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Research on the Interdisciplinary Hierarchical Teaching Path of Industrial Design Mediated by AI in the Context of Emerging Engineering Education

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Abstract: ***Background:*** Interdisciplinary learning is increasingly emphasized in industrial design education. Yet teaching practice continues to face challenges, including uneven disciplinary foundations, fragmented knowledge integration, and limited responsiveness to diverse learning needs. ***Purpose:*** This study intends to construct and validate an AI-mediated hierarchical teaching path, which supports interdisciplinary learning in industrial design education against the backdrop of emerging engineering education by aligning instructional content with students' differentiated learning profiles. ***Methods:*** Drawing on precision teaching theory and a constructivist learning perspective, an AI-mediated hierarchical teaching path was designed and implemented. Students' learning profiles were identified through an AI-based diagnostic process and grouped into three levels: basic, improvement-oriented, and innovation-oriented. Differentiated interdisciplinary learning activities were provided for each level, and teaching strategies were iteratively adjusted based on ongoing learning analytics and instructional collaboration. ***Results:*** The implementation led to the establishment of a curriculum system integrating professional core courses, interdisciplinary modules, and AI-supported collaborative learning platforms. Results indicate improved interdisciplinary collaboration among basic-level students, enhanced design feasibility among improvement-oriented students, and a 28% increase in national-level design competition awards among innovation-oriented students compared with previous cohorts. ***Conclusion:*** The findings demonstrate that AI-mediated hierarchical teaching can effectively enhance the adaptability of interdisciplinary instruction in industrial design education. This approach supports stratified student development and targeted instructional support, offering practical implications for interdisciplinary curriculum design and faculty development in higher education.

Keywords: Emerging engineering education; Industrial design education; AI-mediated; Interdisciplinary hierarchical teaching; Interdisciplinary learning

1. Introduction

1.1 Research Background and Significance

Since the Ministry of Education launched the "emerging engineering education" construction in 2017, the talent cultivation concept centered on "cross-border integration and collaborative innovation" has become the core orientation of higher education reform (Li, 2024). As an interdisciplinary subject that connects technology and humanities, industrial design needs to break away from the traditional paradigm of "design aesthetics dominance" in talent cultivation and transform into an interdisciplinary integration model of "design + engineering + AI + humanities" (Xia, 2007). The Special Action Plan for Enhancing Design Capacity in the Manufacturing

Industry (2019–2022) explicitly states that “the cross-integration of industrial design with engineering, materials, information technology and other disciplines should be strengthened,” further highlighting the strategic significance of interdisciplinary cultivation in industrial design.

However, in the current interdisciplinary teaching practice of industrial design, three contradictions are increasingly prominent: First, the diversified student source structure leads to significant differences in disciplinary foundations, making it difficult to balance students with weak engineering backgrounds and cross-disciplinary students with insufficient design foundations (Wang et al., 2024). Second, the industrial design major requires the mastery of multifaceted and interdisciplinary knowledge. The curriculum system is characterized by “modular accumulation,” and interdisciplinary courses such as mechanical design fundamentals and computer programming lack organic connections with core design courses, resulting in the predicament of knowledge fragmentation (Cao, 2021). Third, the update of teaching content lags behind the demands of industrial innovation. Cutting-edge content such as the application of AI design tools and the development of intelligent products is difficult to precisely meet the personalized needs of students at different ability levels (Zhang, 2022). These problems directly lead to poor effectiveness of interdisciplinary teaching and insufficient competitiveness of graduates in emerging fields such as intelligent hardware design and interactive product development.

The evolution of disciplines is always driven by both technological innovation and social demands, and the degree of cross-integration deepens with the times. This further confirms that the interdisciplinary attribute of “AI + industrial design” is an inevitable trend of the times (Yang & Zhao, 2025). The development of AI technology offers new possibilities for solving the abovementioned predicament. The AI-mediated teaching model achieves precision and personalization of the teaching process through data collection, intelligent analysis, and dynamic feedback (Dong, 2021). Previous studies have shown that the application of AI in areas such as learning situation diagnosis and resource push can significantly enhance the efficiency of interdisciplinary teaching. However, most current practices focus on the application of a single AI tool and lack a systematic path design covering the entire process of “diagnosis – teaching – evaluation”. Especially in the interdisciplinary scenario of industrial design, a hierarchical training mechanism has not yet been formed (Wang, 2023). Although AI-generated content (AIGC) can efficiently complete the processes of concept generation and style iteration, it has obvious shortcomings in technical aspects such as parametric design and structural rationality verification. This also reflects that AI-mediated teaching needs to specifically address the shortcomings in technology integration (Feng, 2024). Therefore, constructing an AI-mediated interdisciplinary integrated teaching path for industrial design holds significant theoretical and practical significance for enhancing the quality of design talent cultivation under the background of emerging engineering education disciplines.

1.2 Research Status

Centering on the three core elements of “emerging engineering education”, “interdisciplinary industrial design” , and “AI-mediated teaching” , the existing research is summarized into three major directions:

First, research on interdisciplinary teaching of industrial design under the background of emerging engineering education. Scholars generally emphasize the necessity of interdisciplinary cultivation. Liu (2020) proposed that “the design discipline should be integrated into the engineering technology system to construct a trinity curriculum structure of ‘technology, design, humanities.’” He (2023) proposed that under the background of emerging engineering education, the design discipline needs to strengthen its cross-disciplinary attributes; build a diversified and inclusive teaching system covering intelligent equipment, smart health, and other directions; promote the digital transformation of “data - tools - platforms”; and provide a modular course framework and digital support path for the stratified teaching of AI-mediated industrial design cross disciplines. At the practical level, Tsinghua University, relying on its interdisciplinary advantages of "design + computer science," has established an AI-driven interdisciplinary innovation studio (Fu, 2014). Jiangnan University focuses on cultivating the core capabilities of emerging engineering education talents and has developed a hierarchical cross-disciplinary curriculum system of "intelligent product design" to achieve progressive cultivation of cross-disciplinary knowledge and design capabilities mediated by AI (Deng, 2021).

