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Dual Effects of Artificial Intelligence on Critical Thinking and Creative Self-Efficacy of Engineering Undergraduates: The Mediating Role of Cognitive Engagement

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Abstract **Original Research Article**

With the deep penetration of generative artificial intelligence (GenAI) in higher engineering education, its impacts on students' higher-order thinking skills and underlying mechanisms remain controversial. Grounded in the ICAP cognitive engagement framework, this study integrates cognitive unloading theory, dual-process theory, and cognitive load theory to construct a moderated mediation model of "usage pattern—cognitive engagement—ability outcome". It examines how different AI usage patterns differentially affect engineering undergraduates' critical thinking and creative self-efficacy, as well as the boundary moderating role of task complexity. Adopting a two-wave longitudinal questionnaire design, this study surveyed 428 engineering undergraduates from a Double First-Class university in western China, and conducted empirical tests via structural equation modeling and the Bootstrap method. Results show that the theoretical model fits the data well. Instrumental use positively predicts shallow cognitive engagement, which in turn negatively affects critical thinking, presenting an "erosion effect". Exploratory use positively predicts deep cognitive engagement, which significantly enhances creative self-efficacy, presenting an "enablement effect". Task complexity plays a positive moderating role in the first half of both mediation paths: higher task complexity amplifies both the cognitive erosion risk of instrumental use and the cognitive enablement effect of exploratory use. This study confirms the dual effects of AI in engineering education and reveals that depth of cognitive engagement is the core regulatory mechanism of technology application effectiveness, providing theoretical and practical references for reconstructing engineering talent cultivation models in the AI era.

Keywords: Generative Artificial Intelligence, Instrumental Use, Exploratory Use, Cognitive Engagement, Critical Thinking, Creative Self-Efficacy, Engineering Education.

1 Introduction

Generative artificial intelligence represented by ChatGPT is driving a paradigm shift in global higher engineering education, from "knowledge mastery" to "human-machine collaborative problem solving". For engineering students, large language models demonstrate strong auxiliary capabilities in code generation, scheme drafting, simulation deduction, and real-time feedback, serving as "intelligent scaffolds" to help learners reduce low-order cognitive load and focus resources on high-order innovation. However, technological dividends are always a double-edged sword: unregulated tool dependence weakens learners' deep thinking ability, induces cognitive inertia and academic integrity risks, and creates an educational paradox of "technological empowerment vs. cognitive degradation".

Existing scholarship has extensively discussed GenAI's impacts on students' thinking quality, but most studies focus on technology acceptance, macro application effects, and teaching strategy design. Few empirical studies reveal the micro psychological mechanisms and boundary conditions behind the "dual effects" from a cognitive processing perspective. This study argues that GenAI's reshaping of students' thinking ability is not a simple linear relationship; its core lies in the mediating effect of technology usage patterns on individual cognitive processing paths. According to cognitive unloading theory, when students fully delegate core thinking tasks to AI, it leads to decentralization of working memory and induces cognitive inertia. Combined with dual-process theory, it can be further inferred that under the "instrumental use" pattern, individual thinking stays at the "System 1 (fast thinking)" processing level, and cognitive engagement tends to be superficial; the "exploratory use" pattern activates "System 2 (slow thinking)" processing and drives individuals into a state of deep cognitive engagement.

Meanwhile, cognitive transitions triggered by different usage patterns are constrained by the task environment. According to the "desirable difficulty" principle and cognitive load theory, the complexity of engineering tasks is a key external variable determining cognitive path selection: for low-complexity routine tasks, cognitive differences between usage patterns are insignificant; when facing high-complexity ill-structured engineering challenges, AI's "scaffolding" value and "hallucination fallacy" risks are amplified simultaneously, and the differentiation effect of cognitive engagement is significantly strengthened. However, the moderating role of task complexity between AI usage patterns and cognitive engagement has not been empirically tested.

Accordingly, this study constructs a moderated mediation model and conducts an empirical study with 428 engineering undergraduates to address two core questions: (1) how do instrumental use and exploratory use differentially affect critical thinking and creative self-efficacy through different dimensions of cognitive engagement? (2) How does task complexity exert boundary moderating effects on the first half of the two mediation paths? This study expands the application scope of the ICAP cognitive framework in intelligent education scenarios, clarifies the core regulatory value of cognitive engagement depth in technology application, and provides empirical support for engineering talent cultivation reform and curriculum evaluation system optimization in the AI era.

