From "Experience Flood Irrigation" to "Data Drip Irrigation": Construction and Practice of a Flipped Classroom Teaching Model Based on Generative AI

Xiaoli Wu, Bendalyn.Landicho*

Batangas State University, The National Engineering University
College of Accountancy, Business, Economics & International Hospitality Management
Batangas, 4200 Philippines

*Corresponding Author: bendalyn.landicho@g.batstate-u.edu.ph

Abstract. In the localized practice of flipped classrooms in vocational colleges, there has long been a dilemma of "resembling the form but lacking the essence": pre-class preview lacks depth, in-class interaction fails to go beyond superficial dialogue, and after-class evaluation relies on empirical judgment. The content generation and intelligent interaction capabilities of Generative Artificial Intelligence (GAI) provide a technical fulcrum to break this deadlock. Based on constructivist learning theory and precision teaching theory, this study constructs a "GAI four-dimensional empowered" flipped classroom teaching model. The four dimensions are explicitly defined as: intelligent resource generation, human-machine collaborative scenario construction, real-time interactive feedback, and data-driven learning evaluation. Through the three-stage design of "intelligent pre-class guidance — human-machine collaboration in class — precise after-class improvement", it realizes the transformation of teaching paradigm from experience-driven to data-driven. A quasi-experimental study was conducted taking the course 'Web Crawler Technology' in a higher vocational college as the experimental subject. To control for potential confounds, ANCOVA was applied using pre-test scores as a covariate. The results show that the pre - class preview completion rate of the experimental class increased by 26.8 percentage points. The frequency of high - level classroom interaction was 2.3 times that of the control class [operationalized via the ICAP framework; inter - rater reliability $\kappa = 0.85$]. The average final score of the experimental class was 11.7 points higher than that of the control class ($p < 0.01$).

The research verifies that the core mechanism of GAI empowering flipped classrooms lies in realizing full - link intelligence covering "resources - scenarios - feedback - evaluation". Meanwhile, its application needs to guard against the risk of cognitive outsourcing and build a new human - machine collaborative teaching relationship.

Keywords: Generative Artificial Intelligence; Flipped Classroom; Vocational Education; Precision Teaching; Human-Machine Collaboration

C. V. Garces et al. (eds.), *Proceedings of the 6th International Conference on Internet, Education and Information Technology (IEIT 2026)*, Atlantis Highlights in Social Sciences, Education and Humanities 53,
https://doi.org/10.2991/978-94-6239-733-0_42

1 Introduction

Since the flipped classroom entered China's education landscape in 2007, it has undergone a two-decade evolution from theoretical introduction to localized practice [1]. The core logic of this teaching model lies in "knowledge delivery before class and knowledge internalization during class" — shifting the lecturing session of traditional classrooms to pre-class hours, thereby freeing up in-class time for in-depth interaction and problem-solving. This design has a natural affinity for vocational education that emphasizes "learning by doing": practical training courses require ample classroom time for hands-on practice rather than listening to teachers explain theoretical principles [2].

However, there is a significant gap between ideals and reality. A large number of teaching practices have shown that the flipped classroom in vocational colleges is trapped in a "triple dilemma". First, the dilemma of homogenized resource supply. The preview videos produced by teachers adopt a one-size-fits-all approach, failing to adapt to students' differentiated cognitive starting points, resulting in a situation where students with a solid foundation are unwilling to watch them while those with a weak foundation cannot understand them [3]. Second, the dilemma of superficial classroom interaction. Students lack adequate pre-class preparation, and classroom discussions remain at the superficial level of simple question-and-answer exchanges, making it difficult to cultivate critical thinking and complex problem-solving abilities [4]. Third, the dilemma of lagging learning evaluation. Teachers rely on subjective experience or unit tests to judge students' learning status, failing to realize the real-time diagnosis of learning conditions during class and the accurate push of targeted interventions after class [5].

The rise of Generative Artificial Intelligence (GAI) has provided a new technical approach to solving the above dilemma [6]. Unlike previous educational technologies, GAI possesses three core capabilities: first, personalized content generation, which can dynamically customize learning resources based on student profiles [7]; second, intelligent interactive feedback, which can answer students' questions and guide their thinking in a conversational manner [8]; third, high-fidelity scenario construction, which can simulate complex problems in real workplace scenarios [9]. These capabilities directly address the pain points of the flipped classroom: personalized resources can break the "homogenization dilemma", intelligent interaction can support in-depth pre-class preview and alleviate the problem of "insufficient preparation", and real-time feedback can realize accurate diagnosis of learning status and support precise classroom teaching [10].

