Effects of a Mobile Scaffolding Tool on Design Thinking in Engineering Project-based Learning

Hongyan Li *, Maixia Fu, Yu Yang, and Hongyue Liu

School of Information Science and Engineering, Henan University of Technology, Zhengzhou, China
Email: lihyky@126.com (Hon.Li.); fumaixia@126.com (M.F.); yangxiangyu1168@haut.edu.cn (Y.Y.); liuhongyue@haut.edu.cn (Hon.Liu.)
*Corresponding author

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***Abstract*—Project-based learning is a critical method for cultivating design thinking in engineering students. However, providing personalized, just-in-time learning support in the complex and often mobile contexts of engineering practice remains a significant challenge. This study investigates the effectiveness of a generative artificial intelligence-driven mobile scaffold, named DesignMate, designed to support students in an electronic system design project. Grounded in cognitive load theory, the mobile application integrates four types of scaffolds: concept integration, process simplification, strategy guidance, and metacognitive stimulation. In a quasi-experimental design, 71 students were divided into an experimental group using DesignMate and a control group. Results indicate that, compared to the control group, the experimental group experienced significantly reduced extraneous cognitive load, along with significant increases in germane cognitive load, intrinsic learning motivation, and self-efficacy. Furthermore, their final design projects demonstrated superior overall quality, novelty, and extensibility. No significant differences were found in intrinsic cognitive load or project usability. This study provides empirical evidence that mobile AI scaffolds enhance design thinking in engineering education, highlighting their potential to deliver personalized cognitive support in project-based learning.**

***Keywords*—mobile Artificial Intelligence (AI) scaffold, design thinking, generative AI, engineering education, project-based learning**

I. Introduction

Contemporary engineering education is undergoing a paradigm shift from knowledge transmission to the cultivation of higher-order thinking skills, with Project-Based Learning (PBL) emerging as a key pedagogical approach [1]. PBL guides students to identify and solve problems from multiple perspectives. It effectively promotes collaborative reasoning and knowledge construction [2]. By engaging students in authentic, complex projects, it has been shown to significantly enhance their design thinking capabilities [3]. However, the implementation of PBL in engineering faces dual challenges in today's technology-rich learning environment. First, the complex and ill-defined nature of engineering tasks demands high-level cognitive skills such as autonomous decision-making and strategy adjustment. Without effective support, students often struggle to navigate these challenges [4]. Second, traditional, instructor-led scaffolding struggles to meet the needs for personalized and immediate feedback, particularly as students increasingly work in diverse, non-fixed locations (e.g., labs, workshops, libraries) and rely on mobile devices for information and collaboration. This limitation constrains the deep development of design thinking under the high cognitive load and time pressure characteristic of real-world problem-solving [5].

Learning scaffolds are well-established for their value in promoting students' cognitive development, knowledge construction, and problem-solving abilities, serving as essential support structures in complex learning environments [6]. To address the challenges of PBL in mobile and distributed learning contexts, developing adaptive support tools is crucial. Generative Artificial Intelligence (GenAI), with its distinctive capabilities for content generation, interactive dialogue, and offering multiple solution perspectives, presents a promising pathway for constructing such intelligent scaffolds [7]. Although existing research has begun to explore various forms of GenAI-based scaffolds—such as self-explanation scaffolds in programming education [8] and immediate feedback scaffolds in game-based learning environments [9]—these investigations often remain at the level of individual tool implementation. What remains lacking is a systematic framework that deeply integrates educational theory, intelligent technology, and the specific demands of engineering practice, particularly one designed to accommodate the mobile learning scenarios that characterize contemporary students' learning habits.

Therefore, this study explores the systematic implementation and application of an intelligent, mobile learning scaffold. Guided by cognitive load theory and leveraging retrieval-augmented generation technology, we developed a mobile AI scaffold tool named DesignMate. This tool integrates four scaffold types, including concept integration, process simplification, strategy guidance, and metacognitive stimulation, to create a dynamic support system adapted to the cognitive demands of the entire engineering design process and individual learner differences. This research contributes a transferable design paradigm for mobile AI scaffold aimed at fostering engineering design thinking and provides a practical pathway for integrating GenAI into hands-on engineering education.

The remainder of this paper is structured as follows. Section II presents a systematic review of the relevant literature. Section III elaborates on the three-layer design framework of the mobile AI scaffold and introduces the DesignMate application developed accordingly. Section IV describes the research design, including the participant profile, experimental procedures, data collection instruments, and analytical methods employed. Section V reports the results of the quasi-experiment, followed by a comprehensive discussion that interprets the findings in relation to the proposed hypotheses and prior research. Section VI concludes the paper by summarizing the key contributions,

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acknowledging the limitations of the study, and suggesting directions for future research.

