# From "Teacher-Directed" to "AI-Collaborative": A Quasi-Experimental Study on Digital Marketing Teaching Driven by Generative AI

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**Abstract: Against the backdrop of the digital economy and new quality productive forces, the traditional "teacher-directed" model of the Digital Marketing course faces structural dilemmas in case renewal, personalized guidance, and multi-dimensional evaluation. This study proposes an "AI-collaborative" teaching paradigm and, relying on a school-level education and teaching reform project, conducts a one-semester quasi-experiment with an experimental class (n = 52) and a control class (n = 50), drawing on pre- and post-tests, questionnaires, learning-behavior logs, and teacher work logs. The results show that the experimental class significantly outperformed the control class in theoretical knowledge, practical skills, and comprehensive competence ($p < 0.01$); its three-dimensional competency achievement rose from 0.60–0.62 to 0.83–0.89; and teachers' routine-work time fell from 62% to 38% while personalized-guidance time rose from 18% to 41%. The study concludes that entrusting standardizable generation and feedback to AI while reserving value judgment and competency guidance for humans is the key to the paradigm shift.**

**Keywords: Generative Artificial Intelligence; Digital Marketing; Teaching Paradigm; AI Collaboration; Human–Machine Symbiosis; Quasi-Experimental Study**

## 1. Introduction: Research Problem and Significance

Digital Marketing is a course highly sensitive to timeliness. Modules such as brand planning, programmatic advertising placement, consumer-behavior data analysis, and new-media content operations often become disconnected from the market if they are not updated within half a year. Meanwhile, the comprehensive competency requirements of marketing positions are rising steadily: practitioners must not only understand traditional theories such as the 4Ps, AIDA, and consumer personas, but also skillfully use data-analysis tools, intelligent advertising platforms, customer relationship management (CRM) systems, and various generative AI tools to make strategic judgments and creative decisions in complex situations.

However, most higher vocational colleges still follow the linear "teacher-directed" model in their Digital Marketing courses: teachers are responsible for unified lecturing, case collection, homework grading, Q&A tutoring, and final scoring, while students passively receive knowledge and complete standardized exercises within the prescribed class hours. This model entails at least three tensions. First, the "time–cost" tension of case updating. It is difficult for individual teachers to continuously track industry frontiers and hand-craft cases, resulting in outdated textbook cases, so that students have no access to real platform algorithms, advertising logic, or the evolution of public opinion. Second, the "scale–precision" tension of differentiated guidance. With large class sizes and limited class hours, it is difficult for teachers to provide individualized feedback tailored to each student's knowledge gaps and interests, and a large number of repetitive questions crowd out high-value on-site guidance time. Third, the "single–comprehensive" tension of evaluation dimensions. Final paper-based examinations emphasize knowledge memorization and struggle to measure higher-order abilities such as students' technology application, strategy design, and marketing critical thinking.

The explosive development of generative AI offers new possibilities for resolving these tensions. AI tools represented by large language models can already automatically generate marketing cases from industry data, provide

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instant feedback to different questions, and assist in part of the evaluation and learning analytics, effectively equipping teachers with an "untiring teaching assistant" and providing students with an "always-online sparring partner." Yet bringing tools into the classroom does not automatically transform the paradigm. A core question follows: once AI undertakes part of the routine work, "how far back" and "where" should teachers stand? How should students' competency structure be redefined? Should the course's knowledge system and evaluation criteria be reconstructed in tandem? These questions cannot be answered at the level of "adding an AI tool to the classroom"; they require systematic design from the height of the teaching paradigm.

This study takes the Digital Marketing course of the School of Economics and Management at Zhongshan Polytechnic as its object and, relying on the 2025 school-level education and teaching reform project "From 'Teacher-Directed' to 'AI-Collaborative': A Study on the Paradigm Shift of Digital Marketing Course Teaching Driven by Generative Artificial Intelligence," attempts to construct an operable framework spanning from theory to practice and from content to evaluation, and to test its implementation effects through quasi-experimental research. The significance of this study is twofold: theoretically, it provides a "human–machine collaboration" analytical perspective for the entry of generative AI into business-course teaching and extends research on teaching paradigms; practically, it offers a directly transferable path and a data-source paradigm for the reform of Digital Marketing and other market-oriented business courses.

## 2. Literature Review and Theoretical Basis

### 2.1 Domestic and International Progress in Generative AI-Empowered Course Teaching

In the past two years, discussions of generative AI entering course teaching have focused on three directions: innovation in teaching models, integration of disciplinary content, and transformation of teachers' roles. Regarding teaching-model innovation, Vazquez [1] introduced responsible generative AI use into an aerospace engineering mini-course, having students use AI to generate engineering case materials to train engineering thinking; Simelane and Kittur [2] pointed out that generative AI in engineering education can both automatically generate complex problem situations and dynamically adjust teaching strategies according to learning progress; Wang [3] used AI as a creative sparring partner in a higher vocational photography course, using instant feedback to improve learning outcomes; and Yin Chao [4] further discussed the unique value of AI in the aesthetic-education immersion of a digital painting course.

