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Artificial intelligence in teacher education: Examining critical thinking and creativity through AI usage

Xianfeng Li

Leshan Normal University, Leshan 614004, Sichuan, China; lixf7307@126.com

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Abstract: The integration of Artificial Intelligence (AI) in teacher education has raised important questions about its impact on higher-order cognitive skills, particularly critical thinking and creativity. This study investigates the mediating role of critical thinking in the relationship between AI usage and creativity among pre-service teachers. Grounded in Cognitive Load Theory (CLT) and Dual-Process Theory, the research conceptualizes critical thinking as a second-order reflective construct comprising adaptive exploration (AE) and systematic validation (SV). Using a cross-sectional survey design, data were collected from 107 pre-service teachers at a teacher training institution in Southwest China. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to analyze the relationships among AI usage, critical thinking, and creativity. Results indicate that AI usage significantly enhances critical thinking ($\beta = 0.560, p < 0.001$), which, in turn, has a strong positive effect on creativity ($\beta = 0.707, p < 0.001$). Moreover, critical thinking serves as a partial mediator, amplifying the effect of AI usage on creativity ($\beta = 0.397, p < 0.001, VAF = 65.89\%$). These findings underscore the necessity of fostering AI-supported critical thinking skills in teacher education. As generative AI technologies become increasingly prevalent in digital learning environments, integrating adaptive exploration and systematic validation into pedagogical strategies is essential for cultivating both critical thinking and creativity. The study contributes to the discourse on digital learning innovations and teacher education by providing empirical evidence on AI's role in enhancing cognitive development.

Keywords: AI usage; teacher education; critical thinking; creativity; cognitive load theory; dual-process theory

1. Introduction

Artificial Intelligence (AI) is reshaping education by transforming teaching methodologies and influencing students' cognitive skills. With the rapid advancement of generative AI, a new media ecosystem is emerging, posing both challenges and opportunities for teacher education. AI-powered applications, such as automated tutoring systems, generative content tools, and adaptive learning technologies, are revolutionizing how educators and learners interact with knowledge [1,2]. These technologies offer personalized instructional support and real-time feedback, improving knowledge acquisition and accessibility. However, they also raise concerns regarding the overreliance on AI-generated content, ethical considerations, and the potential erosion of independent reasoning [3,4]. Understanding how AI impacts higher-order cognitive abilities—particularly critical thinking and creativity—is thus essential for developing effective AI-integrated pedagogies.

To explore the cognitive mechanisms underlying AI's role in education, this study employs Cognitive Load Theory (CLT) [5] and Dual-Process Theory (DPT) [6] as its theoretical foundation. Cognitive Load Theory suggests that learning

effectiveness depends on managing intrinsic, extraneous, and germane cognitive loads, all of which can be influenced by AI tools [7]. AI-driven instructional systems, such as adaptive feedback mechanisms and automated content generation, can reduce extraneous cognitive load, thereby allowing learners to allocate more cognitive resources to meaningful learning processes [8].

In parallel, Dual-Process Theory provides a framework for understanding how AI interacts with human cognition by distinguishing between two reasoning modes: System 1 (intuitive, automatic thinking) and System 2 (deliberate, analytical reasoning) [9]. AI-based educational tools, such as content recommendation systems and generative AI models, may stimulate System 1 thinking by providing rapid answers while also fostering System 2 engagement by prompting critical analysis and reflection [4]. The interplay between these two cognitive processes within AI-assisted learning environments remains an essential area of research in teacher education.

Despite the growing adoption of AI in educational settings, empirical research on its direct impact on higher-order cognitive skills, particularly critical thinking and creativity, remains insufficient. Existing studies have primarily focused on AI's role in improving factual knowledge acquisition and task automation, rather than examining how it fosters deeper cognitive processing and problem-solving skills [10,11]. Recent studies indicate that AI-driven learning environments have the potential to enhance cognitive flexibility, encourage knowledge exploration, and support structured reasoning. However, there are ongoing debates regarding the extent to which these systems truly cultivate critical thinking and creativity, rather than simply facilitating procedural knowledge application [12–14]. Furthermore, AI-enhanced learning environments enable adaptive exploration by exposing learners to diverse perspectives and assisting in complex problem analysis. Generative AI tools, for example, can create multiple solution pathways, helping learners to refine and validate their reasoning strategies through iterative testing [15,16]. Moreover, systematic validation—characterized by structured reasoning, hypothesis testing, and critical evaluation—plays a crucial role in ensuring the accuracy and credibility of AI-generated outputs. This is particularly important in educational settings, where students must learn to discern between reliable and misleading AI-assisted recommendations [12–14]. Nevertheless, gaps remain in understanding whether AI-driven cognitive scaffolding effectively translates into long-term improvements in critical thinking and creativity, particularly among pre-service teachers. Further empirical validation is needed to determine how AI-supported learning interventions can be optimized to cultivate these essential skills.

