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Research on the Teaching Practice of Generative AI Practice and Application Course in Higher Vocational Colleges Based on the Task-Driven Approach

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Abstract: Aiming at the problems existing in the course "Generative AI Practice and Application" of higher vocational colleges, including teaching contents easily affected by tool iteration, students focusing on imitation rather than task transfer, lack of verification for generated outputs, and ambiguous evaluation basis, this paper constructs a task-driven teaching model centered on "task traction, human-AI collaboration, evidence verification and transfer application." The model consists of six links: professional scenario introduction, task analysis and prompt design, human-AI collaborative practice, output verification and iteration, achievement display and multi-dimensional evaluation, as well as transfer reflection. Teachers' guidance, students' practice, and generative AI support are embedded into the same teaching process. Progressive tasks are set around prompt design, AI text generation, AI-aided programming, and other content. Two intact classes are taken as research objects to carry out teaching practice, and data are collected through comprehensive tasks, course scores, questionnaires, and classroom observation. The results show that the compliance rate of comprehensive projects in the task-driven group rises from 59.3% at the beginning of the semester to 87.0% at the end, while the compliance rate of the control group reaches 70.6% at the end. The task-driven group also achieves higher scores in comprehensive performance, attendance, and classroom participation. The study proposes that the teaching focus of generative AI courses should shift from tool operation to task analysis, prompt iteration, result verification, and responsibility awareness, and that process records should be adopted to improve the interpretability of evaluation.

Keywords: Generative artificial intelligence; Vocational education; Task-driven teaching; Human-AI collaboration; AI literacy

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1. Introduction

Generative artificial intelligence has been applied in work scenarios such as content creation, software development, intelligent office, and customer service. For vocational colleges, relevant courses are not merely adding a set of new tools, but responding to changes in job competency structures. Recent studies have shown that generative AI can assist programming learning, text generation, formative feedback, and personalized support, yet its teaching effect depends on task design, learners' AI literacy, and school usage rules [1–3]. If classroom teaching still relies on teacher demonstration and student reproduction, students may only master tool interfaces without forming stable problem-solving methods. On this basis, this paper carries out research around three questions: first, how to construct a task-driven teaching model reflecting the characteristics of generative AI courses; second, how to implement this model into tasks including prompt engineering, text generation, programming, and comprehensive projects; third, how to evaluate students' AI application ability based on learning process evidence. This paper first elaborates the curriculum foundation and research design, then introduces the teaching model and implementation cases, finally presents teaching evaluation results and discusses its applicable boundaries.

2. Curriculum foundation and research design

2.1. Curriculum orientation and objectives

The course "Generative AI Practice and Application" targets students majoring in Artificial Intelligence Technology Application, with a total of 48 class hours, among which practical teaching accounts for about 29 hours, over 60%. Building on basic artificial intelligence knowledge and laying a foundation for job tasks such as intelligent content production, AI-aided programming, and application prototype development, the course is not designed to train students to memorize operation steps of a single platform, but to cultivate work methods transferable amid tool updates.

The curriculum objectives are divided into three dimensions. At the knowledge level, students are required to master basic concepts of generative AI, prompts, and multimodal generation. At the ability level, students shall analyze tasks, select tools, design prompts, verify outputs, and complete project delivery. At the literacy level, emphasis is placed on copyright, privacy, academic integrity, teamwork, and accountability for AI outputs. Dimensions including technical understanding, critical evaluation, and responsible use in AI literacy research provide a basis for formulating curriculum objectives and evaluation indicators [4,5].

2.2. Curriculum task chain

Instead of dividing chapters by tool menus, the course sets six progressive modules centered on work tasks. The first four modules train individual capabilities, the fifth module strengthens code comprehension and testing, and the sixth module requires students to comprehensively utilize multiple tools to deliver complete outputs (**Table 1**).

Table 1. Curriculum task modules and core evidence

Module	Typical task	Reference class hours	Core deliverables	Process evidence
Understanding Generative AI	Compare responses of different models to the same question	6	Model comparison report	Fact verification records

Prompt Design	Generate communication plans for campus activities	8	Prompts and output samples	Prompt version logs
AI Text Generation	Write promotion copies for campus cultural and creative products	8	Titles, main texts and slogans	Manual revision explanations
AI Image & Multimedia	Design campus-themed posters	6	Graphic works	Material and copyright statements
AI-Aided Programming	Develop class score statistics program	10	Executable program and test report	Error reporting and revision records
Comprehensive Practice	Digital promotion plan for agricultural specialty products	10	Integrated works and project report	Division of labor, defense and reflection materials