II. Literature Review

A. Integrating Design Thinking and Project-based Learning

Driven by outcome-based education, contemporary engineering education places increasing emphasis on cultivating students' complex problem-solving abilities—a goal that demands pedagogical approaches capable of bridging theoretical knowledge with authentic practice. The integration of design thinking and PBL has emerged as a key strategy to meet this demand. Design thinking, as a human-centered methodology grounded in problem-solving, experimentation, and iteration, offers a structured yet flexible approach for navigating the multifaceted nature of engineering challenges [10]. By prioritizing user needs, rapid prototyping, and iterative testing, it fosters learning through continuous cycles of trial, feedback, and refinement [11]. At its core, design thinking emphasizes interdisciplinary integration and optimization, enabling learners to generate innovative solutions even within ambiguous or ill-defined problem contexts [12].

The pedagogical effectiveness of this integration is supported by a growing body of empirical research. For instance, Lin *et al.* [13] demonstrated that systematically embedding the engineering design process into PBL significantly enhanced students' design thinking structures, helping them internalize iterative and user-oriented problem-solving strategies. Similarly, Jiang and Pang [14] found that combining the user-centered philosophy of design thinking with the "learning by doing" approach of PBL in an AI and algorithms course significantly stimulated students' learning motivation and fostered their creativity. In a related study, Waidelich *et al.* [15] developed an engineering training model by integrating design thinking into project-based engineering processes, highlighting the potential of such integration to prepare students for complex, real-world engineering tasks. Collectively, these findings underscore the value of merging design thinking with PBL to promote deeper learning outcomes and innovation competencies in engineering education.

B. Learning Scaffolds in PBL and the Shift toward Intelligent, Mobile Tools

In PBL, learning scaffolds play an indispensable role in ensuring project success. Their core functions can be conceptualized along two interrelated dimensions. First, they serve to manage cognitive load by directing learners' attention toward core objectives and breaking down complex tasks, thereby enabling students to accomplish what they could not achieve independently [16]. Second, scaffolds facilitate knowledge construction and higher-order thinking; empirical evidence from a meta-analysis indicates that regulated learning scaffolds significantly enhance students' use of learning strategies and academic performance [17]. Despite their importance, traditional scaffolding approaches often depend heavily on instructors' real-time judgment and availability, making it challenging to deliver personalized, timely support in large or diverse student cohorts, particularly when learners work asynchronously or in distributed settings [18, 19]. The integration of technology has thus become essential to address these scalability and personalization challenges [20].

The emergence of GenAI has catalyzed a paradigm shift from static, instructor-dependent scaffolds toward intelligent, generative scaffolding systems. Mobile AI scaffolds can be theorized as a "more capable virtual partner," drawing upon three complementary theoretical foundations: scaffolding theory's principle of fading, self-regulated learning's emphasis on metacognitive monitoring, and human-computer interaction research on adaptive dialogue systems [21]. Unlike traditional pre-configured scaffolds, these AI-driven tools—accessible anytime via mobile devices—can dynamically generate context-sensitive support tailored to the learner's current situation, prior interactions, and evolving needs. Preliminary empirical studies have yielded encouraging results. For instance, embedding such AI "partners" within PBL environments has been shown to enhance students' creativity, design thinking capacity, and learning motivation [22]. From a cognitive perspective, these tools can reconstruct examples and problems in real time, facilitating deeper understanding of complex concepts [23]. Metacognitively, AI-generated prompts have proven effective in triggering self-explanation and strategy monitoring behaviors [24]. Motivationally, personalized and immediate feedback can strengthen self-efficacy, empowering students to become more creative, critical, and collaborative knowledge builders [25].

In summary, although the educational merits of design thinking and PBL, the critical role of instructional scaffolds, and the potential of GenAI have been widely recognized in educational research, existing studies on intelligent scaffolding still face three prominent limitations. First, there is an absence of a holistic framework that deeply integrates educational theories, cutting-edge intelligent technologies, and real-world engineering practices. Second, few integrated intelligent scaffold tools are tailored to the mobile, dynamic, and flexible environments of contemporary project-based learning. Third, empirical investigations into how these tools shape students' cognitive processes and developmental abilities in authentic engineering contexts remain insufficient.

To bridge these research gaps, the present study explores the effects of a mobile AI scaffold on university students' cognitive load and engineering design thinking within a PBL environment. It addresses three core research questions:

RQ1: What is the effect of the mobile AI scaffold on students' intrinsic, extraneous, and germane cognitive load?

RQ2: Does the mobile AI scaffold significantly enhance students' motivation and self-efficacy?

RQ3: Does the mobile AI scaffold significantly improve students' engineering design thinking outcomes?

III. Research Framework and Tool Design

A. Theoretical Foundation

Although Cognitive Load Theory (CLT), Experiential Learning Theory (ELT), and scaffolding theory have been widely applied in educational research, their systematic integration remains underexplored in the context of AI-supported mobile learning. This study therefore synthesizes three complementary theoretical perspectives to elaborate how mobile AI scaffolds shape students' design thinking development: (a) CLT explains cognitive resource optimization—how scaffolds redistribute cognitive load to free capacity for higher-order thinking; (b) ELT explain process engagement—how scaffolds catalyze reflection and constructive interaction during design cycles; and (c) scaffolding theory explains developmental support—how adaptive assistance within the zone of proximal development enables progressive autonomy; Together, these mechanisms account for the transition from scaffolded support to self-regulated design thinking. The following sections elaborate each theoretical component and its operationalization in the DesignMate application.

