

Generative AI-supported Project-based Learning in Design Education: Effects on Creative Thinking, Student Engagement, and AI Literacy

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Manuscript received April 3, 2026; revised May 7, 2026; accepted May 26, 2026; published October 16, 2026

Abstract—Integrating Generative Artificial Intelligence (GAI) into Project-Based Learning (PjBL) provides new approaches to foster students' Creative Thinking (CT) in solving real-world design problems. However, empirical evidence on its impact, particularly on CT, student engagement, and Artificial Intelligence (AI) literacy, remains limited. This study investigates the effects of a GAI-supported PjBL model (PjGAI), in which Kimi and MasterGoAI were systematically embedded within a staged project-based design workflow. A total of 180 undergraduate students were randomly assigned to three groups in an experimental design. All groups used the same conventional digital design software for User Interface (UI) production. The PjGAI group additionally used the designated GAI tools, the PjBL group followed the same project-based workflow without GAI support, and the Traditional Teaching Model (TTM) group followed a lecture-based, teacher-led workflow without GAI support. Multivariate Analysis of Variance (MANOVA) results indicated that the PjGAI group achieved significantly higher CT scores than the TTM group and reported higher student engagement than both comparison groups, although the CT difference between the PjGAI and PjBL groups was not statistically significant. Within the PjGAI group, paired-sample t-tests showed a significant increase in AI literacy from pre-test to post-test. These findings suggest that embedding GAI tools into a structured PjBL process can strengthen student engagement and may support creative exploration and AI literacy development in design education.

Keywords—Generative Artificial Intelligence (GAI), project-based learning, creative thinking, student engagement, Artificial Intelligence (AI) literacy, design education

I. INTRODUCTION

A. Design Education in the Context of Educational Intelligence

Generative Artificial Intelligence (GAI) tools, such as ChatGPT and Midjourney, have been increasingly adopted in higher education [1, 2]. GAI capabilities in content generation, visual expression, and cognitive assistance are reshaping instructional practices, particularly in creativity-driven art and design education [3, 4]. In creativity-driven design education, the core learning pathways include conception generation, prototype development, and multiple rounds of visual iteration. GAI tools may support pedagogical innovation by providing cognitive support and facilitating content generation. Although GAI offers unprecedented potential to enhance creative performance, its misuse has raised growing concerns, including cognitive dependence, decreased student

initiative [5–7], and academic misconduct [8, 9].

According to UNESCO [10], many universities and educational institutions have been integrating generative AI tools into their instructional practices, particularly in areas such as design and digital media, as part of the global trend towards educational digitalization and innovation [10]. As educational institutions increasingly adopt GAI tools, it is important to examine how these tools can be pedagogically integrated into design education while reducing potential negative effects [11].

B. Exploration of the Teaching Path Integrating PjBL and GAI

PjBL is a dynamic classroom approach in which students actively explore real-world challenges through collaboration and reflective practice to deepen their knowledge [12]. It is widely used in design education to enhance students' practical competence, learning motivation and innovative capacity for creative expression [13, 14]. With the development of AI technology, researchers have begun to explore embedding GAI tools into the PjBL teaching process to provide cognitive support and creative stimulation [15, 16].

For instance, ChatGPT can support creative ideation [17, 18], while Uizard and Figma AI plugins can be employed for prototype development and visual articulation [19]. These studies highlight the pedagogical potential of integrating AI tools into project-based and design-oriented learning environments. However, much of the existing work has treated GAI as a supplementary tool for specific learning activities, such as idea generation, information search, or prototype production, rather than as a structured pedagogical component embedded across the full PjBL process.

Although recent studies have examined AI-supported PjBL and reported benefits for information literacy, higher-order thinking, and learning self-efficacy [16], several limitations remain. First, relatively few studies have situated GAI-supported PjBL in non-STEM and design education contexts, where creativity, visual expression, and iterative prototyping are central learning processes. Second, prior studies have rarely examined Creative Thinking (CT), student engagement, and AI literacy, within a single integrated framework. Third, limited empirical evidence is available on whether adding GAI to PjBL provides benefits beyond conventional PjBL. Therefore, a more structured instructional model is needed to clarify how GAI can be pedagogically integrated into PjBL and how such integration

influences multiple learning outcomes in design education [20].

C. Theoretical Basis of the Three Key Learning Variables

This study focuses on three key learning outcome variables in design education: CT, student engagement, and AI literacy. CT refers to the innovative conception and capacity for creative expression demonstrated by students during the learning process, which is the core foundation for completing complex design tasks [12, 13]. Student engagement reflects students' concentration, interaction, and persistent commitment in project tasks [21], and is an important factor in determining learning outcomes. AI literacy refers to students' abilities to understand, apply and reflect on AI technology, and is an indispensable comprehensive quality in the context of GAI teaching [22]. Although previous studies have explored the respective benefits of GAI and PjBL in enhancing CT, student engagement, and AI literacy, there remains limited systematic evidence to support an integrated teaching model that combines GAI and PjBL in order to simultaneously cultivate all three abilities. Notably, UNESCO [10] has emphasized the potential of GAI as a tool for creative exploration and expression, as well as its compatibility with student-centered PjBL learning [10].

D. PjGAI Model Design and Research Framework

This study investigates the pedagogical impact of a Project-Based Learning integrated with Generative Artificial Intelligence (PjGAI) model in design education, which aims to enhance students' CT, student engagement, and AI literacy.

To support learning in a design-based context, this model adopts User Interface (UI) design, guiding students to complete the iterative process from research, conception, and prototype making, through to presentation. During the design process, Kimi (AI ideation assistant: <https://kimi.com/>) was used to facilitate AI-assisted research and ideation, while MasterGoAI (AI-powered prototyping tool: <https://mastergo.com/ai>) supported prototyping and visual expression, thus enabling multimodal and collaborative creation.

Conceptually, the PjGAI model framed GAI as a pedagogical scaffold within the PjBL process rather than as an add-on tool. Kimi and MasterGoAI supported four functions: cognitive scaffolding, creative partnership, feedback support, and reflective support. These functions helped students clarify design problems, generate and refine interface ideas, respond to feedback, and evaluate AI-generated outputs within authentic project tasks.

An experimental design was employed involving three instructional approaches: the PjGAI model integrating GAI tools, a traditional PjBL model using standard digital tools, and a lecture-based Traditional Teaching Model (TTM). Using pre- and post-test data, we compared the effects of the three instructional approaches on CT and student engagement. In addition, we examined within-group pre-post changes in AI literacy in the PjGAI approach, complemented by post-course student satisfaction feedback.

E. Research Questions

To explore the effectiveness of the PjGAI approach, this study proposes and empirically examines the PjGAI model in

a UI design course. Rather than treating GAI as a general add-on tool, the model embeds GAI support into project-based design activities. The study therefore extends prior work by developing a structured PjGAI model, comparing it with PjBL and TTM, and examining CT, student engagement, and AI literacy in a design education context. Accordingly, the following research questions were formulated.

RQ1: How does the PjGAI model affect students' CT and student engagement compared with conventional PjBL and TTM approaches?

RQ2: Within the PjGAI group, are students' AI literacy scores significantly higher after the teaching activity compared to the pre-test level?

RQ3: How satisfied are students with the PjGAI model?

II. LITERATURE REVIEW

PjBL is a teaching strategy driven by real-world tasks and centered on students. Grounded in constructivist learning theory, which traces back to Dewey's [23] concept of "learning by doing", PjBL emphasizes learner autonomy, the construction of knowledge through real-world problem solving, and reflection on iterative experiences. Through engaging students in solving real-world problems and fostering critical thinking, collaboration, and self-management [24, 25], PjBL has been widely adopted in higher education, especially in creativity and design fields [26]. To support structured project execution, Stoller [27] proposed a five-stage PjBL model (1) preparation, (2) information gathering, (3) information processing, (4) information display, and (5) reflection which enhances student participation and cognitive construction. The learning cycle of "conception, production, feedback and reconstruction" emphasized by the model is consistent with the creative practice in the design process, supporting the development of students' CT and student engagement [14].

GAI refers to the use of machine and deep learning-based approaches to create new content, such as text, images, and audio, from existing data. Driven by advances in Generative Adversarial Networks (GANs) and Natural Language Processing (NLP) technologies, GAI has been rapidly adopted across fields such as education, design, and media [1, 2]. In design education, GAI supports students in stimulating creativity, rapidly visualizing prototypes, and refining design solutions in the early stage of projects through text generation, image creation, and intelligent prototyping. Tools such as ChatGPT, Midjourney, and Figma AI plugins play key roles in requirement analysis, visual style generation, and interface design, respectively [19, 28]. However, studies have noted that GAI exhibits templated structures, which are prone to cause problems such as creative homogenization, monotonous expression, and insufficient reflection [29, 30]. Therefore, maximizing the benefits of GAI and avoiding adverse effects on subjectivity and creativity has become a pressing challenge in design education. GAI should not replace cognitive efforts but rather serve as a pedagogical support structure to extend creative exploration and reflection. These challenges have raised the demand for teaching models that can more meaningfully integrate GAI into student-centered PjBL environments.

