Design and Practice of Scenario-Based Teaching Cases for an AI General Education Course in Vocational Colleges

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Abstract. Generative artificial intelligence (GenAI) is rapidly transforming vocational education, yet most existing AI general education courses follow computer-science curricula that are inaccessible to non-technical students. This paper proposes a low-threshold, lightweight, and scenario-oriented teaching framework for AI general education in vocational colleges. The framework comprises a two-layer course module design (foundational awareness + scenario application), a taxonomy of four scenario categories (learning, campus, life, occupational), and a five-step case development process. We implemented the framework over two consecutive cohorts (2024 and 2025) at a public vocational college, covering 2,964 non-computer-major students from three schools. A pre-test–post-test evaluation with 322 paired samples was associated with improvements across all six measures (all $p < .001$; Cohen's $d = 0.39–0.71$), with a 91% task completion rate. No significant disciplinary differences were found for AI knowledge, learning interest, or ethical awareness, supporting the framework's generalizability. The study contributes a reusable design framework, four representative teaching cases, and empirical evidence for large-scale AI general education in vocational contexts.

Keywords: AI general education, scenario-based teaching, vocational education, generative AI, teaching case design, pre-test–post-test evaluation

1 Introduction

1.1 Background

Generative artificial intelligence (GenAI) has rapidly penetrated educational practice worldwide. In China, nearly half of higher vocational colleges have introduced AI-related general education courses [1][2], driven by national policies. Propelled by core algorithmic breakthroughs—Transformer-based large language models, diffusion models for image generation, and retrieval-augmented generation (RAG) for intelligent agents—these technologies require conceptual understanding by all students, not just computer science majors, as algorithmic literacy becomes an essential component of

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AI competence. However, the rapid expansion has outpaced the development of pedagogically sound course designs, particularly for non-technical students who constitute the majority of vocational college enrollments.

1.2 Problem Statement

Three interlocking problems characterize current AI general education practice in vocational colleges [3]. First, content fragmentation—courses often present isolated technical topics without connecting them to students' daily lives or future careers. Second, high entry barriers—many courses assume programming proficiency, alienating non-technical majors who need AI literacy most. Third, the absence of a systematic case repertoire—existing materials are scattered and lack a unified design framework. These problems collectively limit the effectiveness and scalability of AI general education.

1.3 Contributions

This paper makes three contributions.

- **C1 (Design).** We propose a two-layer course module design—a foundational awareness layer (~30% of class hours) and a scenario application layer (~70%)—together with a taxonomy of four scenario categories (learning, campus, life, occupational) and a three-level difficulty progression.
- **C2 (Practice).** We develop four representative teaching cases aligned with the taxonomy and a five-step case development process (scenario investigation, task design, tool matching, case authoring, and pilot refinement), all based on free, browser-based AI tools.
- **C3 (Evidence).** We implemented the framework over two consecutive cohorts (2024 and 2025) at a public vocational college in Huizhou, Guangdong, covering 2,964 non-computer-major students from three schools, and report implementation details, evaluation results, and practical implications.

2 Related Work

2.1 AI General Education Courses in Higher and Vocational Education

The rapid expansion of AI courses in higher and vocational education has drawn increasing research attention. Shi [4] investigated AI-driven personalized learning pathways in vocational education and reported that tailored learning routes can enhance learner competence, engagement, and outcomes, while noting that most existing courses still inherit the structure of computer-science curricula. In the Chinese context, the "general-plus-distinctive" policy encourages each institution to develop its own AI general education course, yet empirical reports on how such courses are designed for non-technical students remain scarce, leaving vocational colleges largely underserved.

2.2 Scenario-Based and Case-Based Teaching

Scenario-based and case-based teaching has long been recognized as an effective bridge between knowledge and practice. Kolesnyk and van Berlo [5] proposed the 4C framework (compile, curate, challenge, contemplate) for integrating AI into case studies, showing that well-structured cases guide students to apply AI tools critically and creatively rather than treating AI as a shortcut. However, existing studies remain situated in discipline-specific professional training rather than general education, and none address the systematic design of a case repertoire covering multiple life and work scenarios—an issue particularly salient for vocational colleges with diverse non-technical majors.