Second, research on the application of AI in design education. Foreign research focuses on the teaching empowerment of AI tools. For example, the AI Design Assistant developed by MIT Media Lab can assist students in the optimization design of engineering structures. Domestic research focuses on the deep integration of AI technology with design teaching scenarios, conducting practical explorations around specific links such as intelligent student situation analysis and the output of design works (Qin, 2017). It emphasizes that the essence of intelligent design is the interdisciplinary integration of "technology + design + data" (Lu & Chen, 2021). Yan (2024) emphasized that AI technology does not replace designers but rather reconfigures the design process through capabilities such as data processing and creative generation. Design talents need to possess a combination of artistic aesthetics, technical cognition, and interdisciplinary collaboration. At present, the application of AI in design education has shown a trend of multiscenario penetration, but it has not yet fully achieved mediated full-process integration. There is still room for development in the intelligent mining and systematic construction of interdisciplinary knowledge association (Süner-Pla-Cerdà et al., 2025). There is still a need for exploration in research to solve the problem of fragmented knowledge.

Third, research on interdisciplinary stratified teaching models. The application of stratified teaching theory in the field of higher education has become relatively mature. Existing research (Zhao, 2024) has proposed an interdisciplinary curriculum design method based on ability levels, dividing students into three levels: basic, advanced, and innovative. Lu (2023) proposed countermeasures such as "course modularization and cross-integration," providing targeted solutions for stratified teaching to address the problem of fragmented knowledge. The stratification standards attempted in the current curriculum for hierarchical task design rely on subjective evaluations by teachers, lack objective data support, and make achieving dynamic adjustment difficult.

In conclusion, the existing research has laid a theoretical foundation. Based on the above research gaps, this paper constructs an AI-mediated interdisciplinary stratified teaching path of "learning situation diagnosis - content adaptation - dynamic iteration," providing new ideas for the precise interdisciplinary training of industrial design.

1.3 Research Ideas and Framework

This paper adopts the research approach of "theoretical construction - path design - practical verification": First, taking the theory of precise teaching and the constructivist learning view as the core, combined with the theory of collaborative innovation, a theoretical framework for AI-mediated interdisciplinary teaching is constructed. Second, a three-stage teaching path of "student situation diagnosis - content adaptation - dynamic iteration" is designed, and the application scenarios and implementation methods of AI in each stage are clearly defined. Third, taking industrial design major students from the 2021–2023 academic years as the research objects, a two-year teaching experiment was carried out to verify the effectiveness of the path through data comparison and effect analysis. Finally, the research conclusions and limitations are summarized, and future optimization directions are proposed. The research framework is shown in Figure 1.

