Research on the Practice of Reconstructing Classroom Teaching Mode Based on AIGC

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Abstract

In the context of the rapid development of generative artificial intelligence (AIGC), classroom teaching in colleges and universities is facing new challenges in structural reconstruction. The traditional blended teaching model has problems such as abstract content and lagging feedback, which is difficult to meet the needs of high-level ability training. To this end, a classroom teaching model based on AIGC empowerment and integration of human-intelligence collaboration mechanism was designed and implemented. Focusing on the three stages of "before-in-class-after-class", the model integrates AIGC's technical advantages in content generation, path recommendation and learning feedback, and builds a collaborative teaching system guided by teachers, participated by students, and supported by AI. Taking the course of "Object-Oriented Programming" in colleges and universities as the object, the pre-test and post-test controlled experimental design was used to carry out empirical research based on academic performance, learning motivation, satisfaction and other dimensions. The experimental results show that compared with the traditional teaching mode, this model has obvious advantages in improving students' programming ability, learning enthusiasm and self-efficacy. In particular, the quality of personalized learning support and real-time feedback has been significantly optimized, indicating that the AIGC-based human-intelligence collaborative teaching model can effectively promote the realization of the deeplearning process in technical courses.

Keywords AIGC; Smart Classroom; Human-intellectual Synergy; Reconstruction of Teaching Mode; Personalized Instruction

1 Introduction

With the rapid advancement of generative artificial intelligence (AIGC) technologies—particularly large language models (LLMs)—in the field of education, classroom instruction is undergoing profound structural transformation. Leveraging capabilities such as language comprehension, content generation, and real-time feedback, AIGC has demonstrated broad applicability in areas including instructional content creation, learning process regulation, and assessment optimization. This shift is propelling classrooms from a model of "technical assistance" toward one of "intelligence-led" instruction [1].While traditional blended learning combines the strengths of online and offline modalities, it still presents notable limitations in terms of content adaptability, personalized support, and intelligent feedback—factors that are increasingly critical for the cultivation of higher-order cognitive skills.

Smart education emphasizes student-centered, data-driven, and in-depth integration of technology, and it is urgent to build a new model that supports self-directed learning and precision teaching. In this context, Human-AI Collaboration, as the key path of smart education, advocates the in-depth collaboration between teachers and AI at the cognitive, emotional, and decision-making levels, and realizes the teaching mechanism of "AI generation, teacher guidance, and student participation" [2].

Using the "Object-Oriented Programming" course as a case study, this research constructs a classroom teaching model empowered by AIGC and grounded in human–AI collaboration. An intelligent instructional process was designed across all phases of learning—before, during, and after class. Through controlled pre-and post-tests and multi-dimensional questionnaire surveys, this study analyzes the model's impact on enhancing learning effectiveness and optimizing instructional structures, aiming to provide both practical pathways and theoretical foundations for the development of smart classrooms.

2 Theoretical Basis and Research Status

2.1 The Theoretical Basis of AIGC Empowering Classroom Teaching

With its advanced natural language understanding and generation capabilities, multimodal expression, and knowledge transfer potential, AIGC demonstrates comprehensive empowering potential in classroom instruction. From the perspective of educational technology theory, the core logic by which AIGC promotes classroom reform operates on three interrelated levels: cognitive support, instructional organization, and intelligent evaluation.

At the cognitive level, AIGC functions as an external cognitive tool that assists learners in constructing knowledge structures, reducing cognitive load, and improving learning efficiency [3]. In terms of instructional organization, AIGC is embedded within the teaching process, reshaping the structure of tasks and activities, and facilitating a shift in the teacher's role—from content deliverer to co-designer and intelligent orchestrator of instruction [4]. At the evaluation and feedback level, AIGC enables the real-time generation of personalized feedback based on student data, supporting timely regulation, precise intervention, and evidence-based instructional decision-making [5]. This reconstruction of teaching driven by generative technologies lays a solid technical foundation for the development of smart classrooms.