The core research questions are: How to construct a GAI-enabled flipped classroom teaching model adapted to the actual teaching situation of vocational colleges, whether this model can effectively improve students' learning outcomes, and what its mechanism of action is

2 Theoretical Basis and Analytical Framework

2.1 Constructivist Learning Theory: The Epistemological Foundation of the Flipped Classroom

The epistemological foundation of the flipped classroom is constructivist learning theory. This theory holds that knowledge is not passively accepted, but actively constructed by learners through interaction with the environment [11]. The core goal of vocational education is to cultivate "the ability to solve real-world problems", which precisely requires students to construct knowledge through "doing" rather than memorizing "knowledge about action" [12].

GAI's support for constructivist learning environments is reflected in three aspects: First, it provides "scaffolding" support. When students encounter difficulties in problem-solving, GAI can instantly offer hints, examples or decomposed steps to help them cross the zone of proximal development. Second, it creates "authentic situations". GAI can simulate unstructured problems in real workplace scenarios, such as "sudden changes in client requirements" and "abnormal equipment failures", allowing students to exercise their adaptability in simulated contexts. Third, it supports "social negotiation". GAI can act as a "virtual peer" to engage in argumentative dialogue with students and prompt them to reflect on their own understanding [13].

2.2 Precision Teaching Theory: From "Experience-Driven" to "Data-Driven"

Precision teaching originates from behavioral psychology, and its core proposition is that teaching decisions should be based on continuous measurement and data analysis of students' learning performance rather than teachers' intuitive judgment [14]. In traditional teaching, teachers' judgment of students' learning status usually relies on two links: classroom questioning and homework correction, resulting in sparse and delayed information collection. The intervention of GAI realizes the "full-process collection" of learning behavior data — everything from video viewing duration, pause and playback positions, to error types in practical training tasks and the number of help-seeking attempts can be recorded and analyzed [15].

The operational path of precision teaching theory can be summarized as the "Three Precisions": precise confirmation (identifying students' current learning level), precise prediction (foreseeing difficulties students may encounter next), and precise intervention (providing targeted support to help students make progress). GAI can play a unique role in all three links.

2.3 Analysis Framework of Flipped Classroom Empowered by GAI: Three-Dimensional Integration of Technology, Teaching and Evaluation

Integrating the above theories, we construct a three-dimensional analytical framework of "Technology-Teaching-Evaluation":

Technical Dimension: As an "Intelligent Teaching Partner", GAI undertakes four major functions: resource generation, Q&A tutoring, learning situation analysis, and scenario construction.

Teaching Dimension: Design GAI intervention points respectively for the three stages of the flipped classroom (pre-class, in-class, and post-class), forming a closed loop of "pre-class guidance — in-class inquiry learning — post-class tutoring".

Evaluation Dimension: Shifting from "result evaluation" to "process evaluation plus value-added evaluation", GAI provides multi-dimensional learning analysis data support.

3 Model Construction: GAI Four-Dimensional Empowerment Flipped Classroom Teaching Design

3.1 The "Triple Dilemma" of the Traditional Flipped Classroom and the Solution Logic of GAI

The practical dilemmas of flipped classrooms in vocational colleges can be summarized as "threefold mismatches" (see Table 1). The solution logic of GAI lies in transforming "standardized supply" into "personalized generation"[16], "delayed feedback" into "real-time interaction", and "empirical judgment" into "data-driven decision-making".

Table 1. Dilemmas of the Traditional Flipped Classroom and GAI-Based Solutions

Source: Compiled from References [3][5][10]

Dilemma Dimension	Manifestation Form	Cracking Path of GAI
Resource Supply	The one-size-fits-all preview videos fail to adapt to individual differences.	Automatic generation of layered preview resources to achieve personalized learning for every student.
Scene Construction	Practical training cases lag behind industrial realities.	Generate high-fidelity simulation scenarios based on real-time industry data.
Feedback Mechanism	Teachers correct assignments 48 hours later, resulting in delayed feedback.	AI instant Q&A + automatic marking to achieve "second-level feedback".
Academic Diagnosis	Relying solely on teachers' empirical judgment and lacking data support.	Multidimensional learning behavior data analysis and visualization report generation.

3.2 Overall Model Architecture: Designed with a "Three Stages and Five Links" Framework

Based on the above analysis, this study constructs the "GAI Four-Dimensional Empowered Flipped Classroom Teaching Model".

