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Adaptive Research on Integrating Artificial Intelligence into University Engineering Education from the Perspective of Innovation Diffusion Theory: A Case Study of Six Chinese Universities

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Abstract

Against the macro backdrop of artificial intelligence profoundly reshaping global industrial landscapes and knowledge systems, engineering education in higher education institutions is poised for a historic paradigm shift. Driving systematic adaptive transformation has become the key pathway to enhancing educational quality and cultivating future-oriented engineering talent. This study, grounded in innovation diffusion theory and employing a multi-case research approach, first selects six universities of distinct types—research-oriented, teaching-research-oriented, and applied technology-oriented—to ensure representativeness and diversity. Through semi-structured interviews with administrators, faculty, and students, alongside multi-source data collection including syllabi and policy documents, it systematically explores integration pathways and adaptive mechanisms for incorporating AI into university engineering education. The study focuses on examining the impacts of AI technology introduction on engineering education's content, methodological frameworks, organizational structures, and evaluation systems. It attempts to identify key elements and conditions for transitioning from "early adopters" to "early majority" adoption. Building on this, the research identifies and summarizes adaptive models for integrating AI into university engineering education, further exploring the adaptive gap between technological iteration speed and educational system responsiveness, along with pathways to bridge this gap. Integrating AI into university engineering education requires systematic strategies to consciously enhance compatibility, reduce complexity, and highlight relative advantages. Throughout this process, universities must clarify the objectives of AI integration, provide technical support and faculty training, develop aligned curricula and teaching resources, and establish mechanisms for continuous feedback and optimization.

Keywords: Innovation Diffusion Theory； Artificial Intelligence； Engineering Education； Educational Ecosystem

1. Introduction

1.1 Research Background and Motivation

Intelligent technologies, represented by generative AI, are triggering a fundamental paradigm shift in engineering practice [1]. This technological wave has profoundly reshaped the global industrial landscape and knowledge systems, imposing new demands on the core competencies of engineering professionals and compelling higher education institutions to undertake adaptive reforms in their engineering education systems. Against this backdrop, national strategies provide clear guidance for educational reform. China has successively issued programmatic documents such as the "Development Plan for the Next Generation of Artificial Intelligence" and the "Opinions on Deepening the Implementation of the 'AI+'

Initiative," explicitly designating AI as a strategic technology that will lead the future [2]. These documents particularly emphasize "integrating AI into all elements and processes of education and teaching" to accelerate the cultivation of interdisciplinary talent proficient in "AI+" [3].

However, despite the impetus of the times and policy guidance, current engineering education in higher education institutions still faces significant practical challenges in integrating artificial intelligence. Course content updates lag behind, faculty members generally face a "digital divide" in terms of knowledge structure and teaching capabilities, and the knowledge-transfer-oriented teaching paradigm struggles to adapt to the new requirements of human-machine collaboration [4]. These challenges collectively point to a core issue: how can engineering education in higher education institutions achieve effective adaptive transformation to respond to the dramatic changes in the external technological environment?

1.2 Research Questions and Objectives

Grounded in innovation diffusion theory, this study delves into the adaptive mechanisms of AI integration in higher education engineering programs, focusing on three core research questions. First, what are the pathways for integrating AI into higher education engineering programs? Second, what are the facilitating factors and barriers influencing the speed and depth of these pathways' diffusion? Third, how do adaptive mechanisms differ across various types of universities? Fourth, how can the "adaptive gap" between rapid technological iteration and the relatively slow response of the educational system be effectively bridged?

Through multi-case empirical analysis of six universities of diverse types in China, this study systematically maps the current landscape of AI integration into engineering education; constructs an analytical framework centered on "educational adaptability" based on innovation diffusion theory; and provides empirical evidence and theoretical references for formulating differentiated, actionable integration strategies tailored to universities with distinct positioning.

2. Literature Review

2.1 Innovation Diffusion Theory and Its Evolution

The theory of innovation diffusion was proposed by American scholar Everett M. Rogers in the 1960s and provides a detailed explanation of the diffusion process of new ideas, products, and phenomena within specific social systems. Its core framework includes five innovation attributes that influence adoption decisions—relative advantage, compatibility, complexity, trialability, and observability—as well as five categories of adopters classified by adoption timing: innovators, early adopters, early majority, late majority, and laggards [5]. This theory provides a classic paradigm for understanding the diffusion and adoption of educational technology, with technological compatibility and relative advantage being key factors in its spread within educational systems [6].

However, artificial intelligence (AI) technology is characterized by rapid iteration, high complexity, and strong pervasiveness, posing a challenge to classical theories. AI is adopted not merely as a tool but as a meta-innovation that triggers restructuring; its rapid development creates a significant “adaptability gap” with the inherent institutional inertia and long curriculum update cycles of educational systems [7]. Consequently, traditional diffusion models based on relatively stable innovation environments struggle to fully account for the continuous learning and dynamic adaptation processes required of educational stakeholders when addressing rapidly evolving technologies [8]. Therefore, innovation diffusion theory must incorporate supplementary dimensions such as dynamic adaptation, system resilience, and ethical considerations [9].

2.2 Current Status of AI Integration in Engineering Education

International research and practice demonstrate a trend toward multi-level, deep integration. Universities in Europe and the United States generally advance this integration through three pathways. First, making AI general education a required course to cultivate data literacy and algorithmic thinking among all engineering students [10]; second, embedding AI into traditional engineering curricula, such as incorporating modules on machine learning and intelligent system design into course design [11]; third, extensively utilizing AI technologies to build personalized, intelligent learning environments, such as employing learning analytics and intelligent tutoring systems to enable adaptive learning and academic risk early warning [12]- [13]. These practices signal that engineering education is shifting from a paradigm of knowledge transmission to one that emphasizes human-machine collaboration, ethical judgment, and complex problem-solving [14].

In contrast, while research in China is becoming increasingly active, it remains largely in an exploratory and developmental phase, with research paradigms actively adapting to local contexts in the East [15]. Research generally holds that the diffusion of AI innovations is key to advancing the application of AI in education, and explores the integration of technology and education to drive transformation in teaching and learning methods [16]. However, most studies focus on introducing application scenarios for specific AI tools or presenting case studies of teaching reforms in individual courses or disciplines [17]. While these studies offer valuable practical insights, they generally suffer from fragmented perspectives and outdated theoretical frameworks, and lack systematic cross-institutional comparisons and empirical research [18]. This has led to an insufficient understanding of the common obstacles and diverse pathways faced by Chinese universities in the process of AI integration.

