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# The chain mediating role of critical thinking and AI self-efficacy in GenAI usage competence and engineering students' creativity

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**This study investigates the impact of generative artificial intelligence (GenAI) on engineering students' creativity, examining the mediating roles of critical thinking and AI self-efficacy in this relationship. We analyze the data collected using SPSS (v.24) and SmartPLS (v.4) to assess the variables' structural relationships and effect sizes. The results demonstrate that GenAI usage competence significantly enhances engineering students' creativity ($t > 1.96$, $p < 0.05$, $f^2 = 0.012$). Furthermore, critical thinking partially mediates the relationships between GenAI usage competence and AI self-efficacy, as well as between GenAI usage competence and creativity ($t > 1.96$, $p < 0.001$). AI self-efficacy is also a partial mediator in the relationships between critical thinking and creativity, and between GenAI usage competence and creativity ($t > 1.96$, $p < 0.05$). This study identifies a chain mediation model in which critical thinking and AI self-efficacy sequentially mediate the relationship between GenAI usage competence and student creativity ($t > 1.96$, $p < 0.001$). These findings highlight the interplay between technological tools, cognitive abilities, and psychological factors, indicating that simply teaching technical skills is not enough. For engineering education, this implies that integrating GenAI tools into the curriculum must go hand in hand with fostering students' critical thinking and AI self-efficacy to truly enhance creativity.**

**Keywords** Creativity, GenAI usage competence, Critical thinking, AI self-efficacy, Engineering students

Cultivating creativity has become an increasingly urgent goal in engineering education as the engineering profession faces complex, uncertain, and rapidly evolving technological contexts[1]. Creativity, defined as the ability to produce ideas/products that are both novel and useful[2,3], is now recognised as essential for addressing open-ended design problems, driving innovation, and maintaining competitiveness in creative industries[4]. Despite widespread agreement on its importance, empirical evidence on how to systematically enhance engineering students' creativity, particularly through emerging technologies such as generative artificial intelligence (GenAI), remains limited[5]. Recent advances in GenAI, which refers to systems capable of autonomously producing novel outputs (e.g., text, images, or code), offer new opportunities to support creative processes[6]. GenAI can generate diverse alternative solutions and inspire iterative refinement[7]. However, the educational benefits of GenAI rely not only on its generative functions but also on students' competence to use, interpret, and apply it critically, that is, their practical ability to interact with, critically evaluate, and integrate GenAI outputs into their own thinking and design processes. In this study, GenAI usage competence is defined as students' practical ability to make informed choices about which GenAI tools to use, design precise and purposeful input prompts, critically assess and verify the relevance and quality of AI-generated results, and adapt these results effectively within their own problem-solving and design tasks[8–10]. It also includes students' awareness of responsible and ethical considerations when applying GenAI outputs to produce original and meaningful work[11].

Prior research has explored various factors that promote creativity in engineering students, such as domain knowledge, self-regulated learning, and collaborative environments[12–14]. Recent studies have also shown that AI tools, such as ChatGPT, can facilitate certain aspects of creative work when students use them actively and reflectively[15]. Yet, little empirical work has examined how competence in using GenAI specifically contributes to creativity in engineering contexts. Moreover, while some studies have highlighted the direct impact of technological competence on creativity[16], there is growing recognition that this relationship is likely to be indirect

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and shaped by important cognitive and psychological processes[17,18]. Critical thinking is widely acknowledged as an essential cognitive skill for creativity[19]. It enables students to analyse and question AI-generated content, discern its strengths and limitations, and refine or adapt ideas rather than accept outputs uncritically[20]. Empirical research suggests that stronger critical thinking enhances students' capacity to transform information into original and appropriate solutions[21]. Similarly, AI self-efficacy, students' belief in their ability to use AI tools effectively, can influence how confidently they experiment with AI and persist through complex, ill-defined tasks, which is vital for sustaining creative engagement[22]. Existing evidence indicates that students with higher self-efficacy are more likely to use emerging technology proactively and creatively[23].

Although previous studies have examined links between technological competence, critical thinking, self-efficacy, and creativity[24], few have systematically tested how these factors interact sequentially in the context of GenAI use in engineering education. Drawing on social cognitive theory, this study proposes that students' competence in using GenAI tools can enhance their critical thinking skills, which in turn strengthen their AI self-efficacy, ultimately fostering creativity. Social cognitive theory provides a suitable basis for this pathway, as it emphasises how cognitive skills and self-beliefs interact to influence individuals' learning and creative performance. Unlike previous models that typically consider these mediators in isolation, this study conceptualises them as a chain process to capture better how GenAI usage competence is translated into creativity through cognitive and self-belief mechanisms. By clarifying these links, this chain mediation model extends existing research and offers a theoretically grounded framework for integrating GenAI more effectively into engineering education. The following research questions (RQs) were addressed:

RQ1: What is the effect of GenAI usage competence on engineering students' creativity?

RQ2: How do critical thinking and AI self-efficacy influence engineering students' creativity?

RQ3: What mediating roles do critical thinking and AI self-efficacy play in the relationship between GenAI usage competence and creativity among engineering students?

## Hypothesis development

### The impact of GenAI usage competence on engineering students' creativity

Based on prior research, there is strong evidence to support the hypothesis that GenAI usage competence has a direct and significant impact on engineering students' creativity. Haase and Hanel (2023) showed that creative self-efficacy, which reflects an individual's belief in their ability to generate creative outcomes, is moderately correlated with creativity measures ($r = 0.39$) and strongly linked to self-rated creativity ($r = 0.53$)[25]. This suggests that higher competence and confidence in using GenAI tools (such as ChatGPT) are key drivers of creativity. Similarly, Avcı (2024) found that a growth creative mind-set ($\beta = 0.413$, $p < 0.000$) and positive attitudes toward AI ($\beta = 0.456$, $p < 0.000$) significantly increased students' acceptance and use of GenAI, highlighting that students with stronger GenAI competence and engagement are more likely to unlock its creative benefits[26]. Supporting this, Wei et al. (2025) demonstrated that university students who actively used GenAI tools significantly improved their team creativity, particularly in generating novel ideas, compared to their peers who used traditional methods[5]. Therefore, we propose the following hypothesis:

H1: GenAI usage competence has a direct and significant impact on the engineering students' creativity.