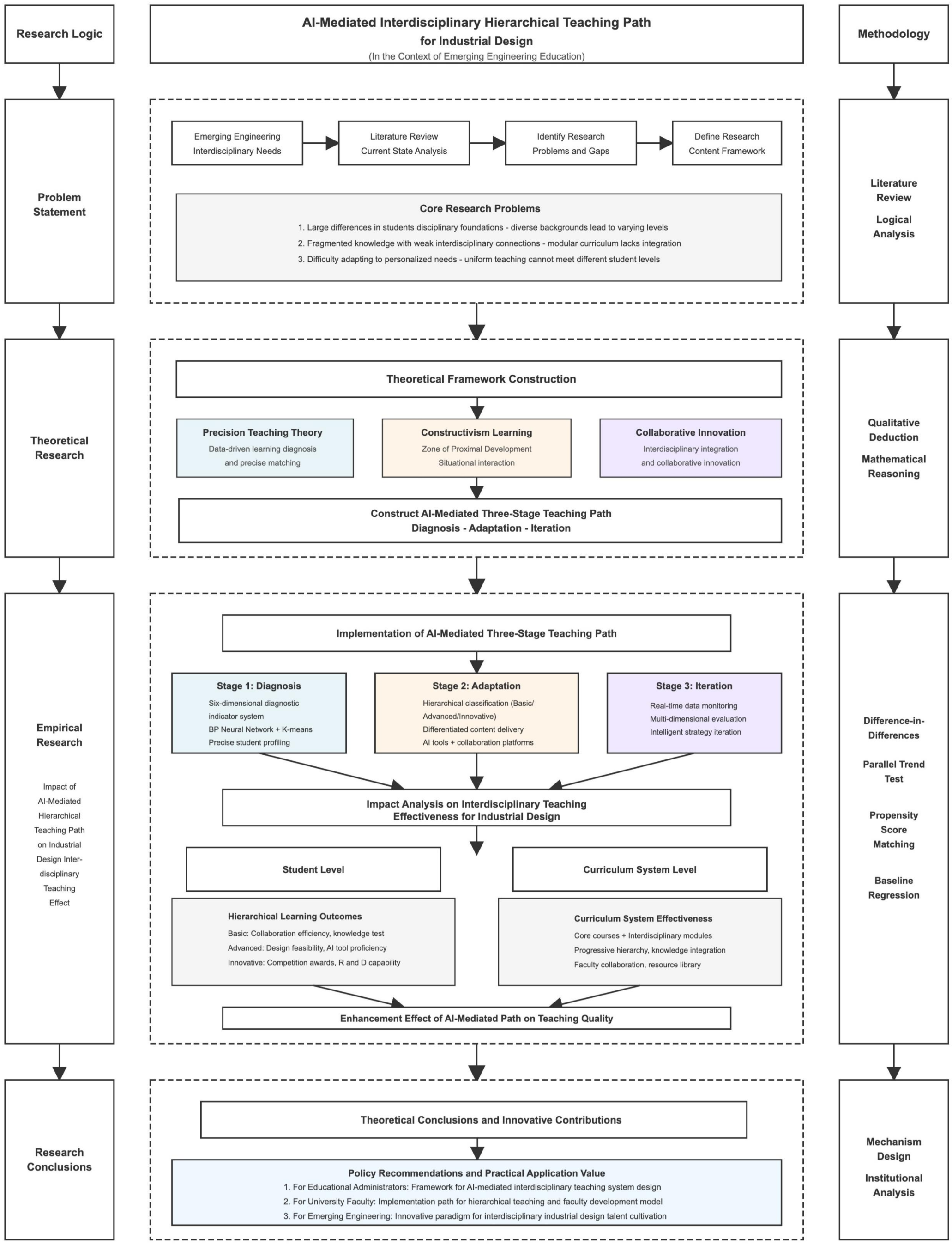

Figure 1. Research Framework Diagram

2. Theoretical Basis

2.1 Precision Teaching Theory

The theory of precision teaching was proposed by Skinner in the 1960s. Its core essence is "to achieve precise matching of teaching objectives, content and methods through data collection and analysis" (Ren, 2023). This theory emphasizes three key links: accurately diagnosing the starting point of learners' abilities, precisely designing teaching content and strategies, and precisely evaluating learning outcomes. In the context of interdisciplinary teaching, the theory of precision teaching provides methodological support for AI-mediated learning situation diagnosis by collecting multidimensional information such as students' professional basic test data and course assignment data. A quantitative analysis model is constructed to achieve precise positioning of students' interdisciplinary abilities and provide an objective basis for stratified teaching (Mou & Zhang, 2022).

2.2 Constructivist Learning Perspective

The constructivist view of learning holds that knowledge is actively constructed by learners in situational interaction rather than passively received (Wen & Jia, 2002). The "zone of proximal development" theory further points out that teaching should focus on students' potential development levels and promote ability improvement by providing appropriate learning scaffolds (Wang, 2000). This theory provides the core basis for AI-mediated content adaptation: For the zone of proximal development of students at different levels, the AI system pushes differentiated interdisciplinary learning resources and collaborative tasks. Basic students focus on building a theoretical framework, while innovative students emphasize inquiry-based learning on cutting-edge topics, enabling each student to enhance their abilities in appropriate challenges (Li, 2022).

2.3 Theory of Collaborative Innovation

The theory of collaborative innovation emphasizes that "different subjects achieve the maximization of innovation efficiency through resource integration and interactive collaboration" (Liu et al., 2024). In interdisciplinary teaching, collaborative innovation is manifested at three levels: interdisciplinary team collaboration among students, teaching collaboration between teachers and students, and teaching and research collaboration among multidisciplinary teachers (Chen, 2012). The AI-mediated collaboration platform provides technical support for collaborative innovation. By sharing learning progress in real time and coordinating task allocation and feedback, it breaks down disciplinary barriers and temporal and spatial limitations, achieving efficient integration and innovative application of interdisciplinary knowledge (McCardle, 2002).

In conclusion, the theory of precision teaching provides data-driven methodological support for AI learning situation diagnosis and establishes the logical starting point for the transformation from empirical judgment to data analysis. The constructivist learning perspective guides the differentiated adaptation of AI content through the zone of proximal development, achieving a transformation from unified teaching to personalized paths. The theory of collaborative innovation has established the foundation for cross-temporal and spatial resource integration and dynamic collaboration mediated by AI, promoting the evolution from static teaching to a dynamic ecosystem. These three theoretical pillars respectively map the three AI-mediated mechanisms of "intelligent diagnosis," "adaptive content," and "dynamic collaboration," jointly forming a logical closed loop pointing to the goal of cultivating emerging engineering education design talents. The specific theoretical logical framework is shown in Figure 2.

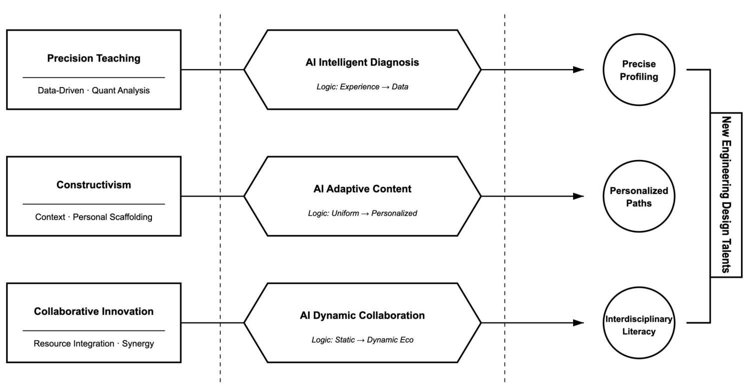

Figure 2. Theoretical Basis of Industrial Design Interdisciplinary Hierarchical Teaching and Logic Diagram of AI-Mediation Mechanism

3. Construction of AI-Mediated Interdisciplinary Hierarchical Teaching Path for Industrial Design

Based on the above theory, a three-stage AI-mediated interdisciplinary stratified teaching path of "student situation diagnosis - content adaptation - dynamic iteration" is constructed, forming a closed-loop teaching system of "data-driven - precise adaptation - continuous optimization."