1) Cognitive load theory

CLT, proposed by Sweller, is a foundational theory in instructional design. It posits that working memory capacity is inherently limited and that instructional effectiveness depends on how cognitive load is managed [26]. The theory distinguishes three types of cognitive load: intrinsic load, determined by the complexity of the material; extraneous load, imposed by poor instructional design; and germane load, the cognitive effort devoted to constructing and automating schemas. Building on these distinctions, CLT offers a set of principles aimed at reducing extraneous load, managing intrinsic load, and promoting germane load [27]. These principles provide a robust theoretical framework for designing effective learning support, such as scaffolding. Recent research further highlights the complementary role of autonomy-supportive teaching, demonstrating that the combination of load reduction strategies and motivational support can synergistically enhance student engagement and learning outcomes [28, 29].

Grounded in CLT, the mobile AI scaffold acts as a cognitive resource optimizer. As typical examples, Process Simplification Scaffolds assist learners with lower-level tasks such as information retrieval and code debugging. This approach effectively reduces extraneous cognitive load and frees up limited working memory capacity. Likewise, Strategy Guidance Scaffolds channel the liberated cognitive resources into germane cognitive processes, including schema construction, systematic reasoning, and reflective evaluation, which are fundamental to design thinking.

2) Experiential learning theory

ELT posits that learning is a cyclic process involving four stages: Concrete Experience (engagement with authentic tasks), Reflective Observation (processing experiences), Abstract Conceptualization (forming generalizations), and Active Experimentation (testing new concepts) [30]. Design thinking aligns closely with this cycle: students engage in concrete design experiences, reflect on failures and successes, conceptualize design principles, and experiment with new solutions.

Based on ELT, the mobile AI scaffold runs through the entire cyclic learning process of students' engineering project practice. It assists students in engaging in authentic project tasks at the Concrete Experience stage, guides reflective summarization at the Reflective Observation stage, helps generalize design rules and engineering principles at the Abstract Conceptualization stage, and supports solution trial and verification at the Active Experiment stage.

From the perspective of learning engagement, well-designed mobile AI scaffolds should facilitate students' active knowledge construction and interactive inquiry. The dialogic interaction mode of generative AI—enabling students to raise questions, obtain targeted guidance, and conduct continuous follow-up inquiry—naturally promotes interactive and constructive learning, which aligns with the ICAP framework's emphasis on generative engagement [31].

3) Scaffolding theory

Vygotsky's concept of the zone of proximal development defines the gap between what a learner can achieve independently and what they can accomplish with appropriate assistance [32]. Scaffolding refers to the temporary, adaptive support provided by a more knowledgeable other—such as a teacher, peer, or intelligent tool—that enables learners to bridge this gap. As the learner's competence grows, the support is gradually withdrawn, a process known as fading [33]. Scaffolds are commonly categorized into two complementary types: cognitive scaffolds, which include conceptual, metacognitive, and strategic support that promote thinking and problem-solving [34]; and affective scaffolds, which provide encouragement and reassurance to sustain motivation and engagement by managing learners' emotional states [35, 36]. Effective scaffolding thus facilitates the learner's transition from other-regulation to self-regulation, fostering autonomy and deeper learning.

Informed by Scaffolding Theory, the mobile AI scaffold operates as a "more capable virtual partner" that provides contingent, adaptive support within the learner's Zone of Proximal Development. Unlike traditional static scaffolds—which are typically pre-designed, non-dialogic, and unable to adjust to a learner's emerging needs in real time—the AI tool developed in this study supports a gradual and personalized transition from external guidance to self-regulation. This is achieved through learner-initiated interactive questioning and dialogue, allowing the scaffold to respond contingently rather than following a fixed script.

B. Design Framework for a Mobile AI Scaffold

Based on the theoretical foundations outlined above and the specific demands of engineering project-based learning, we constructed a three-layer design framework for an intelligent (see Fig. 1). This framework establishes a structured approach to embedding cognitive support within a mobile application, ensuring that assistance is both pedagogically grounded and technically robust.

Fig. 1 illustrates the three-layer architecture of the DesignMate framework. The Theoretical Layer (bottom) translates CLT, ELT and Scaffolding Theory into four scaffold types, each addressing specific cognitive demands: Concept Integration Scaffolds manage intrinsic load by connecting domain knowledge; Process Simplification Scaffolds reduce extraneous load through streamlined workflows; Strategy Guidance Scaffolds promote germane load via structured problem-solving support; and Metacognitive Stimulation Scaffolds further enhance germane load through reflective prompts. The Technology Layer (middle) implements these scaffolds through a RAG-based architecture that grounds LLM outputs in curated domain knowledge. The Application Layer (top) delivers support within authentic mobile learning contexts, enabling just-in-time assistance throughout the engineering design process.