2.2 Human-intelligence Synergy: the Realization Path of Smart Education

With the deepinvolvement of AIGC technology, human-intelligence collaboration has increasingly become an important way to realize smart education. Human-intelligence collaboration emphasizes human-centered intelligent integration, breaks through the traditional tool paradigm of "human-use AI", and emphasizes the dynamic collaborative relationshipbetween teachers and AI. Based on the teaching objectives and students' needs, teachers can cooperate with AIGC to generate teaching content and realize the automation and personalized development of curriculum resources [6]. Through interactive learning with AIGC, students can receive immediate feedback and personalized tutoring to enhance their learning autonomy [7]. Teachers, students, and AI work together to form a dynamic feedback mechanism to form a collaborative optimization of teaching objectives, learning paths, and evaluation strategies [8]. This model not only improves the teaching efficiency, but also strengthens the humanistic characteristics of education, and reshapes the logical relationshipbetween "teaching-learning-evaluation".

2.3 A Review of the Current Research Status at Home and Abroad

In international research, Holstein et al. proposed the teacher–AI co-teaching model, emphasizing the role of interpretable AI tools in shaping a tripartite interactive learning environment involving students, teachers, and AI systems [9]. Luckin further advanced the concept of shared agency, wherein AI and humans collaboratively design educational objectives and learning pathways.

In domestic research, Han Xiaoli validated the synergistic effect of AI tools on enhancing student engagement and empirically demonstrated that AI interventions can significantly improve learners' knowledge transfer capabilities [10]. However, most existing studies remain focused at the level of instructional assistance, while the systematic integration of human–AI collaboration—such as co-designed instructional tasks and intelligent orchestration mechanisms—remains in the exploratory phase. Additionally, He et al. constructed a human–AI collaborative teaching process encompassing seven key components (e.g., collaborative lesson planning and co-evaluation), but issues related to ethical risks and technological alienation still require regulatory frameworks and governance mechanisms [11].

Against the backdropof AIGC-driven educational reform, the reconstruction of teaching models grounded in the concept of human–AI collaboration has become a critical trend in smart classroom research. Leveraging AIGC's technical advantages in content generation, personalized recommendation, and feedback regulation, this study designs an integrated instructional process spanning pre-class, in-class, and post-class stages, with human–AI collaboration as its underlying logic.

Practically, this framework is applied to the university-level course Object-Oriented Programming, where an AIGC-empowered teaching experiment is conducted to empirically examine the model's feasibility and effectiveness in enhancing teaching efficiency and student learning experiences.

3 Design of Classroom Teaching Mode Reconstruction Scheme under AIGC Empowerment

With the widespread application of AIGC technology in the field of education, classroom instruction has shifted from traditional teacher-led models to those driven by generative intelligence. Conventional teaching approaches can no longer meet the growing demands for higher-order thinking, personalized learning, and deeplearning. Based on the Object-Oriented Programming course in undergraduate computer science curricula, this study designs a human–AI collaborative teaching model empowered by AIGC. Anchored in the three stages of pre-class, in-class, and post-class, the model integrates the wisdom of teachers, the subjectivity of students, and the generative and regulatory capabilities of AIGC, forming an intelligent, collaborative, and iterative instructional system [12], as illustrated in Fig. 1.