### The mediating role of critical thinking

Students' competence in using Generative Artificial Intelligence (GenAI) plays an important role in fostering critical thinking skills. Larson et al. (2024) highlight that to use GenAI effectively, students must exercise both individual and social critical thinking to evaluate, interpret, and challenge AI-generated outputs[27]. This implies that higher competence in GenAI usage can directly engage and strengthen their critical thinking. Adarkwah (2025) found that adult learners who engaged with GenAI tools reported better critical thinking abilities, showing that knowing how to use GenAI well encourages learners to question, analyse, and improve GenAI-generated content[28]. Meng et al. (2025) further demonstrated that targeted strategies for developing GenAI competence enhance both GenAI literacy and students' critical thinking performance, suggesting that students who are more competent in using GenAI are better positioned to apply higher-order cognitive skills[29]. Building on this evidence, we propose the following hypothesis:

H2: GenAI usage competence has a direct and significant impact on critical thinking.

There is clear evidence to support the hypothesis that critical thinking has a direct and significant impact on engineering students' creativity. Ellianawati et al. (2025) found that integrating STEAM-based collaborative learning enabled 36 high school students to develop both critical and creative thinking simultaneously, as they critically analysed local renewable energy resources and produced innovative projects, demonstrating how critical analysis directly supported creativity[30]. Sapounidis et al. (2025) conducted a meta-analysis of 22 empirical studies (effect sizes = 53, $N = 2192$) and showed that educational robotics significantly enhanced children's critical thinking (effect size = 0.561) and creativity (effect size = 0.511), highlighting that developing critical thinking skills fosters creativity[31]. Li and Qi (2025) further showed that among 410 university students, arts education significantly strengthened critical thinking, which in turn promoted creative problem-solving skills and innovation in academic tasks[32]. Drawing on these findings, the following hypothesis is proposed:

H3: Critical thinking has a direct and significant impact on the engineering students' creativity.

Recent studies suggest that critical thinking can link GenAI usage competence with students' creativity. For example, Li (2025) showed that AI usage significantly boosts critical thinking ($\beta = 0.560$, $p < 0.001$), which then strongly enhances creativity ($\beta = 0.707$, $p < 0.001$); critical thinking partially mediated this effect ($\beta = 0.397$, $p < 0.001$, VAF = 65.89%)[33]. Akpur (2025) found that metacognitive awareness influenced creativity partly through critical thinking ( $\beta = 0.079$, $p < 0.05$) among 209 university students[34]. Yurt (2025) confirmed with longitudinal data from 529 pre-service teachers that critical thinking supports creativity indirectly via self-efficacy ($\beta = 0.601$, $p < 0.001$), showing how higher-order thinking enables creative growth[35]. Although

Acosta-Enriquez et al. (2025) did not find a significant mediation effect for critical thinking in the context of AI dependency, their results highlight that critical thinking remains a key factor worth examining when exploring how AI skills relate to broader outcomes[36]. Based on the above discussion, the following hypothesis is proposed:

H4: Critical thinking mediates the relationship between GenAI usage competence and the engineering students' creativity.

## The mediating role of AI self-efficacy

GenAI usage competence has a direct and significant impact on AI self-efficacy. Chen et al. (2025) used a quasi-experimental design with 64 undergraduates and found that students who engaged with a ChatGPT-driven learning system reported significantly higher self-efficacy compared to those receiving traditional instruction, showing that hands-on GenAI use strengthens learners' confidence[37]. Ma et al. (2025) surveyed 159 university students and showed that digital safety competence was positively and significantly related to AI self-efficacy ($p < 0.05$), indicating that broader digital competencies, including safe and effective GenAI use, directly enhance students' belief in their AI abilities[38]. Shahzad et al. (2025) found in a study of 362 students that generative AI technologies like ChatGPT significantly influenced learning performance through self-efficacy, highlighting that competence in applying AI tools boosts students' AI self-efficacy and learning outcomes[39]. Based on this comprehensive review, we propose the following hypothesis:

H5: GenAI usage competence has a direct and significant impact on AI self-efficacy.

AI self-efficacy has a direct and significant impact on engineering students' creativity. Wang et al. (2023), using PLS-SEM analysis of 561 valid responses from Chinese higher education institutes, showed that AI capability significantly influences students' self-efficacy and creativity, and that self-efficacy acts as a pathway through which AI capability enhances creativity and learning performance[40]. Jeong and Jeong (2024) found, in a three-wave study with 236 employees, that AI adoption boosts creative self-efficacy, which in turn directly predicts higher creativity, confirming self-efficacy as a key psychological mechanism linking AI use to creative output[41]. McGuire et al. (2025) further demonstrated through two experiments that when people co-create with GenAI, creative self-efficacy plays a vital role in enabling greater creative performance compared to merely editing AI outputs[42]. Chun et al. (2025), studying 385 college students, found that AI literacy enhances creativity both directly and indirectly through self-efficacy, underscoring that students with stronger AI self-efficacy generate more creative outcomes[43]. Based on this extensive review of the literature, we propose the following hypothesis:

H6: AI self-efficacy has a direct and significant impact on the engineering students' creativity.