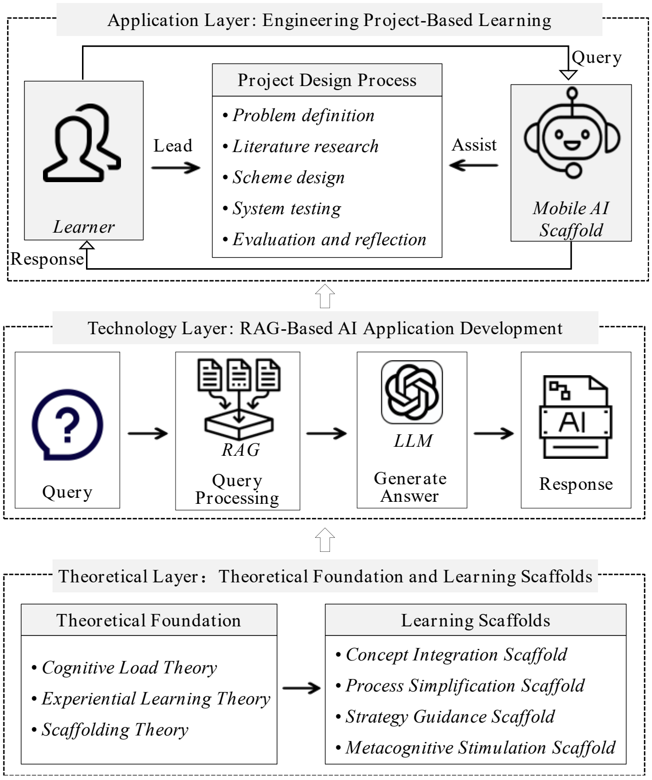

Fig. 1. Design framework for the mobile AI scaffold.

1) Theoretical layer: Design principles and scaffold taxonomy

Grounded in CLT, ELT and scaffolding theory, this layer translates core instructional principles—managing intrinsic load, reducing extraneous load, and promoting germane load—into actionable learning scaffolds. It defines four distinct types of scaffolds, each implemented as specific features within the mobile application to address learners' cognitive needs throughout the engineering design process.

Concept Integration Scaffolds aim to manage intrinsic load by connecting disciplinary knowledge and decomposing complex tasks. For instance, the Literature and Case Library Search function helps students analyze theoretical concepts and provides reference cases, reducing the cognitive burden associated with navigating unfamiliar domains.

Process Simplification Scaffolds reduce extraneous load by optimizing information presentation and providing immediate, task-specific feedback. Features such as Component Search and Report Polish streamline information retrieval and documentation, allowing students to focus on core design activities rather than logistical hurdles.

Strategy Guidance Scaffolds promote germane load by assisting with design trade-offs and systematic debugging. Through tools such as Hardware Troubleshooting and Code Diagnosis, students receive structured support in reasoning through complex problems, thereby improving the accuracy and efficiency of their designs.

Metacognitive Stimulation Scaffolds further promote germane load by guiding self-monitoring, reflection and review. Through interactions with learners, the mobile AI scaffold uses guiding questions to help students clarify their reasoning, while Project Management tools with reflective prompts assist them in tracking progress and evaluating decisions, thereby cultivating habits of self-regulated learning.

2) Technology layer: RAG-based AI application development

This mobile application is built on a Retrieval-Augmented Generation (RAG) architecture, which combines the generative capabilities of a Large Language Model (LLM) with a curated, domain-specific knowledge base. The knowledge base is pre-constructed by ingesting course materials, project cases, and technical documentation, all of which are segmented, embedded as vector representations, and indexed for efficient semantic retrieval. When a user submits a query via the mobile interface, the system first performs semantic search by comparing the query embedding against the knowledge base to retrieve the most contextually relevant information. This retrieved content is then dynamically integrated into a structured prompt that guides the LLM in generating responses that are not only fluent but also contextually grounded and discipline-accurate. This design effectively minimizes hallucinations and enhances output reliability, enabling students to access precise, well-structured guidance at any time via their smartphones.

3) Application layer: Mobile engineering project-based learning

The framework is deployed in a mobile-first environment, supporting students throughout the entire engineering design process—from problem definition and conceptualization to prototyping and testing. Learners lead the design process by leveraging their professional knowledge, engineering design capabilities, AI literacy, and self-regulation skills. The intelligent learning companion serves as a cognitive and emotional collaborative partner, providing real-time support through information retrieval, knowledge reasoning, structured presentation, and immediate feedback. This establishes a human-led, AI-assisted collaborative learning model, in which technology serves to enhance learners' autonomy, critical thinking, and problem-solving abilities in authentic engineering contexts, rather than replacing them.

C. The Mobile AI Scaffold DesignMate

Based on the design framework described above, we developed the mobile application DesignMate. It is designed to provide just-in-time support to junior-year Electronic Information Engineering students during a comprehensive electronic system design project. The app's interface is optimized for mobile use, offering eight core functions that students can access as needed from their smartphones or tablets:

(1) Information Access: Literature Search (retrieves relevant course knowledge and design case resources), Component Search (locates component specifications and datasheets).
(2) Technical Problem-Solving: Code Diagnosis (identifies and resolves code errors), Hardware Troubleshooting (diagnoses hardware connection or functionality issues).
(3) Metacognitive Support: Project Management (prompts for planning and progress tracking), Report Polish (aids in

articulating and refining project reports).