CT is defined as the ability to demonstrate fluency,

flexibility, and originality when addressing open-ended problems [31, 32]. In design education, CT is not only manifested as the ability to generate diverse ideas but also includes the ability to continuously optimize solutions in project iterations [32, 33]. Enhancing CT serves as a critical foundation for completing complex design tasks and achieving innovative expression.

Student engagement refers to students' participation in academic tasks from the three dimensions of emotion, cognition, and behavior [34]. Zhoc *et al.* [21] further refined student engagement into five sub-dimensions: (1) academic engagement, (2) cognitive engagement, (3) emotional engagement, (4) social engagement with peers, and (5) social engagement with the teacher. In a PjBL context, high levels of student engagement can enhance students' task identification, increase learning motivation, and foster deep learning and collaboration, thereby improving team-based outcomes [34, 35].

AI literacy refers to an individual's ability to understand, apply, critically evaluate, and ethically reflect on AI technologies [6, 36, 37]. With the growing prevalence of GAI in education and design, AI literacy has emerged as a critical factor in effective technological integration and creative practice [38–40]. Drawing on Liu *et al.* [22], AI literacy includes four dimensions: (1) cognitive and creative skills, (2) application proficiency, (3) motivation and learning engagement, and (4) information literacy and moral awareness. In PjBL environments, AI literacy enhances students' CT and collaborative problem-solving processes [41], directly influencing learning outcomes and innovative performance [42].

Existing studies have shown that PjBL facilitates the development of students' creative and engaged learning abilities by guiding students through the cyclical process of "conception–production–feedback–reconstruction" [14, 24]. Chen and Yang [26] highlighted in a meta-analysis that PjBL has demonstrated remarkable effectiveness in enhancing students' problem-solving skills and academic engagement across various educational fields. Empirical studies have shown that PjBL can stimulate students' idea fluency and originality [33], and enhance cognitive and emotional engagement through collaborative tasks [21, 34, 35, 43]. Although PjBL was not originally designed specifically for cultivating AI literacy, its characteristics of emphasizing independent inquiry, critical thinking, and multimodal expression indirectly provide favorable conditions for students to understand, apply, and critically evaluate emerging technologies [44]. Therefore, PjBL not only provides a solid foundation for the improvement of CT and student engagement but also creates conditions for the further integration of GAI to promote the development of AI literacy.

GAI provides a new layer of technological support for innovative learning through multimodal functionalities. In terms of promoting students' CT, Gudoniene *et al.* [19] highlighted that the immediate feedback mechanism of GAI can stimulate students to explore diverse solutions and enhance the divergence of thinking and the depth of innovation. Huang *et al.* [45] conducted an empirical study in a product design course and further found that GAI-assisted design concept training enables students to generate more original solutions in a short period, and continuously

optimize creative expression through dynamic prototype iterations, significantly fostering greater fluency, flexibility, and originality.

In terms of promoting student engagement, recent research shows that the GAI environment can effectively enhance students' cognitive engagement and emotional engagement in learning tasks. Huang *et al.* [46] found that personalized recommendation systems based on GAI could significantly enhance students' learning motivation and sense of immersion, especially in human-computer collaboration scenarios, where students demonstrate a higher level of active exploration awareness and deeper interaction behaviors. Khoso *et al.* [47] further conducted an empirical study on Chinese English learners, which demonstrated that the application of GAI not only significantly enhanced students' CT abilities but also increased their student engagement, further verifying the synergistic effect of generative AI in supporting multi-dimensional learning outcomes.

In terms of the cultivation of AI literacy, an increasing body of research has emerged. Holmes and Tuomi [44] pointed out that the GAI practical environment can enhance students' understanding of the essence of AI technology and promote their critical evaluation and ethical reflection in practical applications. Through interaction with generative models, students have not only enhanced their cognitive skills and operational proficiency but also demonstrated positive changes in the dimensions of information judgment and moral awareness. Furthermore, Stolpe and Hallström [40] emphasized that experiential learning in the GAI environment facilitates students to build a comprehensive understanding and the ability to transfer applications of AI technology, laying a foundation for future innovative practices.

Taken together, previous studies provide important evidence for the educational value of PjBL and GAI, but they also indicate that the current literature remains fragmented. PjBL research has mainly emphasized authentic inquiry, collaboration, creative production, feedback, and reflection, but has paid less attention to how generative tools can be systematically embedded into project stages to support design iteration. Conversely, GAI-related studies have often focused on specific tool affordances or short-term learning gains, such as ideation, feedback, prototype generation, or AI-related understanding, but have provided limited guidance on how these affordances should be pedagogically orchestrated within a complete PjBL process. Moreover, few empirical studies have compared GAI-supported PjBL with both conventional PjBL and traditional teaching while examining multiple outcomes, including CT, student engagement, and AI literacy. Therefore, the present study positions PjGAI as a stage-based instructional model that integrates GAI tools into the project process to support ideation, information synthesis, prototype generation, feedback, and reflection in design education. This positioning clarifies how GAI-supported scaffolding can be aligned with the core processes of PjBL in a design education context.

III. MATERIALS AND METHODS

A. Research Design

In order to explore the influence of the PjGAI model on

CT, student engagement, and AI literacy in college students' UI design learning, this study has adopted a three-group experimental design supplemented by qualitative student feedback. As shown in Fig. 1, the independent variable of this study is the teaching intervention method, and three teaching conditions are: (1) PjGAI, (2) PjBL, and (3) TTM (i.e., lecture-based instruction). The primary dependent variables are CT and student engagement, measured at both pre-test and post-test in each of the three groups. AI literacy was only measured in the PjGAI group and served as the targeted outcome variable for this group. Participants were randomly assigned to three groups. The learning tasks focused specifically on mobile interface design, aligned with the objectives of UI Design. To ensure comparability across the approaches, the design brief, expected deliverables, assessment criteria, class duration, and instructor were kept constant. Each group used the same conventional digital design software to produce the required UI artefacts. The approaches differed only in instructional organization and in access to the designated GAI tools, which were provided exclusively to the PjGAI group.

B. Participants

The participants in this study were all third-year undergraduate students from the Department of Art and Design in the School of Art and Media at Kunming University of Science and Technology, Yunnan. An *a priori*

power analysis in G*Power 3.1 for a one-way MANOVA (three groups, two dependent variables; $\alpha = 0.05$, power = 0.95, $f^2(V) = 0.0625$) indicated a minimum sample size of $N = 153$ [48, 49]. The full cohort comprised $N = 180$ students, who were randomly and equally assigned to the PjGAI, PjBL, and TTM groups ($n = 60$ each). The demographic characteristics of the three groups are presented in Table 1. All participants shared similar academic backgrounds at the university and had not received any prior systematic training related to GAI. Ethical consent was obtained from the Research Ethics Committee of Kunming University of Science and Technology (ref. 2024122301), and informed consent was obtained from all participants before data collection.

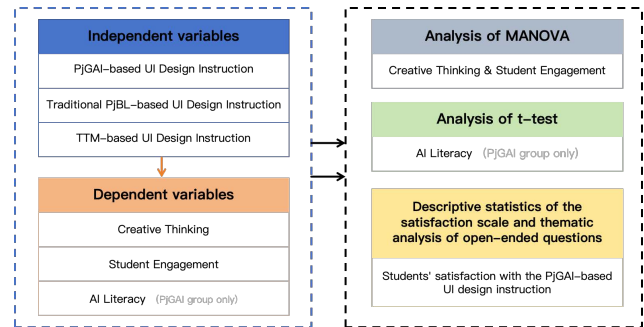


Fig. 1. Research structure of the study.