2.3 Systemic Nature and Adaptability of Education

The deep integration of AI is by no means a simple superimposition of technology, but rather a systemic endeavor that triggers comprehensive innovation across all elements of education. The educational system encompasses multiple interrelated dimensions, including curriculum content, teaching methods, organizational structures, assessment, and culture [19]- [20].

Approaching this from the perspective of educational systemicity implies viewing AI as a technological agent capable of reshaping the roles of teachers and students, knowledge structures, and interactive relationships; the success of its integration depends on the synergistic evolution and balance of various elements within the system.

This study defines “educational adaptability” as the dynamic capacity and process by which an educational system undergoes internal structural adjustments and institutional innovations in response to external technological shocks, manifested specifically at three levels. At the operational level, this requires dynamic updates to curriculum content and innovation in teaching methods; at the organizational level, it necessitates breaking down disciplinary barriers to form interdisciplinary teaching teams; and at the institutional and cultural levels, it demands the establishment of error-tolerance mechanisms, professional development support systems, and closed-loop processes for formative assessment and feedback.

3. Research Design

To thoroughly explore the specific pathways, underlying mechanisms, and adaptive challenges involved in integrating AI technology into higher education engineering programs, this study employs a multi-case study methodology. This approach not only allows for in-depth analysis of individual cases but also enables the extraction of more generalizable patterns and theoretical insights through comparative analysis, thereby yielding research findings with greater robustness and explanatory power than those from single-case studies. Regarding case selection, to ensure that the research sample fully reflects the diversity of China’s higher education engineering system and maximally captures the differentiated patterns in the AI integration process, the study employs a combination of purposive sampling and maximum diversity sampling strategies. Based on the common classification of Chinese higher education institutions, six universities with significant differences in institutional positioning, resource endowments, and social service functions were selected as research cases. The aim is to reveal the distinct logics, pathways, and adaptation strategies exhibited by different types of institutions when responding to the diffusion of the same technological innovation. Specifically, the case studies include two research universities (University A and University B), which aim to cultivate talent for academic innovation and high-end R&D, possess national-level research platforms, and play a leading role in cutting-edge AI research and advanced engineering applications;two teaching and research-oriented universities (University C and University D), which balance teaching and research, focus on serving regional economic and social development, and emphasize the integration of engineering education with local industries, serving as key drivers of technology diffusion and popularization; and two applied technology colleges (College E and College F), which are oriented toward cultivating high-quality applied and technical-skilled talent, emphasize the integration of industry and education as well as university-enterprise collaboration, and design their curricula to closely align with the practical needs of the industry.

The research was primarily conducted through semi-structured interviews and text analysis.

The interviewees encompassed three categories of key actors related to “AI + Engineering Education,” totaling 24 individuals (see Table 1 for basic information). All interviews were conducted using tailored outlines based on the respondents’ roles. With their consent, the sessions were audio-recorded, and the interviewers maintained flexibility in follow-up questioning throughout the process. Concurrently, the study systematically collected relevant textual materials, primarily including engineering course syllabi or teaching plans incorporating AI content, policy documents such as institutional “AI+Education” action plans, and related teaching achievement reports, to supplement and corroborate the interview data. To ensure the timeliness and contextual sensitivity of the study, data collection was completed between September 2024 and June 2025. During this period, generative AI technologies (such as GPT-4) continued to evolve rapidly, and discussions regarding AI ethics and educational applications both domestically and internationally became increasingly in-depth.

Table 1: Basic Information on Interview Participants

<table>
<tr><th>No.</th><th>Role</th><th>Professional Background</th><th>School (Type)</th><th>Key Focus of Interview</th></tr>
<tr><td>L01</td><td>University Leadership / Head of Academic Affairs</td><td>Computer Science</td><td>University A (Research-oriented)</td><td rowspan="3">University-level strategic planning, policy support, resource allocation, and top-level design</td></tr>
<tr><td>L02</td><td>University Leadership / Head of Academic Affairs</td><td>Educational Technology</td><td>University C (Teaching and Research-oriented)</td></tr>
<tr><td>L03</td><td>University Leadership / Head of Academic Affairs</td><td>Electronic and Information Engineering</td><td>College E (Applied Technology)</td></tr>
<tr><td>T01</td><td>Engineering Faculty</td><td>Computer Science and Technology</td><td>University A (Research-oriented)</td><td rowspan="8">How to integrate AI content or tools into specific courses and teaching practices, experiences gained, major challenges encountered, and support needed</td></tr>
<tr><td>T02</td><td>Engineering Faculty</td><td>Artificial Intelligence</td><td>University A (Research-oriented)</td></tr>
<tr><td>T03</td><td>Engineering Faculty</td><td>Control Science and Engineering</td><td>University B (Research-oriented)</td></tr>
<tr><td>T04</td><td>Engineering Faculty</td><td>Mechanical Engineering and Automation</td><td>University C (Teaching and Research-oriented)</td></tr>
<tr><td>T05</td><td>Engineering Faculty</td><td>Robotics Engineering</td><td>University C (Teaching and Research-oriented)</td></tr>
<tr><td>T06</td><td>Engineering Faculty</td><td>Electrical Engineering</td><td>University D (Teaching and Research-oriented)</td></tr>
<tr><td>T07</td><td>Engineering Faculty</td><td>Intelligent Manufacturing Engineering</td><td>College E (Applied Technology)</td></tr>
<tr><td>T08</td><td>Engineering Faculty</td><td>Software Engineering</td><td>College F (Applied Technology)</td></tr>
</table>

T09	Engineering Faculty	Internet of Things Engineering	College F (Applied Technology)	
S01	Doctoral Student	Intelligent Control Technology	University A (Research-oriented)	Learning Experiences, Cognitive Changes, Skill Acquisition, and Future Expectations Regarding Courses Incorporating AI Content
S02	Sophomore	Automation	University A (Research-oriented)	
S03	Master's Student	Software Engineering	University B (Research-oriented)	
S04	Doctoral Student	Computer Vision	University B (Research-oriented)	
S05	Senior	Mechanical Design and Automation	University C (Teaching and Research-oriented)	
S06	Junior	Automotive Engineering	University C (Teaching and Research-oriented)	
S07	Master's Student	Next-Generation Electronic Information	University D (Teaching and Research-oriented)	
S08	Second Year of Master's Program	Control Engineering	University D (Teaching and Research-oriented)	
S09	Junior	Industrial Robotics Technology	College E (Applied Technology)	
S10	Senior	Mechatronics	College E (Applied Technology)	
S11	Senior	Mechanical Design and Automation	College F (Applied Technology)	
S12	Junior	Industrial Internet	College F (Applied Technology)	

Note: In the codes, L stands for university leadership/administrators, T stands for faculty, and S stands for students

All interview recordings were transcribed and analyzed using thematic analysis. First, open coding was conducted to extract key concepts from the original statements; second, axial coding was performed to categorize concepts into higher-level categories; finally, selective coding was carried out to integrate categories around core themes such as the "adaptability gap," "innovation diffusion attributes," and "integration pathways".