Fig. 2 illustrates typical student interactions with the DesignMate mobile app. In this example, a learner uses Component Search to instantly access a component's official datasheet and then updates the project progress via Project Management, receiving encouraging feedback along with next-step prompts. Learners can interact with the app either by clicking the function buttons or by entering input through the dialog box.

Fig. 2. Learner interactions with DesignMate.

IV. Research Design

A. Research Hypotheses

This study tests the following hypotheses:

H1: The mobile AI scaffold significantly optimizes students' cognitive load structure by: (a) significantly reducing extraneous load; (b) significantly increasing germane load; (c) having no significant effect on intrinsic load, which is primarily task-dependent.

H2: The mobile AI scaffold significantly enhances students' autonomous motivation and self-efficacy.

H3: The mobile AI scaffold significantly improves students' engineering design thinking, as evidenced by both product dimensions—higher novelty, usability, and extensibility of their final project artifacts—and process dimensions—enhanced design reasoning, iterative prototyping patterns, and metacognitive reflection.

B. Participants

A quasi-experimental design was employed within the context of a required comprehensive electronic system design course. A total of 71 third-year Electronic Information Engineering students participated, assigned to two groups based on their existing class divisions to preserve the natural classroom setting. The experimental group ($n = 35$) used the DesignMate mobile application throughout their project, while the control group ($n = 36$) completed the same project without access to the app. Pre-test analyses confirmed no significant differences between the two groups in terms of demographic characteristics (gender, age), prior academic achievement (Grade Point Average), or prior knowledge relevant to the engineering design project ($p > 0.05$), establishing baseline equivalence. Both groups received identical instructional content and project requirements, ensuring that the only variable was the use of the DesignMate application.

C. Data Collection

Design thinking is a multidimensional construct encompassing both process dimensions (e.g., problem framing, iterative prototyping, reflective evaluation) and product dimensions (e.g., creative outcomes, user-centered solutions). To capture this multidimensionality, we adopted a dual-measurement strategy combining product-oriented evaluation of final project artifacts and process-oriented analysis of learner–scaffold interaction logs and interviews.

A mixed-methods approach was employed, comprising questionnaires, project evaluation, and process measures.

1) Questionnaires

Validated instruments were administered both pre- and post-intervention to assess changes in key learning outcomes. Cognitive load was measured using a scale adapted from Leppink *et al.* [37], capturing intrinsic, extraneous, and germane load dimensions (Cronbach's $\alpha = 0.89$). Autonomous motivation was assessed using the instrument from Ryan and Deci [38], which measures students' perceived autonomy and self-determination in learning activities ($\alpha = 0.90$). Self-efficacy was measured using a scale from Bandura [39], reflecting students' confidence in completing engineering design tasks ($\alpha = 0.93$). All scales employed a 0–10 visual analog scale (0 = strongly disagree; 10 = strongly agree). All questionnaires demonstrated strong internal consistency reliability.

2) Project evaluation

The Project-Based Learning framework in engineering education emphasizes that the quality of the designed artifact serves as a valid indicator of students' design thinking proficiency, particularly when evaluated by expert judges using standardized rubrics. In this study, three dimensions adapted from Cropley [40] were assessed:

- Novelty (40% weight): Originality and creativity of the design solution, including unique feature combinations and innovative problem-solving approaches. This dimension captures the divergent thinking central to design thinking.
- Usability (30% weight): Feasibility, functionality, and user-centeredness within given technical constraints. This reflects the convergent thinking and user empathy emphasized in design thinking methodology.
- Extensibility (30% weight): Potential for future development, adaptation, and integration with other systems. This indicates systems thinking and forward-looking design orientation.

3) Process measures

Because product-based outcomes alone provide only a partial proxy for design thinking, we triangulated project scores with two process-oriented data sources: system log analysis and semi-structured interviews.

System log analysis: All learner-scaffold interactions were logged throughout the project. The analysis focused on longitudinal changes in scaffolding usage patterns, the gradual shift from dependent to autonomous inquiry, and the developmental trajectory of scaffolding fading. These logs captured students' iterative question-posing and strategy-adjustment behaviors, reflecting their iteration patterns and design reasoning.

Semi-structured interviews: Fifteen students from the experimental group were purposively sampled to represent high, medium, and low levels of project performance, ensuring diverse viewpoints. The interview protocol explored students' perceived usability of the mobile scaffold, its influence on their design workflows, and overall learning experiences. Special attention was given to how students reflected on their design decisions and adjusted strategies, which directly tapped into metacognitive reflection—a key process indicator of design thinking.

V. Result and Discussion

A. Quantitative Analysis

Table 1 presents the descriptive statistics and results of repeated-measures Analysis of Covariance (ANCOVA) for the cognitive and psychological variables, with group assignment as the independent variable and pre-test scores as covariates.