2.3 Generative AI in Education

A growing body of literature has examined the opportunities and risks of generative AI in teaching and learning. Systematic reviews [6] identify both significant potential for personalized support and persistent concerns about academic integrity and over-reliance. Large-scale student surveys [7] reveal ambivalent attitudes—students appreciate efficiency gains while worrying about skill atrophy and fairness. Empirical studies in academic literacy [8] show that students increasingly incorporate AI-generated content into reading and writing practices, calling for explicit guidance on responsible use. In the vocational context, qualitative research [9] reports an "engaged but amotivated" phenomenon, suggesting that engagement alone does not guarantee sustained motivation. Meanwhile, human-centered frameworks [10][11] emphasize that AI should serve as a pedagogical co-pilot that empowers rather than replaces teachers. Collectively, these studies highlight the need for AI pedagogies embedded in authentic tasks while preserving teacher leadership.

2.4 Research Gap

Despite this growing body of work, three gaps remain. First, although AI general education courses have been widely mandated by policy, few studies provide an operational design framework that connects course structure, scenario taxonomy, and case development for vocational colleges. Second, existing case-based studies are concentrated in professional training contexts, and evidence from large-scale implementations of scenario-based AI general education for non-computer-major vocational students is lacking. Third, the process by which such cases can be systematically developed and replicated by teachers has rarely been formalized. This paper addresses these gaps by proposing a low-threshold, lightweight, and scenario-oriented framework, developing four reusable cases, and reporting its implementation with 2,964 students from three schools across two cohorts.

3 Design Framework

3.1 Design Principles

Three principles guide the design: low-threshold (no programming background required, free tools), lightweight (2–3 class hours per case), and scenario-oriented (authentic tasks from coursework, campus life, and future careers).

3.2 Two-Layer Course Module Design

The course is organized into two layers. The foundational awareness layer (approximately 30% of the total class hours) introduces basic AI concepts, the development of AI technology, and the entry-level use of common tools. The scenario application layer (approximately 70% of the class hours) delivers the four categories of scenario-based cases. The two layers are mutually reinforcing: the foundational layer provides the tool support needed by the application layer, while the application layer offers authentic contexts that consolidate the foundational knowledge.

The two layers are delivered through a teaching implementation layer comprising lecture, practice, discussion, and assessment, and are continuously strengthened by a mutual reinforcement mechanism—foundation support, application consolidation, iterative improvement—driving the progression from foundational AI knowledge to scenario-based comprehensive application, as illustrated in Figure 1.

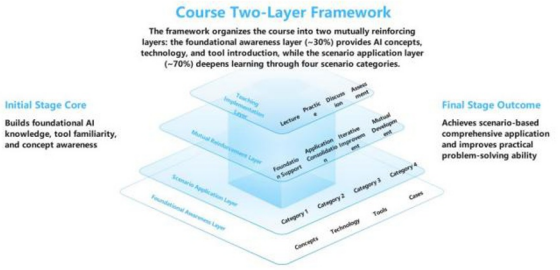


Fig. 1. Structure of the two-layer course module and the four scenario categories.

3.3 Taxonomy of Scenario-Based Teaching Cases

To ensure that the scenario application layer covers the full range of vocational students' lives, we propose a taxonomy of four scenario categories: learning, campus, life, and occupational. Learning scenarios address tasks within formal coursework, such as report writing and document formatting; campus scenarios involve activities in student organizations and campus events, such as poster design; life scenarios concern personal daily needs, such as travel planning; occupational scenarios simulate real workplace tasks, such as data visualization. Each category is further assigned a difficulty level—

beginner, intermediate, or advanced—so that the case repertoire forms a three-level progression. Table 1 summarizes the four categories, their representative cases, core skills, AI tools, and difficulty levels.