3.1 AI Multidimensional Learning Situation Diagnosis and Stratification

The core objective of this stage is to collect multidimensional data through the AI system, build an accurate student profile, and achieve scientific stratification. The specific implementation is divided into three steps:

The first step is to build a six-dimensional diagnostic index system for students' learning conditions. Drawing on the interdisciplinary practice characteristics of industrial design in the AI era (innovation-driven and process-oriented) as well as the results of data collection, this study designs an indicator system from six core dimensions: "professional foundation, interdisciplinary knowledge reserve, design process management capability, collaboration propensity, learning style, and innovation potential" (see Table 1).

Table 1. Six-Dimensional Index System for Interdisciplinary Academic Situation Diagnosis in Industrial Design

Primary Dimension	Secondary Indicators	Data Collection Method	Weight
Industrial design professional foundation	Three compositions, product form design, design history and theory	Course grades, entrance tests	18%
Interdisciplinary knowledge reserve	Engineering drawing, computer programming basics, interaction design basics	Online tests, knowledge graph questionnaires	18%
Design practice ability	Modeling software operation, prototype production, scheme presentation	Practice assignment scoring, portfolio analysis	25%
Team collaboration tendency	Communication initiative, task execution, conflict resolution ability	Simulated collaboration tasks, personality tests	15%
Learning style preference	Visual, auditory, kinesthetic, inquiry-based	VARK learning style questionnaire	8%
Innovation potential performance	Quantity of creative proposals, uniqueness of schemes, problem-solving ability	Creative competition scores, brainstorming performance	16%

The second step is AI-driven collection and analysis of student situation data. An AI-based learning situation diagnosis platform is established to integrate three types of data collection channels: First, objective data—course grades are obtained by connecting to the academic affairs system, and knowledge reserve data are collected through an online testing system (equipped with standardized scales). Second, behavioral data—collaborative behaviors such as students' participation duration in collaborative tasks and speech frequency are recorded via Feishu AI smart spreadsheet, and practical behaviors like modeling operation trajectories are collected through design software plug-ins. Third, subjective data—learning style preferences are gathered using the standardized VARK questionnaire, and innovation potential performance data are collected through blind evaluations conducted by three interdisciplinary experts (one each from the fields of design, engineering, and AI technology). The AI system uses the backpropagation (BP) neural network model to analyze the data, outputs a six-dimensional ability radar map, and forms an accurate student profile.

The third step is scientific stratification and team building. Based on the AI analysis results, the K-means clustering algorithm is employed to classify students into three levels (matching the corresponding learning stages): First is basic type (accounting for approximately 35%)—characterized by a weak professional foundation or insufficient interdisciplinary knowledge, requiring strengthened basic theoretical learning. The potential problem lies in difficulty in getting started with interdisciplinary integration, and the corresponding solution involves AI virtual simulation basic courses plus one-on-one tutor guidance. Second is improvement-oriented type (accounting for approximately 50%)—possessing a certain level of professional foundation and interdisciplinary reserves, needing to enhance practical capabilities. The potential issue is inadequate proficiency in integrating AI tools with professional scenarios, and the solution includes adding AI tool hands-on workshops plus case analysis and practical training. Third is innovation-oriented type (accounting for approximately 15%)—boasting solid foundations and outstanding innovation potential, requiring a focus on cutting-edge research and development of topics. The potential challenge is insufficient practical feasibility of research topics, and the solution involves connecting with enterprise mentor resources plus industry/university/research project incubation. Meanwhile, the AI system forms cross-level collaborative teams based on the principle of "heterogeneous complementarity," with each team consisting of two basic students, three advanced students, and one innovative student, promoting knowledge transfer among different levels.

3.2 AI-Mediated Differentiated Content Adaptation and Teaching Implementation

Based on the stratified results and relying on the AI teaching resource library plus smart collaboration platform, differentiated interdisciplinary teaching content and implementation models are provided for students at different levels. The specific design is shown in Table 2. The "technology layer, design layer, application layer" design system constructed by Lu et al. (2020) provided a systematic basis for the hierarchical design of differentiated content modules, ensuring that the content at each level is both independently focused and collaboratively progressive.

Table 2. Differentiated Teaching Content Design for Students at Different Levels

Student Level	Core Cultivation Goal	Interdisciplinary Content Module	AI Tool Support	Collaborative Task Design
Basic type	Consolidate "design + engineering" foundation	Engineering drawing basics, introduction to mechanics of materials, design psychology basics	AI knowledge decomposition tools, virtual simulation experiment platforms	Participate in simple product component design, complete modeling and basic analysis (Reference: MIT introductory collaboration task model)
Advanced type	Strengthen "AI tools + practice" ability	Parametric modeling, interaction design principles, AI-aided design methods	Midjourney / Stable Diffusion (gen AI tools), SolidWorks/Rhino model simulation testing and AI plug-ins, Feishu smart tables (collaboration tools)	Lead small smart product design, complete full process from concept to prototype (Reference: MIT intermediate project-based model)
Innovative type	Cultivate "frontier + R&D" ability	Smart hardware development, generative design, interdisciplinary frontier topics	TensorFlow, Grasshopper, AI trend prediction tools	Lead interdisciplinary R&D projects, docking with real enterprise needs or competition topics (Reference: MIT Media Lab maker model)

During the teaching implementation process, the AI system plays three core roles: First, it precisely delivers resources. Based on students' learning progress and weak points, it automatically pushes suitable microlesson videos, case tutorials, and other resources. For instance, it sends a microlesson on product structure design to basic students with weak engineering foundations. Second, real-time process guidance is provided. Common questions are answered through AI assistants, such as module construction errors in parametric modeling, and personalized questions are connected to corresponding subject teachers. Third, collaboration and efficient empowerment are achieved. Through collaboration tools such as Feishu AI smart table, task allocation, progress tracking, and result sharing are realized. Collaboration behavior analysis reports are automatically generated to assist teachers in optimizing collaboration strategies. Luo (2020) proposed that industrial design innovation in the AI 2.0 era has shifted from "individual innovation" to "collective intelligence innovation," emphasizing the integration of multisubject wisdom through AI technology. This concept provides a logical reference for the formation of cross-level collaborative teams and task design.