Shahzad et al. (2025) found, using PLS-SEM with 362 students, that GenAI tools like ChatGPT significantly influenced learning performance and creativity through self-efficacy, highlighting its key mediating role[39]. Hwang and Wu (2025) confirmed through mediation analysis ($\beta = 0.256$, $p < 0.001$) that self-efficacy significantly mediates the positive effect of GenAI on students' innovative thinking[44]. Zhang et al. (2025) demonstrated that the use of GenAI promotes creativity through mediators such as exploratory and exploitative learning, processes that require learners to have confidence in using AI effectively, aligning with self-efficacy theory[41]. Hu et al. (2025) further demonstrated in a quasi-experiment with 53 students that a ChatGPT-based learning approach significantly increased learners' self-efficacy, which in turn supported better learning outcomes and creative engagement[45]. Building on these insights, we propose the following hypothesis:

H7: AI self-efficacy mediates the relationship between GenAI usage competence and engineering students' creativity.

Critical thinking has a direct and significant impact on AI self-efficacy. Jia et al. (2024), using SEM with data from 637 students, showed that general self-efficacy significantly shaped students' critical thinking awareness, highlighting the mutual reinforcement between critical thinking and self-efficacy within AI-enhanced learning contexts[46]. Li et al. (2023) found in a large-scale study of 663 Chinese college students that critical thinking significantly predicted academic self-efficacy, which in turn boosted students' technology competence, confirming that stronger critical thinking skills directly strengthen self-efficacy related to technology use[47]. Wang et al. (2023) demonstrated that critical thinking plays an implicit role in activating this pathway by fostering self-efficacy[40]. Therefore, we propose the following hypothesis:

H8: Critical thinking has a direct and significant impact on AI self-efficacy.

## The chain mediating effect of critical thinking and AI self-efficacy

Chang and Huang (2025) found that students' thinking styles influenced their critical thinking mainly through intermediate evaluation performance, confirming a mediating pathway[48]. Xu et al. (2024), with 704 students, showed that learning support indirectly improved learners' abilities through the chain of self-efficacy and critical reflection, demonstrating how competence can shape self-efficacy via critical thinking (β values significant)[49]. Long and Long (2023) ($n = 413$) confirmed that critical thinking directly boosts creativity, and this link is partially mediated by self-efficacy[50]. Likewise, Zhang et al. (2025), studying 517 students, showed that higher AI literacy increased self-efficacy, which acted as a mediator, improving learners' confidence[51]. Large-scale studies by Cai et al. (2024) ($n = 8499$) and Xiang et al. (2024) ($n = 1308$) further verified that self-efficacy consistently plays a mediating role in sequential pathways linking competence, thinking, and positive outcomes, with clear indirect effects (e.g., mediation effect 18.84%)[52,53]. These findings strongly support the notion that GenAI competence enhances AI self-efficacy through critical thinking, which in turn strengthens creativity. Furthermore, the two factors jointly act as mediators linking GenAI competence to students' creativity. Accordingly, the following hypothesis is proposed:

H9: Critical thinking mediates the relationship between GenAI usage competence and AI self-efficacy.

H10: AI self-efficacy mediates the relationship between critical thinking and the engineering students' creativity.

H11: Critical thinking and AI self-efficacy sequentially mediate the relationship between GenAI usage competence and engineering students' creativity.

Based on the above hypotheses and literature review, the theoretical framework of this study is presented in Fig. 1.

## Methods

### Research procedures

This study employed chain mediation models to examine the impact of GenAI usage competence on engineering students' creativity, with particular attention to the sequential mediating roles of critical thinking and AI self-efficacy. Participants were engineering undergraduates who completed a structured questionnaire designed to measure GenAI usage competence, critical thinking, AI self-efficacy, and creativity. Before hypothesis testing, SPSS (v.24.0) was employed to assess the reliability and validity of the measurement instruments and to compute correlation coefficients among the study variables, thereby ensuring the robustness of the dataset for subsequent modelling. Following this preliminary validation, partial least squares structural equation modelling (PLS-SEM) was conducted using SmartPLS (v.4) to examine the hypothesised sequential mediation mechanisms. This analytic strategy enabled a rigorous two-stage approach: first, the establishment of psychometric soundness and inter-variable associations; second, the testing of sequential, hierarchical, and synergistic pathways between GenAI usage competence, critical thinking, AI self-efficacy, and creativity. Through this procedure, the study sought to capture the complex intermediary processes by which GenAI usage competence may foster creativity in engineering students.

### Pilot survey and instrumental design

The questionnaire was developed based on established scales and adapted to the context of GenAI competence and creativity. To ensure the content validity of the instruments, we conducted a pilot survey with 100 engineering students. Participants were asked to provide feedback on item clarity, wording, and relevance. Based on their suggestions, several ambiguous items were rephrased and redundant questions were removed, resulting in a clearer and more concise instrument. The questionnaire included two parts: the first part collected background information about the sample, such as gender, region of origin, education level, major, and GenAI experience; the second covered the following four scales (see Appendix A).

The seven-item Generative Artificial Intelligence Usage Competence Scale, synthesized from elements developed by Arslankara and Usta[54] and Ling et al.[55], was used to measure students' competence in using GenAI tools. The reliability and validity of the scale were rigorously evaluated. Cronbach's alpha (CA) was 0.901, composite reliability (CR) was 0.912, average variance extracted (AVE) was 0.630, and the Kaiser–Meyer–Olkin (KMO) value was 0.886, exceeding the threshold of 0.7 [96], with a statistically significant *p*-value ($p < 0.05$).

The Engineering Students' Creativity Scale, integrated from elements developed by Tang and Kaufman[56] and Tierney et al.[57], demonstrated a CA of 0.905, CR of 0.966, AVE of 0.829, and KMO value of 0.936, exceeding the threshold of 0.7, with a *p*-value less than 0.05.

The six-item Critical Thinking Scale was developed by Hwang et al.[58], yielding a CA of 0.921, CR of 0.938, AVE of 0.730, and KMO value of 0.911, exceeding the threshold of 0.7, with a *p*-value less than 0.05.