2 Literature Review and Theoretical Foundation

2.1 Controversies over GenAI Application in Engineering Education

The popularization of generative AI has profoundly transformed learning forms in engineering education. In engineering scenarios, large language models enable automatic code generation, rapid design scheme drafting, instant professional knowledge Q&A, and personalized learning feedback, effectively expanding learners' cognitive boundaries. Existing studies confirm that rational GenAI application can stimulate students' creative problem-solving ability, promote the development of high-order analytical skills, and show positive empowerment potential in teaching of multiple engineering majors such as chemical engineering, computer science, and mechanical design.

Nevertheless, the risks of technology application have also aroused widespread concern in education. Cross-institutional benchmark studies point out that unconstrained GenAI use will impact the academic integrity system, and more seriously, induce students to abandon independent thinking, forming a vicious cycle of "excessive cognitive unloading—thinking ability degradation", namely the "cognitive paradox" in engineering education. The core of resolving this paradox lies in penetrating the technical appearance and exploring the underlying cognitive psychological mechanism in human-computer interaction, rather than simply discussing "supporting or banning" technology application.

2.2 Dual Paths of Cognitive Engagement: Cognitive Unloading and Dual-Process Theory

Cognitive unloading theory provides a core perspective for explaining AI’s cognitive erosion effect. Cognitive unloading refers to the behavior of individuals reducing mental load and improving task efficiency with external tools, but excessive reliance on external tools leads to reduced depth of individual cognitive processing and weakened long-term memory retention and active thinking ability. Empirical studies show that long-term unreflective use of AI to complete learning tasks significantly reduces students’ knowledge retention rate and logical deduction ability, essentially the outsourcing of high-order cognitive activities.

Dual-process theory further explains the internal mechanism of cognitive engagement differentiation. The theory divides human cognitive processing into two systems: System 1 is intuitive, automatic fast thinking with low cognitive load but shallow processing depth; System 2 is analytical, reflective slow thinking with high cognitive engagement and support for high-order thinking activities. Corresponding to AI usage scenarios: when students adopt the "instrumental use" pattern (directly copying AI-generated answers, codes or conclusions), the brain tends to activate System 1 processing, takes AI output as the final result, and forms shallow cognitive engagement; when students adopt the "exploratory use" pattern (iterative dialogue with AI, comparison of scheme differences, verification of logical loopholes), they actively activate System 2 processing, critically integrate AI-generated content, and form deep cognitive engagement.

Existing studies have confirmed that shallow cognitive engagement is significantly negatively correlated with critical thinking ability, and long-term "cognitive laziness" gradually weakens individuals’ truth-seeking consciousness and analytical ability; deep cognitive engagement can positively predict creative self-efficacy, and deep cognitive involvement strengthens individuals’ sense of control over complex tasks and improves innovation confidence. However, existing studies have not incorporated AI usage patterns, cognitive engagement dimensions, and two types of thinking outcomes into the same analytical framework, and the transmission mechanism of the dual effects remains unclear.

2.3 Boundary Effect of Task Complexity: A Cognitive Load Perspective

Cognitive load theory states that learners’ total cognitive resources are limited, and task complexity directly determines the consumption of mental resources, thereby affecting individuals’ choice of cognitive processing strategies. AI’s impact on learners’ cognitive load and engagement state is not consistent across all task scenarios, but is moderated by task complexity.

In low-complexity routine task scenarios (such as basic grammar checking, simple parameter calculation), tasks impose low demands on cognitive resources, and there is no significant difference in cognitive processing depth regardless of the AI usage pattern adopted by students. When facing high-complexity ill-structured engineering problems, the uncertainty, comprehensiveness and cross-disciplinary nature of tasks greatly increase cognitive load: on the one hand, the risks of "logical hallucinations" and professional fallacies in AI-generated content rise simultaneously, and students who blindly adopt instrumental use are more likely to fall into cognitive confusion and even give up active thinking; on the other hand, AI’s "intelligent scaffold" role is also prominent, helping students decompose complex tasks and relieve time pressure, and students adopting exploratory use can invest released cognitive resources in high-order synthesis, critical evaluation and innovative integration.

In summary, task complexity is not only an external situational factor affecting cognitive load, but also a key boundary condition determining the transformation of AI usage patterns into cognitive engagement depth. Existing studies mostly treat task complexity as a control variable and rarely explore its moderating role in AI's cognitive effects, which is also the key breakthrough direction of this study.