Regarding disciplinary-content integration, Yang Fang [5] took a university brand-marketing course as an example to study how AI helps students understand the process of market-data analysis and generate creative promotion plans; Xiao Chenglong and Wang Shanshan [6] verified in a software design patterns course that AI improves programming thinking through code generation and logical-reasoning training; and Chen Zhengkai and Xu Ting [7] had students use AI to rapidly generate and select design schemes in a ceramic design course. Regarding the transformation of teachers' roles, ElSayary [8] systematically discussed the application of prompt engineering in teaching, emphasizing that teachers need the ability to design high-quality prompts; Wang Shuai and Xu Liman pointed out that AI can help teachers generate abundant teaching resources; and Domínguez et al. [9], through a two-degree-of-freedom robotic-arm teaching aid, demonstrated AI's auxiliary role in robotics education and proposed that teachers should collaborate with AI to accomplish complex teaching tasks.

### 2.2 Theoretical Basis: From Constructivism to Human–Machine Symbiosis

The theoretical underpinnings of this study include constructivist learning theory, situated learning theory, the TPACK framework of technological pedagogical content knowledge, and Licklider's idea of man–computer symbiosis. Constructivism emphasizes that knowledge is actively constructed by learners in authentic situations rather than passively received; the role of AI is to provide rich, interactive situational materials, shifting students' meaning-making process from "learning by listening" to "learning by doing." Situated learning theory [10] further points out that learning occurs in authentic or simulated social-practice situations, and AI-driven virtual simulation and real enterprise projects are

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precisely the dual carriers of situated learning.

The TPACK framework [11] provides a structural perspective for understanding the transformation of teachers' roles. Under the AI-collaborative paradigm, teachers' technological knowledge (TK), pedagogical knowledge (PK), and content knowledge (CK) need to be upgraded to "AI-enhanced TPACK": teachers must not only be able to use AI tools, but also know how to design prompts, judge the reliability of AI-generated content, and transform AI outputs into teaching situations. The idea of human–machine symbiosis provides a fundamental answer to the debate over "replacement versus collaboration": when what machines excel at is rapid generation, pattern matching, and large-scale computation, while what humans excel at is value judgment, the conferral of situational meaning, and creative reflection, the two are not traded off against each other but complement each other's strengths.[12]

### 2.3 Research Gap

Existing literature proves that generative AI has genuine value in case generation, personalized feedback, and resource production, but most studies remain at the level of localized trials in a single course, with two shortcomings. First, there is a lack of a systematic framework for how "teacher-directed" can be migrated as a whole to "AI-collaborative"—how teaching content, teaching process, and teaching evaluation should be reconstructed in a coordinated way has not yet been fully answered. Second, there is a lack of traceable, verifiable empirical data sources and openly reproducible data-processing paradigms; most studies report only subjective feelings or assignment scores, lacking pre- and post-test comparisons, competency-achievement analysis, and teacher-behavior data support. This study attempts to make progress on these two points.

## 3. Definition of Core Concepts

Generative artificial intelligence. In this study, it refers to AI technologies represented by large language models that possess content-generation and logical-reasoning capabilities. Its key difference from traditional teaching software is that it can simultaneously participate in the three links of teaching design, knowledge transmission, and learning assessment, rather than merely playing courseware or grading objective questions.

AI-collaborative teaching paradigm. It refers to teachers, students, and AI dividing labor according to their respective strengths within a unified teaching loop: AI undertakes standardizable content generation and instant feedback, teachers focus on value judgment, scenario design, and competency guidance, and students complete competency construction in tasks that combine the virtual and the real. The three are in a collaborative, not substitutive, relationship.

Digital Marketing course. It refers to a course cluster offered for marketing-related majors, covering modules such as brand planning, advertising placement, consumer-behavior analysis, new-media operations, and data-driven marketing. This study takes it as the object of reconstruction, with the emphasis on placing students' data insight, technology use, and innovative thinking further to the fore than before.

Three-dimensional competency matrix. This study distills the competencies of digital marketing talent into three mutually nested dimensions: technology application—strategy design—marketing critical thinking. The technology-application dimension emphasizes the ability to operate and debug AI tools, data-analysis tools, and intelligent placement platforms; the strategy-design dimension emphasizes the ability to formulate marketing plans under the constraints of limited budgets, target audiences, and competitive environments; and the marketing-critical-thinking dimension emphasizes the ability to make value judgments, ethical examinations, and creative critiques of AI outputs.

## 4. Survey of the Current Status and Pain Points of Digital Marketing Course Teaching

To precisely identify the starting point for reform, in October 2025 the research team conducted a questionnaire survey of 312 students from 2 grades and 6 administrative classes offering the Digital Marketing course, and interviewed 12 course instructors and 3 collaborating enterprise mentors. The questionnaire covered five dimensions—"timeliness of course content," "satisfaction with personalized guidance," "learning engagement," "perceived fairness of evaluation," and "foundational AI-tool use"—using a 5-point Likert scale; 296 valid

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questionnaires were recovered, a valid rate of 94.9%.