Table 1. Demographic information of the participants

Group	N	Gender		Age			Nationality	Prior AI Course
		M	F	19 years old	20 years old	21 years old		
PjGAI Group	60	26	34	18	33	9	Chinese	No
PjBL Group	60	27	33	21	30	9	Chinese	No
TTM Group	60	25	35	20	31	9	Chinese	No
Total	180	78	102	59	94	27	Chinese	No

C. Experimental Procedures

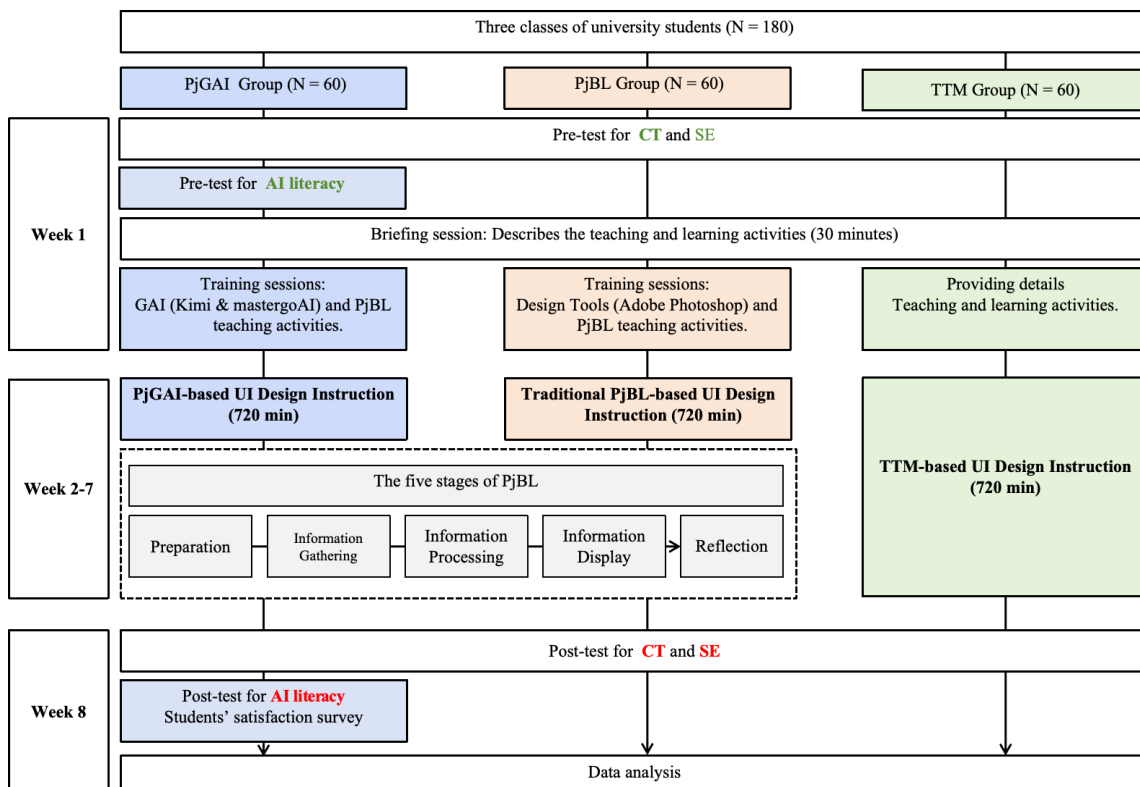


Fig. 2. Overview of the experimental procedures.

Fig. 2 presents the overall experimental procedure of this study. The experiment was conducted based on the previously assigned three-group structure. Across all three approaches, students worked on the same UI design brief and produced the same set of deliverables, using identical project requirements and assessment criteria. The implementation followed the tool and access-control specified in the research design. The PjGAI group students were systematically guided to use Kimi and MasterGoAI tools throughout the PjBL teaching process. The PjBL group completed the same design process without the support of GAI tools, while the TTM group adopted a standard lecture-based teaching model without the PjBL structure or GAI tools. All teaching activities were conducted by the same instructor using standardized instructional materials and task descriptions.

In the first week, three groups of students completed pre-tests to measure their initial levels of CT and student engagement. Students in the PjGAI group also completed an AI literacy questionnaire to assess their levels of AI literacy before the intervention. Then, the instructor delivered a common course briefing to each group, introducing the course objectives, design brief, expected deliverables, and learning arrangements. In addition, students in the PjGAI group received structured training on the designated GAI tools, including basic functions, operation procedures, and appropriate use during subsequent learning activities.

In the second to seventh weeks, students engaged in UI design activities. The PjGAI and PjBL groups progressed through the project-based workflow with milestone-based activities; the PjGAI group was allowed to use the designated GAI tools to support ideation and content generation, whereas the PjBL group completed the same workflow

without any GAI support. The TTM group followed a lecture-based, teacher-led sequence consisting of instructor explanations and demonstrations, and students completed the design work through phased homework assignments aligned with the same brief and deliverables.

In the eighth week, all students completed the post-tests to measure CT and student engagement, and the PjGAI group completed the AI literacy post-test. To learn more about their perceptions of the learning experience, the PjGAI group filled out a separate satisfaction questionnaire with open-ended questions.

D. Instructional Design of the PjGAI Model

Undergraduate students majoring in art and design participated in the learning activities of the “UI and Human-Computer Interface Design” course as part of their academic coursework. The course was designed for undergraduate students specializing in art and design disciplines. The activities took place from Week 2 to Week 7. The course aimed to develop students’ skills in mobile interface design, creative thinking, and AI literacy. During this period, the teaching activities were organized into five stages. We used the five-stage PjBL model proposed by Stoller [27]. These five stages include ten core instructional activities from their framework. Throughout the teaching process, each of these ten activities was intentionally implemented and matched with the weekly tasks to increase student participation and improve learning outcomes through structured and focused engagement. Table 2 summarizes the PjGAI activities, tools, instructional functions, and timelines.

Table 2. Summary of PjGAI activities, tools, instructional functions, and timelines

Stage	Activity	Adapted task in the course	Tools and instructional functions	Timeline
Preparation	Agree on a theme	Choose project topic and define user context	Kimi: cognitive scaffolding for topic clarification	Week 2
	Determine the outcome	Clarify expected deliverables (≥ 15 UI screens)	Kimi: cognitive scaffolding for deliverable clarification	Week 2
	Structure the project	Form groups, assign roles, and develop project plans	Kimi: planning support for role allocation and milestones	Week 2
Information gathering	Conduct research	Analyze existing apps and UI cases using Zcool	Zcool: design reference	Week 3
	Analyze and synthesize information	Build information architecture and user flow diagrams	Kimi: information organization and synthesis support	Week 3
Information processing	Plan the project	Create style guide, define UI layout and component system	MasterGoAI: creative support for style and layout planning	Week 4
	Implement the project	Generate mid- to high-fidelity UI designs based on the defined plan	MasterGoAI: creative partnership for prototype generation and visual variation	Weeks 4–5
Information display	Prepare the final product	Finalize ≥ 15 high-fidelity UI screens with consistent style and logic	MasterGoAI: feedback and refinement support	Week 6
	Present the project	Upload final work to Zcool and present group outcomes	Zcool: project display and sharing platform	Week 6
Reflection	Reflect on the project	Receive feedback, revise designs, and document AI usage reflections	Kimi: reflective support for AI-use documentation and evaluation	Week 7

During the Preparation Stage (Week 2), each group was required to develop a mobile application centered on international food sharing. Guided by the project goals and evaluation criteria introduced during the initial briefing, students used the GAI tool Kimi to generate and refine sub-themes. With teacher support and peer discussion, each group finalized a theme aligned with the design objectives. During this process, the teacher facilitated group discussions to help students clarify the project goals and expected outcomes. With the support of Kimi, students clarified their

expected deliverables, such as producing at least 15 UI screens, to align with the evaluation rubric. They then structured their project workflow, formed teams, assigned roles, and used Kimi to plan task sequences and define milestones. These activities ensured readiness for the collaborative design stages in the following weeks.

Fig. 3 illustrates how students used Kimi to generate content planning suggestions for the guide page of their international food app. Through prompt-based interaction, students received AI-generated recommendations on layout

principles, key interface functions, and visual elements, which helped inform the subsequent UI structure design.

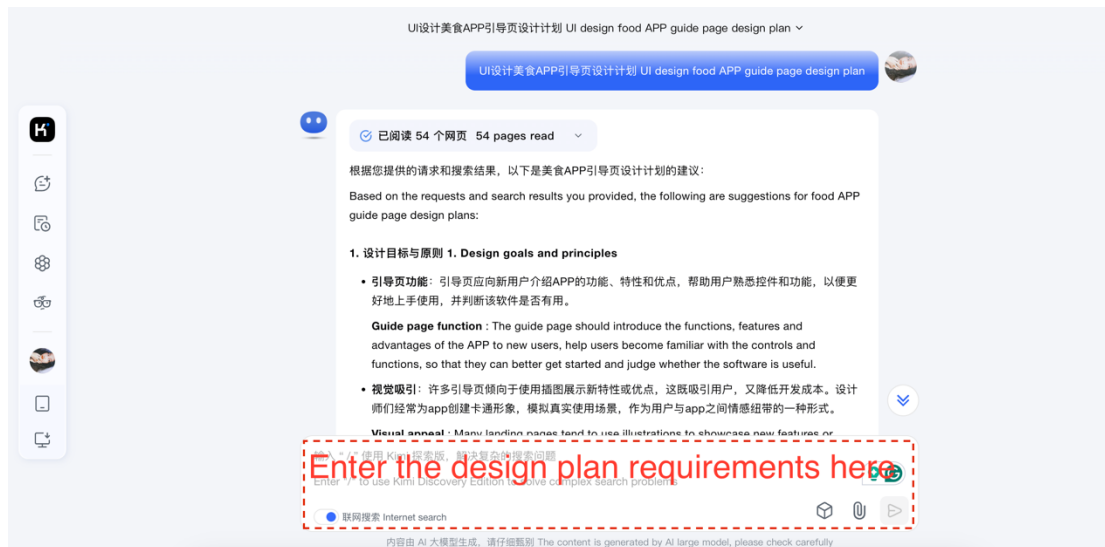


Fig. 3. Planning the project guide page using Kimi.