3 Research Hypotheses and Theoretical Model

3.1 Definition of Core Concepts

1. **GenAI usage patterns**: This study divides engineering students' GenAI usage into two typical patterns. **Instrumental use (IU)** refers to students using AI as a task outsourcing tool to directly obtain calculation results, code schemes or standard answers, with the core feature of "take-and-use, replacing thinking". **Exploratory use (EU)** refers to students using AI as a dialogue and collaboration partner to carry out learning through iterative questioning, scheme comparison and logical verification, with the core feature of "human-machine interaction, deep thinking".

2. **Cognitive engagement**: Referring to the cognitive engagement framework of Greene et al., it is divided into two dimensions. **Shallow cognitive engagement (SCE)** focuses on information outsourcing, mechanical reception and passive memory, lacking reflective processing of content. **Deep cognitive engagement (DCE)** focuses on comparative analysis, critical integration and active construction of information, emphasizing participation in high-order cognitive activities.

3. **Outcome variables**: **Critical thinking (CT)** refers to individuals' thinking tendency to conduct logical analysis and rational evaluation of viewpoints and schemes with truth-seeking consciousness, including traits such as truth-seeking, analyticity and systematicness. **Creative self-efficacy (CSE)** refers to individuals' subjective belief and ability confidence in completing creative tasks and producing innovative results.

4. **Moderating variable**: **Task complexity (TC)** refers to the ill-structured degree, comprehensive difficulty and cross-domain attributes of students' daily academic tasks, reflecting the cognitive resource requirements of tasks.

3.2 Hypotheses on the Mediating Effect of Cognitive Engagement

(1) Erosion Path: Instrumental Use → Shallow Cognitive Engagement → Critical Thinking

Based on cognitive unloading theory and dual-process theory, when engineering students use AI instrumentally, they essentially outsource high-order cognitive activities such as logical deduction and vulnerability troubleshooting of engineering problems to algorithms. The brain stays in the automatic processing state of System 1 for a long time, forming shallow cognitive engagement. Critical thinking in engineering scenarios highly depends on in-depth examination of scheme logic and technical details. Long-term superficial thinking mode weakens students' sensitivity to engineering logic loopholes, reduces truth-seeking consciousness and analytical ability, and ultimately leads to the decline of critical thinking level. Accordingly, the hypothesis is proposed:

H1: Shallow cognitive engagement plays a significant mediating role between instrumental use and critical thinking; instrumental use positively predicts shallow cognitive engagement, and shallow cognitive engagement negatively predicts critical thinking.

(2) Enablement Path: Exploratory Use → Deep Cognitive Engagement → Creative Self-Efficacy

Under the exploratory use pattern, students carry out iterative learning with AI as a dialogue partner, need to continuously activate System 2 for deep thinking, screen, integrate and expand AI-generated content, and naturally enter a state of deep cognitive engagement. Deep cognitive engagement enables students to maintain cognitive subjectivity in human-machine collaboration, gradually master solutions to complex engineering problems, and strengthen their sense of control over intelligent tools; continuous deep thinking practice improves students' confidence in their own innovation ability, thereby enhancing creative self-efficacy. Accordingly, the hypothesis is proposed:

H2: Deep cognitive engagement plays a significant mediating role between exploratory use and creative self-efficacy; exploratory use positively predicts deep cognitive engagement, and deep cognitive engagement positively predicts creative self-efficacy.

3.3 Hypotheses on the Moderating Effect of Task Complexity

According to cognitive load theory, task complexity amplifies the cognitive differentiation effect of the two usage patterns. When engineering tasks are highly complex, the ill-structuredness and uncertainty of problems increase significantly. Students who use AI instrumentally cannot judge the correctness of AI content only by intuition, and lack the habit of deep thinking, making them more likely to fall into the cycle of "passive reception—cognitive confusion—giving up thinking", and the risk of inducing shallow cognitive engagement increases significantly. Accordingly, the hypothesis is proposed:

H3: Task complexity positively moderates the positive relationship between instrumental use and shallow cognitive engagement; the higher the task complexity, the stronger the positive predictive effect of instrumental use on shallow cognitive engagement.