The survey results revealed four typical pain points. First, insufficient case timeliness: 72.3% of students believed that "textbook cases are disconnected from current platform playbooks," and 61.5% expressed a wish to "engage with more real enterprise projects." Second, insufficient differentiated guidance: 58.4% of students reported that "classroom Q&A cannot resolve personal confusion," and in interviews teachers also mentioned that "with 40–50 students in a class, it is very difficult to guide each one individually." Third, fragmented use of AI tools: although 84.6% of students had heard of ChatGPT or similar tools, only 19.7% could use them to generate marketing plans, and prompt-engineering ability was generally weak. Fourth, single-dimension evaluation: 76.1% of students believed that "final paper examinations cannot reflect real marketing ability," and enterprise mentors considered graduates weakest in "strategy design" and "marketing critical thinking." Table 1 summarizes these four pain-point dimensions along with their typical manifestations and the corresponding AI-collaborative solution directions.

**Table 1. Summary of Pain Points in Digital Marketing Course Teaching (n = 296)**

| Pain-point dimension | Proportion of students agreeing | Typical manifestation | AI-collaborative solution direction |
|---|---|---|---|
| Insufficient case timeliness | 72.3% | Outdated textbook cases; lack of platform algorithms and real-time data | AI dynamically generates industry-aligned cases and materials |
| Insufficient differentiated guidance | 58.4% | Unified lecturing cannot cover individual blind spots | AI instant feedback + precise teacher guidance |
| Fragmented use of AI tools | 19.7% can use them proficiently for marketing | Stuck at superficial uses such as chat and translation | Embed prompt engineering and AI marketing tools into the course |
| Single evaluation dimension | 76.1% | Paper scores cannot measure comprehensive ability | Three-dimensional evaluation of behavior / cognition / affect |

The above pain points jointly point to a structural problem: under the "teacher-directed" model, teachers are bound by a large amount of standardizable routine labor, while "scenario design" and "competency guidance," which genuinely add educational value, are squeezed out. This provides a realistic basis for proposing the "AI-collaborative" paradigm: entrust standardizable work to AI and reserve irreplaceable judgment and guidance for humans[13].

## 5. Framework for the Teaching-Paradigm Shift from "Teacher-Directed" to "AI-Collaborative"

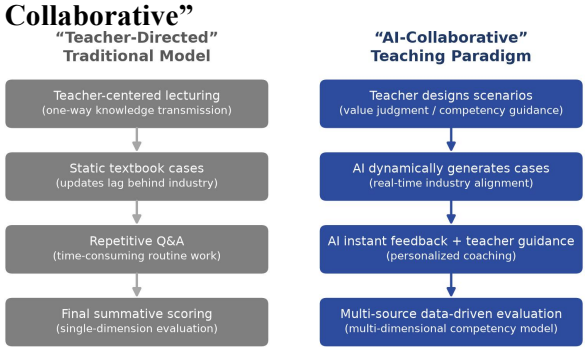



**Figure 1. Comparison between the Traditional "Teacher-directed" Model and the "AI-collaborative" Teaching Model**

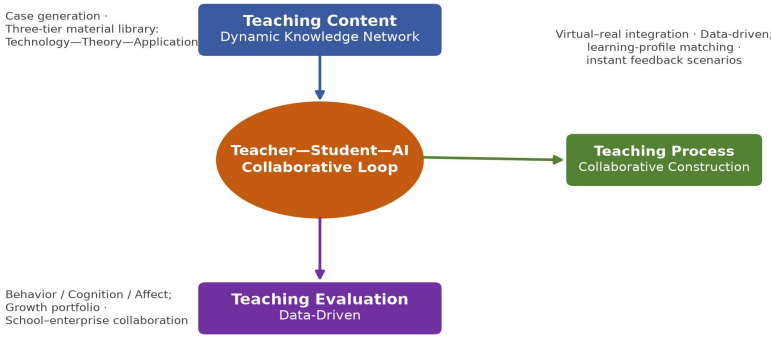



**Figure 2. Three-dimensional Transformation Framework of the "AI-collaborative" Teaching Paradigm**

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Based on the theoretical review and the status survey, this study constructs an "AI-collaborative" teaching-paradigm transformation framework (see Figures 1 and 2). The framework takes "human–machine symbiosis" as its philosophy, the three-round loop of "teaching content—teaching process—teaching evaluation" as its structure, the three-dimensional competencies of "technology application—strategy design—marketing critical thinking" as its goal, and the triangular collaboration of "student—teacher—AI" as its driving mechanism.