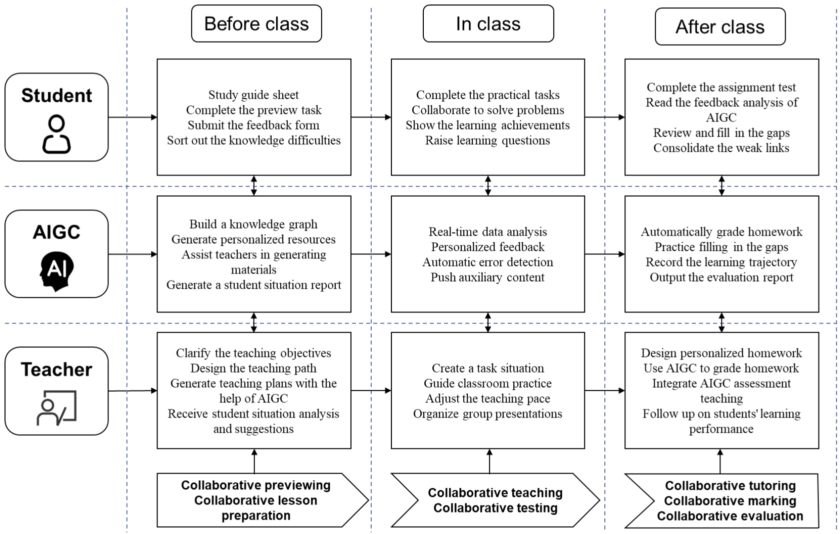

Fig. 1. Classroom teaching mode empowered by AIGC

3.1 Pre-course Preparation Stage

In the pre-class stage, teaching preparation no longer relies on one-way planning by teachers, but is completed through the collaboration between teachers and the AIGC system. Based on the curriculum standards and teaching objectives, teachers set core knowledge points and ability requirements, and AIGC generates matching teaching resources according to instructions, including micro-lesson videos, code examples, concept maps, and problem tasks. In courses such as Object-Oriented Programming, which are conceptual abstract and highly technical, AIGC can quickly generate diversified learning materials that fit students' cognitive levels, and assist teachers in completing the enrichment and precision of teaching resources.

At the same time, teachers can use AIGC to plan personalized teaching paths, such as setting differentiated mentoring tasks for students with different learning levels. Students complete the online preview on the platform, and AIGC generates a personalized learning analysis report according to the learning trajectory and interactive behavior, identifies the weak points of their knowledge mastery and pushes the corresponding learning content. Teachers adjust their teaching strategies accordingly, realize the pre-implementation of "teaching according to aptitude" and "dynamic adjustment", and strengthen the application depth of human-intelligence collaboration in the teaching design stage [13].

3.2 In-class Implementation Phase

In-class teaching is the core link of the human-in-mind collaborative teaching model, which is characterized by the real-time interaction between teachers, students and AIGC. In the specific implementation, the classroom is not only a space for knowledge impartation, but also a collaborative field for cognitive generation and problem solving. Through situational guidance and task-driven methods, teachers create practical software development cases, such as bank account systems or student management platforms, to stimulate students' sense of situational engagement and problem awareness.

In the teaching process, students use AIGC to complete the understanding of problem situations, code design, and debugging optimization. AIGC not only supports code generation and result verification, but also interprets program logic through natural language to provide students with understandable process feedback. In the continuous exploration, students formed an iterative dialogue process with AIGC of "asking questions, generating solutions, obtaining feedback, correcting and optimizing", which effectively enhanced their programming practice ability and problem-solving ability. Teachers monitor students' learning behavior data in real time through the teaching platform, such as code submission frequency, debugging time, error type, etc., and dynamically intervene in teaching guidance and support. AIGC can also automatically generate personalized supplementary materials and learning suggestions after teachers publish tasks to helpstudents deeply understand knowledge points and promote knowledge transfer. The whole in-class stage reflects the typical human-intellectual collaborative form: the teacher leads the teaching rhythm, the AIGC provides real-time generation and regulation support, and the students realize the knowledge construction in the tripartite collaboration.

3.3 After-school Extension Stage

The after-class learning session focuses on the consolidation of knowledge, feedback and ability improvement. In this model, AIGC extends the temporal and spatial boundaries of teaching through the functions of exercise generation, homework correction, and knowledge transfer training. After the teacher assigns the task, AIGC can automatically generate questions covering key concepts and skill points according to the teaching focus, and attach answer analysis and cognitive path map, reducing the teacher's repetitive work burden. After students complete their assignments, the platform can automatically complete the correction and output a personalized learning report, including error analysis, concept mastery, and recommended practice suggestions. If students do not perform well in a certain knowledge point, AIGC can push targeted reinforcement tasks based on the variable training mechanism to build an "intelligent gap-filling" mechanism. At this stage, teachers are mainly responsible for the interpretation of learning data and the guidance of learning behaviors to ensure the accurate implementation of technical services. Through this mechanism of "human guidance-intelligent generation-personality feedback", the sustainable optimization of after-school learning is realized.