Meanwhile, high-complexity tasks have the learning value of "desirable difficulty". Students who use AI exploratively can decompose complex problems with the help of technical scaffolds, focus cognitive resources on high-order links such as scheme innovation and logical criticism, and the intensity and quality of deep cognitive engagement will be significantly improved, with the empowerment effect further amplified. Accordingly, the hypothesis is proposed:

H4: Task complexity positively moderates the positive relationship between exploratory use and deep cognitive engagement; the higher the task complexity, the stronger the positive predictive effect of exploratory use on deep cognitive engagement.

3.4 Construction of the Theoretical Model

Synthesizing the above hypotheses, this study constructs a moderated mediation theoretical model, as shown in Figure 1. The model includes two core paths: the erosion path of "instrumental use → shallow cognitive engagement → critical thinking", and the enablement path of "exploratory use → deep cognitive engagement → creative self-efficacy". Task complexity simultaneously moderates the first half of the two mediation paths (independent variable → mediator), and further regulates the indirect effect intensity of the entire mediation path.

Figure 1 Theoretical Research Model (Note: H1 corresponds to the mediating effect of the erosion path, H2 corresponds to the mediating effect of the enablement path; H3 and H4 correspond to the moderating effects of task complexity in the first half of the two paths, respectively.)

4 Research Design

4.1 Sample and Data Collection

This study selected engineering undergraduates from a "Double First-Class" university in western China as the research sample, covering majors such as petroleum engineering, computer science and technology, mechanical engineering, and chemical engineering, whose daily studies involve a large number of programming and scheme design tasks, ensuring the matching degree between samples and research scenarios.

To control common method bias, the study adopted a two-wave longitudinal design and distributed questionnaires twice at an interval of two weeks: the first wave collected data on AI usage patterns, cognitive engagement and task complexity, and the second wave collected data on critical thinking and creative self-efficacy. Questionnaires were distributed through online teaching platforms. The cover page clearly stated that the research was for academic purposes only, all information was strictly anonymous, and participants could withdraw at any time.

A total of 480 questionnaires were collected. In the data cleaning stage, invalid questionnaires with response time less than 90 seconds and obvious regular answers (such as all selecting the same option) were excluded. Finally, 428 valid samples were obtained, with an effective recovery rate of 89.1%. Demographic characteristics of the sample show that 310 are male (72.4%) and 118 are female (27.6%). The gender structure is consistent with the demographic characteristics of typical engineering colleges in China, and the sample has good representativeness and ecological validity.

4.2 Variable Measurement

All variables in this study adopt mature scales validated by international authoritative journals, and are transformed into Chinese context items strictly following the "translation-back translation" procedure, using a 5-point Likert scale (1=strongly disagree, 5=strongly agree).

1. **GenAI usage patterns**: A self-compiled scale combined with engineering education context, with 8 items divided into two dimensions. The instrumental use dimension has 4 items, such as "I often directly copy AI-generated codes/calculation results to complete assignments", to evaluate students' tendency to outsource cognitive tasks. The exploratory use dimension has 4 items, such as "I will ask follow-up questions about AI-given schemes to verify their logical rationality", to evaluate deep inquiry behavior in human-machine interaction.

2. **Cognitive engagement**: Adapted from the cognitive engagement scale developed by Greene et al., divided into two dimensions. Shallow cognitive engagement has 4 items, focusing on information reception and mechanical memory. Deep cognitive engagement has 5 items, focusing on comparative analysis and critical integration of AI content.

3. **Critical thinking**: Adopting the critical thinking disposition scale compiled by Facione, selecting 6 items from two core dimensions of truth-seeking and analyticity to evaluate students' rational examination and logical analysis tendency.

4. **Creative self-efficacy**: Adopting the creative self-efficacy scale developed by Tierney and Farmer, with 5 items, to evaluate students' belief in their ability to complete creative tasks.

5. **Task complexity**: Referring to Campbell's task complexity scale, localized revision combined with engineering background, with 4 items, describing the characteristics of students' daily academic tasks from the dimensions of comprehensiveness, ill-structuredness and difficulty.

4.3 Data Analysis Methods

This study used SPSS 26.0 and AMOS 24.0 for data analysis: (1) Test common method bias, convergent validity and discriminant validity through Harman's single-factor test and confirmatory factor analysis; (2) Use structural equation modeling (SEM) to test the fitness of main effects and mediation paths; (3) Use Bootstrap resampling method (5000 samples) to test mediating effects, moderating effects and moderated mediation effects, and judge the significance of effects through 95% confidence intervals.