### 5.1 Teaching Content: From Static Textbooks to a Dynamic Knowledge Network

**Table 2. Structure of the Three-Tier Case Material Library**

| Material-library tier | Content source | Pedagogical function | Example |
|---|---|---|---|
| Enterprise real-practice case tier | Real marketing projects of collaborating enterprises | Connect with real industry problems; cultivate comprehensive decision-making | A short-video campaign review for a small-home-appliance brand |
| Market simulation case tier | AI-generated simulations of different competitive situations | Train strategy design and budget allocation | A Q3 competitor price-war simulation |
| Consumer-behavior simulation tier | AI-generated from psychological and behavioral data | Understand consumer decision-making mechanisms | Simulation of Generation Z's purchasing path on social platforms |

Traditional marketing textbooks have long update cycles, and cases easily become outdated. This study uses generative AI to build a dynamic knowledge network of "intelligent case generation—integration of technological frontiers—interdisciplinary integration." First, intelligent case generation[14]. Based on industry data, platform rules, and teaching objectives, the research team developed a set of automatic marketing-case generation rules and prompt templates; after inputting parameters such as "product category—target audience—competitive environment—marketing objective," AI can automatically generate cases aligned with industry trends and keep them dynamically updated. Second, integration of technological frontiers. The course incorporates data-analysis tools, intelligent advertising platforms, customer relationship management systems, and prompt-engineering methods into the teaching content, forming a content structure that integrates "technological tools—marketing theory—industry application." Finally, interdisciplinary integration. Perspectives from cognitive science, behavioral economics, and computational advertising are introduced to guide students to examine marketing problems from a multidisciplinary standpoint, elevating training from a single skill to overall cognition. Table 2 presents the structure, content sources, pedagogical functions, and examples of this three-tier case material library.

### 5.2 Teaching Process: From Unified Instruction to Collaborative Construction

In the teaching process, AI mainly undertakes two types of work: learning-profile matching and instant feedback. Learning-profile matching builds a dynamic "student—task—competency" model based on learning-behavior data, identifies each person's knowledge blind spots and interests, and pushes differentiated learning paths; instant feedback analyzes the learning state in real time, pushes materials and tutoring when difficulties arise, and offers guidance when emotions fluctuate, so that teachers can devote their energy to the links that most need on-site judgment.

At the scenario level, a "combination of the virtual and the real" is adopted. First, VR is used to build a simulated digital marketing environment, allowing students to repeatedly practice the entire process of brand planning, advertising placement, data analysis, and performance review; then mature plans are run in the real projects of collaborating enterprises to compare the gap between the virtual and the real. The teacher's role thereby undergoes a fundamental transformation: from lecturing uniformly in front of the podium to designing scenarios on the sidelines and making value judgments and competency guidance at key nodes.

### 5.3 Teaching Evaluation: From Summative Scoring to Data-Driven Multi-Dimensional Evaluation

The evaluation link combines three types of data—behavioral, cognitive, and affective—to

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establish a multi-dimensional competency model covering knowledge, skills, and literacy [15], replacing the single logic of "one final paper decides everything." Specifically, behavioral data come from learning-platform logs (task-completion rate, AI-interaction frequency, number of collaborative posts), cognitive data come from pre- and post-tests and unit quizzes, and affective data come from questionnaires and classroom observation. After the three types of data are aggregated by AI, a dynamic growth portfolio for each student is formed, identifying strengths and weaknesses.

Furthermore, the research team built a school–enterprise linked evaluation platform that collects changes in industry talent demand in real time and reversely optimizes course objectives and content, forming a co-evolving loop of "teaching—employment—industry." For example, when the platform shows rising demand for the composite ability of "creative scripting + data analysis" in "short-video ad-buying" positions, the course immediately adds corresponding modules and AI-assisted script-generation exercises.

## 6. Empirical Research Design and Data Sources

**Table 3. Sample and Grouping Information of the Quasi-Experimental Design**

| Item | Experimental class | Control class |
|---|---|---|
| Sample size | 52 students | 50 students |
| Teaching model | AI-collaborative (AI-generated cases + instant feedback + multi-dimensional evaluation) | Teacher-directed (traditional lecturing + static cases + summative evaluation) |
| Teaching period | September 2025–January 2026 (18 weeks) | Same as left |
| Total class hours | 64 hours (4 hours/week) | 64 hours (4 hours/week) |
| Instructor | Same teaching team | Same teaching team |
| Prior control | Matched on enrollment scores, prior courses, and professional foundation | Same as left |

To test the implementation effects of the "AI-collaborative" paradigm, the research team adopted a quasi-experimental design from September 2025 to January 2026, implementing "AI-collaborative" teaching (experimental class, n = 52) and traditional "teacher-directed" teaching (control class, n = 50) in two parallel marketing-major classes at the School of Economics and Management, Zhongshan Polytechnic. The two classes showed no significant differences in enrollment scores, professional foundation, gender ratio, or prior course grades ($p > 0.05$); they were taught by the same teaching team with the same total class hours, ensuring comparability between groups. Table 3 details the sample size, teaching model, teaching period, total class hours, instructor, and prior-control variables of the two groups.