In the Information Gathering stage (Week 3), students conducted data retrieval and analysis focused on the selected project theme. The teacher emphasized the importance of information retrieval and guided the students to master the methods of optimizing keywords, identifying the credibility of information sources, and conducting critical analysis. With the assistance of Kimi, students quickly retrieved relevant information and conducted preliminary integration. Subsequently, by adjusting their retrieval strategies, students further enhanced the relevance and accuracy of the data. The teacher provided personalized guidance to students, assisting them in sifting through high-quality information and constructing the knowledge framework required for the project. In addition to textual resources, students were also encouraged to explore Zcool (a Chinese design sharing platform; <https://www.zcool.com.cn>), to analyze layout styles, visual language, and interaction logic from existing

mobile applications. In the Information Processing stage (Weeks 4–5), the teacher guided the students based on the information gathered in the previous phase and clarified the responsibilities of each group member. Students were divided into 10 teams of 6 members for collaborative design tasks throughout the course. Fig. 4 illustrates an interface design image generated by MasterGoAI during this stage. Students expanded their design ideas, using Kimi and collaboratively using MasterGoAI, to develop interface prototypes, and conducted multiple rounds of iterative refinement. The teacher regularly organized feedback discussions, encouraging students to revise the design plans and refine the prototype details based on peer and instructor feedback. After each round of feedback, students not only revised the design but also reflected to ensure that the final plan achieved the project goals to the greatest extent.

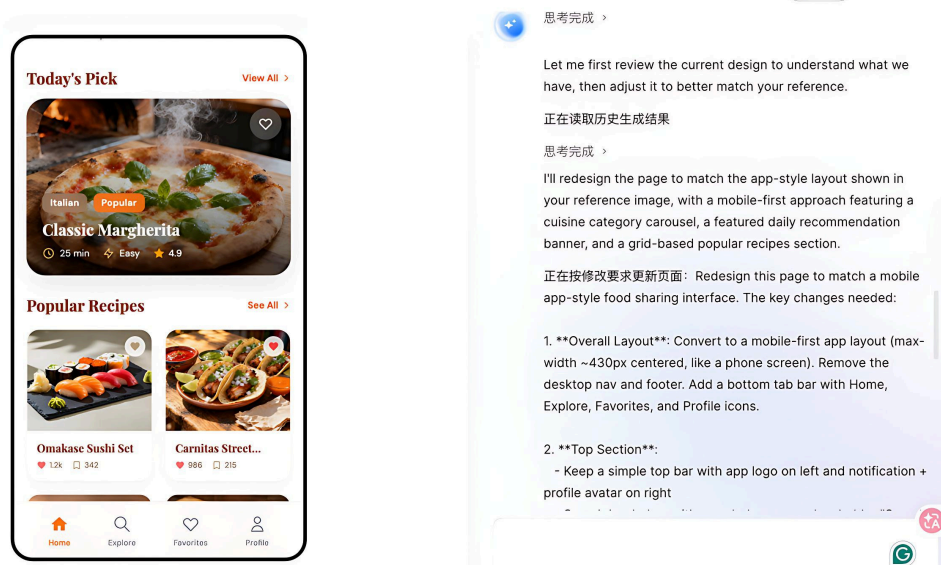


Fig. 4. Interface designs generated using MasterGoAI.

During the Information Display stage (Week 6), the teacher clarified the evaluation criteria and presentation requirements for the project and guided students in conducting peer feedback sessions using built-in evaluation

functions in MasterGoAI, gradually improving the visual details of the UI design. Students then used MasterGoAI to finalize the interface design and published the project results on the Zcool platform with a written project description

explaining the design concept (see Fig. 5). The teacher encouraged students to pay attention to the logic of the content and the clarity of the visual presentation to ensure that the design plan could be effectively conveyed to the target audience.

During the Reflection stage (Week 7), the teacher provided a structured reflection outline to help students systematically review the entire project process. The key aspects include

critical decisions, experiences with applying AI tools, and the effectiveness of team collaboration. Students wrote individual and group reflection reports based on the reflection outline generated by Kimi, summarized the successful experiences in the project, and identified encountered problems and proposed specific improvement strategies.

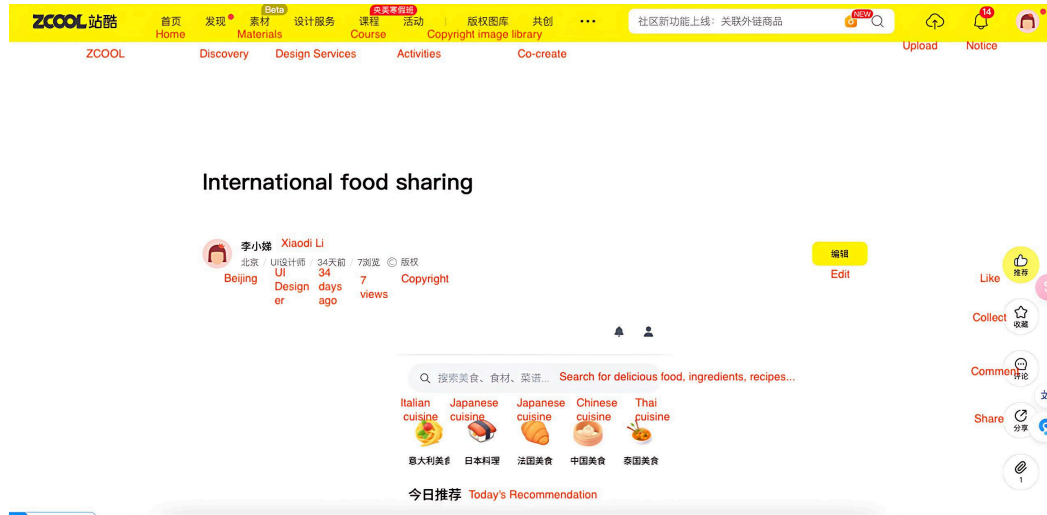


Fig. 5. Final UI interfaces published on the Zcool platform.

E. Instruments and Measures

Four instruments were used to assess students' CT, student engagement, AI literacy, and student satisfaction. Except for the CT test, all instruments were designed using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The CT test and student engagement questionnaire were administered to all three groups in both pre- and post-test phases to explore changes before and after the intervention. The AI literacy questionnaire was administered to the PjGAI group before and after the intervention to examine within-group changes in AI literacy associated with participation in the GAI-supported project-based learning activities. The student satisfaction questionnaire was administered only after the course and was designed to survey the satisfaction and learning experience of students in the PjGAI group.

The CT test, adapted from Yang *et al.* [32], consisted of three aspects: (1) fluency, (2) flexibility, and (3) originality, and was rated according to a three-level scoring rubric adapted from the Torrance Tests of Creative Thinking (TTCT). The scoring rubric is provided in Appendix A.

The student engagement questionnaire, adapted from Zhoc *et al.* [21], consisted of 20 items across five aspects: (1) academic engagement, (2) cognitive engagement, (3) emotional engagement, (4) social engagement with peers, and (5) social engagement with the teacher. A representative item was: 'I hope the class content challenges my thinking and promotes deep learning.'

The AI literacy questionnaire, adapted from Liu *et al.* [22], consisted of 15 items across four aspects: (1) cognitive and creative thinking ability, (2) application ability, (3) motivation and learning engagement, and (4) information literacy and ethical awareness. A representative item was: 'I can evaluate AI-Generated Content designs and decide on

modifications.' This questionnaire was administered to the PjGAI group before and after the intervention and was designed to assess the development of students' AI literacy in the context of GAI-integrated instruction.

The student satisfaction questionnaire was adapted from Fakhri *et al.* [50], and consisted of 14 Likert-scale items across five aspects: (1) course content and learning effectiveness, (2) application and perceived utility of GAI tools, (3) teaching organization and program evaluation, (4) communication and feedback, and (5) overall satisfaction. A representative item was: 'I am satisfied with this course.' The questionnaire also included three open-ended questions, such as 'What aspect of this course gave you the most satisfaction? Why?'