To avoid "black-box" tool operation and foster algorithmic literacy, each case integrates a core AI algorithm at a conceptual level: the learning case (AI-assisted document formatting) introduces Transformer-based large language models and the self-attention mechanism. Under this mechanism, the model assigns differential weights to context words, producing coherent text; the campus case (AI poster design) introduces diffusion models and the iterative denoising principle, where images are generated by progressively removing noise from a random map guided by text prompts; the life case (AI travel planning) introduces retrieval-augmented generation (RAG). In this retrieve-rank-generate pipeline, where relevant information is first retrieved from knowledge sources and then used to guide generation, reducing hallucination; and the occupational case (AI data visualization) introduces data processing algorithms including statistical aggregation (sum, mean, grouping) and intelligent chart-type selection. Following a "light-on-formula, heavy-on-concept" approach, students understand these algorithmic principles through analogies, visualizations, and interactive demonstrations without deriving mathematical formulas or writing code.

Table 1. Taxonomy of scenario-based teaching cases.

Scenario Category	Representative Case & Core Skill	AI Tool	Level
Learning	AI-assisted document generation (text generation & document formatting)	Wenxin Yiyan, WPS AI	Beginner
Campus	AI poster design (prompt engineering & creative design)	Chuangkit, Jimeng AI	Intermediate
Life	AI travel planning (information retrieval & plan generation)	DeepSeek	Intermediate
Occupational	AI data visualization (data processing & visualization)	Wenxin Yiyan, Tencent Docs	Advanced

3.4 Case Development Process

To make the taxonomy operational and reusable, we formalize a five-step case development process: (1) scenario investigation—identify authentic tasks by observing students' real coursework and daily activities; (2) task design—transform the scenario into a concrete, artifact-producing task with clear requirements; (3) tool matching—select appropriate AI tools from the low-threshold toolset; (4) case authoring—develop the case package including scenario sheet, step-by-step instructions, and sample prompts; (5) pilot and refinement—deliver in a pilot class, collect feedback, and revise. This process closes the loop between the taxonomy and classroom practice.

4 Implementation

4.1 Research Context and Participants

The framework was implemented over two consecutive cohorts (2024 and 2025) at a public vocational college in Huizhou, Guangdong Province, China. The AI General Education course is a mandatory general education requirement for all first-year non-computer-major students. Three schools participated in the evaluation: Intelligent Manufacturing (1,260 students), Education (823), and Tourism & Culinary Arts (881), totaling 2,964 students across the two cohorts. All students had basic computer literacy but no prior programming or AI background, matching the target population of the low-threshold design. For the pre–post evaluation, we employed cluster sampling and selected one intact class from each school per cohort (six classes in total), yielding 322 valid paired questionnaires, covering all three schools and both cohorts. All survey data were collected anonymously with students' informed consent, and the study was approved by the college's research ethics committee.

4.2 Teaching Procedure

The course follows a flipped classroom procedure organized around three phases. Pre-class: students watch a 5–8 minute micro-video introducing the case scenario, target AI tool, and basic prompts. In-class: a brief 10-minute lecture clarifies requirements and ethical considerations, followed by 25–30 minutes of hands-on practice with teacher guidance. Post-class: students present artifacts, receive peer feedback, and complete a reflection worksheet. All materials (micro-videos, case sheets, prompt templates) are released on the college learning management system for self-paced review. This procedure keeps the teacher's role as designer, facilitator, and ethical supervisor.

4.3 Case Overview

Following the taxonomy in Table 1, four representative cases were developed and delivered, one for each scenario category: C1 (AI-Assisted Document Formatting, learning, beginner), C2 (AI Poster Design, campus, intermediate), C3 (AI Travel Planning, life, intermediate), and C4 (AI Data Visualization, occupational, advanced). The cases were selected to cover a progression from familiar, low-stakes tasks to occupation-related tasks.

4.4 Sample Case: AI-Assisted Document Formatting

To illustrate the case design, consider C1 (AI-Assisted Document Formatting), the first case in the learning scenario. The case is organized into four steps. First, students receive a scenario sheet describing a course report assignment with specific requirements. Second, they use Wenxin Yiyan to draft content, applying prompt engineering techniques such as specifying the target audience, tone, and document structure. Third, they

use WPS AI to format the document according to academic standards, including headings, citations, and page layout. Fourth, students conduct a critical review of the AI-generated content, verifying factual accuracy, checking for plagiarism, and revising inappropriate passages. The case emphasizes that AI is an auxiliary tool, and students retain final responsibility for the quality and originality of their work.