The four dimensions are: (1) intelligent resource generation, (2) human - machine collaborative scenario construction, (3) real - time interactive feedback, and (4) data - driven learning evaluation. Taking "precision teaching and personalized learning" as its core philosophy, the model adopts GAI's four-dimensional capabilities as its technical foundation, and reconstructs the teaching process into three stages — pre-class, in-class, and post-class — with five key links.

Pre-class Stage: Intelligent Guidance and Precise Diagnosis.

Teachers assign preview tasks via the GAI teaching platform. The system automatically generates differentiated preview packages based on students' historical learning data, including pre-test scores and weak points in knowledge graphs. Students with weak foundational knowledge receive resources featuring concept explanations and step-by-step breakdowns, while advanced students get materials with extended cases and inquiry-based questions. During the preview process, students can interact with the GAI intelligent teaching assistant at any time. GAI records behavioral data such as students' questions, page stay duration, and types of assistance sought, generates a learning profile, and pushes it to the teacher terminal. Specifically, we used GPT-4 (via prompt engineering) to generate preview materials; the fine-tuned "Course-Specific AI Assistant" (based on Qwen-7B) handled Q&A interactions.

In-class Stage: Human-Machine Collaboration and In-depth Inquiry.

The design of in-class sessions follows the "three-stage progressive" principle: The first stage is "Problem Focusing" — teachers concentrate on explaining common difficult points of the whole class based on the learning situation reports generated by GAI. The second stage is "Collaborative Inquiry" — students complete practical tasks generated by GAI in group form, and GAI acts as a "virtual tutor" throughout the process; groups can turn to AI for hints (instead of direct answers) when encountering difficulties. The third stage is "Presentation and Debate" — each group presents their solutions, while other groups and the AI raise questions and challenges together, forming a three - dimensional interaction mode of "human - human - machine".

In this phase, GAI performed Socratic questioning and provided real - time debugging suggestions.

After-class Stage: Precision Push and Cyclic Improvement.

After class, GAI generates a personalized learning report for each student based on classroom performance data, including task completion quality, types of questions raised, and participation frequency, and pushes targeted extended learning resources. A specially designed "varied practice for wrong questions" mechanism is adopted: GAI analyzes the types of errors in students' assignments and automatically generates modified questions of the same type until students fully master the corresponding knowledge points. GAI also conducted automated grading accompanied by diagnostic feedback. For instance, it identified prevalent regular expression (regex) errors and proposed corrective exercises.

3.3 Selection and Functional Adaptation of GAI Tools

The specific GAI tools and models employed included: GPT-4 (for resource generation and Socratic questioning), a fine-tuned Qwen-7B model serving as the course-specific intelligent assistant, and an auto-grading module with rule-based validation for coding exercises.

As shown in Table 2, different GAI tools are matched to corresponding teaching links and meet differentiated functional requirements.

Table 2. GAI Tool Function Matrix

Teaching Link	Core Task	Recommended Tool Type	Key Functional Requirements
Before class	Hierarchical Resources Generation	Large Language Model (GPT-4, ERNIE Bot)	Supports prompt templates and allows adjustment of output difficulty
Before class	Intelligent Q&A	Course-exclusive AI Teaching Assistant (fine-tuned Qwen-7B)	Based on course knowledge base and capable of recording interactive data
During class	Scenario Simulation	Vertical Domain GAI Tools	Generate professional scenario cases and simulate real-world problems
After class	Homework Correction	Intelligent Grading System	Support automatic evaluation of code/design works with diagnostic feedback
Whole process	Academic Situation Analysis	Learning Analytics Platform	Multi-dimensional data visualization and early warning push notification

4 Research Design and Implementation

4.1 Experimental Design

A quasi-experimental research design was adopted, with two parallel second-year classes majoring in Artificial Intelligence Technology Application at a higher vocational college as the research subjects. The experimental class (n=43) adopted the "GAI-enabled Flipped Classroom Teaching Model" constructed in this study, while the control class (n=41) adopted the traditional flipped classroom teaching mode (teacher-made preview videos + in-class group discussion + after-class assignments). Both classes were taught by the same teacher, with the teaching content focusing on the unit of "Dynamic Web Page Data Collection" in the course of Web Crawler Technology, and the teaching duration lasted for 6 weeks (12 class hours). To mitigate selection bias, ANCOVA was conducted with pre-test scores as a covariate. Additionally, there were no significant differences in instructor or time-of-day between the two groups.