The Artificial Intelligence Self-Efficacy Scale, combined from elements developed by Lérias et al.[59] and Basri[60], includes nine items and was developed to evaluate individuals' beliefs in using AI tools. It had a CA of

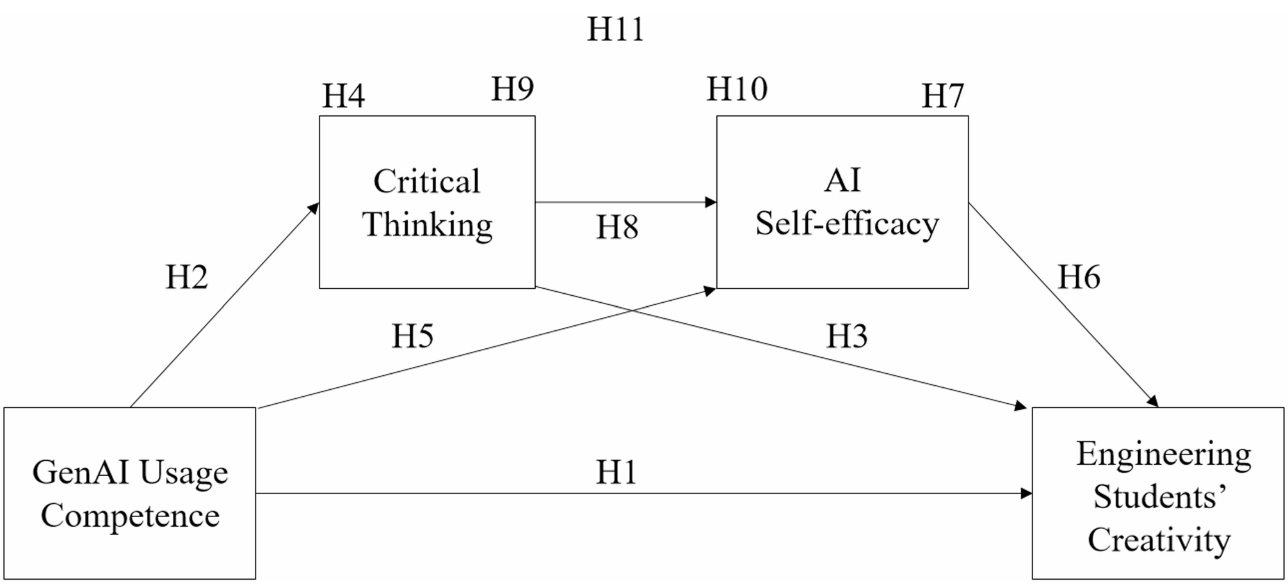


**Fig. 1**. Theoretical framework.

0.909, CR of 0.961, AVE of 0.755, and KMO value of 0.915, exceeding the threshold of 0.7, with a statistically significant $p$-value ($p < 0.05$).

## Sampling Technique

We employed a random sampling method to select undergraduate engineering students from multiple universities across different regions of China to ensure representation of diverse backgrounds and academic contexts. Data were collected in December 2024 through an online questionnaire distributed via WeChat, which is widely used among Chinese university students. An invitation link was disseminated through official university WeChat groups and student societies, accompanied by an informed consent statement. All procedures were conducted by institutional ethical guidelines, and informed consent was obtained from all participants. All methods were performed in accordance with the relevant guidelines and regulations. In total, 877 responses were collected. Of these, 73 questionnaires were excluded because they were incomplete (more than 10% missing data) or contained patterned responses (e.g., selecting the same option for all items). Following this screening, 804 valid responses remained, resulting in a final valid response rate of 92%. Following the "10 times" rule, which recommends a minimum sample size of 60 for models with up to six structural paths, our final sample of 804 students comfortably exceeded this recommended threshold[61]. The demographic information of the sample is also presented in Table 1.

## Measurement model assessment

Testing the reliability and validity of the measurement model was essential. We assessed reliability and validity using SmartPLS (v.4), with criteria including construct reliability and validity, discriminant validity, the Fornell–Larcker criterion, and cross-loadings. The results presented in Table 2, according to the criteria set by Hair et al.[62], all of the results met the standards, indicating the satisfactory reliability and validity of the measurement model.

To test the reliability and validity of the measurement model, we assessed the indicator's newness and evaluated the model's reliability and validity, including Cronbach's alpha, composite reliability, and AVE. The results showed that Cronbach's alpha was greater than 0.8, composite reliability exceeded the recommended threshold, and AVE was above 0.5, all meeting the required standards. Additionally, all indicator weights exceeded the minimum threshold of 0.1, and each factor loading was greater than its corresponding cross-loading[61], thus satisfying the criterion for discriminant validity. These measures met the full set of criteria required for a comprehensive evaluation of the model's validity while confirming its reliability. These results are presented in Table 3.

## Structural model assessment

We used $R^2$, $Q^2$, SRMR, NFI, and goodness of fit (GOF) to evaluate the structural model, as shown in Table 4. The threshold criteria for $R^2$, $Q^2$, SRMR, NFI, and GOF are specified in the note beneath the table. The results of these tests indicated that the structural model fitted the data well, providing a credible and statistically sound representation of the interrelationships among the variables examined.

| Variable | | N | % |
|---|---|---|---|
| Gender | Male | 337 | 41.9 |
| | Female | 467 | 58.1 |
| Education Level | 1 Year | 103 | 12.8 |
| | 2 Year | 104 | 12.9 |
| | 3 Year | 498 | 61.9 |
| | 4 Year | 99 | 12.3 |
| Major | Materials Science and Engineering | 143 | 17.8 |
| | Robotics | 100 | 12.4 |
| | Mechanical Engineering | 190 | 23.6 |
| | Electrical Engineering | 252 | 31.3 |
| | Civil Engineering | 119 | 14.8 |
| Region of Origin | Urban | 550 | 68.4 |
| | Rural | 254 | 31.6 |
| GenAI Experience | > 6 months | 60 | 7.5 |
| | > 1 year | 328 | 40.8 |
| | > 2 years | 274 | 34.1 |
| | > 3 years | 142 | 17.7 |
| Frequency of GenAI Usage | Once a month | 4 | 0.5 |
| | Once a week | 14 | 1.7 |
| | Several times a week | 38 | 4.7 |
| | Once a day | 75 | 9.3 |
| | Several times a day | 673 | 83.7 |