3.3 AI Dynamic Tracking and Teaching Iteration

Build a dynamic closed loop of "data monitoring - effect evaluation - strategy iteration" to ensure the continuous optimization of the teaching path.

First, the construction of the AI dynamic monitoring module. Set up three types of monitoring indicators: learning progress indicators (course completion rate, resource learning duration), ability growth indicators (difference in test scores before and after, improvement in work scores), and collaboration performance indicators (task contribution, team communication efficiency). By collecting these data in real time through an AI system, individual growth curves for students and heat maps of the overall teaching effectiveness of the class are generated, presenting the strengths and weaknesses in the teaching process intuitively.

Second, multidimensional effect evaluation. Adopt a combined approach of "formative assessment + summative assessment": Formative assessment relies on the process reports generated weekly by the AI system, accounting for 60%. The final evaluation includes the defense of interdisciplinary design works and the review by enterprise mentors, accounting for 40%. The basis for this weight allocation is as follows: the core essence of "process data-driven teaching optimization" in precision teaching theory; the full-dimensional capture advantage of AI technology in interdisciplinary learning processes (including collaborative behaviors, resource utilization, and ability development trajectories); and verification and determination through the Delphi method by an interdisciplinary teaching team (comprising experts from design, engineering, and educational technology). The evaluation subjects include professional teachers, engineering discipline teachers, enterprise experts, and students for mutual evaluation, ensuring the comprehensiveness and objectivity of the evaluation.

Finally, intelligent iteration of teaching strategies. Based on monitoring and evaluation data, the AI system automatically generates iterative suggestions: For individual students, it adjusts the direction of resource push and the difficulty of tasks, such as reducing the task volume and increasing basic tutoring for basic students who are lagging behind in progress. For the entire class, the course content and teaching methods are optimized. For instance, in response to the weak points of improvement-oriented students in the interaction design module, practical class hours for AI-assisted interaction prototype design are increased. For the teaching team, suggestions for enhancing cross-disciplinary teaching capabilities are pushed, such as recommending AI teaching tools for engineering drawing and training on the design and development of AI products for design teachers.

4. Teaching Practice Effect Assessment and Analysis

The teaching practice was carried out with a certain university's industrial design major students from the 2021–2023 academic years as the research objects. Among them, the 2021 cohort was the control class (adopting the traditional interdisciplinary teaching mode, with 23 students), and the 2022 and 2023 cohorts were the experimental classes (adopting the AI-mediated stratified teaching mode of this study, with 20 and 25 students, respectively). The effectiveness of the teaching path was verified through a comprehensive assessment of "process data + result data + qualitative analysis" (Başkan A & Curaoğlu F, 2017).

4.1 Construction of Curriculum System

Based on the practice of teaching paths and relying on the AI product design course, a cross-disciplinary course group system for industrial design has been constructed, which consists of "professional core + cross-disciplinary modules + AI collaboration carriers." This system includes three core courses, eight cross-disciplinary modules, and five AI collaboration projects. The specific structure is shown in Table 3. The core feature of the course cluster lies in "hierarchical progression and interdisciplinary integration"—from the basic integration of "design + engineering" to the advanced "research and development of cutting-edge topics"—forming a progressive chain of ability cultivation. Each course module integrates at least two interdisciplinary knowledge points to ensure the systematicness and relevance of the knowledge (Zhang et al., 2023).

Table 3. Structure of Industrial Design Interdisciplinary Curriculum Group System

System Primary Module	Specific Content	Core Explanation
Professional core courses (3)	Introduction to design, rapid product representation, product system design	Compulsory for all students, establishing industrial design professional foundation
Interdisciplinary modules (8)	Basic difficulty: mechanical basics, materials science basics Advanced difficulty: AI design tools, smart interaction design Frontier difficulty: sustainable design, smart hardware/software development, etc.	Layered by difficulty, adapting to learning needs of students at different levels
AI collaboration carriers (5)	Basic type: decompression product design Advanced type: biofermentation equipment design Innovative type: smart walkie-talkie R&D with traditional Chinese character forms.	Design practice projects corresponding to student levels, strengthening knowledge application
Support platform	AI teaching resource library, Feishu AI smart tables, AIGC tools	Providing support for resource supply, collaboration management, and process tracking

4.2 Effect Evaluation and Qualitative Analysis

Using a dual comparison method of "control class vs. experimental class" and "different levels within experimental class," the learning effects of students at different levels were evaluated. The core evaluation data is shown in Table 4.

