MODESTUM EURASIA Journal of Mathematics, Science and Technology Education, 2026, 22(10), em2927
ISSN:1305-8223 (online)
OPEN ACCESS Research Paper https://doi.org/10.29333/ejmste/19399

Artificial intelligence as cognitive scaffolding in the engineering design process: A STEM education perspective

Nguyen Chi Le [1], Nhung Hong Thi Chu [1*], Ha Thi Nguyen [1], Dung Hong Thi Le [2], Nga Thuy Thi Tran [3], Quyen Hoai Thi Nguyen [4]

[1] University of Education – Vietnam National University, Hanoi, VIETNAM
[2] Faculty of Tourism and Hotel-Restaurant Management, Nam Can Tho University, Can Tho, VIETNAM
[3] Vinh University, Nghe An Province, VIETNAM
[4] Nghe An University, Nghe An Province, VIETNAM

Received 21 May 2026 ▪ Accepted 09 September 2026

Abstract

Artificial intelligence (AI) is increasingly used in STEM education; however, limited evidence explains how it functions as cognitive scaffolding within the engineering design process. This study examined the effects of AI-supported scaffolding on students' problem-solving competence, engineering design performance, and redesign competencies. A quasi-experimental pre-/post-test control group design was used, involving 124 lower-secondary students completing a six-week hydraulic robotic arm project. The experimental group received AI support during solution selection and prototype improvement, whereas the control group received conventional instructional resources. Data were collected using an eight-dimensional engineering design rubric and analyzed using t-tests, analysis of covariance, and effect size statistics. After controlling for baseline differences, the experimental group significantly outperformed the control group in problem-solving competence, $F(1, 121) = 30.35$, $p < .001$, partial $\eta^2 = .348$; engineering design performance, $F(1, 121) = 42.43$, $p < .001$, partial $\eta^2 = .420$; and redesign competence, $F(1, 121) = 16.94$, $p < .001$, partial $\eta^2 = .118$. The strongest improvements were observed in solution selection, problem understanding, scientific reasoning, and reflective reasoning. These outcome-level findings are consistent with the proposed role of conversational AI as adaptive cognitive scaffolding in STEM education. However, because the student-AI interaction processes were not directly measured, the results should not be interpreted as an empirical verification of the scaffolding mechanism.

Keywords: artificial intelligence, cognitive scaffolding, engineering design process, problem-solving competence, STEM education

INTRODUCTION

Science, technology, engineering, and mathematics (STEM) education has increasingly emphasized the development of students' problem-solving competence, engineering reasoning, creativity, and higher-order thinking skills required in the 21st century (Bybee, 2010; Honey et al., 2014). Contemporary STEM instruction no longer focuses solely on disciplinary knowledge acquisition but increasingly prioritizes authentic problem-solving and engineering design experiences that require students to investigate problems, generate solutions, construct prototypes, test designs, and improve products through reasoning (Kelley & Knowles, 2016; National Research Council, 2012). From this perspective, the engineering design process (EDP) has become one of the most widely adopted pedagogical frameworks for organizing STEM learning activities because it engages students in recursive cycles of designing, testing, evaluating, and redesigning engineering solutions (Dym et al., 2005).

✉ Lcnguyendhhl@gmail.com ✉ chunhung@vnu.edu.vn **(*Correspondence)** ✉ nguyenha27579@vnu.edu.vn
✉ lthdung@nctu.edu.vn ✉ tttnga@vinhuni.edu.vn ✉ quyennth@nau.edu.vn

Contribution to the literature

- This study conceptualizes conversational AI as targeted cognitive scaffolding within STEM-oriented engineering design.
- It proposes a pedagogical approach for selectively integrating AI into the critical stages of the EDP in STEM education.
- It provides empirical evidence of improved problem-solving, engineering design, and redesign competence among upper-secondary students.

Despite the growing popularity of EDP-oriented STEM instruction, many students experience substantial difficulties during engineering design activities, particularly in the prototype evaluation and iterative redesign stages (Crismond & Adams, 2012; Kolodner et al., 2003). In many classroom contexts, students can construct initial prototypes but struggle to identify technical weaknesses, compare alternative solutions, justify engineering decisions and refine designs based on testing evidence. Consequently, STEM activities often become product-oriented rather than reasoning-oriented, with limited reflective analysis and insufficient improvement. These challenges are especially evident among secondary school students with limited prior engineering experience and underdeveloped metacognitive regulation skills (English & King, 2015). Without adequate cognitive support, learners may experience cognitive overload when simultaneously coordinating scientific reasoning, technical decision-making, and prototype refinement (Sweller, 1988).

To address these challenges, researchers have increasingly emphasized the importance of cognitive scaffolding in STEM learning. Cognitive scaffolding refers to the temporary support that enables learners to perform cognitively demanding tasks beyond their independent capabilities (Wood et al., 1976). Grounded in socio-constructivist theory, scaffolding supports learners' reflective thinking, inquiry regulation, and problem-solving processes through guided interactions (Vygotsky, 1978). In engineering education, scaffolding is particularly important because engineering design involves continuous cycles of evaluation, justification, testing, and redesigning (Hmelo-Silver et al., 2007). Previous studies have shown that effective scaffolding can significantly improve students' reasoning quality, inquiry engagement, and problem-solving performance in STEM learning contexts (e.g., Belland et al., 2013).

Recent advances in artificial intelligence (AI), particularly in conversational AI systems such as ChatGPT, have created new opportunities for adaptive cognitive scaffolding in STEM education (Kasneci et al., 2023). Conversational AI systems can provide real-time feedback, explanatory prompts, reflective questioning, and adaptive support during complex learning activities (Dwivedi et al., 2023; Tlili et al., 2023). Through natural language interaction, AI may help students compare design alternatives, analyze prototype weaknesses, explain engineering principles, and support reflective redesign processes. From the perspective of distributed cognition theory, cognitive processes are distributed across individuals, technological tools, and learning environments, rather than residing solely within the learner (Hutchins, 1995; Salomon, 1993). Consequently, conversational AI systems may function as external cognitive resources that extend students' reflective engineering reasoning during STEM problem-solving.

However, despite the increasing interest in AI-supported education, existing applications of AI in STEM learning remain largely dominated by information retrieval, automated tutoring, and answer-generation functions (Holmes et al., 2019; Zawacki-Richter et al., 2019). In many educational contexts, students use AI primarily to obtain direct answers or ready-made solutions rather than engaging in reflective reasoning and iterative engineering thinking. Such use may unintentionally reduce opportunities for independent analysis, design justification, and metacognitive regulation during engineering problem-solving activities. Comparatively limited research has investigated how conversational AI can support iterative engineering reasoning processes, particularly during cognitively demanding stages, such as solution comparison, prototype evaluation, and redesign. Moreover, insufficient empirical attention has been devoted to examining AI as reflective cognitive scaffolding embedded in authentic engineering design activities in secondary STEM education.

This study addresses this research gap by conceptualizing AI not as an automated problem-solving system but as adaptive cognitive scaffolding integrated into the EDP in STEM education. Unlike AI-supported approaches that generate complete solutions or replace learners' thinking processes, the present study positions AI as a reflective engineering support tool used only during two critical design stages:

(1) comparing and selecting design alternatives and

(2) improving existing prototypes after testing.