**Table 1.** Background information (N = 804). N = Frequency, % = Percentage.

| Construct | AISE | CT | ESC | GUC |
|---|---|---|---|---|
| AISE | 0.869 | ***0.864*** | ***0.739*** | ***0.700*** |
| CT | 0.817 | 0.854 | ***0.795*** | ***0.693*** |
| ESC | 0.714 | 0.750 | 0.910 | ***0.607*** |
| GUC | 0.662 | 0.643 | 0.573 | 0.794 |

**Table 2**. Results of Fornell–Larcker and HTMT analyses. The lower triangle represents the Pearson correlation coefficients between constructs, while the diagonal contains the square roots of the AVE. The upper triangle represents the heterotrait–monotrait (HTMT) ratio with values in bold and italics. AISE, Artificial Intelligence Self-Efficacy; CT, Critical Thinking; ESC, Engineering Students' Creativity; GUC, Generative Artificial Intelligence Usage Competence.

| | | Factor loadings/Cross-loadings | | | |
|---|---|---|---|---|---|
| Construct/Item | Indicator weight | AISE | CT | ESC | GUC |
| Artificial intelligence self-efficacy (AISE) | | | | | |
| AISE1 | 0.139 | ***0.872*** | 0.789 | 0.670 | 0.576 |
| AISE2 | 0.119 | ***0.807*** | 0.691 | 0.544 | 0.549 |
| AISE3 | 0.139 | ***0.909*** | 0.787 | 0.660 | 0.594 |
| AISE4 | 0.131 | ***0.900*** | 0.733 | 0.618 | 0.606 |
| AISE5 | 0.119 | ***0.855*** | 0.652 | 0.580 | 0.557 |
| AISE6 | 0.121 | ***0.882*** | 0.663 | 0.571 | 0.600 |
| AISE7 | 0.123 | ***0.886*** | 0.674 | 0.582 | 0.596 |
| AISE8 | 0.128 | ***0.850*** | 0.668 | 0.664 | 0.556 |
| AISE9 | 0.132 | ***0.854*** | 0.707 | 0.676 | 0.546 |
| Critical thinking (CT) | | | | | |
| CT1 | 0.197 | 0.707 | ***0.877*** | 0.608 | 0.590 |
| CT2 | 0.213 | 0.760 | ***0.928*** | 0.682 | 0.619 |
| CT3 | 0.205 | 0.736 | ***0.925*** | 0.689 | 0.552 |
| CT4 | 0.212 | 0.766 | ***0.908*** | 0.678 | 0.610 |
| CT5 | 0.202 | 0.707 | ***0.862*** | 0.698 | 0.544 |
| CT6 | 0.129 | 0.462 | ***0.570*** | 0.455 | 0.327 |
| Engineering students' creativity (ESC) | | | | | |
| ESC1 | 0.164 | 0.702 | 0.702 | ***0.841*** | 0.527 |
| ESC2 | 0.149 | 0.604 | 0.652 | ***0.907*** | 0.514 |
| ESC3 | 0.160 | 0.655 | 0.698 | ***0.925*** | 0.535 |
| ESC4 | 0.153 | 0.640 | 0.660 | ***0.910*** | 0.514 |
| ESC5 | 0.157 | 0.636 | 0.683 | ***0.920*** | 0.528 |
| ESC6 | 0.156 | 0.639 | 0.683 | ***0.938*** | 0.507 |
| ESC7 | 0.160 | 0.667 | 0.691 | ***0.928*** | 0.525 |
| Generative artificial intelligence usage competence (GUC) | | | | | |
| GUC1 | 0.159 | 0.463 | 0.450 | 0.389 | ***0.644*** |
| GUC2 | 0.181 | 0.501 | 0.517 | 0.462 | ***0.830*** |
| GUC3 | 0.154 | 0.425 | 0.449 | 0.383 | ***0.780*** |
| GUC4 | 0.143 | 0.398 | 0.408 | 0.364 | ***0.768*** |
| GUC5 | 0.192 | 0.524 | 0.527 | 0.530 | ***0.803*** |
| GUC6 | 0.208 | 0.636 | 0.566 | 0.492 | ***0.843*** |
| GUC7 | 0.218 | 0.656 | 0.602 | 0.520 | ***0.865*** |

**Table 3**. Indicator validity. Factor loadings are indicated by values in bold and italics; CA, Cronbach's alpha; CR, Composite Reliability; AVE, Average Variance Extracted.

| | AISE | CT | ESC | GUC |
|---|---|---|---|---|
| $R^2$ | Moderate explanatory power | Weak explanatory power | Moderate explanatory power | |
| $Q^2$ | High predictive relevance | Medium predictive relevance | High predictive relevance | Medium predictive relevance |
| SRMR | Accepted | | | |
| NFI | Good fit | | | |
| GOF | High fit | | | |

**Table 4**. $R^2$ and construct reliability and validity. The coefficient of determination was $R^2$; construct reliability and validity included Cronbach's alpha, composite reliability, and AVE; and the measure of predictive relevance was Q2. $R^2 \geq 0.75$: Strong explanatory power; $0.50 \leq R^2 < 0.75$: Moderate explanatory power; $0.25 \leq R^2 < 0.50$: Weak explanatory power; $R^2 < 0.25$: Very weak explanatory power. $Q^2 \geq 0$: Minimum threshold (indicates predictive relevance); $Q^2 > 0.35$: High predictive relevance; $0.15 < Q^2 \leq 0.35$: Medium predictive relevance; $Q^2 \leq 0.15$: Low predictive relevance. GOF ≥ 0.10: Poor fit; GOF ≥ 0.25: Medium fit; GOF ≥ 0.36: High fit. AISE = Artificial Intelligence Self-Efficacy; CT = Critical Thinking; ESC = Engineering Students' Creativity; GUC = Generative Artificial Intelligence Usage Competence. SRMR = Standardized Root Mean Square Residual. A commonly accepted cut-off value is SRMR < 0.08. NFI = Normed Fit Index. NFI value > 0.90 indicates a Good Fit.