Table 4. Comparison of Learning Effects Between Experimental Class and Control Class

Evaluation Indicator	Control Class (Traditional Mode)	Experimental Class – Basic Type (20 Students)	Experimental Class – Advanced Type (15 Students)	Experimental Class – Innovative Type (10 Students)	Experimental Class Overall Improvement
Interdisciplinary collaboration efficiency (task completion time）	14.2 days	10.5 days (−26.1%)	8.8 days (−38.0%)	7.2 days (−49.3%)	35.2%
Design feasibility compliance rate (%)	65.8%	78.6%（+19.4%）	92.0%（+39.8%）	98.0%（+48.9%）	32.8%

Interdisciplinary knowledge test average (max 100)	68.5	79.2（+15.6%）	86.7（+26.6%）	92.3（+34.7%）	23.5%
Design competition awards (person-times)	8	3	5	8（+28%）	100.0%

As can be seen from the data in Table 4, the learning outcomes of the experimental class have been enhanced, and students at different levels have all achieved targeted improvements: The average score of the interdisciplinary knowledge test for basic students has increased by 15.6%, and their collaboration efficiency has improved by 26.1%. The goal of laying a solid foundation has been achieved. The design feasibility compliance rate of the improvement-oriented students reached 92.0%, an increase of 34.7% compared with the control class. The reinforcement strategy of "AI tools + interdisciplinary practice" has achieved remarkable results. The number of design competition awards won by innovative students increased by 28% compared with the same level of the control class. The overall number of awards won by the experimental class (16 person-times) doubled compared with the control class, and the ability of independent research and development and innovation was fully stimulated. It should be noted that the sample of this study is limited to the industrial design major of a single university, with an experimental period of two years. Thus, the research results are of a preliminary nature and contextual specificity, and their generalizability needs to be further verified in practice across different types of institutions (comprehensive universities, science and engineering universities, and art universities) and over a longer period (three to five years).

The above quantitative data confirm the significant improvements in interdisciplinary collaboration efficiency, design feasibility, and innovation output among students at different levels. This study selected some design cases from the three levels of "basic type," "advanced type," and "innovative type" in the experimental class for presentation. These works reflect the step-by-step advancement of students' abilities from "basic design specifications" to "AI-assisted interaction prototypes" and then to "cutting-edge topic research and development." The specific teaching achievements are shown in Figure 3.

Figure 3. Teaching Outcomes Display

4.3 Analysis of Effectiveness and Limitations of the Teaching Path

Teaching practice verification shows that the effectiveness of the AI-mediated interdisciplinary stratified teaching path is reflected in three aspects: Precise stratification solves the problem of basic differences, and through six-dimensional student situation diagnosis and dynamic adjustment, it realizes "teaching students in accordance with their aptitudes." The adaptation of differentiated content and AI resources meets personalized demands, enhancing learning efficiency and effectiveness. The closed-loop mechanism of "diagnosis - adaptation - iteration" has continuously optimized the teaching process and ensured the stability of teaching quality.

Meanwhile, teaching practice has also exposed the limitations of the path: One is the issue of AI technology threshold. Some teachers are not proficient in operating the AI teaching system and need to enhance technical training. Another is insufficient coverage of the resource library. Resources in emerging interdisciplinary fields are scarce and need to be further expanded. Further, the flexibility of dynamic stratification needs to be enhanced: The ability improvement speed of some students is relatively fast, and the current stratification adjustment cycle of once per semester is slightly lagging behind.

5. Conclusion

5.1 Research Conclusions

Under the background of the emerging engineering education discipline, interdisciplinary teaching of industrial design is confronted with core pain points such as significant differences in students' foundations, fragmented knowledge, and insufficient content adaptability. Based on the theory of precision teaching and the constructivist learning perspective, this study has constructed an AI-mediated interdisciplinary stratified teaching path for industrial design. The main research conclusions are as follows:

First, a six-dimensional student situation diagnosis index system and an AI precise stratification mechanism have been established. Student profiles are drawn from six core dimensions (such as the foundation of industrial design and cross-disciplinary knowledge reserves) and divided into three levels: "basic type," "advanced type," and "innovative type." Combined with dynamic assessment, the stratification of students is made precise and dynamic. It has solved the pain points of traditional layering, such as "single standards" and "static solidification."

Second, a differentiated interdisciplinary teaching content system and AI collaboration model were designed. Relying on the three-dimensional resource library of "professional core + interdisciplinary module + AI tools," personalized content was pushed to students at different levels. Heterogeneous collaboration tasks were designed by drawing on the model of MIT Media Lab, achieving the hierarchical training goals of "consolidating the foundation, enhancing ability, and stimulating innovation." The precise supplies of teaching resources, tasks, and strategies were realized.

Third, an iterative mechanism of "AI dynamic tracking + teacher collaboration" has been established. Through three dimensions, the learning process is monitored in real time; and cross-disciplinary teacher teams are linked to optimize teaching strategies, forming a closed loop of "diagnosis - adaptation - iteration." This has enhanced the continuous optimization ability of cross-disciplinary teaching and improved the efficiency of the formation and operation of cross-disciplinary teaching teams.

5.2 Research Limitations and Future Outlook

This study has certain limitations: First, the sample is from only one university, and the applicability of different types of institutions needs to be further verified. Second, the diagnostic accuracy of AI systems relies on data accumulation, and there is still room for improvement in adapting to niche interdisciplinary knowledge points. Third, the long-term career development effects of students have not been tracked.

Future research can be carried out from three aspects: First, expand the sample range, select universities at different levels and in different regions for multicase verification, and optimize the universality of the path. Second, intensify the application of AI technology, introduce generative AI to build personalized learning path graphs, and enhance the intelligent level of content adaptation. Third, establish a long-term tracking mechanism to further verify the long-term effectiveness of the path through the career development data of graduates. In addition, AI-mediated cross-school and cross-disciplinary collaborative teaching models can be explored to build a broader system for sharing high-quality resources.