For the performance-based creative thinking test, two trained raters independently scored all responses using the three-dimensional analytic rubric. Cohen's kappa values exceeded 0.80 for each dimension, indicating almost perfect inter-rater agreement [51]. The questionnaire instruments showed acceptable internal consistency, with Cronbach's alpha values of 0.84 for student engagement, 0.79 for AI literacy, and 0.85 for student satisfaction. Content validity was assessed using the Item-Objective Congruence method by five experts, and all retained items met the criterion of 0.50 or above. The expert review focused on the alignment between each item, its intended construct, and the corresponding learning objective. The adapted instruments were based on previously published measures with prior validation evidence, and their contextual appropriateness was further supported by expert review and acceptable internal consistency coefficients. Exploratory or confirmatory factor analysis was not conducted in the present study. All instruments were administered in printed form during scheduled class time under the researcher's supervision.

F. Data Analysis Methods

For RQ1, MANOVA was conducted to compare the post-test scores of CT and student engagement across the three groups. Post-test MANOVA was used because random assignment and non-significant pre-test differences supported baseline comparability among the three groups, although ANCOVA or MANCOVA would have provided stronger control of baseline scores. Descriptive statistics, including Mean (M) and Standard Deviation (SD), were reported to illustrate group performance and distribution patterns. A significance threshold of $p < 0.05$ was adopted.

To answer RQ2, a paired-sample t-test was conducted within the PjGAI group to examine the changes in students' AI literacy scores before and after the intervention.

For RQ3, the closed-ended questionnaire items were analyzed using descriptive statistics (M and SD), while the open-ended responses were examined through thematic analysis.

Before conducting the main statistical analyses, three assumption checks were performed: (1) normality was tested using the Kolmogorov–Smirnov method, which is appropriate for samples larger than 50 participants [52], (2) homogeneity of variances and covariance matrices was assessed using Levene's test and Box's M test, respectively, and (3) Pearson correlations were calculated to ensure sufficient intercorrelation among dependent variables for MANOVA. Because the pre-test Box's M result indicated a violation of the homogeneity of covariance matrices assumption, Pillai's Trace was adopted as the multivariate test statistic due to its robustness [53]. For consistency and conservatism, Pillai's Trace was used for both pre- and post-test MANOVA. When significant differences were detected in MANOVA, Tukey's Honestly Significant Difference (HSD) test was performed to identify specific between-group differences. To address potential distributional bias and the effects of small-to-moderate

sample sizes, the study adhered to the methodological recommendations of Kim and Park [54].

All statistical analyses were conducted using IBM SPSS Statistics (Version 27.0), while the thematic analysis of qualitative data was carried out using NVivo 12 Plus.

IV. RESULTS

A. Pre-test Results of CT and Student Engagement

1) Results of the normality test

Kolmogorov–Smirnov test results (see Table 3) indicated no significant deviation from normality for CT and student engagement variables in all three groups ($p > 0.05$), supporting the use of parametric tests in subsequent analyses.

Table 3. Normality test results of CT and student engagement across groups (pre-test)

Variable	Group	N	Kolmogorov–Smirnov		
			Statistic	df	Sig.
CT	PjGAI	60	0.108	60	0.077
	PjBL	60	0.110	60	0.069
	TTM	60	0.111	60	0.065
Student Engagement	PjGAI	60	0.090	60	0.200*
	PjBL	60	0.090	60	0.200*
	TTM	60	0.097	60	0.200*

Note. * This is a lower bound of the true significance.

2) Assumption testing for MANOVA

As presented in Table 4, Box's M test revealed significant differences in the covariance matrices across groups (Box's $M = 108.210$, $F = 17.741$, $p < 0.001$), indicating that the assumption was violated. Accordingly, Pillai's Trace was used in the subsequent analysis. Additionally, Pearson correlation analysis was conducted to examine the relationships among the dependent variables. A significant correlation was found ($r = 0.346$, $p < 0.001$). These results indicate a sufficient level of intercorrelation between CT and student engagement to proceed with MANOVA in the following analysis.

Table 4. Assumption test results of CT and student engagement across groups (pre-test)

Variable	Box's test of equality of covariance					Correlation analysis	
	Box's M	F	$df1$	$df2$	$Sig.$	r	p
CT and Student Engagement	108.210	17.741	6	780815.077	<0.001	0.346**	<0.001

Note. ** $p < 0.01$

3) Multivariate test results

Table 5. Multivariate test results of CT and student engagement across groups (pre-test)

	Effect	Value	F	p
Group	Pillai's Trace	0.012	0.525	0.717
	Wilks' Lambda	0.988	0.524 ^b	0.718
	Hotelling's Trace	0.012	0.523	0.719
	Roy's Largest Root	0.012	1.054 ^c	0.351

Note. ^b: Exact statistic. ^c: The statistic is an upper bound on F that yields a lower bound on the significance level.

As shown in Table 5, none of the multivariate statistics reached significance ($p > 0.05$). Specifically, Pillai's Trace was 0.012 ($F = 0.525$, $p = 0.717$), indicating no significant differences in the pre-test scores of CT and student engagement among the three groups.

4) Comparison of pre-test results between groups

Table 6. ANOVA results of CT and student engagement (pre-test)

Dep. Variable	Group	n	M	SD	Levene's Test		ANOVA				Interpretation
					W	p	SS	MS	F	p	
CT	PjGAI	60	4.68	1.88	0.278	0.757	0.744	0.372	0.105	0.901	n.s.
	PjBL	60	4.80	1.98							
	TTM	60	4.65	1.79							
Student Engagement	PjGAI	60	60.35	4.46	0.526	0.592	21.033	10.517	0.644	0.526	n.s.
	PjBL	60	59.63	3.68							
	TTM	60	60.37	3.94							

Note: "n.s." indicates no statistically significant difference ($p > 0.05$).

As shown in Table 6, Levene's test of homogeneity of variance indicated no significant differences ($p > 0.05$) for both CT and student engagement, confirming that the assumption of homogeneity was met. Descriptive results showed that the mean CT scores across groups were at a moderate level, while student engagement scores were relatively high. A subsequent one-way Analysis of Variance (ANOVA) revealed no significant differences among the three groups in CT scores ($F = 0.105$, $p = 0.901$) or student engagement scores ($F = 0.644$, $p = 0.526$). These results suggest that the participants had comparable baseline levels in both variables before the intervention, ensuring the validity of subsequent intervention comparisons.

B. Post-test Results of CT and Student Engagement

1) Results of the normality test

As shown in Table 7, the Kolmogorov–Smirnov test indicated that the post-test data for CT and student engagement did not significantly deviate from normality across the three groups ($p > 0.05$), suggesting that the assumption of normality was met and the data were suitable

for subsequent parametric analyses.

Table 7. Normality test results of CT and student engagement across groups (post-test)

Variable	Group	N	Kolmogorov–Smirnov		
			D	df	p
CT	PjGAI	60	0.113	60	0.053
	PjBL	60	0.101	60	0.200
	TTM	60	0.103	60	0.180
Student Engagement	PjGAI	60	0.065	60	0.200*
	PjBL	60	0.090	60	0.200*
	TTM	60	0.079	60	0.200*

Note. * This is a lower bound of the true significance.

2) Assumption Testing for MANOVA

As shown in Table 8, Box's Test of Equality of Covariance Matrices was not significant (Box's $M = 6.460$, $F = 1.059$, $df_1 = 6$, $df_2 = 780815.077$, $p = 0.385$), suggesting that the homogeneity of covariance matrices assumption was not violated at the post-test stage. Pearson correlation analysis between CT and student engagement revealed a weak but statistically significant positive correlation ($r = 0.163$, $p = 0.029$), meeting the intercorrelation requirement for conducting MANOVA.

Table 8. Assumption test results of CT and student engagement across groups (post-test)

Variable	Box's Test of Equality of Covariance					Correlation Analysis	
	Box's M	F	df ₁	df ₂	p	r	p
CT and Student Engagement	6.460	1.059	6	780815.077	0.385	0.163*	0.029

Note. * $p < 0.05$

3) Multivariate Test

Table 9. Multivariate test results of CT and student engagement across groups (post-test)

Effect	Value	F	Sig
Pillai's Trace	0.405	22.494	<0.001
Wilks' Lambda	0.595	26.040 ^b	<0.001
Hotelling's Trace	0.678	29.600	<0.001
Roy's Largest Root	0.676	59.811 ^c	<0.001

Note. ^b : Exact statistic. ^c: The statistic is an upper bound on F that yields a lower bound on the significance level.

Table 9 presents the results of MANOVA for CT and student engagement scores of the three groups of students in the post-test stage. The results reveal statistically significant group differences (Pillai's Trace = 0.405, $F = 22.494$, $p < 0.001$), indicating that at least one group significantly

outperformed the other groups in the post-test scores of CT and student engagement.