| | GN | EL | MA | RO | GE | FU | GUC | CT | AISE | ESC |
|---|---|---|---|---|---|---|---|---|---|---|
| GN | 1 | | | | | | | | | |
| EL | 0.050 | 1 | | | | | | | | |
| MA | − 0.246** | − 0.077* | 1 | | | | | | | |
| RO | 0.013 | 0.031 | − 0.128** | 1 | | | | | | |
| GE | 0.081* | 0.079* | − 0.081* | − 0.017 | 1 | | | | | |
| FU | 0.028 | 0.020 | 0.078* | − 0.235** | 0.031 | 1 | | | | |
| GUC | 0.108** | − 0.046 | 0.004 | − 0.059 | − 0.001 | 0.187** | 1 | | | |
| CT | 0.087* | − 0.092** | 0.013 | − 0.018 | 0.034 | 0.204** | 0.618** | 1 | | |
| AISE | 0.086* | − 0.109** | − 0.014 | − 0.015 | 0.047 | 0.219** | 0.640** | 0.810** | 1 | |
| ESC | 0.073* | − 0.077* | − 0.062 | − 0.049 | 0.010 | 0.158** | 0.562** | 0.747** | 0.713** | 1 |
| M | – | – | – | – | – | – | 4.570 | 4.367 | 4.568 | 4.306 |
| SD | – | – | – | – | – | – | 0.650 | 0.742 | 0.627 | 0.734 |

**Table 5**. Descriptive statistics and correlation coefficients. ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed). GN = Gender; EL, Education Level; MA, Major; RO, Region of Origin; GE, GenAI Experience; FU, Frequency of GenAI Usage. AISE, Artificial Intelligence Self-Efficacy; CT, Critical Thinking; ESC, Engineering Students' Creativity; GUC, Generative Artificial Intelligence Usage Competence.

## Results

### Descriptive statistics and correlation analysis

Table 5 presents the descriptive statistics and correlation coefficients among the study variables. The results demonstrate several significant associations, particularly among the psychological constructs, GenAI usage competence, critical thinking, AI self-efficacy, and engineering students' creativity, while demographic variables such as gender, education level, major, and region of origin show weaker or more inconsistent relationships.

Engineering students' creativity exhibits strong positive correlations with critical thinking ($r = 0.747$, $p < 0.01$), AI self-efficacy ($r = 0.713$, $p < 0.01$), and GenAI usage competence ($r = 0.562$, $p < 0.01$). These findings indicate that students who demonstrate higher competence in using GenAI tools, greater confidence in their AI-related abilities, and stronger critical thinking skills also tend to report higher levels of creativity. The interrelations among GenAI-related variables are particularly noteworthy. GenAI usage competence is significantly associated with both AI self-efficacy ($r = 0.640$, $p < 0.01$) and critical thinking ($r = 0.618$, $p < 0.01$), suggesting that students who perceive themselves as competent users of GenAI tools are also more likely to report higher levels of confidence in their AI abilities and stronger critical thinking capacities. Moreover, AI self-efficacy and critical thinking are highly correlated ($r = 0.810$, $p < 0.01$), underscoring the possibility that students' cognitive and self-belief systems reinforce one another in the process of creative problem-solving.

By contrast, demographic variables display comparatively weaker associations. For example, gender is positively related to GenAI usage competence ($r = 0.108$, $p < 0.01$), AI self-efficacy ($r = 0.086$, $p < 0.05$), and creativity ($r = 0.073$, $p < 0.05$), though these effects are modest in magnitude. Major is negatively correlated with education level ($r = -0.077$, $p < 0.05$) and region of origin ($r = -0.128$, $p < 0.01$), whereas region of origin is negatively associated with frequency of GenAI usage ($r = -0.235$, $p < 0.01$). These suggest some demographic

| Hypothesis | STDEV | 95% CI | | Statistical Significance | Decision | Effect Size |
|---|---|---|---|---|---|---|
| | | Low | High | | | |
| H1: GUC→ESC | 0.039 | 0.016 | 0.169 | 2.394* | Accepted | 0.012^small^ |
| H2: GUC→CT | 0.034 | 0.577 | 0.708 | 19.148*** | Accepted | 0.703^large^ |
| H3: CT→ESC | 0.049 | 0.374 | 0.570 | 9.545*** | Accepted | 0.174^moderate^ |
| H5: GUC→AISE | 0.045 | 0.154 | 0.328 | 5.245*** | Accepted | 0.107^moderate^ |
| H6: AISE→ESC | 0.058 | 0.156 | 0.380 | 4.629*** | Accepted | 0.054^small^ |
| H8: CT→AISE | 0.039 | 0.583 | 0.737 | 17.018*** | Accepted | 0.865^large^ |

**Table 6**. Bootstrap analysis of direct effects. STDEV, Standard Deviation; CI, Confidence Intervals. AISE, Artificial Intelligence Self-Efficacy; CT, Critical Thinking; ESC, Engineering Students' Creativity; GUC, Generative Artificial Intelligence Usage Competence. Effect size ($f^2$): 0.02 to 0.15 (weak); 0.15 to 0.35 (moderate); > 0.35 (strong). *$t > 1.96$ at $p < 0.05$, **$t > 2.576$ at $p < 0.01$, and ***$t > 3.29$ at $p < 0.001$.