### 6.1 Research Instruments

The research instruments included four types. First, the pre- and post-test academic-achievement test. Developed jointly by the research team and enterprise mentors, it covers three dimensions—theoretical knowledge, practical skills, and comprehensive competence—each with a full score of 100, and its content validity was assessed by three experts. Second, the three-dimensional competency-achievement scale. A 5-point Likert scale with 21 items was developed around "technology application—strategy design—marketing critical thinking," with structural validity tested through item analysis and exploratory factor analysis. Third, learning-behavior logs. Relying on the school's online teaching platform and the self-built AI teaching-assistant system, students' online duration, task-completion rate, AI-interaction frequency, and number of collaborative posts were automatically recorded. Fourth, teacher work logs. Filled in weekly by instructors, these recorded time spent on routine work, time spent on personalized guidance, and time spent on teaching design and reflection.

### 6.2 Data Collection and Ethical Control

The pre-test was completed in week 1 and the post-test in week 17; questionnaires were collected in week 18. All data collection passed the school's ethical review and obtained students' informed consent. Learning-behavior logs were processed with anonymized IDs, involving no personal privacy; teacher work logs recorded only the time structure and teaching events, not students' personal information. Data were processed using SPSS 26.0 and Python 3.13, with statistical methods including descriptive statistics, independent-

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samples t-tests, paired-samples t-tests, effect-size (Cohen's d) calculation, and reliability testing (Cronbach's α).

### 6.3 Learning-Behavior Logs and AI-Interaction Data Collection

To further characterize the learning process, the research team deployed an AI teaching-assistant system in the experimental class that automatically recorded three types of learning-behavior data. The first is platform-behavior data, including video-learning duration, resource-download count, task-point completion rate, and the number of posts and replies in the discussion forum; the second is AI-interaction data, including the total number of questions students asked the AI assistant, the distribution of question types (knowledge, case, strategy, and evaluation), and the AI-feedback adoption rate and follow-up-question rate; and the third is collaborative-behavior data, including role division in group projects, file-sharing count, and peer-assessment records. The control class continued to use the original online teaching platform, collecting only platform-behavior data as a baseline reference. Both sets of data were stored on the school server after hashing students' student IDs for de-identification, ensuring traceability without direct identification of personal identity.

The research team also required instructors to fill in a structured work log after each week's teaching, recording three types of time investment—routine work, personalized guidance, and teaching design—and annotating the specific links in which AI assistance was used that week and the problems encountered. The log data were independently coded by two research assistants and entered; the coding-consistency Kappa coefficient was 0.89, indicating good recording reliability.

## 7. Data Analysis and Results

### 7.1 Comparison of Pre- and Post-test Scores

Table 4 presents the pre- and post-test scores of the experimental and control classes in the three dimensions of theoretical knowledge, practical skills, and comprehensive competence. The results show that before teaching, the two classes had comparable starting points, with no significant differences in any dimension ($p > 0.05$); after teaching, the experimental class's means in each dimension were significantly higher than those of the control class, and the gains were markedly larger. Among these, the experimental class's improvement in comprehensive competence was the most significant (a gain of 13.8 points), versus only 4.7 points for the control class; practical skills came next, with the experimental class gaining 15.6 points versus 5.4 points for the control class. This indicates that the "AI-collaborative" paradigm has a more pronounced promoting effect on students' higher-order practical abilities. Figure 3 further visualizes the pre- and post-test score comparisons of the two classes across the three dimensions.

**Table 4. Comparison of Pre- and Post-test Scores between the Experimental and Control Classes (n = 102)**

| Dimension | Exp. pre-test M ± SD | Exp. post-test M ± SD | Gain | Ctrl. pre-test M ± SD | Ctrl. post-test M ± SD | Gain | t (gain) | Effect size d |
|---|---|---|---|---|---|---|---|---|
| Theoretical knowledge | 71.20 ± 8.12 | 82.40 ± 7.35 | 11.20 | 70.80 ± 8.46 | 76.30 ± 8.01 | 5.50 | 3.41** | 0.68 |
| Practical skills | 68.50 ± 9.23 | 84.10 ± 7.94 | 15.60 | 68.10 ± 9.05 | 73.50 ± 8.72 | 5.40 | 4.58** | 0.91 |
| Comprehensive competence | 69.80 ± 8.65 | 83.60 ± 7.28 | 13.80 | 70.20 ± 8.90 | 74.90 ± 8.56 | 4.70 | 4.03** | 0.80 |

*Note: ** indicates $p < 0.01$; Cohen's $d \geq 0.8$ is a large effect, and $0.5 \leq d < 0.8$ is a medium effect.*

### 7.2 Changes in Three-Dimensional Competency Achievement

The radar chart in Figure 4 presents the changes in the experimental class's achievement of the three-dimensional competencies of "technology application—strategy design—marketing critical thinking." Before the reform, the achievement of the three dimensions was 0.60, 0.58, and 0.62, respectively, showing a low-level equilibrium; after the reform, they rose to 0.86, 0.89, and 0.83, respectively, with the strategy-design dimension improving most significantly. Notably, the relative gap between "technology application" and "strategy design" widened somewhat after the reform (from 0.02 to 0.03), indicating that the enabling effect of AI tools on strategy design is particularly prominent and that students are better able to translate tool capability into plan capability.