4) Comparison of post-test results between groups

For CT, as shown in Table 10, Levene's test confirmed the assumption of homogeneity of variances ($F = 0.390$, $p = 0.678$). One-way ANOVA indicated a statistically significant difference in post-test CT scores among the three groups ($F = 3.992$, $p = 0.020$). Descriptively, the PjGAI group showed the highest mean CT score ($M = 5.98$, $SD = 1.99$), followed by the PjBL group ($M = 5.10$, $SD = 2.21$) and the TTM group ($M = 4.98$, $SD = 2.15$). The effect size ($\eta^2 = 0.043$) corresponds to a small effect size based on Cohen's [48] guidelines.

Table 10. ANOVA test results for CT across groups (post-test)

Dep. Variable	Group	n	M	SD	Levene's Test		ANOVA				η^2
					F	p	SS	MS	F	p	
CT	PjGAI	60	5.98	1.99	0.390	0.678	35.878	17.939	3.992	0.020	0.043
	PjBL	60	5.10	2.21							
	TTM	60	4.98	2.15							

Table 11. Post-hoc test results for CT across groups (post-test)

Group Comparison	Mean difference (I-J)	p	Interpretation
PjGAI - PjBL	0.833	0.061	n.s.
PjGAI - TTM	1.000*	0.028	PjGAI > TTM
PjBL - TTM	0.117	0.951	n.s.

Note. * $p < 0.05$

As shown in Table 11, Post-hoc comparisons using Tukey's HSD test revealed that the PjGAI group significantly outperformed the TTM group (Mean difference = 1.000, $p = 0.028$). However, the difference between the PjGAI and PjBL groups did not reach statistical significance (Mean difference = 0.833, $p = 0.061$), and no significant difference was found between the PjBL and TTM groups (Mean

difference = 0.117, $p = 0.951$). A significant difference was only found between the PjGAI and TTM groups; the other pairwise comparisons showed no statistical significance in post-test CT scores.

For student engagement, as shown in Table 12, Levene's test confirmed the assumption of homogeneity of variances ($F = 2.395$, $p = 0.094$). One-way ANOVA revealed a statistically significant difference in post-test student engagement scores among the three groups ($F = 57.262$, $p < 0.001$). The PjGAI group ($M = 74.62$, $SD = 6.34$) scored significantly higher than both the PjBL group ($M = 64.43$, $SD = 4.79$) and the TTM group ($M = 65.63$, $SD = 5.95$). The effect size ($\eta^2 = 0.393$) suggests a large effect based on

conventional benchmarks [48].

As presented in Table 13, Post-hoc comparisons further confirmed that the PjGAI group significantly outperformed both the PjBL group (Mean difference = 10.283, $p < 0.001$) and the TTM group (Mean difference = 8.983, $p < 0.001$). No

significant difference was found between the PjBL and TTM groups (Mean difference = 1.300, $p = 0.430$). These results show statistically significant differences in student engagement scores across groups, with the PjGAI group scoring significantly higher than the others.

Table 12. ANOVA results of student engagement across groups (post-test)

Dep. Variable	Group	<i>n</i>	<i>M</i>	<i>SD</i>	Levene's Test		ANOVA				η^2
					<i>F</i>	<i>p</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>p</i>	
Student Engagement	PjGAI	60	74.62	6.34	2.395	0.094	3762.744	1881.372	57.262	<0.001	0.393
	PjBL	60	64.43	4.79							
	TTM	60	65.63	5.95							

Table 13. Post-hoc test results for student engagement across groups (post-test)

Group Comparison	Mean difference (I-J)	<i>p</i>	Interpretation
PjGAI - PjBL	10.283*	<0.001	PjGAI > PjBL
PjGAI - TTM	8.983*	<0.001	PjGAI > TTM
PjBL - TTM	-1.300	0.430	n.s.

Note. * $p < 0.05$

C. Within-group Changes in AI Literacy in the PjGAI Group

1) Results of the normality test

As shown in Table 14, the Kolmogorov-Smirnov tests indicated that both the pre-test ($D = 0.097$, $p > 0.200$) and post-test ($D = 0.076$, $p > 0.200$) AI literacy scores in the PjGAI group did not deviate significantly from normality, supporting the use of a paired-sample t-test.

Table 14. Normality test results for AI literacy pre-test and post-test scores in the PjGAI group

Variable	Group	<i>N</i>	Kolmogorov-Smirnov Test		
			<i>D</i>	<i>df</i>	<i>p</i>
AI literacy (Pre-test)	PjGAI	60	0.097	60	0.200*
AI literacy (Post-test)	PjGAI	60	0.076	60	0.200*

Note. * This is a lower bound of the true significance.

2) Paired-sample t-test results

Table 15. Paired-sample t-test results for AI literacy (PjGAI Group)

Measure	<i>N</i>	<i>M</i>	<i>SD</i>	<i>t</i>	<i>df</i>	<i>Sig</i>	Effect size
AI literacy (Pre-test)	60	40.07	3.49	-24.52	59	<0.001	3.17
AI literacy (Post-test)	60	56.33	3.59				

Table 15 reports that the paired-sample t-test mean score of AI literacy in the PjGAI group significantly increased from the pre-test ($M = 40.07$, $SD = 3.49$) to the post-test ($M = 56.33$, $SD = 3.59$), with the improvement reaching statistical significance ($t = -24.52$, $p < 0.001$). The effect size (Cohen's $d = 3.17$) indicates an extremely large effect based on Cohen's [48] criteria. These findings indicate a substantial within-group increase in AI literacy among students in the PjGAI condition after the intervention.

D. Student Satisfaction toward PjGAI

1) Student satisfaction (quantitative results)

Table 16 presents the descriptive statistics of student satisfaction in the PjGAI group. The overall satisfaction level was relatively high ($M = 3.91$, $SD = 0.66$). Among them, Teaching Organization and Project Evaluation received the highest average score ($M = 3.96$, $SD = 0.75$), followed by Communication and Feedback ($M = 3.92$, $SD = 0.80$),

Personal Satisfaction ($M = 3.91$, $SD = 1.07$) and Applications and Interests of GAI Tools ($M = 3.91$, $SD = 0.98$). Although Course Content and Learning Outcomes had the lowest mean score ($M = 3.81$, $SD = 0.91$), it still exceeded the neutral midpoint of 3.00, indicating generally favorable levels of student satisfaction.

Table 16. Descriptive statistics of student satisfaction (PjGAI Group)

Dimension	Item Code	<i>M</i>	<i>SD</i>
Course content and learning outcomes	Q1-Q3	3.81	0.91
Applications and interests of GAI tools	Q4-Q5	3.91	0.98
Teaching organization and project evaluation	Q6-Q9	3.96	0.75
Communication and feedback	Q10-Q13	3.92	0.8
Personal satisfaction	Q14	3.91	1.07
Overall		3.91	0.66

2) Student satisfaction (qualitative results)

Fig. 6 illustrates the main themes and sub-themes identified through thematic analysis. In the theme of "satisfaction with teaching model and tool application", students generally expressed positive perceptions of the PjGAI model and the integration of GAI tools. On the one hand, students perceived that the PjGAI course improved design efficiency and reduced the technical threshold by deeply embedding GAI tools, effectively expanding the space for creative expression. For example, a student pointed out: "Using GAI to generate user requirement documents is extremely convenient, saving a significant amount of time for organization" (No. 41). On the other hand, students highly agreed with the teaching process based on real tasks, considering it "clear in process", "clear in goals", and "highly immersive". Additionally, students also affirmed the deep integration of teaching content and tools, such as: "The MasterGoAI part is very practical and helpful for future work" (No. 9).

In the theme of "learning needs fulfillment and suggestions for improvement", students generally reported that the course effectively fulfilled their individual learning goals, technical skill development, and knowledge expansion. One student pointed out: "The course meets my expectations for the combination of AI tools and design processes". However, several students also offered constructive suggestions for improvement, including insufficient guidance on software operation, an overly fast course pace, and feedback that lacked specificity in certain sections. One student mentioned: "I think the teaching part of the prompts can be more detailed" (No. 10). Another student suggested incorporating cross-group peer evaluation to enhance both the assessment and the interactivity of learning. Additionally, some students expressed the need for continued access to learning resources and platforms after the course. One student recommended: "Provide more design templates in the early stage of the

project” (No. 25).