In this framework, AI supports students in analyzing engineering problems, evaluating design feasibility, identifying technical weaknesses, and refining prototypes through reasoning, without generating entirely new engineering principles or replacing students' decision-making processes.

The theoretical foundation of this study integrates socio-constructivist theory, scaffolding theory, distributed cognition theory, and engineering design perspectives. Socio-constructivist theory explains how guided interaction supports learners' cognitive development within the zone of proximal development (ZPD) (Vygotsky, 1978). Scaffolding theory emphasizes the role of temporary support in enhancing learners' reasoning during complex tasks (Wood et al., 1976). The distributed cognition theory conceptualizes technological tools as external cognitive resources that extend human thinking processes (Hutchins, 1995). Finally, engineering design perspectives emphasize reasoning, testing, evaluation, and redesign as core processes in STEM learning (Dym et al., 2005). Integrating these perspectives provides a theoretical basis for examining AI-supported engineering design as a scaffolded, reflective reasoning process.

Therefore, this study investigates the role of AI as cognitive scaffolding in EDP-oriented STEM learning activities. Specifically, this study examined the effects of AI-supported scaffolding on students'

(1) problem-solving competence,

(2) engineering design performance, and

(3) iterative redesign competence during STEM engineering design activities involving robotic arm prototype construction.

The following research hypotheses are proposed:

H1. Students participating in AI-supported engineering design activities demonstrated higher problem-solving competence than those receiving conventional STEM instruction.

H2. Students receiving AI-supported guidance demonstrated higher engineering design performance during solution selection and prototype construction than those receiving conventional STEM instruction.

H3. Students participating in AI-supported engineering design activities demonstrated higher levels of prototype evaluation and iterative redesign competence than those in conventional STEM learning environments.

This study contributes to the emerging field of AI-supported STEM education by proposing a theoretical and empirical framework for integrating conversational AI into engineering design learning as reflective cognitive scaffolding, rather than automated answer generation. The findings are expected to provide theoretical insights into AI-mediated engineering reasoning and practical implications for designing STEM learning environments that promote reflective problem-solving, iterative redesign thinking, and higher-order engineering competence.

LITERATURE REVIEW

Engineering Design Process in STEM Education

The EDP has become one of the most influential instructional frameworks in contemporary STEM education because it promotes authentic problem-solving, engineering reasoning, and learning through design activities (Dym et al., 2005). Unlike traditional teacher-centered instruction, EDP-oriented STEM learning emphasizes recursive cycles of identifying problems, generating solutions, constructing prototypes, testing designs, evaluating evidence, and redesigning products based on constraints and performance outcomes (Crismond & Adams, 2012). From this perspective, engineering learning is not conceptualized as a linear process of obtaining correct answers but as a reasoning process that requires continuous reflection and refinement.

Previous studies have consistently shown that EDP-based STEM instruction can positively influence students' problem-solving competence, scientific reasoning, creativity, and higher order thinking skills (Kelley & Knowles, 2016; Moore et al., 2014). Engineering design activities also create opportunities for students to integrate disciplinary knowledge through collaboration, reflective experimentation, and evidence-based decision-making (English & King, 2015). Furthermore, engineering design has been recognized as a core scientific and engineering practice within K-12 STEM education because it engages learners in authentic inquiry and problem-solving (National Research Council, 2012).

However, despite broad agreement regarding the educational value of the EDP, existing research has identified persistent difficulties in effectively implementing engineering design in STEM classrooms. Engineering design tasks are frequently ill-structured, cognitively demanding, and characterized by multiple constraints and competing solutions (Jonassen, 2011). Consequently, students often experience difficulties in evaluating alternative solutions, interpreting testing evidence, and systematically revising prototypes during redesign processes (Kolodner et al., 2003). Crismond and Adams (2012) argued that novice learners frequently focus on constructing products rapidly rather than engaging in informed engineering reasoning and reflective redesign.

Importantly, existing STEM studies reveal a contradiction between the theoretical emphasis on engineering reasoning and the actual implementation of engineering activities in the classroom. Although EDP frameworks conceptually prioritize redesign, reflective evaluation, and recursive improvement, many classroom STEM activities remain strongly product-oriented and linear in practice. Students often construct initial prototypes but perform only limited redesigns and evidence-based refinements. Consequently, engineering reasoning, one of the most theoretically important dimensions of EDP, remains insufficiently developed in many STEM learning environments. This unresolved issue suggests the need for more effective cognitive support mechanisms that sustain reflective reasoning during the prototype evaluation and redesign stages.

Cognitive Scaffolding and Reflective Engineering Reasoning

Cognitive scaffolding refers to temporary support that enables learners to perform cognitively demanding tasks beyond their independent capabilities (Wood et al., 1976). Grounded in Vygotsky's (1978) socio-constructivist theory, scaffolding supports learners' cognitive development through guided interaction within the ZPD. In STEM learning environments, scaffolding is widely recognized as an important mechanism for supporting inquiry processes, problem-solving, and metacognitive regulation (Hmelo-Silver et al., 2007).

Within engineering design contexts, scaffolding is particularly important because engineering reasoning requires students to simultaneously coordinate scientific understanding, design evaluation, testing evidence, and iterative redesign. Students must continuously compare alternatives, identify technical weaknesses, justify engineering decisions, and refine prototypes based on the evidence and constraints (Crismond & Adams, 2012). Without sufficient support, learners may experience an excessive cognitive load during these recursive reasoning processes (Sweller, 1988). Consequently, scaffolding may help students sustain reflective engagement while managing the complexities of engineering problem-solving.

Research on scaffolded STEM learning has generally demonstrated positive effects on inquiry competence, reasoning quality, conceptual understanding, and problem-solving performance (Belland et al., 2013). In particular, computer-based scaffolding has been shown to support learners during complex cognitive tasks by providing adaptive prompts, feedback, and guidance. Scaffolding is also associated with metacognitive regulation because it encourages learners to monitor, evaluate, and revise their cognitive strategies during problem-solving activities (Schraw & Dennison, 1994; Zimmerman, 2000).

Nevertheless, existing scaffolding research has primarily focused on inquiry learning, conceptual understanding, and general problem-solving support rather than specifically on engineering reasoning. Comparatively limited attention has been devoted to understanding how scaffolding may support redesign cognition, prototype refinement, and reflective engineering evaluation during EDP activities in the literature. Moreover, many scaffolded STEM interventions emphasize procedural guidance rather than supporting reflective decision making and evidence-based redesign. This reveals another unresolved issue in STEM education research: Although redesign is theoretically central to engineering learning, relatively few studies have examined how adaptive cognitive scaffolding can sustain iterative engineering reasoning processes in authentic classroom settings.

Theoretical perspectives on distributed cognition further extend this discussion by conceptualizing cognition as being distributed across individuals, technological tools, and learning environments, rather than residing solely within the learner (Hutchins, 1995; Salomon, 1993). From this perspective, technological systems may function as external cognitive resources that support reflective reasoning and decision making during engineering activities. This theoretical orientation provides an important foundation for examining the role of conversational AI systems as adaptive cognitive scaffolding in STEM learning.