This human–AI collaborative model, underpinned by AIGC technologies, facilitates a comprehensive reconstruction of the teaching process. Its operational logic is embodied in the sequential phases of generation–analysis–design (pre-class), guidance–collaboration–feedback (in-class), and evaluation–reinforcement–regulation (post-class). By embedding AIGC into the core instructional workflow, teachers not only gain enhanced pedagogical support but also redefine classroom role distribution and knowledge flow, fostering student autonomy and creative development.

Through this AIGC-powered instructional model, driven by human–AI synergy, teachers are transformed from knowledge transmitters to learning designers and facilitators, while students shift from passive recipients to active participants and co-constructors. AIGC serves as an intelligent bridge and generative engine connecting the two. This model not only realizes full-process intelligent integration of teaching–learning–assessment but also offers a practical pathway and theoretical foundation for the continuous evolution of smart classrooms.

4 Teaching Evidence and Effect Analysis

To evaluate the effectiveness of the AIGC-empowered human–AI collaborative teaching model in higher education, a 16-week teaching experiment was conducted in the 2023 "Object-Oriented Programming" course offered to computer science majors at H University. This study employed a pre-test/post-test control groupdesign. Multidimensional data—including students' learning outcomes, motivation, satisfaction, and academic self-efficacy—were collected using validated measurement instruments. Statistical analysis was conducted using SPSS to systematically assess both the practical impact and intervention efficacy of the proposed teaching model.

4.1 Study Design

In this study, two parallel classes were set as the experimental class and the control class respectively. The experimental class (2402 class, N=55) adopted the human-intelligence collaborative teaching mode based on AIGC empowerment, while the control class (2401 class, N=52) followed the traditional teaching mode combining lectures and exercises. Before the experiment, the basic information and academic level of the two classes were tested to ensure the comparability of the research samples and the scientificity of the experimental intervention.

To comprehensively evaluate the instructional intervention, a composite assessment instrument was developed, comprising academic test items and structured questionnaires. The questionnaire measured four dimensions: learning motivation, attitude, satisfaction, and academic self-efficacy. The scales were adapted from established instruments widely used in domestic and international educational research and revised according to the specific context of this study. Reliability and validity analyses confirmed the suitability of the instruments for further investigation. The detailed psychometric results are presented in Table 1.The academic assessment is based on the core knowledge points of the course, and the questions are reviewed by experts to ensure the validity and differentiation of the content of the test.

Table 1. Reliability and validity analysis of each dimension of the questionnaire

Dimension	Reliability	Validity	
	Cronbach's α	KMO value	Bartlett spherical test (p-value)
Learning motivation	0.874	0.817	<0.001
Learning attitude	0.832	0.794	<0.001
Learning satisfaction	0.861	0.801	<0.001
Academic self-efficacy	0.846	0.776	<0.001

4.2 Comparative Analysis of Academic Performance

Prior to and following the teaching intervention, both classes underwent standardized academic assessments. An independent samples t-test was conducted to analyze the data, with results presented in Table 2. The pre-test scores revealed no statistically significant difference between the experimental and control groups ($p=0.902$), confirming the equivalence of their academic baseline at the outset of the study. However, the post-test scores demonstrated a significant performance advantage for the experimental group($M=85.23$) over the control group($M=78.12$), with the difference reaching statistical significance ($p=0.002$). These findings suggest that the integration of AIGC and teacher collaboration substantially enhanced students' comprehension and application of course content.

Further analysis of learning process data indicated a positive correlation between students' interaction frequency with the AIGC platform (e.g., number of code generation queries, frequency of assignment retries) and their post-test performance ($r=0.47$, $p<0.01$). This correlation suggests that AIGC not only served as a cognitive support tool but also increased students' engagement with practice and feedback mechanisms, contributing to improved learning outcomes.

Overall, the results demonstrate that AIGC significantly reduces cognitive load by offering personalized resource generation and real-time feedback, which facilitate deeper and broader knowledge acquisition. Additionally, AIGC-supported learning analytics enabled teachers to implement more precise instructional interventions and deliver differentiated teaching. The reconstructed classroom model, driven by human–AI collaboration, effectively optimized the learning process and promoted the attainment of instructional objectives.