Table 2: Interview Coding

Selective Coding (Core Themes)	Axial Coding (Main Categories)	Open Coding (Initial Concepts)
Adaptation Gap	Outdated Curriculum Content	Long curriculum revision cycles; difficulty integrating cutting-edge technologies; Disconnect between classroom knowledge and

		industry; Perception lag among younger students
	Disconnect in Faculty Development	Outdated training content; heavy self-study workload; Lack of a platform for ongoing support; training lacks specificity
	Mismatch in the evaluation system	Excessive weight given to written exams; project outcomes not included in evaluations; Certification standards do not include AI capabilities; project strengths are not reflected
Key attributes of innovation diffusion	Relative Advantages	Improved efficiency; personalized learning; enhanced employability; interview bonus points
	Compatibility	Rigid curriculum structure; evaluation inertia; marginalization of course templates
	Complexity	Teachers' concerns about technology; Programming barriers for students; Interdisciplinary knowledge requirements
	Feasibility	Pilot projects lower barriers; innovation labs provide support; micro-projects offer incentives
	Observability	Exemplary competition wins; dissemination of outcomes; peer influence
Pathways for AI Integration	Content Integration	Add-on modules; Surface-level integration
	New Course Development	Launching standalone required courses; systematic training; introductory courses
	Project Integration	Incorporating AI into course design; Industry-academia collaboration projects; Deep learning in graduation projects; competition-driven
	Organizational Restructuring	Establish interdisciplinary centers; Break down departmental barriers; School of Future Technologies
	Platform Empowerment	Intelligent teaching platforms; Low-code platforms
	Community-Driven	Faculty learning communities; student clubs
Conditions for the Transition from Early Adopters to the Early Majority	Demonstration and Leadership	Local success stories; replicable experiences; role models
	Institutional Support	Resource allocation; incentive policies; credit substitution policies
	Capacity Building	Tiered training; tool platforms; teaching resource repositories
	Demand-Driven	Labor market signals; students' intrinsic interests; requirements for further education

4. Research Findings

This chapter presents research findings across four dimensions, collectively outlining the complex landscape and adaptive mechanisms of AI integration in university engineering education. First, by examining “the concrete manifestations of the adaptation gap,” it reveals the structural barriers encountered in the process of integrating AI into engineering education, addressing the question “What is the problem?” Second, based on the five key attributes of innovation diffusion theory, it analyzes “the specific manifestations of these key attributes,” addressing “why these barriers exist and how to effectively leverage the five attributes”;Third, by examining “diverse pathways for AI integration,” this section presents the differentiated strategies adopted by various types of universities in practice, addressing the question “how to respond”; finally, by focusing on “conditions for the transition from early adopters to the early majority,” this section explores the key elements driving integration from isolated explorations toward large-scale diffusion, addressing the question “how to scale up.”

4.1 Specific Manifestations of the Adaptation Gap

A significant adaptability gap exists in the process of integrating AI into engineering education at universities. This is specifically manifested in three interrelated aspects—curriculum content updates, faculty professional development, and educational evaluation systems—which collectively constitute the primary barriers to the evolution of technology diffusion from superficial, isolated applications to deep, systematic integration.

(1) Curriculum Content Updates Lags Behind Technological Iteration

The sluggish pace of curriculum updates is the most obvious manifestation of the adaptability gap. At the case study institutions, the revision cycle for engineering program curricula and course syllabi is typically 2–3 years, and some foundational course syllabi have not undergone major revisions for over five years. This stands in stark contrast to the rapid pace of iteration in AI technology [21]. This mismatch in speed makes it difficult for course content to reflect the latest technological advancements. On the one hand, instructors struggle to incorporate cutting-edge knowledge in a timely manner.“Revising a syllabus involves a strict review process; even the fastest cycle takes at least a year and a half from initiation to approval. A single technological iteration doesn’t take a year—this speed disparity puts us at a significant disadvantage.” (L01) “I just added foundational applications to my course design last year, but this year I’ve already noticed students discussing large language models. So I can only briefly mention them in extracurricular activities; I can’t cover them systematically.” (T04) On the other hand, the lag in course content diminishes students’ perception of the value of AI technology. “The course is still covering classic algorithm cases from several years ago; it feels like what we learn in class is severely disconnected from actual research and industry needs.” (S01) “The professor says they’ll cover it next semester, but I’ve seen online that many companies are already using newer versions, so it feels like the teaching is always a step behind.” (S07)

(2) The Discrepancy Between Faculty Professional Development Needs and Technological Evolution

Faculty members are key adopters and implementers of educational innovation. However, the professional development support system for engineering faculty struggles to meet their needs in addressing the impact of AI technology in terms of content, pace, and format, creating a significant digital divide [22]. First, faculty training lacks timeliness. Official training often focuses on established, relatively basic AI concepts or tools, making it difficult to keep up with the technological frontier.“Last year’s training was still covering Python basics, but I’ve already figured those out on my own. What I urgently need now is guidance on how to integrate the latest developments into my courses.” (T06) Second, teachers face immense pressure to keep themselves updated and struggle with time constraints. Teachers without an AI background must devote significant time to self-study, a process fraught with anxiety and uncertainty. “I have to read papers and study open-source code just to barely keep up. But this takes up a lot of my research and lesson preparation time.” (T07) “Teachers are also self-learning the practical applications of AI, so sometimes when we ask deeper questions, they suggest we look up the information ourselves.” (S09) Furthermore, knowledge sharing within the teaching community has not yet evolved into an institutionalized, sustainable support system. “The teaching community lacks a continuous support platform where teachers can ask questions and receive professional feedback at any time.” (T04) “Many faculty members at applied universities come from industry; their primary concern is how to translate the latest AI tools from the corporate sector into training programs for teaching projects. We are currently attempting to establish a ‘dual-qualified’ training base through university-industry collaboration.” (L03)