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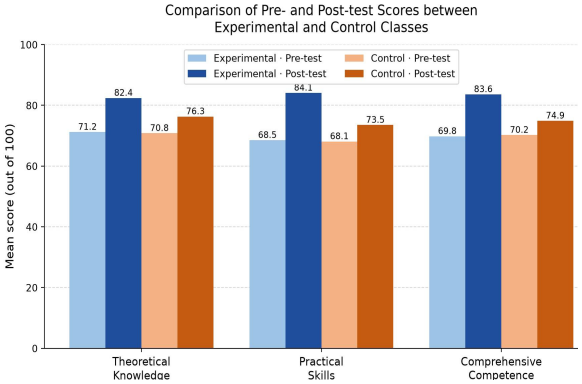



**Figure 3. Comparison of Pre- and Post-test Scores between the Experimental and Control Classes**

### 7.3 Questionnaire Reliability and Changes in Learning Experience

The learning-experience questionnaire contained three dimensions—learning interest, AI-tool use, and practical self-efficacy—with 18 items in total. The Cronbach's α of the pre-test questionnaire was 0.87 and that of the post-test was 0.91, indicating good reliability. The post-test results showed that, in the experimental class, the mean of learning interest rose from 3.42 to 4.18, AI-tool-use ability from 2.71 to 4.05, and practical self-efficacy from 3.18 to 4.12, with all three dimensions achieving significant improvement ($p < 0.01$). Although the control class also improved slightly (possibly related to the maturity of the course itself), the increase was markedly smaller than that of the experimental class. Table 5 reports the item counts, reliability coefficients (α), and pre/post-test means with effect sizes for the three learning-experience dimensions in the experimental class.

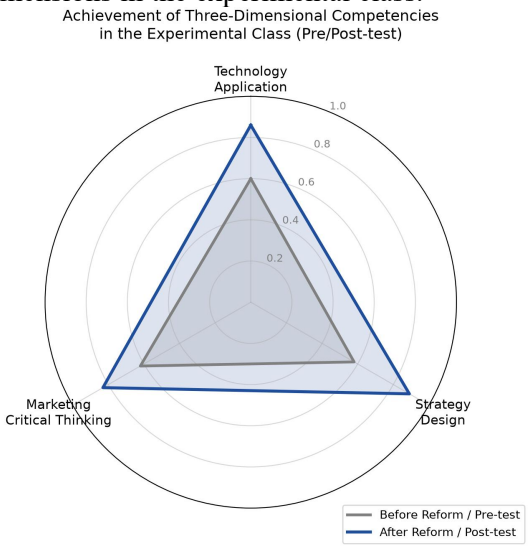



**Figure 4. Radar Chart of Three-dimensional Competency Achievement in the Experimental Class (Pre-/Post-test)**

**Table 5. Reliability of the Learning-Experience Questionnaire and Pre-/Post-test Comparison (Experimental Class, n = 52)**

| Dimension | Items | Pre-test α | Post-test α | Exp. pre-test M | Exp. post-test M | t | Effect size d |
|---|---|---|---|---|---|---|---|
| Learning interest | 6 | 0.82 | 0.88 | 3.42 | 4.18 | 4.21** | 0.78 |
| AI-tool use | 6 | 0.85 | 0.90 | 2.71 | 4.05 | 5.63** | 1.12 |
| Practical self-efficacy | 6 | 0.84 | 0.89 | 3.18 | 4.12 | 4.89** | 0.96 |

### 7.4 Changes in Teachers' Time Structure

Teacher work logs showed that AI-collaborative teaching significantly optimized the structure of teachers' time. Before implementation, the proportion of time teachers spent on routine work (case collection, homework grading, repetitive Q&A) was about 62%, while personalized guidance accounted for only 18%; after implementation, the proportion of routine work fell to 38%, personalized guidance rose to 41%, and time for teaching design and scenario creation increased from 20% to 21%. This indicates that AI effectively frees teachers from routine labor, enabling them to invest more time in high-value competency guidance and scenario design. Figure 5 illustrates this structural shift in teachers' time allocation between routine work and personalized guidance before and after implementation.