Artificial Intelligence as Cognitive Scaffolding in STEM Education

Recent advances in AI, particularly conversational AI systems, have created new possibilities for adaptive learning support in STEM education (Kasneci et al., 2023). Unlike traditional digital learning technologies, conversational AI systems can generate real-time responses, explanatory feedback, reflective prompts, and adaptive guidance through natural language interactions (Dwivedi et al., 2023). Consequently, AI systems have increasingly been conceptualized as cognitive partners capable of supporting inquiry learning, metacognitive regulation, and problem-solving (Holmes et al., 2019; Luckin, 2018).

Existing research suggests that AI-supported learning environments may positively influence engagement, self-regulated learning, reasoning quality, and academic performance (Tlili et al., 2023; Zawacki-Richter et al., 2019). Conversational AI systems may support learners by explaining concepts, interpreting information, providing immediate feedback, and guiding reflective thinking during cognitively demanding tasks. Within STEM education, AI may also help students compare engineering alternatives, analyze technical problems, interpret testing evidence, and iteratively improve prototypes.

However, despite these potential benefits, important contradictions and concerns remain unresolved in the current AI-supported STEM research. Most existing applications of AI in education continue to emphasize automated tutoring, information retrieval, instructional efficiency, and answer generation rather than reflective engineering cognition. In many classroom contexts, AI is primarily used as a tool to obtain immediate answers or generate solutions automatically. Such use may unintentionally reduce students' independent reasoning, metacognitive engagement, and problem-solving processes if they passively rely on AI-generated outputs (Kirschner et al., 2006; Rudolph et al., 2023).

This contradiction is particularly significant in engineering design learning. Engineering reasoning fundamentally depends on reflective evaluation, redesign, and evidence-based decision-making, whereas many AI-supported educational applications prioritize efficiency and rapid solution generation. Consequently, there is limited understanding of how conversational AI can support iterative engineering reasoning without replacing students' cognitive engagement. Existing research has devoted comparatively little attention to how AI may function as reflective cognitive scaffolding embedded within authentic EDP-oriented STEM activities, particularly during cognitively demanding stages, such as solution comparison, prototype testing, and redesign.

The present study addresses this unresolved issue by conceptualizing conversational AI not as an automated problem-solving substitute, but as adaptive cognitive scaffolding integrated within EDP-oriented STEM learning. Specifically, AI is positioned as a reflective engineering support tool that assists students during two critical engineering stages:

(1) comparing and selecting design alternatives and

(2) improving existing prototypes after testing.

Rather than generating entirely new engineering solutions, the AI-supported scaffolding in this study focused on supporting reflective reasoning, evidence-based evaluation, and redesign processes during authentic STEM engineering activities.

THEORETICAL FRAMEWORK

This study proposes a theoretical framework in which AI functions as adaptive cognitive scaffolding embedded within the EDP to enhance students' engineering reasoning and problem-solving competence in STEM education. The framework is grounded in the socio-constructivist, scaffolding, and distributed cognition theories, and engineering design perspectives. It conceptualizes AI not as a replacement for human thinking but as a cognitive partner that supports reflective reasoning during the critical stages of engineering design activities.

The framework is primarily informed by Vygotsky's (1978) socio-constructivist theory, which emphasizes that learners achieve higher cognitive performance through guided interaction within the ZPD. Extending this perspective, Wood et al. (1976) conceptualized scaffolding as a temporary support that enables learners to perform tasks beyond their independent cognitive capabilities. Scaffolding is particularly important in engineering design learning environments because students are required to coordinate scientific reasoning, design thinking, testing, and iterative redesign simultaneously (Crismond & Adams, 2012). Without sufficient cognitive support, learners may struggle to sustain reflective reasoning and effective decision-making during complex design tasks.

The framework is also supported by the distributed cognition theory (Hutchins, 1995), which conceptualizes cognition as distributed across individuals, tools, and learning environments rather than residing solely within the individual mind. From this perspective, AI systems function as external cognitive resources that extend learners' reasoning, reflection, and decision-making processes. Therefore, conversational AI systems may support students in evaluating design alternatives, visualizing prototype structures, interpreting engineering principles, and improving solutions iteratively throughout the design process.

Unlike generalized AI-supported instructional models, the present framework integrates AI selectively into two critical stages of the EDP:

(1) solution selection and

(2) prototype construction.

This selective integration is theoretically important because these stages often impose the greatest cognitive demands on students during STEM problem-solving (Jonassen, 2011). During solution selection, students must compare multiple alternatives, evaluate their feasibility, analyze constraints, and justify design decisions. During prototype construction, students must translate conceptual ideas into physical or functional models while simultaneously evaluating the structure, stability, efficiency, and testing outcomes. These activities require substantial reflective reasoning and regulations.

Accordingly, the proposed framework positions AI as adaptive cognitive scaffolding that supports learners during these cognitively demanding stages. During solution selection, AI-supported scaffolding may assist students in comparing engineering alternatives, evaluating trade-offs, clarifying design criteria, and selecting viable solutions. Through reflective prompting and explanatory guidance, AI systems may encourage students to justify their design decisions rather than simply accept the generated answers. During prototype construction, AI-supported scaffolding may support learners in visualizing structures, explaining design principles, identifying weaknesses in prototypes, and revising models based on the testing outcomes. Consequently, AI-supported scaffolding is expected to strengthen reflective engineering reasoning and iterative redesign.

The framework also emphasizes that AI should support, rather than replace, learners' cognitive activities. Consistent with recent educational

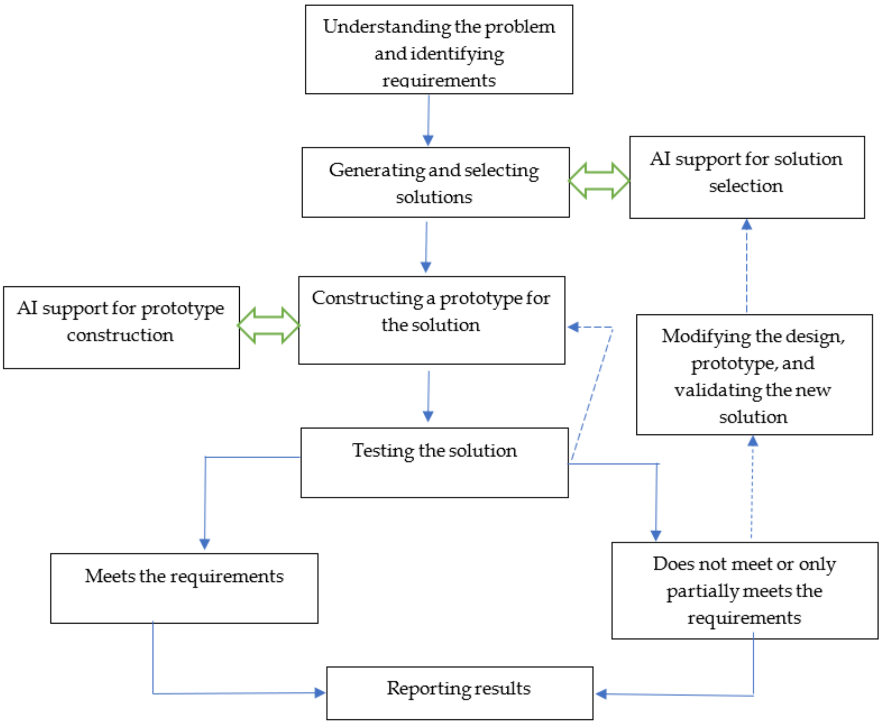

Figure 3. AI-supported EDP in STEM education (adapted from Dym et al., 2005; Kolodner, 2003; National Research Council, 2012)

psychology perspectives (Luckin & Holmes, 2016), the proposed model conceptualizes AI as a cognitive partner that facilitates reflective thinking, metacognitive engagement, and engineering reasoning while maintaining students' active participation in the problem-solving process. This perspective differs from automation-oriented approaches, in which AI primarily delivers information or generates direct solutions without promoting learner reflection.