(3) Mismatch Between Traditional Evaluation Systems and Emerging AI Competency Goals

Traditional evaluation methods, which rely primarily on paper-and-pencil tests, are severely incompatible with the competency goals emphasized in the AI era—such as solving complex problems, human-machine collaboration, algorithmic thinking, and ethical judgment [23]. At the operational level, traditional evaluation struggles to assess the core value of AI project practice.“I asked students to use AI tools to solve a real-world engineering optimization problem. The process was fascinating, and the students’ skills improved significantly. But in the end, for the sake of fairness and convenience, the final written exam still accounted for 60% of the grade.” (T02) Students also deeply feel this mismatch. “Our group spent a month working on a machine learning-based project and learned a lot. But the final exam still focused on formula derivation and memorizing concepts.” (S05) Institutional factors reveal deeper underlying causes. The case university’s course quality assessment and professional accreditation standards have yet to incorporate metrics such as AI tool application proficiency or human-machine collaborative problem-solving. The inertia of the evaluation system maintains the stability of teaching models but has become an institutional barrier hindering the shift toward a competency-based, innovation-oriented educational paradigm.“The university-industry collaboration on AI projects has been quite successful, but the grading criteria for graduation projects are the same as for regular projects. It feels like the advantages of the project experience aren’t being reflected.” (S04, S08)

4.2 Specific Manifestations of Key Attributes of Innovation Diffusion

Comparative advantage refers to the advantages of an innovation over existing solutions. Faculty and students generally recognize the significant comparative advantages that AI brings to engineering education, and this recognition serves as a key internal driver for technology adoption [24]. In terms of improving efficiency, AI tools significantly reduce the time required for iterations and computations in traditional engineering education. “With the introduction of AI-assisted optimization, multiple rounds of iterative calculations and validation can now be completed within the course design cycle, allowing students to focus more on innovative solutions rather than repetitive calculations.” (T04) In terms of providing personalized learning support, the intelligent teaching platforms introduced by some universities have demonstrated significant potential. The commercial learning analytics platform purchased by University C provides early warnings and resource recommendations based on students’ online learning behavior data. “The platform pushes relevant literature and case studies based on my knowledge gaps, making my learning feel more targeted.” (S05) Regarding the handling of complex data, AI’s data analysis and pattern recognition capabilities are highly recognized. “In the past, there was a heavy emphasis on theory, which students found difficult to grasp. Now, by using simple algorithms to process real-world data, students can see tangible results, transforming their understanding of AI from an abstract concept into a practical tool.” (T06) “Using AI to write code is much more efficient; it will save a lot of time on course projects in the future.” (S02)

Compatibility refers to the degree to which innovation aligns with existing values, past experiences, and the needs of potential adopters. The integration of AI into higher education engineering programs faces significant compatibility challenges. The rigid constraints of the curriculum system are the biggest obstacle. The vast majority of faculty members interviewed mentioned that existing major curricula have fixed class hours and saturated content, making it extremely difficult to squeeze in AI content. “The curriculum is already packed enough; adding AI content would mean cutting other courses.It’s hard on the teachers, and it’s hard on us.” (S06) “Curriculum revisions follow a fixed cycle; we can’t just change things whenever we want. The whole university operates as a single system—a change in one part affects the whole.” (L02) Course syllabi from University D show that newly added AI modules are often placed in the latter half of the course, and their assessment weight is typically less than 15%, reflecting the difficulty of deep integration. The inertia of assessment methods also poses a barrier. Traditional written exams focus on knowledge retention and struggle to effectively assess the new competencies required in the AI era. “Course design requires using AI tools to solve real-world problems, but the final exam still accounts for the lion’s share of the grade. This may be because it’s difficult to standardize project evaluation criteria.” (T02)

Complexity involves the difficulty and cost of understanding and utilizing innovation. The complexity of integrating AI into university engineering education poses challenges on multiple fronts for both faculty and students. For faculty, this complexity manifests as technical concerns and the pressure to update their knowledge. “I’m learning as I teach; I have to spend a lot of time self-studying, which is very stressful.” (T09) This complexity stems not only from the technology itself but also from the pedagogical process of effectively translating it into instructional content.“Many teachers, especially senior faculty, feel daunted by new technologies and worry that their teaching outcomes will be poor despite investing significant effort.” (L03) For students, complexity manifests as a steep learning curve driven by programming skills and interdisciplinary concepts. Although students are highly interested in AI, they easily feel frustrated when faced with the multiple demands of programming skills and new concepts. “When the teacher explains machine learning formulas, we’ve mostly forgotten our calculus and linear algebra. We don’t know how to debug code errors either—it feels like a very high barrier to entry.” (S11) “Low-code platforms are indeed user-friendly, but you have to write code as soon as you delve a little deeper. As mechanical engineering majors with a weak programming foundation, getting stuck is very frustrating.” (S10) Although S01 and S03 have a stronger foundation, they also noted that they need to invest extra time to digest interdisciplinary knowledge.

Trialability refers to the risks and barriers associated with initial attempts at innovation. Small-scale, low-risk pilot projects are a key mechanism for overcoming initial obstacles and stimulating widespread adoption. Successful pilots lower the psychological barriers and practical costs of adoption by providing a safe testing ground. Successful pilot projects can generate a powerful demonstration effect within the community. University B’s “AI + Mechanical Fault Diagnosis” student competition project was initially led by T03 with a small team. They successfully developed a deep learning-based prototype system for bearing fault diagnosis and won an award in a national competition. “The project’s success created a demonstration effect within the college; both faculty and students came to consult us. The college then incorporated this case into its promotional materials and supported the establishment of a student interest group.” (T03) “Our college supports students in undertaking AI micro-projects. When students succeed, faculty members also feel a sense of accomplishment, and gradually, a supportive atmosphere has taken shape.” (T01)

Observability refers to the extent to which innovative achievements can be observed by others—that is, their visibility and replicability. Highly visible successful outcomes—whether explicit achievements such as competition awards or project implementations, or implicit improvements in student capabilities—can effectively accelerate the social dissemination of innovation. Explicit outcomes possess the strongest dissemination power and serve as powerful testimonials to the value of AI education.“My research project on deep learning monitoring was eventually included in a patent application. After seeing this, several younger students came to ask me for advice, believing that this direction could yield results.” (S03) Although implicit outcomes are difficult to quantify directly, they can be observed through student word-of-mouth and feedback regarding employment and further education. “During my interview, my experience with AI projects piqued the interviewers’ interest; they believed it demonstrated my potential to solve cutting-edge engineering problems.” (S01) Furthermore, internal observations within the teaching community are crucial. “Seeing faculty from other disciplines demonstrate how they integrate AI into their courses has provided me with significant inspiration and motivation.” (T04)

4.3 Diverse Pathways for AI Integration

The integration of AI into engineering education in higher education institutions exhibits diverse and differentiated pathways. These pathways not only reflect the strategic choices made by individual institutions based on their positioning and resource endowments but also reveal the hierarchical and phased characteristics of innovation diffusion within the higher education system. Specifically, they can be categorized into the following four main pathways, with additional practical models identified.