To bridge this gap, this study examines how critical thinking mediates the relationship between AI usage and creativity within the context of teacher education. Given the dynamic nature of AI-enhanced learning environments, understanding this mediation is essential for optimizing AI's impact on cognitive skill development. This study conceptualizes critical thinking as a second-order reflective construct composed of adaptive exploration and systematic validation. These dimensions represent the dual aspects of cognitive engagement: exploratory thinking, which fosters curiosity and knowledge expansion, and analytical reasoning, which ensures structured evaluation and logical decision-making.

1.1. Conceptual framework

The conceptual model of this study is presented in **Figure 1**, which illustrates the hypothesized relationships among AI usage, critical thinking, and creativity. Critical thinking is modeled as a second-order reflective construct, composed of adaptive exploration (AE) and systematic validation (SV).

- H1. AI usage positively influences creativity.
- H2. AI usage positively influences critical thinking.
- H3. Critical thinking positively influences creativity.
- H4. Critical thinking mediates the relationship between AI usage and creativity.

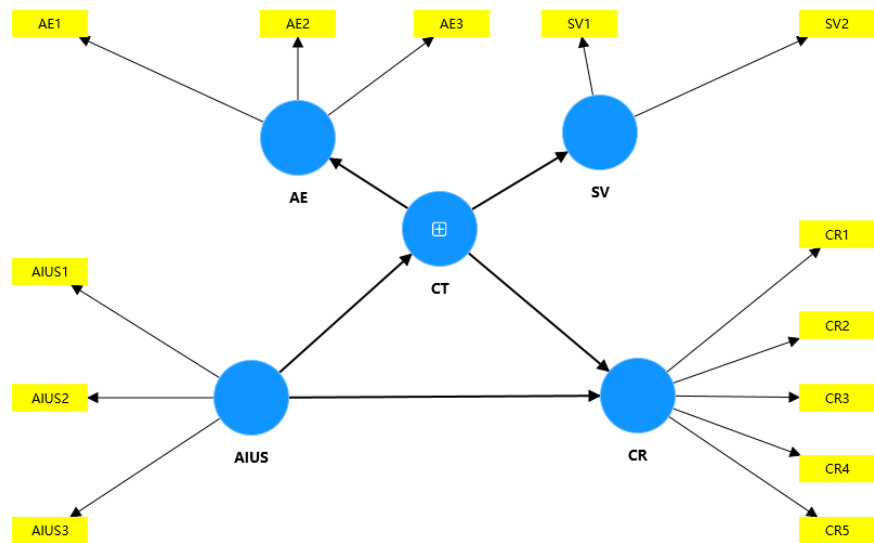


Figure 1. Conceptual framework of the study.

AIUS = AI Usage, CR = Creativity, AE = Adaptive Exploration, SV = Systematic Validation; CT = Critical Thinking, modeled as a second-order reflective construct combining AE and SV.

1.2. Research objectives

To examine the direct effect of AI usage on critical thinking and creativity among pre-service teachers.

To analyze the mediating role of critical thinking, conceptualized as adaptive exploration and systematic validation, in the relationship between AI usage and creativity.

To provide empirical evidence on how AI contributes to higher-order cognitive skill development in teacher education.

By fulfilling these objectives, this study expands the current literature on AI-driven education, offering valuable insights for integrating AI into instructional strategies to foster critical thinking and creativity in future educators. Moreover, this research informs policy development for effective AI incorporation in teacher training programs, ensuring that AI serves as a cognitive enhancer rather than a substitute for essential intellectual skills.

2. Design and methods

This section provides a detailed account of the methodology used in this study to ensure replicability and clarity for future research. The study design, participant

recruitment, measurement instruments, and data analysis procedures are outlined below. All methodologies applied in this study are based on established research protocols and previously validated approaches.

2.1. Study design

The study employed a descriptive quantitative research design using structural equation modeling (SEM) to examine the relationships between AI usage, critical thinking, and creativity. Following the recommendations of Creswell and Creswell [17], a systematic approach was adopted to ensure validity and reliability. Given the complexity of the conceptual model and the presence of a mediating variable, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed using SMART-PLS 4.0 [18]. This approach is well-suited for analyzing models with latent variables and is particularly effective for small to medium sample sizes.

2.2. Respondents

A total of 107 pre-service teachers participated in the study. Convenience sampling was used to recruit participants, allowing for accessibility while maintaining diversity in gender, academic year, and field of study. To ensure relevance to the research focus, participants were required to have prior exposure to AI-driven educational tools, including adaptive learning platforms, automated feedback systems, or generative AI assistants.

The demographic composition included a majority of female participants, and the distribution of academic levels indicated that most respondents were in their junior or sophomore years. AI usage among participants varied, with some reporting frequent use in learning and writing activities, while others indicated occasional engagement.

2.3. Measurement instruments

The survey instrument was constructed through methodological synthesis of established psychometric tools, incorporating cross-cultural adaptation protocols to ensure contextual relevance. **Table 1** provides a comprehensive taxonomy of theoretical constructs, encompassing operational definitions, calibrated measurement items, and their respective disciplinary provenance.