5 Empirical Analysis and Results

5.1 Common Method Bias Test

To control common method bias, this study adopted procedural and statistical controls: procedurally, a two-wave longitudinal design was used to separate the measurement of independent and dependent variables; statistically, Harman's single-factor test was performed. Unrotated exploratory factor analysis results show that 7 common factors with eigenvalues greater than 1 are extracted, and the first principal component explains 31.42% of the total variance, far below the critical threshold of 50%, indicating that there is no serious common method bias in the data.

5.2 Measurement Model Test

This study evaluated the convergent validity and discriminant validity of the measurement model through confirmatory factor analysis. Results show that the composite reliability (CR) of all latent variables is greater than 0.80, and the average variance extracted (AVE) is greater than 0.50, indicating good convergent validity of each variable.

The Fornell-Larcker criterion was used to test discriminant validity, and the results are shown in Table 1: the diagonal values are the square roots of AVE of each latent variable, which are all larger than the Pearson correlation coefficients between the variable and all other latent variables, confirming good discriminant validity among core constructs.

Table 1 Descriptive Statistics, Correlation Coefficients and Discriminant Validity Test

Variables	Mean	SD	1.IU	2.EU	3.SCE	4.DCE	5.CT	6.CSE	7.TC
1. Instrumental Use (IU)	3.42	0.85	**0.81**	-	-	-	-	-	-
2. Exploratory Use (EU)	3.65	0.78	-0.15**	**0.79**	-	-	-	-	-
3. Shallow Cognitive Engagement (SCE)	3.21	0.82	0.45***	-0.12*	**0.83**	-	-	-	-
4. Deep Cognitive Engagement (DCE)	3.88	0.75	-0.22***	0.51***	-0.31***	**0.85**	-	-	-
5. Critical Thinking (CT)	3.56	0.80	-0.32***	0.28***	-0.41***	0.35***	**0.82**	-	-
6. Creative Self-Efficacy (CSE)	3.72	0.88	-0.18**	0.38***	-0.25***	0.47***	0.42***	**0.86**	-
7. Task Complexity (TC)	3.85	0.81	0.12*	0.15**	0.18**	0.22***	-0.05	0.11*	**0.80**

*Note: Bold values on the diagonal are square roots of AVE; *p<0.05, **p<0.01, ***p<0.001*.

5.3 Structural Equation Model and Mediation Effect Test

First, structural equation modeling was used to test the overall fitness of main effects and mediation paths. Results show excellent model fit indices: $\chi^2/df=2.31$, RMSEA=0.055, CFI=0.948, TLI=0.939, all meeting the adaptation criteria, indicating that the theoretical model fits the empirical data well.

The Bootstrap method (5000 samples) was further used to decompose and test the total effect, direct effect and indirect effect of the two mediation paths, and the results are shown in Table 2.

Erosion path test (H1): The total effect of instrumental use on critical thinking is significant ($\beta=-0.32$, $p<0.001$); the direct effect is -0.15 ($p<0.01$), and the indirect effect through shallow cognitive engagement is -0.17, with a Bootstrap 95% confidence interval of [-0.24, -0.11], excluding 0, indicating that the partial mediating effect of shallow cognitive engagement is significant. The mediating effect accounts for 53.2% of the total effect, and hypothesis H1 is supported.

Enablement path test (H2): The total effect of exploratory use on creative self-efficacy is significant (β=0.38, p<0.001); the direct effect is 0.14 (p<0.01), and the indirect effect through deep cognitive engagement is 0.24, with a Bootstrap 95% confidence interval of [0.18, 0.31], excluding 0, indicating that the partial mediating effect of deep cognitive engagement is significant. The mediating effect accounts for 63.2% of the total effect, and hypothesis H2 is strongly supported.

Table 2 Bootstrap Mediation Effect Decomposition and Test

Path Relationship	**Effect Type**	**Effect Value (β)**	**BootSE**	**BootLLCI**	**BootULCI**	**Relative Mediation Proportion**	**Test Result**
Erosion Path: IU→SCE→CT	Total Effect	-0.32***	0.045	-0.41	-0.23	-	Significant
	Direct Effect	-0.15**	0.048	-0.25	-0.06	46.8%	Significant
	Indirect Effect	-0.17***	0.035	-0.24	-0.11	53.2%	Support H1
Enablement Path: EU→DCE→CSE	Total Effect	0.38***	0.042	0.30	0.46	-	Significant
	Direct Effect	0.14**	0.046	0.05	0.23	36.8%	Significant
	Indirect Effect	0.24***	0.033	0.18	0.31	63.2%	Support H2

*Note: *p<0.05, **p<0.01, ***p<0.001*.