In the theme of “motivations and satisfaction factors”, students identified several key contributing factors, including instructor guidance, peer collaboration and inspiration, and a sense of achievement and motivation. Instructor guidance was repeatedly mentioned, with many students reporting that timely and encouraging feedback enhanced their confidence in experimenting with new approaches. As one student shared: “The teacher often encouraged me to try new methods, giving me more confidence” (No. 2). Peer

collaboration and inspiration also provided valuable opportunities for communication and comparison, fostering creative inspiration. One student pointed out: “Seeing others’ excellent works inspired me to do well too” (No. 3). At the same time, when students completed stage-specific achievements and received positive feedback, they would have a strong sense of achievement, thereby enhancing their learning motivation. As student No. 20 said: “Learning AI tools improving efficiency to complete a complete project, and my confidence also increased.”

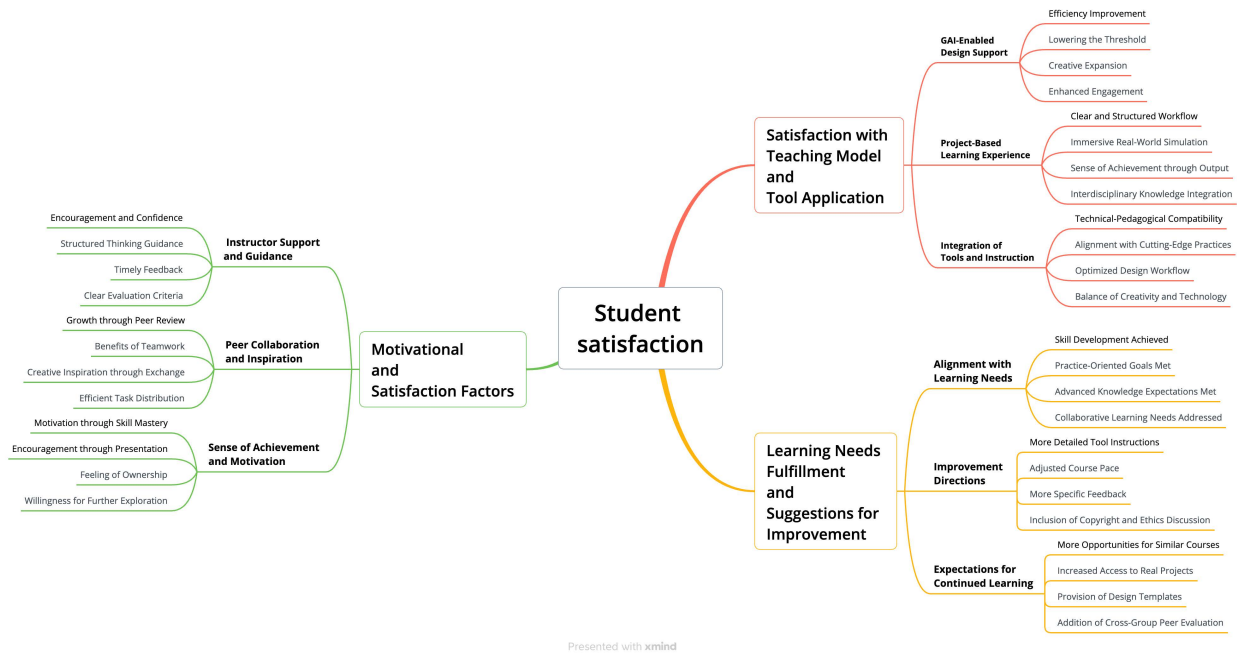


Fig. 6. Thematic map of student satisfaction in the PjGAI group.

Overall, students expressed high levels of satisfaction with PjGAI. Their feedback provides an important basis for subsequent instructional optimization and research discussion.

V. DISCUSSION

A. Effects on Creative Thinking

The findings of this study suggest that the PjGAI model may support students’ CT, particularly when compared with lecture-based instruction. The post-test results showed that the PjGAI group scored significantly higher than the TTM group, indicating that the integration of GAI within a project-based design process may offer advantages over lecture-based instruction. However, the difference between the PjGAI and PjBL groups did not reach statistical significance, despite the higher mean score observed in the PjGAI group. This finding provides partial support for RQ1.

This pattern may be attributed to the combined support of authentic tasks and GAI technologies. During the PjGAI course, students integrated the use of Kimi and MasterGoAI tools across multiple task stages. These tools not only provided structured and timely feedback but also offered diverse interface styles that served as new sources of design inspiration. As one student remarked, “Sometimes, just changing a prompt led to completely different results, which helped me break away from my usual design style.” Such experiences suggest that GAI may help expand students’ sources of inspiration and support more flexible exploration

during design iterations. However, because conventional PjBL also supports creativity through authentic tasks, collaboration, feedback, and reflection, the non-significant difference between the PjGAI and PjBL groups suggests that GAI may have complemented, rather than clearly surpassed, the creative affordances of PjBL in this study [12, 13]. These findings are broadly consistent with Gudoniene *et al.* [19], who highlighted GAI’s role in expanding CT pathways. However, they also suggest that the added value of GAI beyond conventional PjBL may be limited or context-dependent.

This pattern aligns with existing research indicating that PjBL alone already provides considerable support for creativity development [12, 13].

In summary, the PjGAI model showed a significant advantage over TTM in fostering CT, but its additional advantage over conventional PjBL was not statistically confirmed in this study. This pattern suggests that GAI may enrich creative exploration by expanding students’ sources of inspiration and design alternatives, while the project-based learning process itself already provides important conditions for creativity development through authentic inquiry, collaboration, feedback, and reflection.

B. Effects on Student Engagement

Student engagement showed the clearest advantage for the PjGAI model. Rather than merely reflecting higher post-test scores, this finding suggests that embedding GAI tools into project milestones may have strengthened students’

cognitive, emotional, and social participation throughout the learning process.

This positive outcome can be attributed to the synergy between “authentic task orientation” and “GAI technology integration” within the PjGAI framework. In this study, students worked on UI design tasks rooted in real-world problems. Across various project phases, they used Kimi for AI-assisted research and user persona development, receiving more targeted feedback that enhanced their task understanding and academic engagement. As one student noted, “Using GAI tools gave me a stronger sense of participation; I felt like I was truly working on my design project.” This reflects the role of GAI as an external cognitive scaffold that supports learners’ situational projection and role identification, aligning with Liang *et al.*’s [55] concept of Cognitive Engagement.

Additionally, students collaborated using MasterGoAI to co-create and iterate on project solutions, which effectively strengthened peer collaboration and fostered peer engagement. One participant remarked, “Our team discussed the AI-generated interfaces together and selected the best version. This was a great process.” Meanwhile, teachers provided specific and timely feedback based on students’ GAI-generated outputs at each project stage. This enhanced both the frequency and quality of teacher-student interactions and increased students’ perception of instructional support and trust. One student shared, “Our teacher gave us clear guidance at every stage, so we never felt lost; we felt reassured.” These interactions reflect social engagement with teachers. Furthermore, the immediacy and visual nature of GAI tools boosted students’ immersion and sustained motivation, thereby fostering stronger and more lasting emotional engagement. These multi-dimensional effects align with Zhoc *et al.*’s [21] framework of student engagement and further validate the synergistic mechanism between structured PjBL and GAI integration in activating diverse engagement dimensions, as demonstrated by Wei *et al.* [42] and Xia *et al.* [56].

In conclusion, the PjGAI model effectively supported student engagement among art and design students, offering theoretical insights into the mechanism of educational technology integration in advanced-level courses and providing actionable pathways for future instructional practices.

C. Within-group Development of AI Literacy in the PjGAI Group

The AI literacy findings provide within-group evidence of students’ development in AI literacy within the PjGAI condition. The magnitude of this pre-post change may be understood in relation to the instructional context. Before the intervention, students had not received systematic training in GAI, whereas the PjGAI activities provided repeated opportunities to use, evaluate, refine, and reflect on GAI outputs. In addition, the AI literacy measure was closely related to the learning activities, including tool operation, prompt refinement, output evaluation, and ethical awareness. These factors may help explain the large pre-post change observed in the PjGAI group. This finding addresses RQ2.

This within-group development may be attributed to the cognitively progressive learning structure centered on GAI tools embedded in the course design. Through a sequence of

project-based tasks, students utilized tools such as Kimi and MasterGoAI to complete activities including needs analysis, user profiling, interface design, and design reflection. This process guided them to progressively shift from basic tool use to deeper understanding and critical reflection. As one student noted, “The part where the teacher explained the principles and ethical issues of GAI was particularly thorough, it impressed me.” This indicates that the instructional design not only improved students’ operational and strategic competencies but also deepened their understanding of AI mechanisms and technical responsibility.

During the interface design phase, students enhanced their control over the functionality and applicability of GAI tools through prompt tuning, evaluation of outputs, and repeated optimization. One student commented, “Sometimes I found that some of its feedback was repetitive, so I started rewriting some parts myself before asking it to optimize.” This ability to recognize limitations and engage in adaptive strategies reflected growth in both “cognitive and creative thinking skills” and “applied proficiency.” Meanwhile, authentic UI projects and the immediacy of feedback significantly boosted students’ engagement and sustained motivation. These findings suggest that students reported measurable development in AI literacy within the PjGAI condition, particularly in tool use, output evaluation, and adaptive refinement [22].