Table 2. Pre-and post-test independent sample t-test results of academic performance

Test stage	Variance hypothesis	F	Distinctiveness	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	upper
Pretest of academic performance	Equal variance is assumed	0.003	0.956	0.120	105	0.902	0.14	1.17	-2.17	2.45
	Equal variance is not assumed			0.120	103.625	0.902	0.14	1.17	-2.17	2.45
Post-test of academic performance	Equal variance is assumed	5.444	0.021	-3.244	108	0.002	-5.127	1.581	-8.260	-1.994
	Equal variance is not assumed			-3.244	105.390	0.002	-5.127	1.581	-8.261	-1.993

4.3 Difference Analysis of Non-cognitive Variables

In addition to cognitive performance changes, non-cognitive variables (including learning motivation, learning attitude, satisfaction and academic self-efficacy) are also important dimensions to measure the effectiveness of teaching interventions. In this study, a structured questionnaire was used to quantify the four dimensions and the independent samples t-test in the pre- and post-test, and the results are shown in Table 3.

Regarding learning motivation, the average value of the post-test in the experimental class increased to 4.12, which was significantly higher than that in the control class ($p<0.001$). Further analysis shows that the task-driven and reward mechanisms (such as "code challenge" integral feedback) of the AIGC platform in the in-class stage can effectively stimulate students' goal-oriented behaviors, especially for students with low original learning motivation. Behavioral data analysis also showed that the students in the experimental class took the initiative to initiate more problem consultations in the platform, reflecting that their awareness of active learning was significantly enhanced.

In terms of learning satisfaction, the experimental groupachieved a post-test mean of 4.21, significantly higher than the control group($p< 0.001$). Notable areas of improvement included students' perceptions of content comprehensibility, difficulty alignment, teacher–AI synergy, and the responsiveness of feedback. These results underscore the pivotal role of AIGC in enhancing classroom interactivity and immediacy of support, thereby elevating students' overall satisfaction with the learning experience.

For academic self-efficacy, the post-test score of the students in the experimental class ($M=3.98$) was significantly higher than that in the control class ($p=0.009$). It is worth noting that the two sub-items of "Problem Solving Confidence" and "Programming Debugging Persistence" in this dimension have the most obvious improvements. Combined with the process analysis, it is found that AIGC can provide structured feedback with a neutral tone after multiple debugging failures, effectively alleviate students' frustration, and form a "low anxiety and high resilience" programming experience to a certain extent.

As for learning attitude, although the score of the experimental class was slightly improved ($M=3.95$), there was no significant statistical difference ($p=0.182$). This may be related to the relative stability of learning attitudes, and its transformation requires longer-term value recognition and deepinvolvement. At the same time, it may also reflect the lack of trust or inadaptability of some students in the early stage of the formation of dependence on AI intervention in teaching.

Further correlation analysis between variables showed that there was a significant positive correlation between students' learning satisfaction and academic self-efficacy ($r=0.52$, $p<0.01$), indicating that students not only "learned well", but also "were more willing to learn" and "more daring to learn" in an environment where AIGC and teachers provided clear support and feedback.

Table 3. The results of the pre-and post-test independent sample t-test of learning motivation, learning attitude, learning satisfaction and academic self-efficacy