Table 1. Pre-test and post-test results and between-group comparisons

Variable	Time	Experimental (M±SD)	Control (M±SD)	F	p	η^2
Intrinsic Load	Pre	6.87±0.66	6.93±0.72	0.359	0.551^{ns}	0.005
	Post	6.63±0.26	6.82±0.68			
Extraneous Load	Pre	4.82±0.66	4.93±0.68	10.416	0.002**	0.131
	Post	3.97±0.45	4.81±0.57			
Germane Load	Pre	6.71±1.10	6.78±0.93	7.915	0.006**	0.103
	Post	7.73±0.52	6.98±0.65			
Motivation	Pre	7.21±0.65	7.19±0.82	7.933	0.006**	0.103
	Post	8.03±0.57	7.36±0.93			
Self-Efficacy	Pre	7.25±0.54	7.31±0.63	6.059	0.016*	0.081
	Post	7.91±0.54	7.42±0.81			

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. ns indicates non-significant ($p > 0.05$).

The results support H1 and H2. The experimental group demonstrated significantly lower extraneous load ($p = 0.002$, $\eta^2 = 0.131$, 95% CI [−1.137, −0.568]) and significantly higher germane load ($p = 0.006$, $\eta^2 = 0.103$, 95% CI [0.891, 1.149]), motivation ($p = 0.006$, $\eta^2 = 0.103$, 95% CI [0.511, 1.135]), and self-efficacy ($p = 0.016$, $\eta^2 = 0.081$, 95% CI [0.383, 0.931]) compared to the control group post-intervention.

As predicted by H1c, no significant difference was found between the two groups in intrinsic load ($p = 0.551$, $\eta^2 = 0.005$, 95% CI [−0.510, 0.041]). This indicates that both groups faced engineering design tasks of comparable inherent complexity, and the introduction of the mobile AI scaffold did not alter the nature of the tasks themselves. Instead, it functioned by optimizing the distribution of cognitive load.

Table 2 presents the comparison of project outcomes between the experimental and control groups, providing partial support for H3. The experimental group scored significantly higher than the control group in novelty ($p = 0.004$, $\eta^2 = 0.114$, 95% CI [0.320, 1.615]) and extensibility ($p = 0.004$, $\eta^2 = 0.114$, 95% CI [0.315, 1.581]), as well as in overall quality ($p = 0.013$, $\eta^2 = 0.087$, 95% CI [0.149, 1.195]). These results suggest that the mobile AI scaffold effectively enhanced students' creative design and system integration capabilities. No significant difference was found in usability ($p = 0.298$, $\eta^2 = 0.016$, 95% CI [−0.219, 0.705]), indicating that usability, as a fundamental requirement of engineering design, was achieved at a comparable competent level by both groups through project practice. In contrast, the scaffolding provided by the intelligent learning companion more effectively stimulated students' performance in higher-order dimensions such as innovation and extensibility.

Table 2. Comparison of project design outcomes (post-test only)

Variable	Experimental (M±SD)	Control (M±SD)	F	p	η^2
Project Novelty	7.24±1.92	6.27±1.82	8.89	0.004**	0.114
Project Usability	7.84±1.07	7.60±0.83	1.102	0.298^{ns}	0.016
Project Extensibility	7.71±1.69	6.76±1.89	8.915	0.004**	0.114
Overall Quality	7.62±1.25	6.95±1.19	6.571	0.013*	0.087

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. ns indicates non-significant ($p > 0.05$).

The correlation analysis matrix (Fig. 3) presents correlation coefficients in the upper triangle (with colors indicating the degree of correlation), scatter plots of samples in the lower triangle, and variable distribution histograms along the main diagonal. The results show significant correlations among all variables ($p < 0.05$). Specifically, strong correlations are observed between project quality and extraneous cognitive load ($R = −0.78$) and between project quality and germane cognitive load ($R = 0.80$), indicating that lower extraneous load and higher germane load are associated with greater improvements in project quality. Moderate correlations (0.50–0.69) are found between project quality and motivation ($R = 0.67$) as well as self-efficacy ($R = 0.56$), suggesting notable interactions among these variables. Weak correlations (0.30–0.49) indicate certain associations among variables, though with limited strength. Overall, the widespread and significant correlations among the variables further reveal the interplay of various factors throughout the engineering design process.

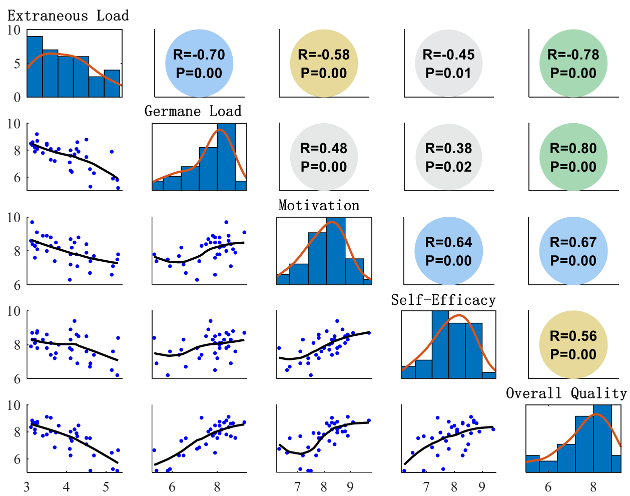

Fig. 3. Correlation matrix of key study variables.