Within the EDP, iterative redesign is a particularly important component of problem-solving development. As illustrated in the framework, students engage in recursive cycles of testing, evaluating, modifying, and reconstructing prototypes until the design satisfies the intended requirements. AI-supported scaffolding is expected to facilitate this recursive process by helping learners analyze weaknesses in solutions, interpret testing results, and identify potential improvements for the redesign. Consequently, AI-supported EDP may strengthen both engineering reasoning and problem-solving competencies.

Based on these theoretical foundations, this study proposes that AI-supported cognitive scaffolding enhances STEM learning by facilitating reflective engineering reasoning during critical stages of the design process. Specifically, AI-supported scaffolding is expected to improve students' problem-solving competence, engineering design performance, and iterative redesign ability through adaptive guidance during the solution selection and prototype construction. The theoretical framework of this study is illustrated in **Figure 1**.

METHOD

This study employed a quasi-experimental pre-/post-test control group design to examine the effects of AI-supported cognitive scaffolding integrated into the EDP on students' problem-solving competence, engineering design performance, and redesign competence.

A total of 124 grade 8 students participated in the study, including 62 students in the experimental group and 62 in the control group. Intact classes were selected using convenience sampling under normal conditions. Both classes followed the same STEM curriculum, were taught by the same teacher, and completed a pre-test to establish baseline equivalence before the intervention.

The six-week intervention centered on a STEM project in which students designed and constructed a hydraulic robotic arm (**Appendix A**). Both groups completed identical engineering design activities following the EDP. The experimental group received AI-supported cognitive scaffolding only during solution selection and prototype improvement, which are the two stages requiring the greatest engineering reasoning. Students used ChatGPT to compare alternative designs, justify engineering decisions, analyze prototype weaknesses, and propose evidence-based improvements. Typical prompts included *"Compare these two design alternatives and justify which better satisfies the engineering requirements"* and *"Identify weaknesses in our prototype and suggest improvements based on the testing results."* The AI system functioned as a reflective learning partner by providing questions, explanations,

Table 1. Performance assessment rubric for eight engineering design dimensions

Dimension	CA	M I-CVI	CK
Problem understanding	0.84	1.000	0.719
Scientific reasoning	0.82	0.917	0.794
Solution selection	0.88	1.000	0.774
Prototype construction	0.87	1.000	0.769
Prototype testing	0.84	1.000	0.797
Identification of design limitations	0.81	0.917	0.796
Redesign quality	0.89	1.000	0.732
Reflective reasoning	0.85	1.000	0.765

Note. CA: Cronbach's alpha; M I-CVI: Mean I-CVI; & CK: Cohen's κ

and feedback, rather than complete engineering solutions. The control group completed the same activities using teacher guidance, textbooks, and peer discussions without AI support.

Student performance was assessed using a performance-based rubric adapted from established STEM engineering design frameworks (Crismond & Adams, 2012; Kelley & Knowles, 2016; National Research Council, 2012). The rubric evaluates eight engineering design dimensions: problem understanding, scientific reasoning, solution selection, prototype construction, prototype testing, identification of design limitations, redesign quality, and reflective reasoning. Each dimension was scored on a four-level performance scale (**Table 1**).

The eight dimensions were subsequently grouped into three outcome variables: problem-solving competence, engineering design performance, and redesign competence. Content validity was established through expert review (mean I-CVI = .917-1.000), internal consistency was acceptable (Cronbach's α = .81-.89), and inter-rater reliability indicated substantial agreement (Cohen's κ = .719-.797).

Data were analyzed using R. Descriptive statistics and independent-samples t-tests were used to examine participant characteristics and baseline equivalence. The three composite outcomes were designated as the primary outcomes and analyzed using analysis of covariance (ANCOVA) with their corresponding pretest scores as covariates; the same model was retained for all three outcomes to ensure analytical consistency. Paired-samples t-tests were used to examine within-group improvement. The eight rubric dimensions were analyzed as secondary, exploratory posttest contrasts to describe the performance profile underlying the composite outcomes. Because eight comparisons were conducted, Holm-adjusted p-values were used to control the family wise error rate. These dimension-level contrasts were interpreted as descriptive follow-up evidence rather than as baseline-adjusted estimates of the intervention effect. Cohen's (1988) d and partial η^2 were reported as effect sizes. Statistical significance was set at $p < .05$. The assumptions of normality, homogeneity of variance, homogeneity of regression slopes, and independence were satisfactory.

RESULTS

Participant Characteristics and Baseline Equivalence

A total of 124 lower-secondary students participated in the study, with 62 students assigned to the control group and 62 students assigned to the experimental group. Sex distribution was generally comparable across the groups. The control group comprised 31 boys (50.0%) and 31 girls (50.0%), whereas the experimental group included 25 boys (40.3%) and 37 girls (59.7%) (**Table 2**).

Baseline equivalence was examined using independent-samples *t*-tests prior to the intervention. As shown in **Table 2**, the two groups demonstrated similar levels of redesign competence in the pre-test, $t(121.51) = 0.13$, $p = .893$, with a negligible effect size ($d = 0.02$), suggesting that students entered the study with nearly identical abilities in evaluating and improving engineering solutions.

However, statistically significant baseline differences were observed for problem-solving competence, $t(121.88) = -2.47$, $p = .015$, $d = 0.44$, and engineering design performance, $t(121.23) = -2.31$, $p = .023$, $d = 0.41$. In both cases, the experimental group obtained slightly higher pre-test scores than the control group. Nevertheless, the corresponding effect sizes were small to moderate, indicating modest rather than substantial differences between the groups before the intervention.

Because significant pre-intervention differences were identified for two of the three primary outcomes, subsequent analyses employed ANCOVA, with pre-test scores entered as covariates. This analytical approach adjusts posttest comparisons for initial group differences, thereby providing a more rigorous estimate of the intervention effect and reducing the potential influence of baseline variability on the interpretation of instructional outcomes. Consequently, all between-

Table 2. Participant characteristics and baseline equivalence

Characteristic	Control	Experimental	t	df	p	Cohen's d
Sample size, n	62	62				
Boys, n (%)	31 (50.0%)	25 (40.3%)				
Girls, n (%)	31 (50.0%)	37 (59.7%)				
Problem-solving competence (pre-test)	2.90 (0.46)	3.10 (0.44)	-2.47	121.88	.015	0.44
Engineering design performance (pre-test)	2.96 (0.53)	3.17 (0.48)	-2.31	121.23	.023	0.41
Redesign competence (pre-test)	2.96 (0.52)	2.95 (0.48)	0.13	121.51	.893	0.02

Table 3. ANCOVA for the three primary outcomes

Outcome	F	p	Partial η^2
Problem-solving competence	30.35	< .001	0.348
Engineering design performance	42.43	< .001	0.420
Redesign competence	16.94	< .001	0.118

group comparisons of the primary outcome variables reported in the following sections are based on adjusted post-test scores rather than raw post-test means. This approach is widely recommended for quasi-experimental pre-/post-test designs in educational research because it improves the validity of treatment effect estimation when complete randomization is not feasible.