(1) Content Embedding: Integrating AI Modules into Traditional Courses

This is the most common and fundamental form of integration, widely observed across all types of case study universities. Its core feature involves adding AI-related knowledge modules or tool-usage units while keeping the original course framework largely unchanged. The syllabus for University C's "Fundamentals of Mechanical Design" explicitly includes a new chapter on "Machine Learning-Based Component Lifespan Prediction"; "It's difficult for us to launch a completely new AI course, but we can allocate 4–6 class hours within existing major courses to specifically cover basic concepts of AI frontiers relevant to the discipline, and use a simple case study to give students a hands-on experience." (T07) The advantage of this approach lies in its high compatibility and minimal resistance to reform; it enables a rapid response to the "AI+" policy call and is the most common superficial integration model during the early stages of technology diffusion [25]. However, the depth of this diffusion is typically limited, and it often devolves into a piecemeal introduction of isolated knowledge points. "The instructor just sprinkled in a few new concepts here and there; the connection to the rest of the course wasn't very tight." (S11) While content embedding is easy to implement, the depth of integration is limited. Some institutions with more abundant resources have begun to explore more systematic approaches to curriculum development.

(2) New Course Development: Building a Foundation for AI Literacy Through Independent Curricula

This approach is more common at research-oriented and teaching-research universities, reflecting more systematic and specialized integration efforts. Institutions offer standalone required or elective courses such as "Introduction to Artificial Intelligence" and "Intelligent System Design and Practice" to provide engineering students with a structured AI knowledge framework, demonstrating deeper resource investment and a shift in educational philosophy. For example, University A offers a required general education course titled "Artificial Intelligence and Engineering Ethics" to all engineering students. Institutions offering such courses typically include explicit curriculum development plans within their "New Engineering Disciplines Development Plans" or "Artificial Intelligence Education Action Plans," ensuring the implementation of this approach at the institutional level. "To equip future engineers with AI thinking, we must have a robust, systematic curriculum as the foundation, rather than treating it as a supplement to other courses." (L02) Offering standalone courses requires corresponding faculty resources and investment in curriculum development, making it a key measure for research-oriented and teaching-research-oriented universities to demonstrate their comparative advantages and cultivate interdisciplinary talent

[26]. While standalone courses provide a systematic knowledge framework, the true development of skills requires honing in real or simulated practical scenarios.

(3) Project Integration: Hone AI Skills in Practical Settings

This approach emphasizes "learning by doing," treating AI as a tool and a way of thinking for solving complex engineering problems or completing innovative projects. It is particularly prominent in the practical teaching at research-oriented universities and some applied technology colleges [27]. This approach enhances the usability of technology and the observability of outcomes. Specific forms include integrating AI technology into course design, graduation projects, academic competitions, and industry-university collaboration projects. At University D, course design requires students to integrate simple machine learning algorithms for data filtering or pattern recognition; College F, meanwhile, collaborates with local enterprises to have students participate in practical projects such as "product quality sorting based on visual recognition." "My graduation project involved using deep learning for structural health monitoring. The entire process gave me a deep and comprehensive understanding of AI—from theory to code, and finally to real-world engineering problems." (S03) While the pathways described above primarily occur at the course and project levels, organizational restructuring represents a more fundamental institutional transformation.

(4) Organizational Restructuring: Coordinating Systemic Change Through Institutional Entities

This is the most in-depth and systematic approach to integration, emerging in select research universities with ample resources and a strong commitment to reform. It is characterized by the establishment of dedicated interdisciplinary entities, such as "Schools of Intelligent Engineering" or "Schools of Future Technologies," which coordinate the deep integration of AI and engineering education at the organizational level. University A has established the "Center for Collaborative Innovation in Intelligent Education," which is responsible for coordinating the development of university-wide AI general education courses, faculty training, and the development and research of teaching platforms. "The impact of AI on engineering education is comprehensive; a robust organizational framework is essential to break down departmental barriers and integrate diverse disciplines—including artificial intelligence, education, and engineering—to facilitate top-level design and sustained implementation." (L01) This approach seeks to restructure the system at the ecosystem level, directly addressing the need for adaptability at the institutional and cultural levels. It aims to systematically address technological disruptions by reducing the complexity of cross-departmental collaboration, representing the highest-level organizational strategy for bridging the adaptability gap [28].

The four pathways described above are not mutually exclusive; in practice, there is significant overlap and interpenetration. Intelligent modules within the "content embedding" pathway may gradually evolve into standalone courses; successful project outcomes from the “project integration” pathway sometimes give rise to new course modules or platform development; and the “organizational restructuring” pathway often provides institutional safeguards for the coordinated advancement of other pathways. Particularly in research-intensive universities, the “project integration” pathway often runs parallel to the “new course development” pathway, forming a synergistic mechanism where “projects drive curriculum reform.” Therefore, these pathways should be understood as distinct nodes on a continuum rather than isolated models. The clarity of their boundaries is jointly influenced by institutional resources, the institutional environment, and the individual agency of faculty members.