B. Design Thinking Processes: Qualitative Evidence

Beyond product-oriented outcomes, interview data revealed how the scaffold shaped students' design thinking processes—directly addressing the process-dimension indicators of H3 (design reasoning, iteration patterns, and metacognitive reflection). Three recurring patterns were identified.

(1) Problem identification and framing. Students described using the scaffold to clarify ambiguous project requirements. One participant noted: "When I first read the project brief, I wasn't sure what 'line-tracking' really meant in practice. I asked DesignMate to break down the problem into sub-tasks, and it helped me see that I needed to think about sensor placement, algorithm logic, and motor control separately. That changed how I approached the whole project". This illustrates how Concept Integration Scaffolds supported problem decomposition.

(2) Iterative prototyping and debugging. The Hardware Troubleshooting and Code Diagnosis functions facilitated rapid iteration cycles. A student explained: "Before, when my circuit didn't work, I'd spend hours checking every connection randomly. With the scaffold, I could describe the symptoms and get a systematic debugging checklist. It didn't give me the answer directly but helped me think through possible failure points methodically". This pattern reflects the scaffold's role in structuring iterative testing—consistent with design thinking's emphasis on "fail fast, learn fast".

(3) Metacognitive reflection and design justification. The Project Management prompts encouraged students to articulate design rationale. One high-performing student stated: "The question 'What assumptions are you making about user needs?' made me realize I had designed the car for ideal conditions, not real-world environments. I went back and added obstacle detection because of that prompt." This demonstrates how metacognitive scaffolds triggered reflective practice, a hallmark of expert design thinking.

Collectively, interview findings complement the product-oriented results and fully support H3 from the process dimension.

C. Scaffold Usage Dynamics

Analysis of system logs revealed evolving patterns of learner-scaffold interaction, indicating developmental trajectories toward self-regulation.

First, prompt frequency varied significantly across project phases. During the problem definition stage, frequency was high ($M = 4.2$ prompts/day), with predominantly open-ended queries such as "How should I approach this project?" In the prototyping stage, frequency moderated ($M = 2.8$ prompts/day), shifting toward technical implementation questions like "Why is my infrared sensor not detecting the line?" Finally, in the testing/refinement stage, frequency declined ($M = 1.5$ prompts/day), accompanied by increased self-directed queries, for example, "Verify my reasoning about why the car drifts on curves."

Second, prompt complexity evolved over time. Early prompts were predominantly comprehension-level (62% in Week 2: "What is a PID controller?"), whereas late prompts shifted to analysis/evaluation-level (71% in Week 5: "Compare PID and fuzzy control for my specific scenario"). This shift suggests that as domain competence developed, students used the scaffold for higher-order thinking rather than basic information retrieval.

Taken together, the declining frequency and increasing higher-order thinking are consistent with the "fading" construct in scaffolding theory—the gradual withdrawal of support as learner competence increases. Notably, this fading emerged from students' changing query patterns rather than algorithmic reduction of support, raising interesting questions about intentional versus emergent scaffold regulation in AI systems.

D. Discussion

This study provides robust empirical evidence for the effectiveness of a mobile AI scaffold in enhancing engineering students' design thinking. The findings illuminate the underlying mechanisms through three interconnected lenses.

1) Cognitive load optimization as a foundation for design thinking

The mobile AI scaffold successfully restructured students' cognitive load profiles and validated Hypothesis 1 (H1). It significantly reduced extraneous cognitive load while elevating germane cognitive load, which aligns with classic CLT scholarship asserting that well-designed instructional scaffolding minimizes irrelevant cognitive distractions and redirects mental resources to deep learning [26, 27]. Consistent with Sharma and Hannafin [41] and Sun *et al.* [42], Technology-Supported Scaffolds (TSS) outperform traditional static paper-based or fixed digital supports by delivering dynamic, context-adaptive guidance tailored to real-time learner needs. This adaptive nature largely accounts for the moderate-to-large effect sizes observed in the present study.

The significant increase in germane load carries particular theoretical and empirical value. Although CLT posits that reduced extraneous load enables learners to allocate cognitive resources to schema construction and knowledge internalization [27], prior empirical reviews on technology-enhanced scaffolding noted that most studies focused only on cognitive outcome gains, with limited evidence germane load redistribution in project-based design contexts [21]. Our results confirm that metacognitive embedded prompts and reflective guidance within the mobile AI scaffold effectively directed students' attention toward design rationale elaboration and systematic design evaluation.