2.3. Research subjects and implementation process

This study adopts a quasi-experimental design with intact classes. Two Grade 2024 classes majoring in Artificial Intelligence Technology Application from a vocational college are selected as research objects. Class 1 (54 students) is set as the task-driven group, and Class 2 (51 students) as the control group. The same teacher teaches both groups with consistent teaching content, total class hours, and core assessment tasks. The task-driven group adopts the six-link teaching model proposed in this paper, while the control group receives conventional teaching combining teacher lectures, tool demonstrations, and individual student exercises. The implementation period covers Weeks 1–16 of the second semester of the 2024–2025 academic year.

Since intact natural classes are adopted without random grouping, the initial comprehensive task results show close starting levels: the compliance rate of the task-driven group is 59.3%, and that of the control group is 58.8%. The same teacher delivers lessons for both groups with unified curriculum objectives, teaching hours, and final comprehensive tasks to reduce interference from teachers, content, and assessment tasks.

2.4. Data sources and analysis methods

Four types of data are adopted to evaluate teaching implementation. First, initial and final comprehensive tasks, assessed with a unified competency rubric covering task analysis, human-AI collaboration process, work quality, result verification, and presentation reflection. Second, final comprehensive scores, presented as mean values and standard deviations to reflect the score distribution of the two groups. Third, classroom observation records including attendance and active participation. Fourth, student questionnaires and feedback to understand students' perceptions of task-driven teaching and AI verification behaviors.

Descriptive statistics are adopted for data analysis. Results of comprehensive tasks are presented by the number of compliant students and compliance rate; course scores by mean and standard deviation; questionnaire results by quantity and percentage; classroom participation is summarized based on teaching observation records. This paper mainly presents pre-post changes and inter-group differences without causal inference.

3. Construction of task-driven teaching model

3.1. Core mechanism

Conventional task-driven procedures cannot automatically solve problems such as proxy completion, AI hallucinations, and over-reliance in generative AI courses. Based on authentic tasks, this paper integrates human-AI work division, process archiving, and output verification to form a core mechanism of "task traction–human-AI collaboration–evidence verification–transfer application."

Professional scenario introduction clarifies entrusting parties, target users, constraints, and deliverables. Task analysis and prompt design require students to decompose problems and divide work between humans and AI. Human-AI collaborative practice allows students to generate drafts, code, and materials via AI while retaining core prompts and revision logs [6]. Output verification and iteration optimize deliverables through fact-checking, functional testing, source confirmation, and peer review. Achievement display and multi-dimensional evaluation examine both final works and process evidence. Transfer reflection requires students to illustrate applicable scenarios of each method for new tools and posts [7].

3.2. Responsibilities of Teachers, Students and AI

In this model, teachers are responsible for task design, scaffolding provision, risk monitoring, and evaluation organization. Students make task decisions, judge output quality, and take accountability for final deliverables. Generative AI only undertakes functions including resource generation, interactive support, and auxiliary feedback. The three parties do not follow a simple model of "teacher assigns, AI completes, student submits." Instead, students dominate the whole task process with differentiated support from teachers and AI.

4. Teaching practice

4.1. Copywriting task: From prompt design to manual finalization

In the task of "promotion copy for campus canvas bags," teachers first provide target users, product information, communication channels, and word count limits. After task analysis, students design prompts containing roles, audiences, product facts, stylistic requirements, and output formats. After AI generates drafts, students cannot submit directly; they must cross-check product information, identify vague or false expressions, and complete at least two rounds of revisions. Final submissions include finished copies, prompt versions, AI drafts, and manual revision explanations.

The focus of this task is not the speed of copy generation, but enabling students to observe how prompt conditions affect outputs and distinguish fluent language from usable content. During presentation, peers propose revisions from three dimensions: factual accuracy, audience adaptability, and original expression. Teachers mainly examine whether students can elaborate their selection criteria.

4.2. AI-aided programming task: From code generation to test interpretation

The task "class score statistics and visualization" requires students to complete data reading, statistical calculation, and chart output. Students may utilize AI to generate code frameworks, interpret error reports, and provide refactoring suggestions, but they must run programs independently and design test cases. Each group records one typical error, explains the accuracy of AI interpretations and adopted revisions, and verifies final functionality.

Existing studies indicate that generative AI helps beginners comprehend code and obtain instant feedback, yet copying code without understanding logic weakens learning outcomes [2,5]. Therefore, both operability and interpretability are included in evaluation. During defenses, teachers randomly designate group members to explain core code, preventing a few students or AI tools from completing the whole task alone.