In addition to the aforementioned pathways, there are two supplementary approaches worthy of attention, each emphasizing foundational support and community dynamics for integration, respectively. These serve as indispensable “enabling” components in the process of technology diffusion. The first is platform empowerment, wherein institutions deploy or introduce intelligent teaching platforms and build open-source case repositories and datasets to provide faculty and students with a low-threshold environment for AI teaching and application. University C purchased a commercial AI learning analytics platform to monitor student learning trajectories and provide early warnings. Such initiatives lower the initial barriers for faculty and students to experiment with and apply AI technologies by providing easily accessible and user-friendly tools and resources, thereby promoting the technology’s trial-and-error potential on a broader scale. “The university bought an online training platform with ready-made experimental environments and case studies, which saved us a lot of trouble.” (S12) The second approach is community-driven, which involves bridging the digital divide among faculty and promoting the dissemination and sharing of practical knowledge through organizing cross-departmental AI teaching seminars, workshops, and establishing faculty learning communities. “Attending the ‘AI+ Course Design’ salon organized by the Faculty Development Center and exchanging ideas with teachers from different disciplines on how to use AI tools is far more effective than figuring it out on my own.” (T08) This approach directly targets faculty—a key group of adopters—and effectively alleviates the digital divide and pressure to update knowledge through social networks and peer influence. It represents a crucial social process for the internal diffusion of innovation within an organization.

In summary, the integration of AI into engineering education in higher education institutions is not a single linear process, but rather a complex landscape characterized by progression from shallow to deep, from specific points to broader applications, and the coexistence and advancement of multiple pathways. Based on their types, resources, and objectives, different institutions have formed combination models with distinct emphases within the aforementioned pathways, collectively constituting the spectrum of adaptive practices currently employed by Chinese higher education institutions in engineering education to respond to the wave of AI technology.

4.4 Conditions for the Transition from Early Adopters to the Early Majority

Theories of innovation diffusion indicate that the spread of a new technology or practice within a social system is not uniform or linear, but rather exhibits distinct temporal characteristics. Based on the timing of adoption, individuals or organizations are categorized into five groups: innovators, early adopters, early majority, late majority, and laggards. In the context of integrating AI into higher education engineering programs, a small number of research-oriented universities—those with forward-looking vision, ample resources, or strong reform momentum—along with some individual faculty members, have already taken the lead in making the transition from conceptual understanding to substantive integration, playing the roles of innovators and early adopters. However, the breadth and depth of technological integration still exhibit significant disparities, with a large number of institutions and faculty members remaining in the early stages of the early majority phase, characterized by a wait-and-see attitude, tentative experimentation, or superficial application.

Compared to focusing on the initial breakthrough from innovators to early adopters, or the lag issues among late majority and laggards, a deeper exploration of the conditions for innovation to leap from early adopters to the early majority holds more urgent practical significance and theoretical value. First, this leap marks a shift from point-based exploration led by a few pioneers to area-based diffusion among a broader group, and is the key to determining whether AI can truly integrate into engineering education and achieve large-scale implementation. Second, the obstacles encountered during this transition are the most concentrated and representative; strategies to overcome them hold universal reference value for driving adaptive transformation across the entire education system. Finally, if an effective support ecosystem and diffusion mechanisms cannot be established during the early majority phase, technological applications may remain in a "potted plant" state for an extended period, struggling to transform into widespread educational productivity, thereby leading to the solidification and widening of the adaptability gap.

(1) Demonstrative Leadership from Successful Cases

Observability is a crucial attribute driving diffusion. For the early majority still in a wait-and-see phase, the persuasive power of policy calls or the experiences of benchmark institutions pales in comparison to visible, replicable, and localized success stories emerging from within their own systems. Such cases effectively reduce the perceived risks and uncertainties for potential adopters. Cases capable of generating a demonstration effect typically possess the following characteristics. First, the outcomes are highly visible. For example, students winning awards in national academic competitions or graduation projects being transformed into patents or academic papers serve as vivid demonstrations of the value of AI education. Second, the implementation path is replicable. The tools, resources, and teaching methods used in the case are accessible and adaptable by other teachers. Third, the experience is shareable. The case leaders are willing to share their specific processes, challenges encountered, and solutions through formal or informal channels, thereby making tacit knowledge explicit and facilitating its dissemination.

(2) Systemic Guarantees of Institutional Support

When integration practices move beyond the spontaneous exploration of individual teachers and require systematic promotion, institutional support becomes an indispensable safeguard. One of the core challenges of compatibility lies in the disparity between existing educational systems and innovative practices, and systematic institutional support aims to proactively reduce this disparity through top-level design. First, a stable resource allocation mechanism. Whether launching new courses or building intelligent teaching platforms, sustained financial support is essential. Second, effective incentive and evaluation policies. Explicitly incorporating the outcomes of AI-driven teaching reforms into faculty teaching awards and even the professional title evaluation system is key to reversing the inertia of "prioritizing research over teaching" and motivating teachers to engage in complex teaching reforms. Third, coordinated policy support. Integration often involves collaboration among the Academic Affairs Office, the Faculty Development Center, the IT department, and multiple academic departments. If the university can clearly define the responsibilities of each department and establish cross-departmental collaboration processes, it will significantly reduce the institutional resistance faced by individual teachers when driving reforms.

(3) Comprehensive Empowerment of the Support System

Complexity is one of the barriers hindering early widespread adoption; therefore, providing systematic support and user-friendly tools and resources is essential for lowering the barriers to adoption and expanding the user base. The support system should cover three levels. First, systematic, tiered, and categorized teacher training and development programs. For teachers with varying professional backgrounds and foundational knowledge, a series of training programs should be provided—ranging from general AI literacy and hands-on tool operation to workshops on "AI+disciplinary" course design—to alleviate teachers' feelings of isolation and anxiety. Second, the development of AI teaching tool platforms and resource repositories. Deploy or introduce low-code or no-code AI development platforms and intelligent teaching assistance systems, allowing teachers and students to experience AI applications without delving into programming details, thereby lowering the initial technical barrier for both groups. Third, develop and accumulate localized teaching resources. These include sample course syllabi incorporating AI modules, lab manuals, project datasets, and exemplary teaching cases. These mature, ready-to-use resources can significantly reduce the marginal cost of lesson preparation for teachers, making them more willing to try integration.

(4) The Driving Force of Student Demand

The perception of relative advantages in innovation, whether among institutions or faculty, is largely influenced by shifts in student demand. When students demonstrate a clear and strong demand for AI skills, it creates powerful momentum that drives reform on the supply side of education. This momentum manifests in the following ways: First, clearer signals from the job market. An increasing number of companies explicitly require data literacy and experience with AI tools in their hiring, continuously reinforcing the market value of AI. Second, students' intrinsic interest in learning and their career planning needs. When students recognize that integrating AI with their major can solve more complex engineering problems, their motivation to learn significantly increases. Third, the orientation toward further education and advanced studies. As cutting-edge engineering fields place increasingly higher demands on AI-related competencies, students are more motivated to take relevant courses or participate in projects. Student demand is conveyed to departments and faculty through channels such as course selection data and employment reports, serving as a direct driving force for adjusting training programs and updating teaching content, thereby providing sustained external momentum for achieving a qualitative leap.