4.2 Research Object

There were no significant differences between the two groups of students in terms of age, gender, and prior course performance (pre-test average score: experimental class 72.3 points, control class 71.8 points, $t = 0.34$, $p > 0.05$). All students had completed the basic Python programming course and possessed the prior knowledge required for learning web crawling.

4.3 Measuring Tool

The study adopts a multi-dimensional evaluation strategy, and the measurement tools include:

Completion Rate and Depth of Pre-class Preview: The platform automatically records the video viewing completion rate, pre-class quiz accuracy rate, and number of pre-class questions raised.

ClassParticipation: High−levelinteractionwasoperationalizedusingtheICAPframework(Interactive,Constructive,Active,Passive).Two trained researchers coded classroom discourse; inter-rater reliability Cohen's $\kappa = 0.85$. High-level interaction was operationalized using the ICAP framework (Interactive, Constructive, Active, Passive). High-level interaction specifically referred to "Constructive" (e.g., generating new ideas) and "Interactive" (e.g., debating, co-constructing solutions) categories.

Learning Effectiveness: Includes immediate quizzes (on the day the unit ends) and delayed quizzes (two weeks later), covering three cognitive levels: knowledge memory, procedural operation, and problem-solving.

Learning Attitude: Learning attitude scale adapted from the Technology Acceptance Model (Cronbach's $\alpha = 0.87$).

4.4 Implementation Process

The experiment was strictly implemented in accordance with a three-stage process: Weeks 1-2 were the pre-experiment preparation stage, covering the deployment of the GAI platform, teacher training, and student training on tool usage; Weeks 3-8 were the experimental intervention stage, where the experimental class conducted teaching based on the model while the control class adopted the traditional flipped classroom teaching mode; Week 9 served as the post-test and data collection stage.

5 Data Analysis and Results

5.1 Pre-class Preview Behavior Analysis

There was a significant difference between the experimental class and the control class in the pre-class preview stage. The data showed (see Table 3) that the preview completion rate of the experimental class was 26.8 percentage points higher than that of the control class, and the indicators of "in-depth preview" (full video viewing rate and preview quiz accuracy rate) were all significantly better than those of the control class. Notably, the average number of preview questions raised by students in the experimental class was 3.1 times that of the control class.

Table 3. Comparison of Pre-class Preview Behaviors

Indicator	Experi-mental Class (n=43)	Control Group (n=41)	Difference Test
Preview Completion Rate	94.2%	67.4%	$\chi^2 = 9.84$**
Full Video View Rate	88.6%	61.3%	t = 4.27**
Preview Quiz Accuracy Rate	78.3%	65.2%	t = 3.15**
Average number of preview questions per person	3.7	1.2	t = 5.63**

Note: *p < 0.01

5.2 Classroom Interaction Quality Analysis

High-level interaction frequency in the experimental class was 2.3 times that of the control class (operational definition: ICAP framework's Constructive+Interactive categories; two coders, $\kappa = 0.85$).The quantitative analysis of classroom interaction adopts two dimensions: "proportion of speaking duration" and "cognitive level coding". The results show that the proportion of students' speaking duration in the experimental class accounts for 41.3% of the total classroom time, while that in the control class is 28.6% ($t = 3.82$, $p < 0.01$). A more crucial difference lies in the quality of interaction: high-level interaction in the experimental class (including cognitive elements such as questioning, debating, and scheme optimization) accounts for 37.2% of the total interaction volume, whereas the figure for the control class is only 16.5%.

Classroom observation records show that the typical interaction pattern in the experimental class has evolved from the three-round structure of "teacher questioning — student answering — teacher evaluation" to the five-round structure of "student presentation — AI questioning — student response — peer supplementation — teacher guidance".

5.3 Learning Effectiveness Analysis

Immediate Quiz Results.

The results of the immediate post-unit quiz (Table 4) show that the average score of the experimental class was 84.6 points, while that of the control class was 72.9 points, with a difference of 11.7 points ($t = 4.52$, $p < 0.01$). ANCOVAusingpre−testscoresasacovariateconfirmedthatthemodeleffectremainedsignificant, $F(1,81)=12.37$, $p<0.01, \eta2=0.13$[17]. ANCOVAusingpre− testscoresasacovariateconfirmedthatthemodeleffectremainedsignificant,$F(1,81)=12.37, p<0.01, \eta2=0.13$.