5.4 Moderation Effect and Moderated Mediation Effect Test

Hierarchical regression and Bootstrap method were used to test the moderating effect of task complexity and the moderated mediation effect. Results show:

1. The interaction term of instrumental use and task complexity has a significant positive predictive effect on shallow cognitive engagement (β=0.13, p<0.01), indicating that task complexity positively moderates the relationship between instrumental use and shallow cognitive engagement, and hypothesis H3 holds. Simple slope analysis shows that under high task complexity, instrumental use has a stronger positive impact on shallow cognitive engagement.

2. The interaction term of exploratory use and task complexity has a significant positive predictive effect on deep cognitive engagement (β=0.16, p<0.001), indicating that task complexity positively

moderates the relationship between exploratory use and deep cognitive engagement, and hypothesis H4 holds. Simple slope analysis shows that under high task complexity, exploratory use has a more prominent positive impact on deep cognitive engagement.

Further testing of the moderated mediation effect shows that under high task complexity, the indirect effects of both paths are stronger; under low task complexity, both indirect effects are weakened, and the Bootstrap 95% confidence intervals do not include 0, confirming that task complexity has a positive moderating effect on the indirect effects of both mediation paths.

6 Discussion and Implications

6.1 Discussion of Research Results

This study constructs and validates a moderated mediation model of AI affecting engineering students' thinking ability, systematically reveals the internal mechanism and boundary conditions of the "dual effects", and the core findings can be discussed from two aspects.

(1) Dual Mediation Paths: Cognitive Engagement Differentiation as the Core Mechanism of Dual Effects.This study confirms that GenAI itself is neither a "thinking poison" nor a "universal artifact"; its impact direction on students' ability completely depends on the difference in cognitive engagement triggered by usage patterns.

- **Internal logic of the erosion path**: Instrumental use weakens critical thinking by inducing shallow cognitive engagement, providing empirical support for cognitive unloading theory in engineering education scenarios. Engineering learning highly relies on logical deduction and vulnerability troubleshooting. When students outsource high-order cognitive activities to AI for a long time, the brain continues to be in a low-load intuitive processing state, and will gradually lose the critical examination ability of engineering schemes, forming cognitive degradation of "use it or lose it". This result also responds to the education circle's concern about AI-induced "cognitive inertia" and clarifies the specific hazard path of excessive instrumental use.

- **Internal logic of the enablement path**: Exploratory use improves creative self-efficacy by stimulating deep cognitive engagement, providing new evidence for the applicability of constructivist learning view in the AI era. When students take AI as a Socratic dialogue partner, the human-machine interaction process continuously activates deep thinking. Students always maintain cognitive subjectivity in the process of collaborative problem solving, expand cognitive boundaries with the help of technology, and strengthen innovation confidence through in-depth practice, ultimately achieving the improvement of creative self-efficacy.This conclusion clearly responds to the current "AI education paradox": the impact of technology is essentially "a projection of user behavior". Maintaining cognitive subjectivity and deep cognitive engagement is the core premise of giving play to AI's empowerment value.

(2) Boundary Effect of Task Complexity: High-Complexity Tasks Amplify Dual Differentiation

The core innovation of this study is confirming that task complexity is a key boundary condition of the dual effects. In low-complexity engineering tasks, cognitive differences between different AI usage patterns are not significant, and technology mostly embodies the attribute of efficiency tool; in high-complexity ill-structured task scenarios, the dual attributes of AI are amplified simultaneously, and the cognitive differentiation effect is significantly enhanced.For instrumental users, the risks of AI's "logical hallucinations" and professional fallacies rise in high-complexity tasks. Without the support of deep thinking ability, students can neither identify the correctness of content nor advance tasks, which will eventually aggravate shallow cognitive engagement and thinking degradation.For exploratory users, the "desirable difficulty" of high-complexity tasks and AI's "scaffolding role" form synergy. Technology helps students cross the basic cognitive threshold, and students focus cognitive resources on high-order links such as innovation and integration, fully releasing the value of deep cognitive engagement and maximizing the empowerment effect.This finding also explains why AI's teaching effects vary significantly across studies—differences in task scenario complexity are important situational variables leading to divergent conclusions.