The non-significant difference in intrinsic load is also theoretically meaningful. The AI scaffold optimized cognitive resource allocation without simplifying the inherent complexity of engineering design tasks. This finding corroborates the consensus in scaffolding research that effective technology-supported interventions regulate extraneous load rather than lowering task intrinsic difficulty, preserving authentic disciplinary challenge while lowering unnecessary cognitive barriers [28].

2) Motivational enhancement through basic psychological needs satisfaction

Optimized cognitive load was positively associated with improved learning motivation and self-efficacy, fully supporting H2. This result extends CLT-SDT integrated perspectives and echoes SDT core propositions on autonomy, competence, and relatedness [38]. Reduced extraneous load strengthened students' perceived competence in design tasks;

the mobile AI scaffold's ubiquitous accessibility and timely positive feedback fulfilled interpersonal relatedness needs; learner-initiated interactive questioning and personalized support further bolstered learner autonomy—an aspect often constrained by rigid, fixed traditional scaffolds [41].

Notably, qualitative interview data uncovered distinct affective scaffolding effects beyond pure cognitive regulation, which has long been understudied in prior TSS literature. Participants perceived the mobile AI scaffold as an emotional "learning companion" that relieved frustration and sustained engagement during iterative design difficulties. Our study proves that GenAI-enabled mobile scaffolds can simultaneously undertake cognitive support and affective motivational functions, blurring the traditional binary boundary between cognitive and affective scaffolding and enriching the dimensional classification of scaffolding design.

3) From cognitive-motivational gains to design thinking outcomes

The synergy between optimized cognitive resources and enhanced motivation translated into superior design outcomes-supporting H3 across both product and process dimensions. The experimental group outperformed the control group in novelty and extensibility, indicating that cognitive surplus was channeled into creative exploration and forward-looking design. Process evidence further confirmed enhanced design reasoning, iteration patterns, and metacognitive reflection, the process-dimension indicators of H3.

Interestingly, no significant between-group difference was found in basic usability performance. This non-significant finding is theoretically enlightening and resolves potential contradictions with prior TSS studies. As summarized by Sun *et al.* [42], existing technology-supported scaffolding research predominantly concentrates on basic cognitive and skill gains while paying insufficient attention to higher-order competencies such as creative thinking and innovative design expansion. In this sense, basic usability can be regarded as a routine baseline competency acquired through general project practice. The core added value of the adaptive AI scaffold lies in freeing cognitive resources to support innovative exploration and advanced design thinking development, rather than merely improving fundamental task performance. This explains why usability showed no significant group difference whereas design novelty and extensibility differed substantially.

E. Limitations and Critical Reflections

1) Limitations of the study

First, measurement limitation: This study adopted self-report scales to assess cognitive load, motivation and self-efficacy, which may be affected by social desirability and retrospective bias. Future research can combine physiological indicators and behavioral logs to achieve multi-method triangulation.

Second, sample limitation: Participants were recruited from a single university cohort, which restricts the generalizability of the findings to other disciplines, institutions and cultural backgrounds.

Third, pedagogical limitation: This study did not explore the optimal collaborative relationship between AI scaffolding and human instruction. Interview evidence indicated that students relied on AI for routine support but still turned to teachers for complex decision-making, suggesting that AI cannot fully replace instructional guidance.

2) Critical reflections on educational application

With the widespread adoption of generative AI in education, it is necessary to reflect on its practical challenges beyond effectiveness validation.

On learner development: A small proportion of students showed over-reliance on AI outputs, passively accepting suggestions without critical reasoning. Such dependence may weaken students' epistemic agency and the ability of independent critical thinking in long-term learning.

On teacher role transformation: The integration of AI scaffolds reshapes teachers' roles from traditional knowledge deliverers to learning experience designers and AI interaction supervisors. Teachers need to monitor AI-generated errors and misconceptions, and organize peer discussions that AI cannot substitute, forming a complementary human-AI teaching ecology.

VI. Conclusion

This study investigated the impact of a mobile AI scaffold on students' cognitive load and design thinking within an engineering project-based learning context. The results demonstrate that the mobile AI scaffold, DesignMate, significantly reduced extraneous cognitive load, increased germane cognitive load, and enhanced students' motivation, self-efficacy, as well as the novelty and extensibility of their design projects. These findings provide strong empirical support for the use of AI-powered mobile tools as effective pedagogical scaffolds in engineering education, directly contributing to the cultivation of design thinking competencies.

Despite these limitations, this study makes a significant contribution by offering a theoretically grounded, empirically validated framework for designing and implementing mobile AI scaffold. It paves the way for a new generation of pedagogical tools that can empower engineering students to become more creative, reflective, and capable problem-solvers in authentic engineering practice.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Hongyan Li conceptualized the study, designed the research framework, developed the mobile AI scaffold, and wrote the original draft. Maixia Fu supervised the research, provided project administration, and reviewed and edited the manuscript. Yu Yang conducted the quasi-experiment, performed data collection and analysis, and contributed to the interpretation of results. Hongyue Liu assisted in data analysis, and revised the manuscript. All authors have read and approved the final version of the manuscript.

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