4.3. Comprehensive project: Multi-tool collaboration to job-oriented delivery

The comprehensive project sets the scenario of designing a digital promotion plan for local agricultural specialty products. Students work in groups to complete demand analysis, copywriting, image generation, simple interactive prototypes, and project reports. Groups submit division forms at project initiation and retain prompt and version logs during implementation. A verification checklist is adopted before delivery to inspect facts, copyright, privacy, and work consistency.

This project tests students' ability to integrate individual tool skills into complete solutions. Evaluation does not solely rely on visual effects of works, but simultaneously covers task analysis, human-AI division, technical realization, verification process, and defense performance. Project-based learning provides integrated scenarios for complex competency cultivation [8,9], while its effectiveness depends on whether task difficulty, scaffolding intensity, and evaluation criteria match curriculum objectives.

5. Analysis of teaching application effects

A total of 105 students are included in this study, with 54 in the task-driven group and 51 in the control group. Evaluation materials cover initial and final comprehensive task scores, course process records, student questionnaires, and classroom observation logs. Comprehensive tasks examine task analysis, human-AI collaboration, work completion, result verification, and presentation reflection; questionnaires investigate students' perceptions of curriculum learning and AI verification behaviors; classroom observation mainly records attendance and active participation.

5.1. Comprehensive skill test results

Comprehensive skill tests include initial and final tasks, assessing task analysis, human-AI collaboration, work quality, result verification, and presentation reflection. Initial compliance rates of the two groups are close: 32 compliant students (59.3%) in the task-driven group and 30 compliant students (58.8%) in the control group. In the final test, 47 students in the task-driven group reached the standard (87.0%), while 36 students in the control group met the standard (70.6%). The average final comprehensive scores of the two groups are 84.6 and 78.4, respectively. The task-driven group achieves better performance in comprehensive task completion and course scores.

5.2. Student questionnaire results

Fifty-four questionnaires were distributed to the task-driven group, and 51 valid responses were recovered. The results show that 45 students (88.2%) believe the task-driven method improves practical abilities, and 46 students (90.2%) are satisfied with the overall course. The proportion of students who take the initiative to verify AI-generated content rises from 33.3% before the course to 80.4% after class. Student feedback mainly focuses on three aspects: authentic tasks help students understand the application purpose of AI tools; prompt and revision logs facilitate discovery of generation defects; project defenses raise awareness of result verification and human accountability.

Questionnaires reflect students' subjective perceptions and serve as supplementary evidence to skill tests. Items are d esigned around perceived practical ability, curriculum satisfaction, and awareness of AI output verification, with results summarized by valid sample size and percentage.

5.3. Classroom observation results

Classroom observation records show the final attendance rate of the task-driven group is 96.3%, compared with 90.6% for the control group. The average number of active participants per class rises from about 6 at the beginning to 15 at the end in the task-driven group, while the control group reaches around 7 at the end. Students receiving task-driven teaching take more initiative to speak and operate in group scheme discussion, prompt comparison, error analysis, and work presentation sessions.

Classroom observation supplements information not reflected by skill tests and questionnaires, yet it is susceptible to subjective judgment of observers and differences in class tasks. Attendance and participation records are adopted as auxiliary evidence and analyzed together with comprehensive tasks, course scores, and questionnaires rather than used alone to judge teaching effects.

6. Discussion

6.1. Mechanism of task-driven teaching effects

From the perspective of the teaching process, the task-driven model rearranges the order of knowledge acquisition. Process records require students to illustrate human-AI participation, turning prompt iteration and manual revision into observable learning evidence. Defenses and transfer reflections demand students explain solutions instead of merely submitting AI-generated works.

This mechanism is consistent with recent research on AI literacy, self-regulated learning, and human-AI collaboration [6–9]. Although multiple indicators of the task-driven group show more obvious improvements, intact non-random grouping cannot attribute all differences solely to the teaching model; class baseline, student motivation, and teacher expectations shall also be taken into consideration.

6.2. Application boundaries of AI

Generative AI reduces costs of material generation and preliminary feedback in this course, yet it cannot replace teachers' instructional judgment or students' accountability for deliverables [10,11]. Model outputs involving code, factual information, and copyrighted materials must be tested or verified. AI can sort process records and generate feedback suggestions during evaluation, while final scoring shall be reviewed by teachers based on standardized rubrics [12,13]. Clear rules on permitted AI usage scope, information disclosure, and violation handling shall be explained before tasks; transparent rules reduce students' uncertainty over usage boundaries [14,15].