Dimension	Test stage	Variance hypothesis	F	Distinctiveness	t	df	Sig.（2-tailed）	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
										Lower	upper
Learning motivation	Pretest	Equal variance is assumed	0.012	0.911	0.111	105	0.911	0.01	0.09	-0.17	0.19
		Equal variance is not assumed			0.111	104.729	0.911	0.01	0.09	-0.17	0.19
	Post-test	Equal variance is assumed	0.232	0.631	3.780	105	0.000	0.57	0.15	0.27	0.87
		Equal variance is not assumed			3.780	104.927	0.000	0.57	0.15	0.27	0.87
Learning attitude	Pretest	Equal variance is assumed	0.159	0.691	0.290	105	0.772	0.03	0.11	-0.18	0.24
		Equal variance is not assumed			0.290	103.671	0.772	0.03	0.11	-0.18	0.24
	Post-test	Equal variance is assumed	0.032	0.858	1.340	105	0.182	0.13	0.10	-0.06	0.32
		Equal variance is not assumed			1.340	104.532	0.182	0.13	0.10	-0.06	0.32
Learning satisfaction	Pretest	Equal variance is assumed	0.042	0.837	0.240	105	0.811	0.02	0.10	-0.18	0.22
		Equal variance is not assumed			0.240	104.387	0.811	0.02	0.10	-0.18	0.22
	Post-test	Equal variance is assumed	0.083	0.774	4.120	105	0.000	0.51	0.12	0.27	0.75
		Equal variance is not assumed			4.120	103.922	0.000	0.51	0.12	0.27	0.75
Academic self-efficacy	Pretest	Equal variance is assumed	0.005	0.944	0.289	105	0.771	0.03	0.10	-0.17	0.23
		Equal variance is not assumed			0.289	103.415	0.771	0.03	0.10	-0.17	0.23
	Post-test	Equal variance is assumed	0.144	0.705	2.650	105	0.009	0.13	0.05	0.03	0.23
		Equal variance is not assumed			2.650	103.762	0.009	0.13	0.05	0.03	0.23

4.4 Discussion and Summary of Results

Through the comprehensive analysis of experimental data, it can be seen that the human-intelligence collaborative teaching model empowered by AIGC has significant results in improving students' cognitive performance and non-cognitive literacy, especially in personalized learning support, process feedback and practical ability improvement. This result confirms that AIGC is not only a content generation tool, but also a structural participation in multiple links such as teaching organization, learning guidance and teaching evaluation. The results show that students show higher learning enthusiasm and self-regulation ability in the AIGC environment, indicating that the teaching ecology constructed by the intelligent system and teachers' wisdom has good adaptability and generalizability. However, as a relatively stable psychological trait, learning attitude still needs to be stimulated through multiple cycle teaching, continuous emotional guidance and social construction support, which puts forward new requirements for follow-upresearch.

In summary, the AIGC-driven classroom teaching model not only improves the efficiency and quality of teaching, but also achieves a paradigm breakthrough in the teaching structure, role division and process mechanism. The deepintegration of human-intellectual collaboration is not only a technical choice, but also a kind of educational value reconstruction and practical logic reshaping.

5 Conclusion

This study focuses on the application and practice of AIGC technology in classroom teaching in colleges and universities, and proposes and implements a teaching mode reconstruction path that integrates the human-intelligence collaboration mechanism. Focusing on the three-stage teaching process of "before-in-class-after-class", the system embeds AIGC's technical capabilities in content generation, personalized push and intelligent feedback, builds a multi-collaborative system of teacher guidance, student participation and AI support, and realizes the reconstruction and optimization of classroom teaching structure and function.

The empirical results show that the teaching model has significant effects in improving students' academic performance, learning motivation, learning satisfaction and academic self-efficacy. Teachers have gradually transformed into designers and regulators of intelligent teaching systems in teaching, while students have shown stronger learning initiative and in-depth participation in the multi-level intelligent support environment, and the teaching process has shifted from "knowledge transfer" to "collaborative co-construction", realizing the essential reshaping of the relationshipbetween teaching and learning.

Although this research primarily focuses on an engineering-oriented course, and its generalizability across other disciplines requires further validation, it nonetheless offers a feasible pathway for smart classroom construction and a practical reference for implementing human–AI collaborative teaching models in AIGC-enabled environments. Future research should aim to expand the range of applicable subjects, deepen the embedding mechanisms of AIGC systems, and further promote the deepconvergence of educational technology and pedagogical value.

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Conflicts of Interest

The authors declare no conflicts of interest.