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References

Başkan, A., & Curaoğlu, F. (2017). Design lab: For future research. *The Design Journal*, *20*(sup1), S4751–S4753. https://doi.org/10.1080/14606925.2017.1352980

Cao, B. (2021). Integration and reconstruction of basic design courses. [Doctoral dissertation]. Nanjing University of the Arts. https://doi.org/10.27250/d.cnki.gnjyc.2021.000020

Chen, W. (2012). Research on future classrooms from the perspective of educational technology. [Doctoral dissertation]. East China Normal University. https://kns.cnki.net/kcms2/article/abstract?v=LYi8dJWcB0Vc934HUn5IEiCeqR1DURS6yWHidNPAztjsgK1npzihZ1Jp59FBLZHbgb_hMj5qFiCRxREyj7k1Rqsg8kpJxKE1ThWSpg8jKoJR4AKSOfqVxUERQv3XSwcXcr5Ka0wYQMSlz8avwXAlQks11IowDSEipVY9k1Tfp9B7FVTvyOg==&uniplatform=NZKPT&language=CHS

Deng, R. (2021). Reflection on Knowledge Structure Transformation and Cultivation Pathway: Taking the Teaching Reform of Product Design and Industrial Design Program of Jiangnan University as an Example. *Zhuangshi*, (06), 40–41. https://doi.org/10.16272/j.cnki.cn11-1392/j.2021.06.028

Dong, Z. (2021). Dong Zhanjun: The development of industrial design discipline and theoretical system construction in the context of new engineering. *Design*, *34*(20), 70–74. https://kns.cnki.net/kcms2/article/abstract?v=YtMUyApXHwYvLmGJwrRqJEk-X_a4vtrajhFAaAdXPgvweoxZ-IUV-cPVKlDFv4Z98ny0mZ91E6JqnGMVI5QhxjgfSl7Yl0Xr49jWzGikSsL9I-hgZ_mX3ErsZm9PENoxYsWcJXuQjZa-bGVmZdADAlDFc8J_ttYZx_-5sKNyu97iMwsj88ws0A==&uniplatform=NZKPT&language=CHS

Feng, Y. (2024). Application and Thinking of AIGC in Industrial Design. *Packaging Engineering*, *45*(08), 337–345. https://doi.org/10.19554/j.cnki.1001-3563.2024.08.036

Fu, Z. (2014). From Cross-disciplinary to Open Innovation Talents Cultivation: For Celebrating the 10th Anniversary of Information Art and Design Departmentat Tsinghua University. *Zhuangshi*, (12), 12–15. https://doi.org/10.16272/j.cnki.cn11-1392/j.2014.12.022

He, R. (2023). A "Pragmatism" Education Paradigm for Design Leading Talents in the New Era. *Journal of Shanghai Jiao Tong University (Philosophy and Social Sciences)*, *31*(04), 51–65. https://doi.org/10.13806/j.cnki.issn1008-7095.2023.04.005

Li, L. (2024). Research on the operation mode of industry-education integration system in engineering universities. [Doctoral dissertation]. Xinjiang Normal University. https://doi.org/10.27432/d.cnki.gxsfu.2024.000116

Li, S. J. (2022). *AI new classroom: PAD ABC*. Zhejiang University Press. ISBN: 978-7-308-22180-1

Liu, G. (2020). The Design Methodolgy: The Plan of Industrial Design in China. *Cultural Studies*, (04), 182–190. https://kns.cnki.net/kcms2/article/abstract?v=YtMUyApXHwajg5Q3YOx3hUPSz3WR8h2L_jt4TU6AFpfjldbN0bGV84t_6FixJPsvGm_tf7kNIzN3fJ5JXS9fdxWymzVTE3ix2nloy2odaku1XI6HkuGO6zQRDSNzbN1u0N4vxIaw2TC43SoVlcQv8LDYDSfyFUVRtABW_7Gkr8YhcWgE9AS23A==&uniplatform=NZKPT&language=CHS

Liu, M., Wei, C., & Tao, L. (2024). Digital Economy Empowering Military-Civilian Collaborative Innovation: Theoretical Mechanisms, Effect Measurement, and Empirical Inspection-a Case Study of the Electronic and Communication Equipment Manufacturing Industry in China's Central and Western Regions. *Journal of Tibet University (Social Science Edition)*, *39*(04), 211–220. https://doi.org/10.16249/j.cnki.1005-5738.2024.04.024

Lu, J., Yu, S., & Lu, C. (2020). Intelligent design system for industrial design. *Journal of Machine Design*, *37*(04), 140–144. https://doi.org/10.13841/j.cnki.jxsj.2020.04.023

Lu, Y., & Chen, G. (2021). The Problems and Solutions of Industrial Design Talent Training in the Background of New Engineering. *Theory and Practice of Education*, *41*(15), 23–26. https://kns.cnki.net/kcms2/article/abstract?v=YtMUyApXHwa-2QfOti-2DbtwqtVfXaIIGZRR0s6ncpuyo7ER71f7xBeeqFACpWW5LrNdBvQucr_DJy5482WSZLLilqDGnOYNlXB3eJv956YdCK6NP_ltbyiJH-h0ta3ISFm1FwZOSeKaZG9nOFstSvLYmGb-Z2A9UofQAyl308ixJGwPjO3_Fg==&uniplatform=NZKPT&language=CHS

Lu, Z., Song, X., & Jin, Y. (2023). State of Arts and Development of Intelligent Design Methods under the AIGC Trend. *Packaging Engineering*, *44*(24), 18–33. https://doi.org/10.19554/j.cnki.1001-3563.2023.24.003