5 Evaluation

5.1 Instruments and Data Collection

We employed a pre-test/post-test design with paired samples (N=322). Instruments were developed by the research team based on established AI literacy frameworks (AI4K12, UNESCO), reviewed by three experts for content validity, and pilot-tested with 50 students. The final instrument package included three components: an AI knowledge test (10 items, 0–10, including 3 items specifically assessing algorithmic understanding of core concepts such as diffusion model denoising, the RAG retrieve-rank-generate pipeline, and Transformer self-attention), a learning interest scale (5 items, 1–5), and four sub-scales (5 items each, 1–10) measuring interest dimension, perceived relevance, self-efficacy, and ethical awareness. The overall instrument (35 items) demonstrated acceptable internal consistency (Cronbach's α=0.87) and construct validity (KMO=0.85). Task completion rate was also recorded as a behavioral indicator.

5.2 Results

To ensure rigorous and reproducible data analysis, the study employed four core statistical algorithms. Each has an established computational principle, described below.

First, the paired-samples t-test was applied to compare pre-test and post-test scores of the same participants. The t-statistic is computed as the mean of the difference scores divided by its standard error:

$$t = \frac{\bar{X}_D - \mu_D}{s_D/\sqrt{n}} \tag{1}$$

where $\bar{X}_D$ is the mean of the difference scores (post-test minus pre-test), μ_D is the hypothesized mean difference (set to 0 under the null hypothesis), s_D is the standard deviation of the difference scores, and n is the number of paired samples (N = 322). The degrees of freedom is df = n − 1 = 321; a p-value below 0.05 indicates that the observed difference is statistically significant rather than attributable to chance.

Second, Cohen's d was computed to quantify the magnitude of improvement independent of sample size:

$$\mathrm{d} = \frac{\bar{\mathrm{X}}_{\mathrm{post}} - \bar{\mathrm{X}}_{\mathrm{pre}}}{\mathrm{s}_{\mathrm{pooled}}} \tag{2}$$

where $\bar{X}_{post}$ and $\bar{X}_{pre}$ are the post-test and pre-test means, respectively, and s_{pooled} is the pooled standard deviation:

$$s_{pooled} = \sqrt{\frac{(n_{pre}-1)s_{pre}^2+(n_{post}-1)s_{post}^2}{n_{pre}+n_{post}-2}} \tag{3}$$

Following Cohen's (1988) conventions, d = 0.2, 0.5, and 0.8 correspond to small, medium, and large effects, respectively.

Third, Cronbach's α was used to assess the internal consistency reliability of each questionnaire sub-scale:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_{total}^2}\right) \tag{4}$$

where k is the number of items in the sub-scale, σ_i^2 is the variance of item i, and σ_{total}^2 is the variance of the total sub-scale score. An α value greater than 0.7 indicates acceptable reliability.

Fourth, one-way analysis of variance (ANOVA) was applied to examine discipline differences across the three schools by comparing between-group variance to within-group variance (F = MSbetween / MSwithin), followed by Tukey HSD post-hoc tests to identify specific pairwise differences when significant F-values were found. All statistical analyses were performed using IBM SPSS Statistics 26.0 with a significance level of α = 0.05.

Paired-samples t-tests revealed significant improvements across all six measures (all p<.001, see Table 2). AI knowledge increased from 6.81 to 7.87 (t=12.68, d=0.71), and learning interest from 3.12 to 3.63 (t=10.76, d=0.60). Effect sizes ranged from small-to-medium (d=0.39 for interest dimension) to medium-to-large (d=0.71 for AI knowledge). Within the AI knowledge test, the three algorithmic understanding items showed the largest relative gain, with mean accuracy improving from 58% at pre-test to 71% at post-test (a 22% relative improvement), suggesting that the concept-level algorithm integration in the scenario-based cases effectively improved students' understanding of how AI technologies work under the hood, rather than merely teaching tool operation. Task completion rate reached 91%, indicating high behavioral engagement.

Table 2. Pre–Post Descriptive Statistics and Paired-Samples t-Test Results (N = 322, df = 321).