Effects of AI-Supported Cognitive Scaffolding on the Three Primary Outcomes

To examine the effectiveness of AI-supported cognitive scaffolding, one-way ANCOVA were conducted for the three primary outcome variables, with pretest scores entered as covariates to adjust for baseline differences identified before. This procedure enabled a more rigorous comparison of post-test performance by controlling for initial variability between the experimental and control groups.

As presented in **Table 3**, statistically significant treatment effects were observed across all three outcome measures after adjusting for pre-test performance. Students who participated in AI-supported STEM instruction demonstrated significantly higher adjusted post-test scores than those who received conventional STEM instruction.

The largest intervention effect was found for engineering design performance, $F(1, 121) = 42.43$, $p < .001$, with a partial η^2 of .420, indicating that approximately 42.0% of the variance in adjusted post-test engineering design performance was attributable to the instructional intervention. According to the commonly accepted benchmarks for partial η^2, this represents a large educational effect, suggesting that AI-supported cognitive scaffolding substantially enhanced students' ability to integrate scientific reasoning with engineering design practices. Similarly, problem-solving competence showed a highly significant treatment effect, $F(1, 121) = 30.35$, $p < .001$, with a partial η^2 of .348. This result indicates that AI-supported learning accounted for approximately 34.8% of the variance in students' adjusted posttest problem-solving competence after controlling for initial differences. The magnitude of this effect suggests that conversational AI effectively supports students in analyzing design problems, generating alternative solutions, and making evidence-informed engineering decisions throughout the EDP.

A statistically significant improvement was also observed for redesign competence, $F(1, 121) = 16.94$, $p < .001$, with a partial η^2 of .118. Although this effect was smaller than those obtained for the other two outcomes, it still represented a meaningful educational impact. Redesign competence involves critically evaluating prototype performance, identifying design limitations, and implementing improvements based on test evidence. These higher-order engineering practices generally require more sophisticated reflective thinking and reasoning, which may explain why improvements, although significant, were comparatively smaller in this study.

Overall, the ANCOVA results consistently supported the effectiveness of AI-supported cognitive scaffolding across all three primary outcome variables. The pattern of effect sizes further suggests that conversational AI exerted its strongest influence on students' engineering design performance and overall problem-solving competence while also producing meaningful improvements in iterative redesign ability. These findings provide strong empirical support for the first hypothesis that AI-supported STEM instruction leads to superior learning outcomes

Within-Group Pre-Post Improvement

Although the ANCOVA results demonstrated significant differences between the experimental and control groups after controlling baseline performance, additional paired-samples t-tests were conducted to examine the magnitude of learning gains within each group across the intervention period. This analysis provides complementary evidence regarding how students' competencies develop over time under the two instructional conditions.

As shown in **Table 4**, statistically significant improvements were observed in both the control and experimental groups across all three primary outcome variables. However, the magnitude of improvement differed substantially between the instructional conditions.

For problem-solving competence, students in the experimental group improved from 3.10 (standard deviation [SD] = 0.44) in the pretest to 3.73 (SD = 0.64) in the posttest, corresponding to a mean gain of 0.63 points. This improvement was highly significant, $t(61) = 11.97$, $p < .001$, with a very large within-group effect size (Cohen's $d = 1.52$). In comparison, students in the control group demonstrated a more modest increase from 2.90 (SD = 0.46) to 3.11 (SD = 0.56), yielding a mean gain of 0.21 points ($t[61] = 3.66$, $p < .001$, $d = 0.47$). Thus, although conventional STEM instruction contributed to measurable improvement, AI-supported cognitive scaffolding produced learning gains approximately three times greater than conventional STEM instruction.

A similar pattern emerged for the engineering design performance. The experimental group's mean score increased from 3.17 (SD = 0.48) to 3.83 (SD = 0.54), representing a mean gain of 0.66 points and an

Table 4. Within-group pre-post improvement

Outcome	Group	Pre M (SD)	Post M (SD)	Mean gain	t(61)	p	Cohen's dz
Problem-solving competence	Control	2.90 (0.46)	3.11 (0.56)	0.21	3.66	< .001	0.47
	Experimental	3.10 (0.44)	3.73 (0.64)	0.63	11.97	< .001	1.52
EDP	Control	2.96 (0.53)	3.17 (0.65)	0.22	4.27	< .001	0.54
	Experimental	3.17 (0.48)	3.83 (0.54)	0.66	13.79	< .001	1.75
Redesign competence	Control	2.96 (0.52)	3.09 (0.67)	0.14	2.07	.042	0.26
	Experimental	2.95 (0.48)	3.46 (0.59)	0.51	7.83	< .001	1.00

Note. M: Mean

Table 5. Comparison of eight engineering design dimensions

Dimension	Control M (SD)	Experimental M (SD)	MD	t	df	Cohen's d	Holm-adjusted p
Problem understanding	3.19 (0.58)	3.85 (0.73)	0.67	5.64	116.04	1.01	< .001
Scientific reasoning	3.10 (0.70)	3.72 (0.74)	0.61	4.73	121.68	0.85	< .001
Solution selection	3.17 (0.75)	3.96 (0.67)	0.79	6.19	120.72	1.11	< .001
Prototype construction	3.17 (0.73)	3.69 (0.59)	0.52	4.34	117.18	0.78	< .001
Prototype testing	3.05 (0.70)	3.53 (0.73)	0.48	3.76	121.71	0.67	< .001
Identification of design limitations	3.09 (0.73)	3.40 (0.76)	0.31	2.29	121.86	0.41	.024
Redesign quality	3.09 (0.84)	3.55 (0.63)	0.46	3.45	113.47	0.62	.002
Reflective reasoning	3.01 (0.58)	3.59 (0.77)	0.58	4.75	112.93	0.85	< .001

Note. M: Mean & MD: Mean difference

exceptionally large effect size ($t[61] = 13.79$, $p < .001$, Cohen's $d = 1.75$). In contrast, the control group showed a comparatively small improvement from 2.96 (SD = 0.53) to 3.17 (SD = 0.65) (mean gain = 0.22, $t[61] = 4.27$, $p < .001$, $d = 0.54$). The substantially larger effect observed in the experimental group indicates that AI-supported cognitive scaffolding was particularly effective in strengthening students' ability to integrate scientific concepts, engineering reasoning, and design decision-making throughout the EDP.

Comparable findings were obtained for redesign competence as well. Students receiving AI-supported instruction improved from 2.95 (SD = 0.48) to 3.46 (SD = 0.59), corresponding to a mean gain of 0.51 points ($t[61] = 7.83$, $p < .001$; Cohen's $d = 1.00$). Conversely, the control group demonstrated only a modest increase from 2.96 (SD = 0.52) to 3.09 (SD = 0.67) (mean gain = 0.14, $t[61] = 2.07$, $p = .042$, $d = 0.26$). Although both instructional approaches facilitated some improvement in students' ability to evaluate and refine engineering solutions, the effect associated with AI-supported learning was considerably larger.