References

1. Yu, H., & Guo, Y. (2023, June). Generative artificial intelligence empowers educational reform: current status, issues, and prospects. In Frontiers in Education (Vol. 8, p. 1183162). Frontiers Media SA.
2. Chan, C. K. Y., & Tsi, L. H. (2023). The AI revolution in education: will AI replace or assist teachers in higher education?. arXiv preprint arXiv:2305.01185.
3. Yu, H., & Guo, Y. (2023, June). Generative artificial intelligence empowers educational reform: current status, issues, and prospects. In Frontiers in Education (Vol. 8, p. 1183162). Frontiers Media SA.
4. Cheng, Y., Zhou, S., Wu, W., Zhu, G., & Yang, G. (2024, September). Application Research of Interactive Teaching Mode Based on AIGC generative Artificial Intelligence. In 2024 International Conference on Artificial Intelligence, DeepLearning and Neural Networks (AIDLNN) (pp. 138-146). IEEE.
5. Song, Y. (2022). Research and Practice of AI Enabled New Classroom Teaching. Global Education, 51(10), 19–29.
6. Bai, M. X., & Guo, F. R. (2024). How Does Artificial Intelligence Generated Content Enable Learning, Ability and Evaluation? Modern Educational Technology, 34(01), 55–63.
7. Tan, K., Pang, T., Fan, C., & Yu, S. (2023). Towards applying powerful large ai models in classroom teaching: Opportunities, challenges and prospects. arXiv preprint arXiv:2305.03433.

8. Xiaoyong, H. U., Shuo, S. U. N., Wenjie, Y. A. N. G., & Geying, D. I. N. G. (2023). Artificial Intelligence Empowering the High-Quality Development of Education: Demands, Visions, and Paths. Frontiers of Education in China, 18(1).
9. Yang, K. B., Lawrence, L., Echeverria, V., Guo, B., Rummel, N., & Aleven, V. (2021). Surveying teachers' preferences and boundaries regarding human-AI control in dynamic pairing of students for collaborative learning. In Technology-Enhanced Learning for a Free, Safe, and Sustainable World: 16th European Conference on Technology Enhanced Learning, EC-TEL 2021, Bolzano, Italy, September 20-24, 2021, Proceedings 16 (pp. 260-274). Springer International Publishing.
10. Chen, K. Q., Han, X. L., Zheng, Z. F., Liu, X. L., & Hu, X. S. (2022). The Analysis of Construction and Application Mode of Scenario Construction in Intelligent Education from the Perspective of Human-machine Cooperation——A Review of Domestic and International Review on Human-machine Cooperative Education in the Past Ten Years. Journal of Distance Education, 40(02), 3–14.
11. He, W. T., Zhang, M. L., Lu, X., & Song, C. T. (2023). The construction of human-machine collaborative teaching mode from the perspective of artificial intelligence. Modern Distance Education, (02), 78–87.
12. Xiang, R. X., Zhao, H. Z., Wang, Z. T., & Li, J. M. (2024). Teaching practice of Web front-end development empowered by AIGC. Computer Education, (10), 153–158.
13. Li, H. J., Huang, Q. R., Chen, W., & Xu, Z. Z. (2025). Research on Human-AI Collaborative Iterative Symbiosis Teaching Mode ——Analysis of the Integration and Practical Effect of AIGC. Modern Educational Technology, 35(01), 81–88.

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基於AIGC的課堂教學模式重構實踐研究

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摘要：高校課堂教學在當前生成式人工智慧（AIGC）快速發展的背景下麵臨結構重構的新挑戰。傳統混合式教學模式存在內容抽象、回饋滯後等問題，難以滿足高階能力培養的需求。為此，設計並實施了一種基於AIGC賦能、融合人智協同機制的課堂教學模式。該模式圍繞「課前—課中—課後」三個階段，集成AIGC在內容生成、路徑推薦與學習回饋方面的技術優勢，構建由教師引導、學生參與、AI支持的協同教學系統。以高校《面向對象程式設計》課程為對象，採用前測—後測對照實驗設計，結合學業成績、學習動機、滿意度等維度開展實證研究。實驗結果顯示，相較於傳統教學模式，該模式在提升學生編程能力、學習積極性及自我效能感方面具有明顯優勢。尤其在個性化學習支持與即時回饋品質上取得顯著優化，表明基於AIGC的人智協同教學模式可在技術課程中有效促進深度學習過程的實現。

關鍵詞：AIGC；智慧課堂；人智協同；教學模式重構；個性化教學

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