However, some students expressed concerns about technological dependence. One student stated, “Sometimes I unconsciously waited for it to generate content and didn’t feel like thinking for myself first.” Such concerns echo the “cognitive offloading” risks discussed by Gerlich [30], highlighting the need for explicit pedagogical guidance and value clarification during the cultivation of AI literacy to prevent over-reliance on technology and the erosion of ethical awareness. This observation also aligns with the findings of Long and Magerko [37], who define AI literacy as a multifaceted capability encompassing not only technical operation but also critical reflection, ethical awareness, and the ability to make informed and responsible decisions when interacting with AI technologies. Therefore, PjGAI activities should include explicit scaffolding that encourages students to articulate their own design ideas before using GAI, critically evaluate AI-generated outputs, and document how AI suggestions are adapted rather than directly accepted.

In summary, the within-group results indicate that students in the PjGAI group improved their AI literacy across multiple dimensions, including operational skills, critical understanding, learning motivation, and ethical awareness.

D. Student Satisfaction toward PjGAI

The satisfaction results indicate that students in the PjGAI group generally perceived the model positively, particularly in relation to instructional organization, tool use, communication, and overall learning experience, supporting RQ3.

The high levels of satisfaction can be attributed not only to the task-driven structure and deep integration of GAI technologies but also to the multi-layered social support fostered by teacher guidance and peer collaboration. According to Biggs and Tang [57], the theory of Constructive Alignment emphasizes that effective instructional design

should ensure coherence between learning objectives, learning activities, and assessment methods. In this study, GAI tools were embedded into authentic project tasks, creating strong alignment between learning goals and task practices, thereby enhancing students' perceived value of the course and their overall satisfaction.

Timely feedback and strategic support provided by instructors also increased students' emotional safety and willingness to express themselves. One student commented, "The teacher often encouraged us to try new methods, which gave me the confidence to explore alternative expressions."

Meanwhile, group collaboration and peer assessment effectively supported social construction and self-efficacy. As Fredricks *et al.* [34] emphasized, cognitive, emotional, and behavioral engagement are not only interrelated but also mutually reinforcing in technology-enhanced collaborative learning contexts. This instructional model, students' active involvement in group discussions and feedback, contributed to sustained participation. One student remarked, "Every time we had group discussions and peer evaluations, I learned a lot from others' work and felt more involved." These experiences demonstrate that the social interaction mechanisms embedded in the PjGAI model successfully fostered students' cognitive engagement and sustained participation.

Moreover, most students reported that the course enhanced their learning autonomy and confidence in integrating AI tools with disciplinary skills. According to Deci and Ryan's [58] Self-Determination Theory, learning motivation is strengthened when learners' needs for autonomy, competence, and relatedness are satisfied. Within the PjGAI context, students were granted considerable autonomy in tool selection and project expression; the feedback from both instructors and peers further enhanced their sense of competence and belonging, thereby driving sustained motivation. This "positive feedback loop" not only illustrates the transfer potential of project-based learning but also validates the role of GAI tools as cognitive partners in authentic design tasks.

Despite the overall high satisfaction, some students also offered constructive suggestions for improvement, including extending the time allocated for software instruction, enhancing guidance on copyright and ethical issues, and incorporating cross-group peer assessment. These suggestions reflect students' adaptive expectations toward course structure and support mechanisms. As emphasized by Lee and Hannafin [59], effective learning environments require not only a coherent initial design but also dynamic responsiveness to learners' evolving needs and feedback.

In summary, students' satisfaction responses suggest that PjGAI was positively perceived as a learning model that integrates GAI tools with authentic project tasks, teacher guidance, peer collaboration, and reflective improvement. Future research could examine the differentiated impacts of various GAI tools on satisfaction and assess their sustainability and scalability across different disciplinary contexts, thus advancing both theoretical and practical innovations in digital instructional design.

Taken together, these findings suggest that the value of PjGAI lies not simply in providing students with access to GAI tools, but in embedding these tools within a structured

project-based learning process. From a theoretical perspective, PjGAI can be understood as a scaffolded learning environment in which GAI tools support ideation, information organization, prototype generation, feedback, and reflection across project stages. This interpretation helps explain why the model showed its clearest effect on student engagement, while its added value for CT beyond conventional PjBL was more limited. It also suggests that AI literacy may develop when students use GAI tools in connection with output evaluation, ethical awareness, and reflective project practice. Therefore, this study positions GAI not as an independent driver of learning outcomes, but as a pedagogical scaffold whose value depends on its integration with authentic tasks, collaboration, feedback, and reflection in PjBL.

VI. LIMITATIONS AND IMPLICATIONS

A. Limitations

This study has several limitations and implications for future researchers.

Firstly, the participants in the study were exclusively undergraduate students majoring in art and design from a Chinese university, resulting in a relatively limited sampling scope, which potentially affects the generalizability of the findings. Future research could include students from more diverse regions and academic backgrounds to enhance the generalizability of the findings.

Secondly, AI literacy was measured only in the PjGAI group. Therefore, the AI literacy findings should be interpreted as within-group developmental evidence rather than as between-group comparative evidence. Without AI literacy data from the PjBL and TTM groups, this study cannot determine whether the observed improvement was uniquely attributable to the PjGAI intervention or whether similar gains might have occurred under other instructional conditions. Future studies should administer AI literacy measures across all comparison groups to provide stronger evidence of the relative effectiveness of GAI-supported PjBL.

Thirdly, several outcome measures, including student engagement, AI literacy, and student satisfaction, were collected through self-reported questionnaires. Although the CT test was assessed using a rubric and independently scored by two faculty members, the questionnaire-based measures may still be influenced by social desirability, students' subjective perceptions, or common-method bias. In addition, exploratory or confirmatory factor analysis was not conducted for the adapted questionnaire instruments. Future research should incorporate multiple data sources, such as classroom observations, learning analytics, behavioral logs, interviews, and external assessments of design artefacts, and further validate the factor structure of the adapted instruments in larger samples.

Finally, the use of post-test MANOVA rather than ANCOVA or MANCOVA is another methodological limitation, as covariate-adjusted analyses could provide more robust control of baseline scores. Future studies should consider using ANCOVA or MANCOVA in pre-test-post-test designs.

B. Implications

Accordingly, the implications of this study are discussed from theoretical and practical perspectives. From a theoretical perspective, the findings support an orchestration view of GAI-supported PjBL. GAI should not be understood simply as a tool that automatically improves learning outcomes, but as a pedagogical scaffold whose value depends on how it is aligned with authentic tasks, collaboration, feedback, and reflection. This perspective highlights the need to examine how different GAI functions are sequenced and regulated within PjBL, rather than assuming uniform effects across learning outcomes.

Practically, this study provides three implications for implementing PjGAI in design education. Firstly, PjGAI may support students' CT by expanding sources of inspiration and design alternatives, but GAI tools should be used to enrich creative exploration rather than to guarantee stronger creative outcomes beyond conventional PjBL. Secondly, PjGAI can be used to strengthen student engagement when AI-supported activities are connected with clear project milestones, teacher guidance, peer collaboration, and iterative feedback. Thirdly, PjGAI activities may support AI literacy development when students are guided to use GAI tools, evaluate AI-generated outputs, consider ethical issues, and reflect on how AI suggestions are adapted in their design decisions.

VII. CONCLUSION

This study examined a GAI-supported PjBL model in a UI design course by comparing PjGAI, conventional PjBL, and TTM approaches, with AI literacy assessed within the PjGAI group. The findings showed that PjGAI provided clear support for student engagement and showed potential for supporting CT when compared with lecture-based instruction. However, the non-significant difference between the PjGAI and conventional PjBL groups indicates that GAI should be understood as enriching creative exploration rather than providing a clearly stronger CT advantage over PjBL. The AI literacy results further showed within-group development among students who participated in the PjGAI activities. Overall, this study highlights the importance of embedding GAI tools within authentic project tasks, teacher guidance, collaboration, feedback, and reflection in design education. These findings contribute empirical evidence on the pedagogical integration of GAI into PjBL in design education and clarify the boundaries of its effects on CT, student engagement, and AI literacy.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Zhaodi Li conceived and designed the study, developed the methodology, conducted the investigation, and provided the research resources. She also drafted the original manuscript. Jirarat Sitthiworachart performed the validation analysis. Both Jirarat Sitthiworachart and Mike Joy reviewed and edited the manuscript and provided supervision throughout the project. All authors read and approved the final version of the manuscript.

ACKNOWLEDGMENT

This work was supported by King Mongkut's Institute of Technology, Ladkrabang.

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