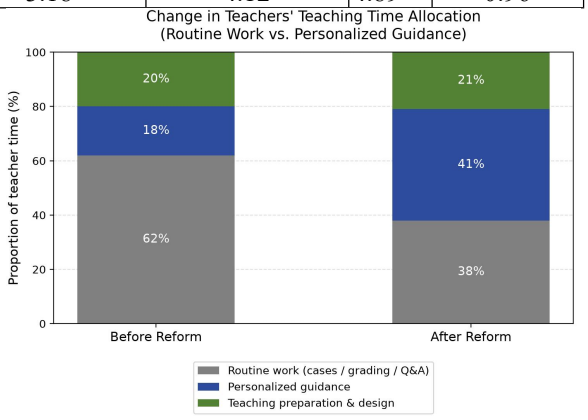



**Figure 5. Change in Teachers' Teaching Time Allocation (Routine Work VS. Personalized Guidance)**

### 7.5 Analysis of Learning-Behavior Characteristics and AI-Interaction Patterns

Learning-behavior logs revealed significant changes in the experimental class's learning

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engagement and AI interaction. In terms of platform behavior, the experimental class's average weekly online learning duration was 127.4 minutes, versus 98.6 minutes for the control class ($t = 2.87$, $p < 0.01$); the task-completion rate was 91.3% for the experimental class and 82.7% for the control class ($t = 2.56$, $p < 0.05$); and the per-capita number of posts in the discussion forum was 4.82 for the experimental class and 2.91 for the control class ($t = 3.14$, $p < 0.01$). This shows that AI-collaborative teaching not only increased students' learning duration but also strengthened their willingness to participate actively and discuss collaboratively.

In terms of AI-interaction patterns, students in the experimental class mainly asked knowledge-type questions in the first 6 weeks (accounting for 64.2%), shifted to case- and strategy-type questions in the middle 6 weeks (together accounting for 58.7%), and in the last 6 weeks the proportion of evaluation-type questions rose to 19.4%. This evolutionary trajectory indicates that, as the course progressed, students' questioning ability gradually migrated from "what it is" to "how to do it" and "why this is better," reflecting the development of higher-order thinking. In addition, the AI-feedback adoption rate rose from 51.3% in week 1 to 78.6% in week 18, and the follow-up-question rate rose from 12.4% to 31.2%, indicating that students' dependence on AI assistance decreased while their critical scrutiny increased. Table 6 summarizes the between-group comparison of learning-behavior indicators and the AI-interaction profile of the experimental class.

**Table 6. Between-Group Comparison of Learning-Behavior Indicators (Experimental Class n = 52, Control Class n = 50)**

| Behavioral indicator | Exp. M ± SD | Ctrl. M ± SD | t | p | Effect size d |
|---|---|---|---|---|---|
| Weekly online learning duration (min) | 127.40 ± 34.20 | 98.60 ± 29.50 | 2.87 | < 0.01 | 0.57 |
| Task-completion rate (%) | 91.30 ± 8.40 | 82.70 ± 10.30 | 2.56 | < 0.05 | 0.51 |
| Per-capita posts in discussion forum | 4.82 ± 2.15 | 2.91 ± 1.86 | 3.14 | < 0.01 | 0.63 |
| Total AI interactions (experimental period) | 38.60 ± 11.40 | — | — | — | — |
| AI-feedback adoption rate (%) | 68.40 ± 16.20 | — | — | — | — |

## 8. Discussion

### 8.1 Re-Dividing the Human–Machine Boundary: Not Replacement, but Division of Labor

The core proposition of this study is that AI-collaborative teaching is not about replacing teachers with machines, but about re-dividing the boundary between humans and machines. What generative AI excels at is standardizable, scalable, and instantly responsive work—case drafting, material generation, instant Q&A, and behavioral-data analysis; what teachers excel at is value judgment, the conferral of situational meaning, emotional support, and creative guidance. Once freed from repetitive routine, teachers can devote their energy to higher-order decisions such as "what kinds of tasks are worth students' effort," "whether AI-generated cases meet teaching objectives," and "what ethical risks exist in students' plans." This division of labor does not weaken teachers but returns them to work closer to the essence of education.

### 8.2 The Leverage Effect of Teachers' Prompt-Engineering Ability

The study found that teachers' prompt-engineering ability directly affects the quality of AI-generated cases and feedback. For the same task of having AI generate a "short-video marketing case," a rough prompt yields only a generic template, whereas a pedagogically designed prompt can embed teaching intentions such as "target-audience persona," "platform-algorithm characteristics," "budget constraints," and "brand tonality." Therefore, prompt-engineering ability should become an important part of teacher professional development in the era of AI-collaborative teaching, and it is recommended to incorporate it into regular teaching-and-research-office training and collective lesson preparation by the course team.

### 8.3 The Compliance Boundary of Data-Driven Evaluation

While improving precision, data-driven evaluation also brings privacy and ethical risks. Learning-behavior logs, AI-interaction data, and inferences of emotional states may all touch the boundary of students' personal-information protection. This study adopted four control measures: anonymized IDs, informed consent, minimal necessary collection, and local data

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storage. In future large-scale promotion, the scope of data collection, storage period, access permissions, and deletion mechanisms should be further clarified to avoid "over-surveillance for the sake of evaluation."

### 8.4 The Triple Leap of the Teacher's Role

AI-collaborative teaching drives a triple leap in the teacher's role: from "knowledge transmitter" to "learning designer," from "grader" to "growth analyst," and from "soloist" to "orchestra conductor." As a learning designer, the teacher needs to decompose teaching objectives into subtasks that AI can support and design high-quality prompts and evaluation rules; as a growth analyst, the teacher needs to interpret the AI-generated learning reports and identify students' strengths, weaknesses, and potential risks; as an orchestra conductor, the teacher needs to coordinate the resources of students, AI, and enterprise mentors so that the classroom becomes a complex system of multi-agent collaboration. These three leaps place higher demands on teachers' TPACK ability, data literacy, and instructional-design ability, and also call for a synchronized upgrade of the teacher-education and teacher-training system.