In addition, greater accessibility of tools requires reserved cognitive challenges. If students skip task analysis and directly request complete solutions from AI, superficial classroom efficiency rises while learning procedures are compressed. Teachers shall control such risks through phased submission, random defenses, and personal reflection instead of simply banning AI usage.

6.3. Research limitations

This study has three limitations. First, intact grouping cannot fully eliminate selection bias, and the research only covers one major at one college, limiting the generalizability of conclusions. Second, scoring consistency and measurement reliability of comprehensive project rubrics, classroom observation indicators, and questionnaire items require further verification. Third, generative AI platforms are continuously updated; tool experience adopted in this course may not be directly applicable to subsequent versions. Follow-up research shall expand sample sources, adopt validated AI literacy scales, retain anonymized process data, and examine long-term retention of learning effects after course completion.

7. Conclusion

Aiming at the disconnection between tool operation and job tasks, the invisible generation process, and the insufficient evaluation basis in the higher vocational course "Generative AI Practice and Application," this paper constructs a six-link task-driven teaching model. Authentic tasks organize curriculum content, with prompt design, human-AI division, output verification, process archiving, and transfer reflection integrated into teaching and evaluation. Students' learning evidence is no longer limited to final deliverables.

Quasi-experimental results show that the task-driven group achieves obvious improvements in comprehensive task compliance rate, course scores, classroom participation, and active verification awareness. Since the research sample consists of two intact classes from a single college, the conclusions need further verification with larger samples and diverse majors. Follow-up research may combine learning platform process data, student work analysis, and interviews to explore specific effects of each teaching link on generative AI application competencies.

Disclosure statement

The authors declare no conflict of interest.

References

[1] Chakraborty S, 2026, Generative Artificial Intelligence in Fifth-Generation Education Systems: A Systematic Review. Engineering Applications of Artificial Intelligence, 173: 114463.

[2] Agbo FJ, Olivia C, Oguibe G, et al., 2025, Computing Education Using Generative Artificial Intelligence Tools: A Systematic Literature Review. Computers and Education Open, 9: 100266.

[3] Wu F, Dang Y, Li M, 2025, A Systematic Review of Responses, Attitudes, and Utilization Behaviors on Generative AI for Teaching and Learning in Higher Education. Behavioral Sciences, 15(4): 467.

[4] Mathews N, Schwartz C, Wright M, 2025, Teaching Generative AI for Cybersecurity: A Project-Based Learning Approach. Journal of The Colloquium for Information Systems Security Education, 12(1): 10.

[5] UNESCO, 2023, Guidance for Generative AI in Education and Research. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000386693

[6] Long D, Magerko B, 2020, What is AI Literacy? Competencies and Design Considerations. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–16, ACM.

[7] Merrill MD, 2002, First Principles of Instruction. Educational Technology Research and Development, 50(3): 43–59.

[8] Doğantan E, 2025, Project Based Learning and Technology Integration on Vocational Students' Learning Experience. Journal of Hospitality Tourism Education, 1–10.

[9] Rehman N, Huang X, Mahmood A, et al., 2024, Project-Based Learning as a Catalyst for 21st-Century Skills and Student Engagement in the Mathematics Classroom. Heliyon, 10(23): e39988.

[10] Ng DTK, Cheung KC, 2026, Interweaving Generative AI Technological and Pedagogical Design: Enhancing

Students' Motivation, Intentions, and AI Literacy for Feedback Seeking. Educational Psychology, 1–22.

[11] Zahid H, Danish M, Ali S, et al., 2026, Generative AI Chatbots in Higher Education: Addiction, Cognitive Offloading, and the Role of AI Literacy. Interactive Learning Environments, 1–18.

[12] Ilieva G, Yankova T, Ruseva M, et al., 2025, A Framework for Generative AI-Driven Assessment in Higher Education. Information, 16(6): 472.

[13] Usher M, Faraon M, 2025, Who Grades Best? Comparing ChatGPT, Peer, and Instructor Evaluations Across Varying Levels of Student Project Quality. Assessment Evaluation in Higher Education, 1–20.

[14] Tan MXY, Qu Y, Wang J, 2025, Student Perceptions of Generative Artificial Intelligence Regulations: A Mixed-Methods Study of Higher Education in Singapore. Higher Education Quarterly, 79(3).

[15] UNESCO, 2023, Guidance for Generative AI in Education and Research. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000386693