From diagnosing the adaptability gap to analyzing the attributes of innovation, and from mapping out diverse pathways to identifying the conditions for overcoming obstacles, this study systematically presents the complex landscape of integrating AI into university engineering education. This is not merely a process of introducing technology, but also a process of adaptive restructuring of the educational system across multiple dimensions, including curriculum, faculty, assessment, and organization. This process is constrained by the inherent attributes of innovation itself, and is also closely related to institutional type, institutional environment, and the agency of actors. Understanding these factors and their interactions serves as the theoretical prerequisite and practical foundation for promoting the deep integration of AI and engineering education.

5. Discussion

5.1 Construction of Adaptive Models

Based on an in-depth analysis of the six case universities, this study attempts to construct a preliminary model framework to summarize the core characteristics and action logic of different types of universities in the process of AI integration.

Research-oriented universities exhibit a “Leadership-Exploration” model. These institutions typically possess robust cutting-edge research capabilities, interdisciplinary platforms, and a positioning closely aligned with national strategies. Their integration pathways demonstrate distinct dual characteristics: top-down and research-to-teaching. On one hand, at the institutional level, top-level design and resource coordination are carried out through the establishment of AI colleges, interdisciplinary research centers, and similar organizations; on the other hand, cutting-edge research achievements in the field of AI are rapidly transformed into specialized courses, experimental projects, and other educational offerings. The advantage of this model lies in its ability to rapidly secure a leading position in knowledge and cultivate top-tier talent with the potential for original innovation. However, the challenge lies in how to integrate cutting-edge exploration into engineering curricula to prevent a disconnect between elite-oriented research and mass education.

Teaching and research-oriented universities exhibit a “balance-integration” model. These institutions seek a balance between teaching and research and possess a relatively well-established and stable engineering education system. Their integration approach emphasizes incremental reform within existing curriculum systems and organizational frameworks. AI typically does not appear as a standalone school or major, but rather as an enabling technology integrated into traditional engineering curricula through a “Smart+” approach. This model aims to update teaching content and upgrade methodologies without triggering drastic organizational changes. Its success hinges on collaboration among the university’s teaching development center, academic departments, and faculty teams, as well as the effective introduction and support of AI teaching tools that are highly compatible and low in complexity [29].

In contrast, applied technology universities adopt an “application-empowerment” model. These institutions prioritize the cultivation of high-quality, application-oriented talent and maintain close ties with local industries. Their integration approach is strongly demand-driven and practice-oriented [30], often manifesting in practical teaching components such as project-based courses and industry-university cooperative internships. AI technology is primarily viewed as a tool for solving practical engineering problems and enhancing students’ employability. The advantage of this model lies in the direct transfer of skills, enabling a rapid response to changes in the labor market. The challenges it faces include the institution’s relatively limited in-house R&D capabilities and high dependence on industry-provided technology and resources, necessitating the establishment of stable industry-education integration mechanisms to ensure the advanced nature and sustainability of the curriculum.

These three models are not mutually exclusive but occupy distinct positions. A healthy higher engineering education ecosystem requires the coexistence of these three models, fostering positive interaction, and allowing them to learn from and evolve alongside one another over time. The “Leadership-Exploration” model provides direction and cutting-edge content for the entire education system; the “Balance-Integration” model serves as the main force for large-scale diffusion, determining the depth and breadth of integration; and the “Application-Empowerment” model ensures the effectiveness and social value of technology diffusion.

5.2 Systemic Strategy Recommendations

To effectively promote the deep and sustainable integration of AI into engineering education, a systematic strategy involving multi-stakeholder collaboration must be established.

At the university level, the first step is to strengthen top-level design and develop an integration roadmap. Universities should define strategic goals and phased priorities for integrating AI into education based on their specific type and positioning, and incorporate these into their institutional development plans. Second, a support system must be established. University- or college-level support units should be created to bring together experts in AI, educational technology, and subject-specific teaching, providing one-stop services to faculty to reduce the technical and time costs of integration. Furthermore, incentive mechanisms must be reformed to recognize investments in teaching innovation. Efforts such as the development of AI-related courses and teaching achievements should be included in performance evaluation criteria, thereby institutionally incentivizing faculty to engage in teaching reform.

At the policy-maker level, the first priority is to allocate more resources. Education authorities should provide concrete resource support to empower educational reform through AI, with a focus on curriculum resource development, the creation of teaching case repositories, and teacher professional development programs. Second, they need to guide the development of standards and clarify competency requirements. Efforts should be made to gradually incorporate guidelines for AI-related literacy and competencies into engineering education accreditation standards and national standards for teaching quality, thereby guiding systematic updates to the training process and curriculum content.

At the faculty level, the first priority is to engage in continuous professional development and embrace microlearning models. Teachers should be encouraged to actively participate in short-term workshops, online specialized training, and other learning activities to stay abreast of rapidly evolving technological knowledge, and to apply this to the restructuring of "AI+discipline" courses and project design. Second, they need to proactively build communities of practice. Faculty should proactively form or join AI teaching discussion groups and course teams across departments and disciplines, transforming individual exploration into collective wisdom through peer support and experience sharing.

5.3 International Perspectives and Local Insights

Higher education institutions worldwide face a series of common challenges in advancing the integration of AI and engineering education. The most prominent of these is the readiness of the faculty: how to effectively train engineering faculty to integrate AI into their discipline's teaching. Additionally, curriculum design, the integration of ethics education, and infrastructure support are also topics of common discussion. Despite these shared challenges, significant differences emerge in the pathways and strategies for integrating AI into engineering education across different countries and regions due to variations in higher education governance structures, policy orientations, and cultural traditions.

The process of AI integration in U.S. universities is distinctly market-driven and characterized by institutional autonomy. At the federal level, while there is some policy guidance (such as the U.S. National Science Foundation (NSF)'s "EducateAI" initiative [31]), specific integration strategies are primarily determined autonomously by institutions based on their own positioning, faculty strengths, and student needs. Research-intensive universities such as MIT and Stanford, leveraging their strong disciplinary foundations in AI, are advancing integration through initiatives such as establishing interdisciplinary colleges (e.g., MIT's Schwarzman College of Computing), offering AI minors, and developing "AI+X" course modules. Driven by both academic frontier exploration and industry talent demands, their integration pathways exhibit a "bottom-up, multi-track" approach.