| Hypothesis | STDEV | 95% CI | | Statistical significance | Decision |
|---|---|---|---|---|---|
| | | Low | High | | |
| Specific indirect effects (Mediating role of critical thinking) | | | | | |
| H4: GUC→CT→ESC | 0.037 | 0.235 | 0.381 | 8.224*** | Partial Mediation |
| H9: GUC→CT→AISE | 0.028 | 0.374 | 0.484 | 15.258*** | Partial Mediation |
| Specific indirect effects (Mediating role of ai self-efficacy) | | | | | |
| H7: GUC→AISE→ESC | 0.019 | 0.031 | 0.106 | 3.230** | Partial Mediation |
| H10: CT→AISE→ESC | 0.039 | 0.102 | 0.253 | 4.628*** | Partial Mediation |
| Specific chain indirect effects (Chain mediating role of critical thinking and ai self-efficacy) | | | | | |
| H11: GUC→CT→AISE→ESC | 0.025 | 0.066 | 0.164 | 4.581*** | Accepted |

**Table 7**. Bootstrap analysis of mediating effects. STDEV = Standard Deviation; CI = Confidence Intervals. *$t > 1.96$ at $p < 0.05$, **$t > 2.576$ at $p < 0.01$, and ***$t > 3.29$ at $p < 0.001$. AISE = Artificial Intelligence Self-Efficacy; CT = Critical Thinking; ESC = Engineering Students' Creativity; GUC = Generative Artificial Intelligence Usage Competence. Partial mediation occurs when the mediator explains part, but not all, of the relationship between an independent variable and a dependent variable. Partial mediation = both direct and indirect effects are significant.

differences in how students access or engage with GenAI, but their influence on creativity is comparatively limited.

### Direct effects analysis

Table 6 shows that all hypothesised direct effects are statistically significant ($T > 1.96$, $p < 0.05$), with confidence intervals excluding zero. The effect sizes range from small to large, suggesting that the practical impact of these direct relationships varies. In particular, the direct effects of GenAI usage competence on critical thinking (H2: $f^2 = 0.703$) and of critical thinking on AI self-efficacy (H8: $f^2 = 0.865$) show large effect sizes, whereas its direct effect on engineering students' creativity is small (H1: $f^2 = 0.012$; H6: $f^2 = 0.054$). Other pathways, such as the effects of critical thinking on creativity (H3: $f^2 = 0.174$) and GenAI usage competence on AI self-efficacy (H5: $f^2 = 0.107$), show moderate effect sizes, indicating meaningful but less pronounced practical impacts.

## Analysis of mediating effects and chain mediating effects

Table 7 shows that all specific indirect effects through critical thinking and AI self-efficacy are statistically significant ($T > 1.96$, $p < 0.05$), with confidence intervals that do not include zero. The results confirm the partial mediating role of critical thinking (H4, H9) and AI self-efficacy (H7, H10) in the relationships among GenAI usage competence, critical thinking, AI self-efficacy, and engineering students' creativity. The chain indirect effect (H11) is also significant, indicating that critical thinking and AI self-efficacy together form a valid chain mediating pathway between GenAI usage competence and engineering students' creativity.

## Discussion

### The effects of demographic variables

Region of origin demonstrated the strongest effect, showing a moderate negative correlation with frequency of GenAI use ($r = -0.235$, $p < 0.01$). This likely reflects disparities in access and opportunity, such as infrastructural resources, regulatory contexts, or language familiarity, which influence how frequently students engage with GenAI. Importantly, this regional variation was not associated with meaningful differences in competence or creativity, suggesting that once exposure is available, subsequent outcomes are primarily determined by skill acquisition and psychological processes rather than regional background. The relationship between gender and major ($r = -0.246$, $p < 0.01$) indicates an uneven gender distribution across fields of study. Gender itself showed only small positive associations with GenAI usage competence, critical thinking, AI self-efficacy, and creativity (all $|r| \leq 0.108$). These effects are minor and most plausibly reflect indirect compositional influences, for example, differences in prior experiences or disciplinary pathways, rather than intrinsic differences[63,64]. This interpretation is reinforced by the likelihood that any apparent gender effects would diminish once major and competence are statistically controlled. Other demographic relationships were weak. Education level was negatively associated with critical thinking ($r = -0.092$, $p < 0.05$) and creativity ($r = -0.077$, $p < 0.05$). One possible explanation is that as students progress academically, increasing specialization and performance pressures may constrain divergent thinking and reduce self-perceptions of creativity[65,66]. Major, meanwhile, showed only a negligible positive correlation with frequency of GenAI use ($r = 0.078$, $p < 0.05$) and no reliable association with creativity, indicating that disciplinary affiliation alone is not a meaningful predictor of creative outcomes in the absence of GenAI competence and related psychological factors.

### The relationship of GenAI usage competence and engineering students' creativity

GenAI usage competence exerts a significant influence on engineering students' creativity, underscoring the evolving interplay between technological proficiency and creativity in engineering education. While prior research has shown that technological competence provides a foundation for problem-solving[67–69], our findings indicate that its value extends beyond technical skill, functioning as a catalyst for students to engage with ill-structured problems in more flexible and original ways. Importantly, this relationship highlights a broader educational imperative: creativity does not emerge from proficiency with GenAI alone but from students' capacity to integrate such tools with critical judgment and imaginative exploration[70,71]. This underscores the need to treat GenAI competence not as an end in itself, but as a springboard for cultivating creativity.

### Mediating role of critical thinking

Critical thinking partially mediates the relationship between GenAI usage competence and both AI self-efficacy and creativity, highlighting the cognitive processes that underpin effective technology use in learning. This suggests that GenAI competence alone may enhance students' confidence and creative output, but its broader educational value emerges when learners actively engage in analysis and reflective judgement. This finding aligns with the wider literature, which underscores critical thinking as central to transforming technical skills into meaningful intellectual and creative growth[32,72]. Accordingly, simply providing GenAI tools is insufficient; pedagogical designs must deliberately prompt students to question, evaluate, and refine AI-generated ideas[73,74]. However, evidence in the field is not entirely consistent. Acosta-Enriquez et al. (2025), for example, found no mediation effect, indicating that the role of critical thinking may depend on how GenAI tools use is conceptualised and the contexts in which it is embedded[36]. When GenAI engagement is framed as dependency, critical thinking may be bypassed rather than stimulated, reducing its mediating influence. Such findings suggest that critical thinking is not a universal mediator but one whose impact depends on whether GenAI tools integration actively requires evaluation and reflection. By situating our results within this nuanced landscape, the present study both confirms the value of critical thinking and points to the need for future work to clarify the conditions under which its mediating role is most influential.