Table 4. Comparison of Unit Immediate Quiz Scores

Cognitive Hierarchy	Experimental Class (n=43)	Control Group (n=41)	Difference
Knowledge Memory (30 Points)	25.1	20.9	+4.2
Procedural Operation (35 Points)	29.4	24.7	+4.7
Problem Solving (35 Points)	30.1	14.8	+15.3
Total Score (100 Points)	84.6	72.9	+11.7

Note: For the problem-solving section, independent samples t-test, $t = 5.31$, $p < 0.001$

Delayed Test Results.

To test the retention effect of learning, a delayed test with the same examination paper was conducted on the students two weeks later. The results showed that the average score of the experimental class was 79.3 points (a decrease of 5.3 points compared with the immediate test), while that of the control class was 61.8 points (a decrease of 11.1 points). The knowledge retention rate of the experimental class (93.7%) was significantly higher than that of the control class (84.8%).

5.4 Changes in Learning Attitude

The pre-test and post-test data of the Learning Attitude Scale show that the total post-test score of the experimental class increased by 0.71 points (5-point scale) compared with the pre-test, while the control class increased by 0.18 points, with a significant difference ($t = 3.42$, $p < 0.01$). Among all dimensions, "Academic Self-Efficacy" saw the most prominent improvement (+0.89 points).

5.5 Mechanism Analysis: What Is at Work?

To further explore the mechanism by which GAI empowers flipped classrooms, a cluster analysis was conducted on students in the experimental class. Based on the indicator of "depth of GAI usage" (including the frequency of seeking AI assistance, quality of prompts, and resource utilization rate), students were divided into a high-usage group (n=16), a medium-usage group (n=18), and a low-usage group (n=9). The results showed that the average final exam score of the high-usage group (89.7 points) was significantly higher than that of the low-usage group (76.3 points), with a score difference of 13.4 points. Notably, there was no significant difference in average scores between the low-usage group and the control class (72.9 points).

6 Discussion

6.1 The Core Mechanism of Flipped Classroom Empowered by GAI

The effectiveness of GAI-enabled flipped classrooms stems from the positive cycle of "accurate diagnosis — real-time feedback — personalized learning paths"[18]. The Achilles' heel of traditional flipped classrooms lies in the lack of effective supervision over pre-class preview, leaving teachers unaware of whether students have truly understood the knowledge. The intervention of GAI transforms students' learning status from a "black box" to a "white box", enabling teachers to clarify what to teach and what not to teach before entering the classroom.

It is worth noting that the role of GAI is not to "replace teachers", but to "empower teachers". In the experiment, the lesson preparation time of teachers in the experimental class increased by about 30%, which was mainly spent analyzing AI-generated academic situation reports and designing targeted classroom activities.

6.2 Boundary Conditions and Applicable Limitations

Research findings need to be understood under specific boundary conditions. First, the experimental course 'Web Crawler Technology' is an engineering course intensive in "procedural knowledge", and GAI has achieved relatively mature capabilities in code generation and error diagnosis. For courses intensive in "conceptual knowledge" or highly reliant on "physical skills", the applicability of GAI may vary. Second, the research subjects are second-year vocational college students who already possess basic information literacy.For lower-grade students or groups with weak information literacy, preliminary training in "AI usage capabilities" may be required. Additionally, the quasi-experimental design without random assignment limits causal inference; however, ANCOVA helped control for pre-existing differences.

6.3 Practical Implications and Promotion Suggestions

Three practical suggestions are put forward: First, schools should build "course-specific AI knowledge bases" instead of relying on general large models. Second, teacher training should shift from "technical operation" to "instructional design". Third, establish teaching norms for "human-AI collaboration" and clarify the boundaries of AI application.

7 Conclusion and Prospect

By constructing and validating the "GAI-enabled Flipped Classroom Teaching Model", the following conclusions are drawn: First, the model can effectively improve vocational college students' pre-class preview depth, classroom interaction quality and learning effectiveness, with the experimental class achieving significantly better final exam scores than the control class ($p < 0.01$). Second, the core mechanism of the GAI-enabled flipped classroom lies in the positive cycle of "accurate diagnosis — instant feedback — personalized learning path", which realizes the transformation of teaching paradigm from "experience-driven" to "data-driven". Third, the performance of GAI efficacy relies on students' "human-machine collaboration capability", and cultivating students' AI literacy is a key prerequisite for the popularization and application of the model.