In contrast, the integration pathways of UK universities are more heavily guided by both research evaluation systems and teaching quality frameworks. The UK's Research Excellence Framework (REF), which assesses the research impact of universities, encourages institutions to prioritize the interdisciplinary application of AI and the translation of its social value; meanwhile, the Teaching Excellence and Student Outcomes Framework (TEF) directs institutions to focus on cultivating students' skills and enhancing their employability. Against this backdrop, UK universities generally emphasize incorporating AI into professional accreditation standards and curriculum design guidelines. For example, the Engineering Council explicitly requires engineering graduates to possess data science and AI application competencies in its Accreditation of Higher Education Programmes (AHEP) [32], reflecting the institutional characteristic of "evaluation-driven, resource-supported" integration.

At the EU level, the focus is on guiding AI integration through ethical standards and talent development frameworks. The EU's "Ethics Guidelines for Trustworthy AI" [33] and "Coordinated Plan on Artificial Intelligence" [34] provide value-oriented guidance and a policy framework for AI education in higher education institutions. In practice, the EU promotes the development of AI general education courses and interdisciplinary programs at member states' universities through the "Digital Education Action Plan 2021–2027," with a particular focus on integrating topics such as AI ethics, data privacy, and social impact [35]. Compared to the market-driven approach of the United States and the institutional autonomy of the United Kingdom, the EU model places greater emphasis on top-down value guidance and transnational collaboration, reflecting the regional governance characteristic of "regulation first, collaborative advancement".

Comparing these international experiences with Chinese practices reveals that the practices of Chinese universities exhibit distinct local characteristics and institutional contexts. First, the integration process is notably policy-driven. Strategic deployments at the national level have provided universities with clear signals and resource leverage, accelerating the integration process and giving the integration pathways certain characteristics of top-level design. This differs from international models driven by institutional autonomy, market forces, or the academic community. Second, integration pathways are deeply tied to the classification and positioning of institutions. Chinese universities are clearly categorized by type. The classification into research-oriented, teaching-and-research-oriented, and applied technology-oriented universities corresponds to distinct roles within China's higher education system in serving different segments of the national innovation chain. Consequently, the exploration of integration pathways must inevitably align closely with institutional positioning, giving rise to differentiated adaptation models. Third, institutional safeguards are highly synchronized with national strategic deployments. Significant resource allocation and policy guidance are provided at the national level, and the pressure to implement these at the institutional level is relatively clear. However, compared to the diverse practical experience accumulated by European and American universities through autonomous exploration and market competition, Chinese universities still have room for improvement in terms of the diversity and flexibility of their integration pathways, as well as their agility in responding to market demands.

China’s experience demonstrates that there is no single integration model that fits all. Institutions of different types have explored pathways suited to their respective resources, cultures, and objectives based on their unique niches. This diversity of experience holds significant reference value for the global community, particularly for developing countries and emerging economies. Higher education systems in these countries similarly face challenges such as resource constraints, uneven development, and the need to serve diverse objectives. Therefore, acknowledging and leveraging the diversity of institutional types, while encouraging categorized exploration and the formation of a complementary integration ecosystem, may prove more effective than pursuing a single, rigid “best practice”.

6. Summary and Reflections

6.1 Theoretical Dialogue and Contributions

Examining the process of integrating AI into university engineering education from the perspective of innovation diffusion theory not only confirms the theory’s explanatory power in the context of technological innovation in higher education but also serves as a foundation for significant extensions and deepening of the theory.The research findings strongly validate the core tenets of the classic innovation diffusion theory. The five key attributes influencing innovation adoption rates were all evident in the case studies, and successful integration pathways all consciously addressed these five attributes to reduce diffusion resistance.

To address the adaptability gap, the adaptability of the education system should be regarded as a key mediating variable in the innovation diffusion process. It is not a single attribute but a multidimensional system comprising strategic foresight, organizational learning, resource reconfiguration, and institutional resilience. Research-oriented universities, leveraging their robust R&D and foresight capabilities, can to some extent proactively shape the pathways for technology integration into education; teaching and research-oriented universities rely on their organizational learning and resource reconfiguration capabilities to adapt within existing frameworks; while applied technology universities compensate for their own response deficiencies by closely coupling with industry and utilizing external resources. Therefore, the diffusion of AI in engineering education is not merely a process of technology adoption, but also a process through which the educational system stimulates and enhances its own adaptive capabilities in response to technological challenges. This perspective extends diffusion theory from a focus on “adoption behavior” itself to a focus on the capacity-building of the system during the diffusion process, providing a more dynamic and systematic theoretical tool for understanding the digital transformation of education.

6.2 Research Limitations and Future Directions

Through in-depth analysis of the case studies, this research has preliminarily revealed the complex landscape and adaptive mechanisms of AI integration in engineering education; however, certain limitations remain, and directions for future research are identified.

First, limitations of the sample. Although the study covers three major types of universities, the number of cases is limited, and all are drawn from the Chinese context. Furthermore, all six universities received varying degrees of government support, which, while helpful for understanding policy-driven integration practices, limits the generalizability of the findings to other institutional contexts. Second, the cross-sectional nature of the data. The study primarily relies on interviews and textual materials collected at a specific point in time, making it difficult to dynamically capture the evolution of integration pathways, long-term effects, and the temporal changes in causal relationships among various attributes.

Based on this, future research could be further deepened. First, conduct large-scale quantitative surveys. By surveying more institutions, faculty, and students via questionnaires, researchers can quantitatively examine the mechanisms and intensity of how various attributes influence integration willingness and effectiveness, thereby enhancing the generalizability of the findings. Second, conduct longitudinal tracking studies. Select several representative institutions or course programs for multi-year tracking to reveal key events, turning points, and influencing factors at each stage of the integration process—from initiation and implementation to institutionalization—and to gain a dynamic understanding of the diffusion trajectory. Third, advance in-depth cross-national comparative research. Select countries with different institutional contexts and educational traditions for comparative analysis to explore the differences and common patterns in integration pathways under various dominant models—such as policy-driven, market-driven, and academic community-driven approaches—thereby further enriching our understanding of this historic transformation process and jointly promoting adaptive reforms in global engineering education for the intelligent era.

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