Luo, S. (2020). Crowd Intelligence Innovation:a New Innovation Paradigm in the AI 2.0 Era. *Packaging Engineering*, *41*(06), 50–56. https://doi.org/10.19554/j.cnki.1001-3563.2020.06.008

McCardle, J. R. (2002). The challenge of integrating AI and smart technology in design education. *International Journal of Technology and Design Education*, *12*(1), 59–76. https://doi.org/10.1023/A:1013089404168

Mou, H. K., & Zhang, Q. (Eds.). (2022). *Exploration and research on digital education*. Zhejiang University Press. ISBN: 978-7-308-23360-6

Qin, J. Y. (2017). Impact of Artificial Intelligence on Interaction Design. *Packaging Engineering*, 38(20), 27-31. https://doi.org/10.19554/j.cnki.1001-3563.2017.20.008.

Ren, F. X. (2023). Research on Data-Driven Precision Teaching From the Perspective of Educational Digital Transformation. *Kunming: Yunnan People's Publishing House*. ISBN: 978-7-222-20470-6

Süner-Pla-Cerdà, S., Şen, G., Kumbasar, E., Şahin, B., & Ünlü, C. E. (2025). Designer experiences and perspectives on the role of generative AI in industrial design. *AI & Society*, 1–24. https://doi.org/10.1007/S00146-025-02504-6

Wang, K., Li, T., & Li, Q. (2024). "Integration of industry and education, cross-disciplinary innovation": Exploration and practice of innovative talent training mode for industrial design majors under the background of emerging engineering education. *Packaging Engineering*, *45*(S1), 608–613. https://doi.org/10.19554/j.cnki.1001-3563.2024.S1.085 https://kns.cnki.net/kcms2/article/abstract?v=YtMUyApXHwbdgI5BTUkeQdN4FUEfqtBFmBS0AYN-4hILAhfOD2h_FLsA_hAqaB_UcEcEYfcCZMsNrXcwdNTByvySgOLm72QPvStYTP7CNQ5dwIDM0XJiIY9aSq_hEDVaan_oz5em5sm3NZyH5tbXR6Ca0746KduC4CqBF4c9KSLQXdF_QaAsaw==&uniplatform=NZKPT&language=CHS

Wang, W. (2000). Implications of Vygotsky's "zone of proximal development" theory for teaching reform in China. *Psychological Exploration*, (02), 17–20. https://kns.cnki.net/kcms2/article/abstract?v=YtMUyApXHwanUJvyP8bsTTem4ahpDDfYr9vFXtH--SRwdx3XLA-3fvTnmOfI63o1T1EOcX8CP5zPXfXHzeEZmjP4iJa8LEfQwsEqWoV913CdKn2uyzwUrZckUf8AnMfZ88glUMxuhoQCWF9-1dNiYMe2a6oLQ0F0aDoUXTJgMhefmukc1xoOvA==&uniplatform=NZKPT&language=CHS

Wang, X. (2023). Research on the construction logic of smart classrooms from the perspective of technological symbiosis. [Doctoral dissertation]. Southwest University. 10.27684/d.cnki.gxndx.2023.000003

Wen, P., & Jia, G. (2002). Constructivist theory and teaching reform: A review of constructivist learning theory. *Theory and Practice of Education*, *22*(5), 17–22. https://kns.cnki.net/kcms2/article/abstract?v=YtMUyApXHwavW3V7Ch0GL-H1hExmnGjXYX6F_OEyhbv16O1Lip4gXfBl_isyFJLmDFBwI45hqoYVjaCRpMUFeqInH11Q3BEoyoed8lFJ8MhU-RziQmU-JHjsPc5Ax5fVFvy9ktGc4tHYOA89KZ8oMDZ6ppjUVbSZ5S1F5W3x0xALCVAGvUiDHg==&uniplatform=NZKPT&language=CHS

Xia, Y. (2007). Discussion on the curriculum structure of undergraduate art and design majors in Chinese universities. [Doctoral dissertation]. Nanjing University of the Arts. https://kns.cnki.net/kcms2/article/abstract?v=LYi8dJWcB0UB1E00ha7UzIYxM75-cvI---oe77T8f0nnxLE0f0Bua7DMlChp4I7kQ6GrGpOma6ZsMvYGtnWtzp8NlYoGz6QBV9WPmkKqJr69_RsJ1pBLh0D8rHJNluQzJ3j2NfFmHKsB6RqjEuzXVqJObBz2T_-HMibBJ03OSlJpT8QIBsB7dg==&uniplatform=NZKPT&language=CHS

Yang, X., & Zhao, Z. (2025). Development History and Exploration of the Design Discipline in China(1949-2024). *Studies in National Art*, *38*(02), 122–132. https://doi.org/10.14003/j.cnki.mzysyj.2025.02.14

Zhang, W. (2022). Collaborative creation: A Living Lab practice study in industrial design education. [Doctoral dissertation]. China Academy of Art. https://doi.org/10.27626/d.cnki.gzmsc.2022.000007

Zhang, Z., Yang, X., Zhang, J., & Huang, K. (2023). Research on the Development Path of Industrial Design and Talent Training Under the New Engineering Discipline. *Furniture and Interior Design*, *30*(06), 139–142. https://doi.org/10.16771/j.cn43-1247/ts.2023.06.022

Zhao, H. (2024). Dissertation Research on Personalized Talent Cultivation Mode of Local Undergraduate Universities. [Doctoral dissertation]. Central China Normal University. https://doi.org/10.27159/d.cnki.ghzsu.2024.000049