Limitations of the study: The experimental period was relatively short (6 weeks), failing to track long-term learning effects; the sample only covered one major at a single vocational college, leaving the external validity to be verified; the "black-box" nature of GAI tools made it difficult to collect partial process data (such as specific content of interactions between AI and students). Future research can be further deepened in three directions: first, conduct multi-site experiments across different majors and colleges; second, explore specific teaching strategies for "human-machine collaboration"; third, pay attention to ethical issues in the application of GAI, such as data privacy, algorithmic bias and cognitive dependence[19].

Acknowledgments

This study is a research achievement of the Teaching Research Fund Project of Anhui Provincial Department of Education and the School-level Project of Hefei Binhu Vocational and Technical College: Research on the Application and Innovation of Flipped Classroom Based on Generative AI in Vocational College Teaching.

References

1. Zhang Jinlei, Wang Ying, Zhang Baohui. Research on the Flipped Classroom Teaching Model[J]. Journal of Distance Education, 2012, 30(4): 46-51.
2. Xu Guoqing. Vocational Education Curriculum Theory[M]. Shanghai: East China Normal University Press, 2015: 78-92.
3. Liu Aihua, Zhu Zhipeng. Research on the Teaching Application of Generative Artificial Intelligence in Flipped Classroom of Higher Vocational Colleges[N]. Hebei Economic Daily, 2026-01-29(09).
4. Xu Biao, Huang Zhigang, Chen Li. Research on the Application Paradigm of Micro-courses in Higher Vocational Software Technology Major[J]. Education Modernization, 2019, 6(80): 127-128.
5. Cui Di, Liu Yanlong. Practical Research on Flipped Classroom Based on ChatGPT Technology — Taking the 3D Printing Course of Mechanical Design and Manufacturing Major as an Example[J]. Paper Making Equipment & Materials, 2024, 53(4): 112-114.
6. Jiao Jianli. New Opportunities and New Challenges of ChatGPT Boosting the Digital Transformation of Education[J]. China Education Informatization, 2023, 29(3): 3-10.
7. Liu Bangqi, Wu Xiaoru. Intelligent Education: Educational Reform in the Era of Artificial Intelligence[M]. Beijing: Beijing Normal University Press, 2021: 156-170.
8. Zhu Zhiting, Hu Jiao. An Analysis of the Essence and Research Prospect of Educational Digital Transformation[J]. China Educational Technology, 2022(4): 1-8.
9. Wang Guoqing, Wang Yan, Yang Shuoqiu. Empowering with AI, Innovating for a Smart Future — Digital Transformation and Innovative Practice of Vocational Education in Jiangsu Vocational Institute of Commerce[N]. China Education Daily, 2025-11-28(11).
10. Ye Zhen. The Entry of Large AI Models Reshapes the Vocational Education Ecosystem[N]. Xinhua Daily, 2026-03-24(3).
11. Vygotsky, L. S. Mind in Society: The Development of Higher Psychological Processes[M]. Cambridge: Harvard University Press, 1978: 84-91.
12. Jiang Dayuan. Structural Logic of Systematic Curriculum Based on Working Process[J]. Education and Vocation, 2017(13): 5-12.
13. Gu Xiaoqing, Li Shijin. Paths and Strategies of Artificial Intelligence Promoting Educational Development[J]. E-education Research, 2021, 42(3): 16-23.
14. Lindsley, O. R. Precision Teaching: Discoveries and Effects[J]. Journal of Applied Behavior Analysis, 1992, 25(1): 51-57.
15. Huang Ronghuai, Yang Junfeng. From Digital Learning Environment to Smart Learning Environment[J]. Open Education Research, 2012, 18(1): 75-84.
16. Zhao Xin, Li Wei. Research on the Application of Generative AI in Vocational Flipped Classroom under the Background of Educational Digital Transformation[J]. Vocational and Technical Education, 2024, 45(10): 32-38.
17. Sun Haiying, Chen Lu. Practical Exploration of ChatGPT Assisted Flipped Classroom Teaching in Higher Vocational Colleges[J]. China Vocational and Technical Education, 2025, 42(6): 55-61.
18. Wang Ruixue. Research on the Integration Path of Generative Artificial Intelligence and Flipped Classroom in Higher Vocational Education[J]. Journal of Educational Technology, 2026, 44(2): 23-30.
19. Li Ming, Zhang Li. A Review of Flipped Classroom Research in the Era of Artificial Intelligence[J]. Modern Educational Technology, 2022, 32(11): 42-49.