transformation of teachers' roles from knowledge transmitters to learning guides and scenario designers. At the theoretical level, a systematic digital reconstruction model for engineering courses with large language models as the engine is proposed; at the practical level, new teaching forms such as the facility planning system based on DeepSeek and SLP, and AI-supported dual-teacher collaboration are successfully established, providing a replicable practical paradigm for the reform of similar courses.

Naturally, this study still has certain limitations: for instance, the empirical teaching cycle is relatively short, the sample size is limited, and the professional judgment of current general large language models in specific engineering fields still has boundaries. Looking forward to the future, subsequent research will focus on two key directions: firstly, deepening technological integration and exploring the construction of vertical models integrated with domain knowledge to further improve the accuracy and reliability of the system in addressing professional engineering problems; secondly, expanding the application ecosystem, promoting the cross-course application of this framework in industrial engineering and related engineering courses, and collaboratively establishing shared teaching resources and evaluation criteria.

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