### 8.5 Research Limitations and Robustness

This study has three limitations. First, although the quasi-experimental design controlled for pre-test variables, it cannot fully rule out selection bias and the Hawthorne effect; future research could further introduce random assignment or multi-school samples. Second, the industry authenticity of AI-generated cases depends on data quality and prompt-engineering level, and when enterprise data sources are unstable, case quality may fluctuate. Third, the research period was one semester, and long-term effects (such as post-graduation job adaptability) still need to be tracked.

## 9. Conclusion and Outlook

Taking the Digital Marketing course as its object, this study systematically explored the teaching-paradigm transformation from "teacher-directed" to "AI-collaborative" driven by generative artificial intelligence. The study constructed a transformation framework covering "teaching content—teaching process—teaching evaluation," proposed a three-dimensional competency matrix of "technology application—strategy design—marketing critical thinking," and provided traceable data support through quasi-experimental research. The empirical results show that AI-collaborative teaching can significantly improve students' theoretical knowledge, practical skills, and comprehensive competence, optimize teachers' time structure, and improve students' learning experience.

Future work can be deepened in four directions. First, extend the experience of a single course to the marketing-major course cluster to form an "AI-collaborative" professional talent-cultivation program. Second, establish a normalized data-supply mechanism with more collaborating enterprises to make the "teaching—employment—industry" evaluation loop more solid. Third, explore more fine-grained human–machine collaboration mechanisms, for example, designing differentiated AI-intervention intensities and teacher-intervention timings in different course types (theory courses, practical-training courses, and project courses), so as to provide a transferable paradigm reference for different course forms. Fourth, conduct longer-term follow-up research to test the sustained impact of AI-collaborative teaching on students' job competence, career-transfer ability, and lifelong-learning ability three years after graduation.

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## References

[1] Vazquez R. Experiences and Insights from a Mini-Course on Responsible Generative AI Use in Aerospace Engineering. IFAC-PapersOnLine, 2024, 58(16): 35–40.

[2] Simelane M P, Kittur J. Use of Generative Artificial Intelligence in Teaching and Learning: Engineering Instructors' Perspectives. Computer Applications in Engineering Education, 2024, 33(1): e22813.

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[3] Wang F. Discussion of AIGC Technology in a Photography Course at a Higher Vocational College. Journal of Research in Vocational Education, 2024, 6(10): 12–20.
[4] Yin Chao. Research on Aesthetic-Education Infusion in Digital Painting Course Teaching Based on Generative Artificial Intelligence. Art Literature, 2024(09): 121–123.
[5] Yang Fang. Research on the Teaching Practice and Reform of University Brand Marketing Courses Based on Artificial Intelligence Technology. Time-honored Brand Marketing, 2024(18): 211–213.
[6] Xiao Chenglong, Wang Shanshan. Application of Generative Artificial Intelligence in the Teaching of Software Design Patterns. Computer Education, 2024(11): 161–166.
[7] Chen Zhengkai, Xu Ting. Exploration of Teaching Design and Practice of a Ceramic Design Course Assisted by Generative Artificial Intelligence Technology. Ceramic Studies, 2024, 39(06): 103–105.
[8] ElSayary A. Prompt Engineering and Generative AI Applications for Teaching and Learning. Hershey: IGI Global, 2025.
[9] Domínguez V A F, Martínez M F L, Tiznado M S, et al. Design of a Two-Degrees-of-Freedom Robotic Arm for Monitoring Applications for Teaching Robotics and Artificial Intelligence Technology. Computer Applications in Engineering Education, 2024, 32(6): e22786.
[10] Lave J, Wenger E. Situated Learning: Legitimate Peripheral Participation. Cambridge: Cambridge University Press, 1991.
[11] Mishra P, Koehler M J. Technological Pedagogical Content Knowledge: A Framework for Teacher Knowledge. Teachers College Record, 2006, 108(6): 1017–1054.
[12] Licklider J C R. Man-Computer Symbiosis. IRE Transactions on Human Factors in Electronics, 1960, HFE-1(1): 4–11.
[13] Huang Ronghuai, Liu Dejian, Liu Xiaolin. Characteristics, Paths and Challenges of Artificial Intelligence Empowering a New Education Ecosystem. Modern Distance Education Research, 2022, 34(4): 3–11.
[14] Zhu Zhiting, Hu Jiao. Development Trends and Key Characteristics of Intelligent Education. Open Education Research, 2022, 28(1): 13–25.
[15] Chen Li, Zheng Qinhua. Research on Educational Big Data Promoting Precision Teaching and Personalized Learning. Modern Educational Technology, 2020, 30(4): 12–17.

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