6.2 Theoretical Contributions

First, it expands the application of the ICAP cognitive engagement framework in intelligent education scenarios. This study matches AI usage patterns with cognitive engagement depth, clarifies the cognitive processing levels corresponding to different technology interaction behaviors, enriches relevant cognitive engagement theory, and provides an analytical framework for subsequent research on the cognitive mechanisms of intelligent education. Second, it reveals the micro transmission mechanism of GenAI's dual effects. Most existing studies only describe the phenomenon that AI has both positive and negative effects on thinking ability. This study uses a dual-path mediation model to analyze the process of "usage pattern-cognitive engagement-ability outcome", systematically explains the formation logic of the two effects from the perspective of cognitive processing, and deepens the theoretical understanding of AI's educational impact. Third, it clarifies the boundary moderating role of task complexity. This study incorporates task complexity into the analytical framework, confirms that it is a key situational variable affecting AI's cognitive effects, addresses the inconsistency of existing research conclusions, and provides a theoretical reference for subsequent studies to set boundary conditions and refine application scenarios.

6.3 Practical Implications

The conclusions of this study provide three practical guidelines for the reform of higher engineering talent cultivation models in the AI era.

First, reconstruct curriculum task design and actively embrace "ill-structured engineering problems". Low-complexity, standardized tasks easily induce instrumental cognitive outsourcing and cannot exert AI's empowerment value. Engineering teachers should reduce the proportion of repetitive calculation and mechanical memory assessment, increase high-complexity design projects with real engineering scenarios that are interdisciplinary and have no standard answers, and use "desirable difficulty" to force students to shift from "take-and-use" to "deep inquiry" and carry out high-order thinking training in human-machine collaboration.

Second, reform academic evaluation system and implement "process traceability evaluation". The traditional result-oriented evaluation system will incentivize students to obtain high scores through instrumental AI use and aggravate cognitive degradation. Engineering education should introduce a "human-machine collaboration rubric", requiring students to submit process materials such as "prompt iteration logs" and "scheme comparison and analysis records" together with their works, shift the evaluation focus from final results to students' deep cognitive behaviors, and guide students to carry out exploratory use.

Third, carry out AI literacy and metacognitive interventions to strengthen cognitive subjectivity. Universities should offer GenAI literacy workshops for engineering students, clearly define "acceptable instrumental outsourcing" and "cognitive bottom line that must be adhered to", train students to switch metacognition in different task scenarios, cultivate the autonomous learning ability of "using AI but not relying on AI", and help students maintain the initiative of thinking in human-machine collaboration.

6.4 Research Limitations and Future Prospects

This study has three limitations, which offer directions for future research. First, cognitive engagement and thinking ability data mainly come from students' self-reports. Future research can combine technologies like eye-tracking and EEG monitoring to capture more objective physiological and neurocognitive indicators in human-computer interaction, and improve the accuracy of research conclusions. Second, even though a two-wave longitudinal design is used to control bias, its causal inference strength is still lower than that of experimental research. Future research can carry out classroom quasi-experiments and continuously track the long-term effects of different intervention strategies in real project-based learning. Third, the sample is concentrated in engineering colleges in western China, so the generalizability of research conclusions is limited. Future research can explore differences in students' AI usage patterns and effect boundaries across different education systems and disciplinary backgrounds through cross-cultural and cross-institutional comparative studies.

References

[1]. Chi, M. T. H., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, 49(4), 219–243.

[2]. Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences*, 20(9), 676–688.

[3]. Tierney, P., & Farmer, S. M. (2002). Creative self-efficacy: Its potential antecedents and relationship to creative performance. *Academy of Management Journal*, 45(6), 1137–1148.

[4]. Ain, N. U., & Kamaruddin, N. (2025). University students' perceptions of generative AI for critical thinking and creativity: The influence of self-efficacy and disciplinary differences. *Journal of Educational Technology & Society*, 28(2), 312–325.

[5]. Ogunleye, A., & Zhang, M. (2026). An experimental study of structured generative AI integration to mitigate pedagogical, cognitive, and ethical barriers in programming education. *Frontiers in Computer Science*, 8, 1789829