### Mediating role of AI self-efficacy

AI self-efficacy partially mediates the links between GenAI competence, critical thinking, and creativity, emphasising the significance of learners' beliefs in their ability to use AI effectively. Consistent with social cognitive theory[37,75,76], our results suggest that technical competence and critical thinking only reach their full creative potential when accompanied by confidence in applying AI tools autonomously. For engineering education, this insight shifts attention from skill acquisition alone to the development of resilient learner mindsets: students who trust their ability to experiment with and adapt GenAI are more likely to take intellectual risks, pursue unconventional solutions, and persist through design challenges. Thus, building AI self-efficacy is not peripheral but central to enabling the creative application of emerging technologies.

### Chain mediating role of critical thinking and AI self-efficacy

The chain mediation of critical thinking and AI self-efficacy reveals how GenAI usage competence translates into creativity through a sequential process: analytical engagement fosters reflective judgement, which in turn nurtures confidence in deploying AI for creative purposes. This finding refines existing accounts of creativity in engineering, showing that technical proficiency alone is insufficient without the interplay of critical thinking and self-belief[77]. The educational implication is clear: GenAI should be embedded within learning designs that couple critical enquiry (such as open-ended problem-solving, structured critique, and peer debate) with opportunities for students to iteratively apply AI and build confidence from experience. By cultivating this progression, from critical analysis to self-assured experimentation, educators can better harness GenAI not only as a technical aid but as a transformative driver of creative growth.

## Implications

### Theoretical implications

This study reveals that the influence of GenAI usage competence on engineering students' creativity is not direct, but operates through a serial mediation mechanism involving critical thinking and AI self-efficacy. While previous research has emphasized the independent contributions of technological tools, cognitive skills, and psychological factors to educational outcomes, these studies often treated them as parallel or isolated variables rather than examining their dynamic interplay[78,79]. Our findings challenge this fragmented perspective by demonstrating that critical thinking and AI self-efficacy do not function independently; instead, they operate sequentially to transmit the effects of GenAI competence onto creativity. This sequential mediation model provides a more nuanced and integrated theoretical framework for understanding technology-enhanced learning, illustrating how cognitive and psychological factors are intertwined in shaping creativity. Consequently, our research provides a theoretical reference for the integration of GenAI into engineering education by illuminating the interdependent developmental pathways through which AI technology, critical thinking, and AI self-efficacy collectively foster creativity.

## Practical implications

This study provides valuable insights into how GenAI technology can be effectively integrated into engineering education to enhance students' creativity. By demonstrating the critical roles of critical thinking and AI self-efficacy in the relationship between GenAI usage competence and creativity, this research offers concrete guidance for shaping engineering curricula. To address the evolving demands of the profession, engineering education should not only incorporate GenAI technology but also focus on fostering critical thinking skills. Curricula should embrace problem-based and project-driven learning approaches that simultaneously develop technical abilities and higher-order cognitive skills, thus preparing students to tackle complex, real-world engineering challenges[80]. Furthermore, educators can enhance students' technological self-efficacy through strategies like goal-setting, positive reinforcement, and mentorship, which can alleviate anxiety and increase confidence in using advanced technologies. By integrating interdisciplinary content, such as data science, ethics, and practical applications, engineering programs can empower students to merge technological tools with critical thinking in solving engineering problems[81]. Ultimately, this research underscores the importance of a holistic approach to education, one that fosters not only technical proficiency but also cognitive flexibility and psychological empowerment, ensuring that students are equipped to navigate the rapidly changing landscape of engineering and contribute to creative solutions in the profession[78].

## Conclusion

This study provides evidence that competence in using GenAI significantly enhances the creativity of engineering students. The results suggest that creativity is most effectively fostered when technological competence is integrated with critical thinking and self-efficacy in applying GAI tools. The study advances our understanding of how emerging AI technologies can be strategically incorporated into educational contexts to cultivate creativity among future engineers.

## Limitations

First, this study relied solely on self-reported data, which may introduce bias. Future research could combine self-reports with performance tasks or peer/teacher evaluations to improve validity. Second, the cross-sectional design restricts causal inference. Longitudinal or experimental studies are needed to examine how students' GenAI competence and creativity evolve in the future. Third, contextual factors such as institutional support, cultural differences, and prior AI experience were not empirically measured, although they may influence students' use of GenAI tools. Future studies should include these factors as controls or moderators to better capture their effects. Finally, although PLS-SEM suits exploratory models, it is sensitive to sample size and non-normality; further studies should compare results using alternative methods and test data assumptions.

## Data availability

The authors will make the raw data supporting this study's conclusions available (dora_guo@e.gzhu.edu.cn or dora777guo@gmail.com) without undue reservation.

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## Author contributions
Z.Z.: Conducted the experiments, analyzed the data, and edited the manuscript. H.F.: Conceptualized the study, designed the experiments, and wrote the manuscript. Q.F.: Provided critical resources, performed statistical analysis, and reviewed the manuscript. C. Y.: Performed data verification and full-text review. Y. G.: Guided data analysis and conducted literature collection.

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## Declarations

## Competing interests
The authors declare no competing interests.

## Ethical approval
This research project has received ethical approval from the Ethics Review Committee of the School of Education, Guangzhou University (GZHUSE2024001). Informed consent was obtained from all of the participants included in this study.

## Additional information
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