Across all three outcomes, the experimental group consistently exhibited substantially greater learning gains and markedly larger effect sizes than the control group did. Whereas the effect sizes in the control group ranged from 0.26 to 0.54, those observed in the experimental group ranged from 1.00 to 1.75, representing large educational effects. These findings indicate that the advantages of AI-supported cognitive scaffolding extend beyond statistically significant group differences, producing meaningful improvements in students' problem-solving competence, engineering design performance, and iterative redesign capability over the duration of the intervention. Collectively, these results provide strong support for the effectiveness of AI-assisted reflective learning during engineering design activities and reinforce the conclusions drawn from ANCOVA analyses.

Comparison Across Eight Engineering Design Dimensions

As secondary analysis, post-test performance was examined across the eight rubric dimensions to describe which aspects of engineering design differed the most between groups. Independent-samples t-tests were used for these exploratory contrasts, and Holm's adjustment was applied across the eight tests. Because these comparisons were not adjusted for dimension-specific baseline scores, they complemented but did not replace the primary ANCOVA results.

As presented in **Table 5**, the experimental group achieved higher post-test scores than the control group in all eight engineering design dimensions, and all comparisons remained statistically significant after Holm correction. The magnitude of these differences varied across dimensions. Because these were secondary posttest contrasts, the results describe the observed outcome profile and should not be interpreted as direct evidence of the cognitive scaffolding process.

The largest improvement was observed for solution selection, where students receiving AI-supported instruction obtained a mean score of 3.96 (SD = 0.67) compared with 3.17 (SD = 0.75) in the control group, producing a mean difference of 0.79, $t(120.72) = 6.19$, $p < .001$, with a large effect size (Cohen's $d = 1.11$). This finding suggests that conversational AI substantially enhances students' ability to compare alternative design solutions, evaluate competing ideas using scientific evidence, and justify engineering decisions before prototype construction.

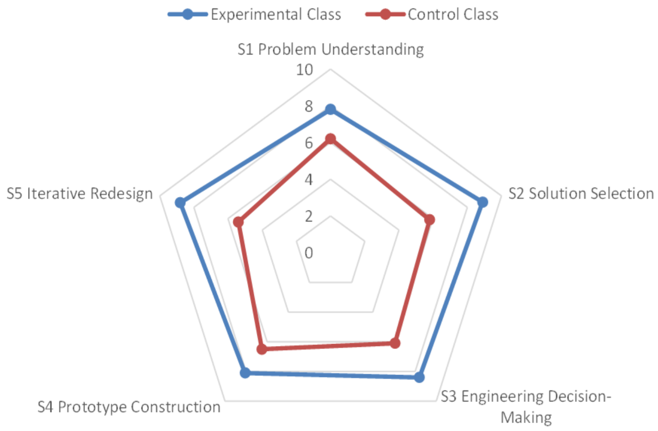

Figure 2. Radar-chart comparison of engineering reasoning competence between the experimental and control classes (the authors' own elaboration)

Similarly, problem understanding demonstrated a significant intervention effect. Students in the experimental group scored significantly higher than those in the control group (3.85 vs. 3.19), corresponding to a mean difference of 0.67, $t(116.04) = 5.64$, $p < .001$, and Cohen's $d = 1.01$. AI-supported questioning and reflective dialogue appear to have facilitated a deeper analysis of design constraints, enabling students to identify essential engineering requirements before initiating solution development.

Substantial improvements were also found in scientific and reflective reasoning, both of which yielded large educational effects ($d = 0.85$, $p < .001$). Students using AI demonstrated a greater ability to connect scientific concepts with engineering decisions, critically evaluate their reasoning, and justify modifications throughout the design process. These findings support the interpretation that conversational AI functions primarily as a cognitive scaffold that promotes higher-order thinking rather than providing direct answers.

Moderate intervention effects were identified for prototype construction ($d = 0.78$), prototype testing ($d = 0.67$), and redesign quality ($d = 0.62$), with all between-group differences being statistically significant ($p < .001$). Although these dimensions involve practical engineering activities, successful performance also depends on physical manipulation, collaboration, and material constraints. Consequently, AI support may have indirectly enhanced these competencies by improving planning, reflection, and evidence-based decision-making, rather than directly influencing hands-on construction skills.

The smallest, yet still statistically significant, effect was observed for the identification of design limitations, where the experimental group achieved a mean score of 3.40 ($SD = 0.76$) compared with 3.09 ($SD = 0.73$) in the control group, $t(121.86) = 2.29$, $p = .024$, with Cohen's $d = 0.41$. Identifying design weaknesses requires students to critically evaluate prototype performance, recognize subtle deficiencies, and integrate testing evidence into subsequent revisions. These complex evaluative processes typically develop gradually and often require repeated cycles of engineering practice, beyond a single instructional intervention.

Radar Chart Analysis

To complement the statistical comparisons presented in Table 5, a radar chart was constructed using the mean post-test scores of the experimental and control classes across five engineering reasoning dimensions: problem understanding (S1), solution selection (S2), engineering decision-making (S3), prototype construction (S4), and iterative redesign (S5) (**Figure 2**). Radar charts provide an effective way to compare multidimensional competence profiles because they simultaneously display strengths, weaknesses, and the overall balance of performance across multiple criteria (Cleveland & McGill, 1985; Friendly, 2008; Porter & Niksiar, 2018).

As shown in Figure 2, the experimental class displayed a substantially larger radar chart area than the control class across all five dimensions. Based on geometric estimation, the experimental class achieved an overall radar area of approximately 186.8 relative units, compared with 113.7 relative units for the control class, representing a difference of approximately 73.1 relative units. This larger and more balanced competence profile suggests that AI-supported cognitive scaffolding promotes integrated development across multiple engineering reasoning processes rather than isolated improvements.

The greatest differences occurred in solution selection (S2) and iterative redesign (S5), corresponding to the stages of the EDP that require analytical comparison, reflective evaluation, and evidence-based decision-making. These visual findings are consistent with the large effect sizes reported in Table 5, indicating that AI particularly enhanced students' ability to evaluate alternative solutions, justify engineering decisions, identify design limitations, and refine prototypes through improvement.

In contrast, the control class exhibited a smaller and less balanced competence profile, particularly in higher-order reasoning dimensions related to evaluation and redesign. Although students in both groups completed the same engineering design activities, those who received AI-supported instruction demonstrated stronger performance in tasks requiring comparison, reflection, and improvement.

Overall, the radar-chart analysis corroborates the statistical findings reported in Table 3-Table 5 by showing that conversational AI functioned as an adaptive cognitive scaffold that strengthened engineering reasoning and reflective problem-solving, rather than serving merely as a tool for answer generation or procedural guidance (Cleveland & McGill, 1985; Porter & Niksiar, 2018).

Table 6. Outcome-level evidence associated with the AI-supported intervention

Evidence level	Indicator	Estimate	Interpretation
Primary outcome	Problem-solving competence	Partial η^2 = .348	Large adjusted posttest difference
	EDP	Partial η^2 = .420	Largest adjusted post-test difference
	Redesign competence	Partial η^2 = .118	Meaningful but smaller adjusted difference
Dimension profile	Solution selection; problem understanding	d = 1.11; d = 1.01	Largest secondary post-test differences
	Identification of design limitations	d = .41; Holm p = .024	Smallest secondary post-test difference

Footnote in 8 punto

Table 6 shows the outcome-level evidence associated with the AI-supported intervention.