Measure	Pre-test M (SD)	Post-test M (SD)	M_D	t	p	Cohen's d
AI Knowledge Test (0–10)	6.81(1.52)	7.87(1.48)	1.06	12.68	< .001	0.707
Learning Interest Scale (1–5)	3.12(0.88)	3.63(0.82)	0.51	10.76	< .001	0.600
— Interest Dimension	8.15(1.48)	8.72(1.45)	0.57	6.98	< .001	0.389
— Perceived Relevance	5.64(1.52)	6.59(1.48)	0.95	11.36	< .001	0.633
— Self-Efficacy	5.58(1.50)	6.44(1.48)	0.86	10.36	< .001	0.577
— Ethical Awareness	5.81(1.52)	6.74(1.42)	0.93	11.35	< .001	0.632
Task Completion Rate (post-	—	91%	—	—	—	—

5.3 Discipline Differences

One-way ANOVA revealed significant differences in self-efficacy across schools ($F(2,319)=4.52$, $p < .05$, $\eta^2=.028$). Post-hoc Tukey HSD tests revealed that Tourism & Culinary Arts ($M=6.60$, $SD=1.42$) scored significantly higher than Intelligent Manufacturing ($M=6.30$, $SD=1.48$), mean difference = 0.30, $p < .05$. No significant school differences were found for five of six measures, as shown in Figure 2 (four representative measures), suggesting the framework is broadly effective across disciplines.

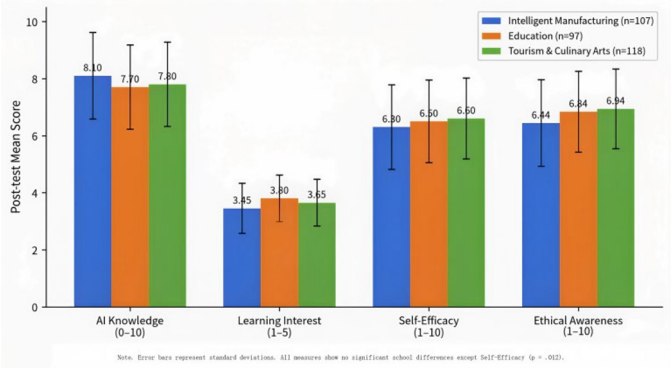


Fig. 2. Post-test mean scores across three schools for four representative measures (N = 322).

5.4 Discussion

Results suggest the framework is associated with improvements in AI knowledge, learning interest, and self-efficacy. Medium-to-large effect sizes (d=0.39–0.71) indicate authentic, low-threshold tasks may be more engaging than abstract instruction. Higher self-efficacy among Tourism & Culinary Arts students may reflect closer alignment with their daily experiences. These findings provide preliminary support for the design principles and suggest the framework may serve as a model for other vocational colleges.

6 Conclusion and Future Work

This paper presented a low-threshold, lightweight, and scenario-oriented teaching framework for AI general education in vocational colleges. The framework includes a two-layer course design (foundational awareness + scenario application), a four-category case taxonomy (learning, campus, life, occupational), and a five-step case development process. Empirical evaluation with 322 paired samples across two cohorts (2024–2025) demonstrated significant improvements in AI knowledge, learning interest, self-efficacy, and ethical awareness (all $p<.001$, d=0.39–0.71), with a 91% task completion rate.

Several practical implications emerge. First, the scenario-oriented approach provides a viable model for making AI education accessible to non-technical students. Second, the low-threshold, lightweight design enables easy integration into existing curricula

without major restructuring. Third, the five-step case development process offers a reusable methodology for teachers. Several limitations should be acknowledged. First, the study used a one-group pre-test/post-test design without a control group, meaning that observed improvements cannot be definitively attributed to the framework alone—maturation, history, and testing effects may also contribute. Second, the evaluation sample (N=322) represents ~11% of total enrollment; cluster sampling may introduce selection bias. Third, all measures are self-reported or researcher-developed; validated standardized instruments are lacking. Fourth, the study was conducted at a single vocational college in southern China, which may limit generalizability. Fifth, the evaluation focused on short-term outcomes within one semester; long-term retention of AI competencies remains unexamined. Future work will expand the case repertoire, incorporate validated instruments and, conduct multi-site validation with control groups, and investigate 3- and 6-month long-term retention.

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