DISCUSSION

Students in the AI-supported condition achieved significantly better adjusted scores for the three primary outcomes. Large intervention effects were observed for engineering design performance (partial η^2 = .420) and problem-solving competence (partial η^2 = .348) in the experimental group. These outcome differences are consistent with, but do not verify, the proposed interpretation of conversational AI as cognitive scaffolding.

Unlike AI systems that primarily generate answers, the present intervention positions conversational AI as a reflective learning partner. Students were encouraged to analyze design problems, justify decisions, compare alternative solutions, and revise prototypes through dialogue. This instructional approach supports recent arguments that the educational value of generative AI depends on its role as an adaptive cognitive scaffold that stimulates learners' reasoning and reflection rather than replacing independent thinking.

The largest improvements were observed in solution selection, problem understanding, scientific reasoning and reflective reasoning. These competencies require students to evaluate evidence, compare alternatives, and justify engineering decisions, all of which involve higher order cognitive processes. AI-supported questioning appears to have strengthened these analytical and reflective activities by encouraging students to reconsider their assumptions and evaluate competing solutions before making design decisions.

Moderate improvements were found for prototype construction, prototype testing, and redesign quality, whereas the smallest effect was observed for the identification of design limitations. These dimensions depend not only on cognitive reasoning but also on hands-on experience, collaboration, and repeated testing cycles. Consequently, while AI effectively supported planning and reflection, mastery of practical engineering skills continued to rely on authentic design experiences. Similar findings have recently been reported in AI-supported STEM research, where the strongest effects have generally been observed for cognitive and metacognitive outcomes rather than manual design performance.

The conceptual contribution of this study is the distinction between AI as cognitive scaffolding and AI as an answer-generation tool. Conversational AI was intentionally integrated into the cognitively demanding phases of the EDP to encourage questioning, reflection, evidence evaluation, and redesign. The observed outcome pattern suggests that this instructional design may be productive; however, the present data do not directly establish which features of the student-AI interaction produced these gains.

From a practical perspective, STEM teachers should employ AI as a structured reflective partner, rather than allowing unrestricted answer generation. Prompt designs that encourage explanation, comparison, justification, and redesign can maximize students' engineering reasoning while reducing passive dependence on AI.

Limitations and Future Research

This study has several limitations. First, its quasi-experimental design in a single educational context limits the causal inference and generalizability. Second, the study measured learning outcomes but did not collect student-AI interaction logs or other process-level evidence for the same. Accordingly, the findings do not empirically verify that cognitive scaffolding is the mechanism responsible for the observed differences; cognitive scaffolding remains a theoretically grounded interpretation of the intervention. Future studies should analyze conversation logs, prompt-response sequences, think-aloud protocols, screen recordings, and interviews to examine how AI feedback shapes reasoning, decision-making, and redesign. Longitudinal research across STEM disciplines and educational levels is also required.

CONCLUSION

This study examined the effectiveness of AI-supported cognitive scaffolding integrated into the EDP in STEM education. The findings showed that students receiving AI-supported instruction achieved significantly higher problem-solving competence, engineering design performance, and redesign competence than those in conventional STEM classrooms. The largest improvements were observed in engineering design performance, with additional gains across the eight engineering reasoning dimensions, particularly in problem understanding, solution selection, scientific reasoning, and reflective reasoning. Radar chart analysis further indicated that AI promoted a more balanced profile of engineering competence.

Theoretically, this study conceptualizes conversational AI as adaptive cognitive scaffolding, rather than an answer-generation tool. Selective AI integration is associated with stronger reflective thinking, evidence-based decision-making, and engineering reasoning. Process-level studies are required to determine whether scaffolding mechanisms account for these outcome differences.

Practically, the findings suggest that AI should be used to facilitate questioning, comparison, reflection, and redesign rather than providing ready-made solutions. This approach enables AI to complement, rather than replace, students' engineering thinking during authentic STEM learning.

The study was limited to a quasi-experimental design in one educational context. Future research should examine the long-term impact of AI-supported cognitive scaffolding across different STEM disciplines, educational levels, and learning environments, while exploring its effects on creativity, self-regulated learning, and collaborative engineering design.

Author contributions: **NCL:** conceptualization, methodology, supervision, writing – original draft; **NHTC:** data curation, formal analysis, writing – original draft; **HTN** & **DHTL:** formal analysis; **NTTT** & **QHTN:** formal analysis, writing – review & editing. All authors agreed with the results and conclusions.

Funding: No funding source is reported for this study.

Ethical statement: This study was conducted in accordance with the ethical principles governing educational research involving human participants. Written informed consent was obtained from all participating students and their parents or legal guardians prior to data collection. Participation was voluntary, all data were anonymized before analysis, and confidentiality was maintained throughout the study period. The research complied with the institutional regulations of the participating school and the ethical principles of the Declaration of Helsinki, applicable to educational research.

AI statement: Selected sections were translated from Vietnamese to English using ChatGPT 5.0 and lightly polished for language. All outputs were reviewed, revised, and fact-checked by the authors of this study. No AI system influenced the study design, analysis, or conclusions.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

REFERENCES

Belland, B. R., Kim, C. M., & Hannafin, M. J. (2013). A framework for designing scaffolds to improve motivation and cognition. *Educational Psychologist, 48*(4), 243-270. https://doi.org/10.1080/00461520.2013.838920

Bybee, R. W. (2010). Advancing STEM education: A 2020 vision. *Technology and Engineering Teacher, 70*(1), 30-35.

Cleveland, W. S., & McGill, R. (1985). Graphical perception and graphical methods for analyzing scientific data. *Science, 229*(4716), 828-833. https://doi.org/10.1126/science.229.4716.828

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Crismond, D., & Adams, R. (2012). The informed design teaching and learning matrix. *Journal of Engineering Education, 101*(4), 738-797. https://doi.org/10.1002/j.2168-9830.2012.tb01127.x

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on the opportunities, challenges, and implications of generative conversational AI for research, practice, and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Dym, C. L., Agogino, A. M., Eris, O., Frey, D. D., & Leifer, L. J. (2005). Engineering design thinking, teaching and learning. *Journal of Engineering Education, 94*(1), 103-120. https://doi.org/10.1002/j.2168-9830.2005.tb00832.x

English, L. D., & King, D. T. (2015). STEM learning through engineering design: Fourth-grade students' investigations in aerospace. *International Journal of STEM Education, 2*, Article 14. https://doi.org/10.1186/s40594-015-0027-7

Friendly, M. (2008). A brief history of data visualization. In *Handbook of data visualization* (pp. 15-56). Springer. https://doi.org/10.1007/978-3-540-33037-0_2

Hmelo-Silver, C. E., Duncan, R. G., & Chinn, C. A. (2007). Scaffolding and achievement in problem-based and inquiry learning: A response to Kirschner, Sweller, and Clark (2006). *Educational Psychologist, 42*(2), 99-107. https://doi.org/10.1080/00461520701263368

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Honey, M., Pearson, G., & Schweingruber, H. (2014). *STEM integration in K-12 education: Status, prospects, and an agenda for research*. National Academies Press. https://doi.org/10.17226/18612

Hutchins, E. (1995). *Cognition in the wild*. MIT Press. https://doi.org/10.7551/mitpress/1881.001.0001

Jonassen, D. H. (2011). *Learning to solve problems: A handbook for designing problem-solving learning environments*. Routledge.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasneci, G. (2023). ChatGPT for good? Opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kelley, T. R., & Knowles, J. G. (2016). A conceptual framework for integrated STEM education. *International Journal of STEM Education, 3*, Article 11. https://doi.org/10.1186/s40594-016-0046-z

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist, 41*(2), 75-86. https://doi.org/10.1207/s15326985ep4102_1

Kolodner, J. L., Camp, P. J., Crismond, D., Fasse, B., Gray, J., Holbrook, J., Puntambekar, S., & Ryan, M. (2003). Problem-based learning meets case-based reasoning in middle-school science classroom: Putting learning by design(tm) into practice. *Cognitive Science Quarterly, 3*(4), 495-547. https://doi.org/10.1207/S15327809JLS1204_2

Luckin, R. (2018). *Machine learning and human intelligence: The future of education in the 21st century*. UCL IOE Press.

Luckin, R., & Holmes, W. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.

Moore, T. J., Stohlmann, M. S., Wang, H.-H., Tank, K., Glancy, A. W., & Roehrig, G. (2014). Implementation and integration of engineering in K-12 STEM education. In Ş. Purzer, J. Strobel, & M. Cardella (Eds.), *Engineering in pre-college settings: Synthesizing research, policy, and practices* (pp. 35-60). Purdue University Press.

National Research Council. (2012). *A framework for K-12 science education: Practices, crosscutting concepts, and core ideas*. National Academies Press. https://doi.org/10.17226/13165

Porter, M. M., & Niksiar, P. (2018). Multidimensional mechanics: Performance mapping of natural biological systems using permutated radar charts. *PLoS ONE, 13*(9), Article e0204309. https://doi.org/10.1371/journal.pone.0204309

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning and Teaching, 6*(1), 342-363. https://doi.org/10.37074/jalt.2023.6.1.9

Salomon, G. (1993). No distribution without individuals' cognition: A dynamic interactional view. In G. Salomon (Ed.)., *Distributed cognition* (pp. 111-138). Cambridge University Press.

Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology, 19*(4), 460-475. https://doi.org/10.1006/ceps.1994.1033

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257-285. https://doi.org/10.1207/s15516709cog1202_4

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of the use of chatbots in education. *Smart Learning Environments, 10*, Article 15. https://doi.org/10.1186/s40561-023-00237-x

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem-solving. *Journal of Child Psychology and Psychiatry, 17*(2), 89-100. https://doi.org/10.1111/j.1469-7610.1976.tb00381.x

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education, 16*, Article 39. https://doi.org/10.1186/s41239-019-0171-0

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 1339). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7

APPENDIX A: STEM TOPIC DESIGN OF HYDRAULIC ROBOT ARM

Time: 3 periods in class + 2 weeks at home

Introduction to the topic: Robots are being applied in all areas of life and society, bringing about significant changes in the economy. Robot Technology is one of the four key areas of the 4.0 industrial revolution. One of the most popular and important Robot arms are used in various applications.

Objectives:

1. The basic content of some mechanical processing methods is also presented.
2. A technological process for mechanical product processing and manufacturing was established.
3. A hydraulic robot arm was designed according to the requirements.
4. Mechanical materials and processing tools are selected and used to design and manufacture products safely and effectively.
5. Contribute to the formation and development of communication and cooperation skills, technology design, skills, use of technology and technology assessment.

Activity 2. Proposed Solutions

Purpose

1. State the basic concepts of some mechanical processing methods, mechanical product manufacturing
1. processes.
2. A technological process for manufacturing mechanical products was developed in this study.
3. Options for the design and manufacture of robotic arms were proposed.
4. Establish a technological process for manufacturing robotic arms based on the selected option.

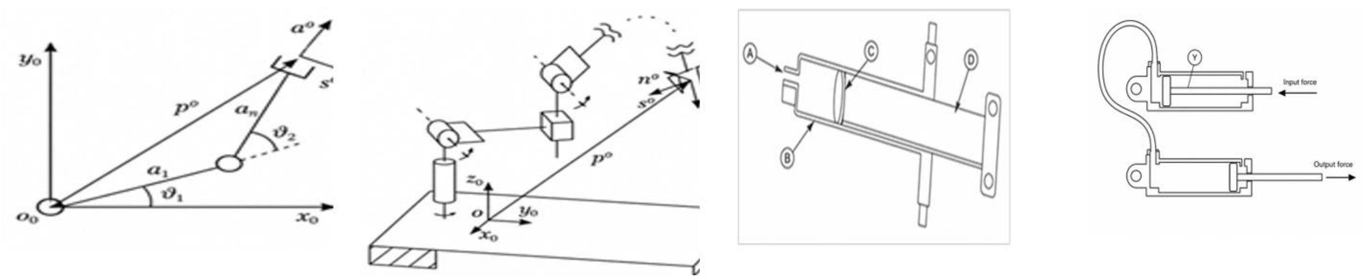

Figure A1. Students learning products (student academic results)

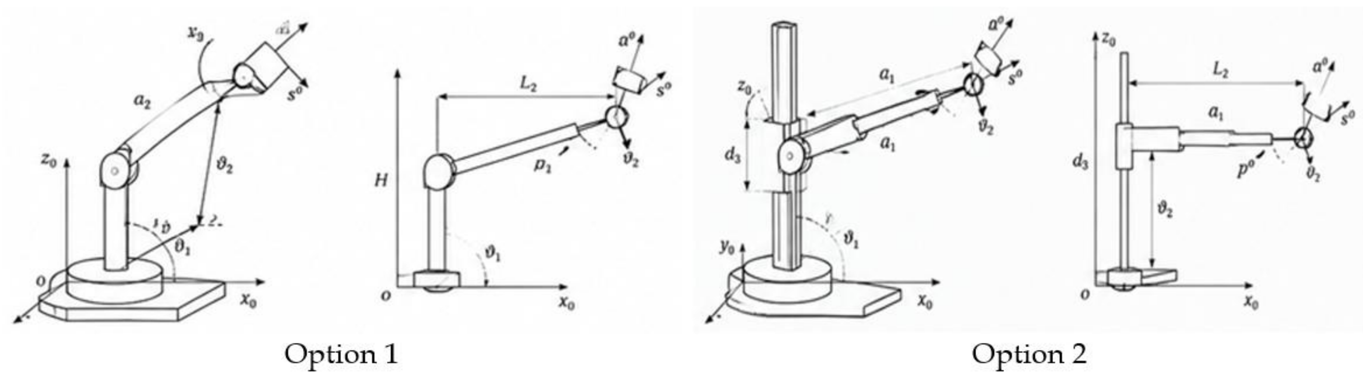

Figure A2. AI proposes two design options (student academic results)

Activity 4 & Activity 5. Build a Prototype, Testing, Evaluation, and Adjustment

Purpose

1. Select and use the tools and materials required to manufacture the robotic arm
2. Implement the approved technological process and manufacture products

In this STEM experiment, AI was integrated only during two stages:

(1) comparing design alternatives and

(2) improving the prototype during construction.

During solution selection, AI functioned as cognitive scaffolding by helping students compare robotic-arm designs based on lifting capability, stability, movement control, material cost, and construction feasibility. AI did not generate new design principles but only explained the strengths and limitations of students' proposed solutions.

Figure A3. AI assists in prototyping (student academic results)

Figure A4. Students learning products (student academic results)