The research instrument was meticulously crafted through systematic integration of psychometrically established measurement frameworks, incorporating rigorous cross-cultural adaptation procedures to ensure contextual fidelity. As detailed in **Table 1**, the operational architecture of this study's measurement paradigm comprises three foundational elements: theoretically anchored construct definitions, empirically refined survey items, and explicit disciplinary origination traces for each latent variable.

Table 1. Construct, definitions, items, source.

Constructs	Definition	Items
AI Usage (AIUS)	Reflects the extent to which individuals use AI tools in their daily learning, writing, language support, and problem-solving processes. This dimension encompasses three specific application scenarios: seeking academic assistance, writing and language support, and seeking help with life-related issues [19].	<p>AIUS1—I use AI tools to obtain academic support, such as homework tutoring, conceptual understanding, or research guidance.</p> <p>AIUS2—I use AI tools to solve real-life problems, such as time management, health advice, or financial planning.</p> <p>AIUS3—I use AI tools to translate texts, proofread written content, or improve grammar and sentence structure.</p>
Creativity (CR)	The ability of an individual to propose innovative solutions when faced with ambiguous or undefined problems. Creativity not only involves generating novel ideas but also includes adaptive adjustments to challenges and flexibility in responding to external feedback during the creative process [20]. Creativity can be regarded as a higher-order cognitive ability, encompassing five core dimensions [21].	<p>CR1—When faced with an ambiguous or undefined problem, I can propose multiple innovative solutions.</p> <p>CR2—I believe in my ability to find effective solutions in situations requiring creative thinking.</p> <p>CR3—In daily life, I often devise new methods to solve problems.</p> <p>CR4—When my creative ideas are challenged, I am willing to adjust or alter my thinking.</p> <p>CR5—I consider myself highly creative in certain fields.</p>
Adaptive Exploration (AE)	Refers to an individual’s willingness to accept different viewpoints, listen to opposing opinions, and actively seek new information to enrich their knowledge system [22]. This dimension emphasizes cognitive openness and information exploration [23].	<p>AE1—I am open to rethinking a problem from others’ perspectives, even if they differ from my own.</p> <p>AE2—In discussions or debates, I listen to opposing viewpoints and strive to understand their reasoning, even when they contradict mine.</p> <p>AE3—When information is insufficient, I actively seek additional data to make informed decisions.</p>
Systematic Validation (SV)	Refers to an individual’s ability to logically break down complex problems, evaluate assumptions, and systematically reason to make rational decisions [24]. This dimension emphasizes analytical reasoning and hypothesis testing [25].	<p>SV1—I can break down complex problems to identify optimal solutions.</p> <p>SV2—I can identify hidden assumptions in an argument and evaluate their validity.</p>
Critical Thinking (CT)	It is a second-order dimension that integrates open exploration and systematic reasoning, reflecting the two core dimensions of critical thinking. It represents how individuals process information and problems through adaptive exploration (AE) and systematic verification (SV).	NULL

Note: NULL, CT is a reflective second-order construct comprising AE and SV, thus lacking direct measurement items.

2.3.1. AI usage (AIUS)

Measured through three items evaluating participants’ engagement with AI for academic support, writing assistance, and self-directed learning.

2.3.2. Critical thinking (CT)

Operationalized as a second-order construct composed of Adaptive Exploration (AE) and Systematic Validation (SV). Five items captured individuals' openness to diverse perspectives and their ability to evaluate assumptions [26].

2.3.3. Creativity (CR)

Assessed using five items evaluating innovative problem-solving skills and adaptability [27].

All theoretical constructs were quantitatively assessed using a seven-point psychometric response continuum, with scale anchors explicitly defined as complete disagreement (1) through full endorsement (7). The measurement instruments' psychometric robustness—encompassing both validity and reliability metrics—was initially established through rigorous prior empirical investigations, with additional confirmatory verification conducted within the current research paradigm.

2.4. Reliability and validity assessment

To ensure the robustness of the measurement model, this study conducted a multi-faceted assessment of reliability and validity using well-established statistical criteria.

2.4.1. Internal consistency reliability

The internal consistency of all latent variables was rigorously examined through two complementary psychometric indices: Cronbach's alpha coefficient (α) for scale homogeneity and composite reliability (CR) for measurement stability. Adhering to conventional psychometric standards, a reliability benchmark of ≥ 0.70 was implemented to ensure unidimensional construct representation, thereby verifying that constituent items collectively captured their intended theoretical domain with statistical precision.

2.4.2. Convergent validity

Convergent validity was examined through the Average Variance Extracted (AVE) metric, serving as a statistical measure to determine the proportion of collective variance accounted for by the observed indicators within each latent construct. Latent variables demonstrating AVE values exceeding the psychometric threshold of 0.50 were established as meeting rigorous convergent validity criteria, in alignment with established methodological standards [28].

2.4.3. Discriminant validity

Discriminant validity was systematically validated through a dual analytical strategy. The initial phase employed the Fornell-Larcker criterion, wherein the square root of each latent variable's average variance extracted (AVE) was evaluated against its cross-construct correlation coefficients, confirming theoretical independence. In the subsequent phase, the heterotrait-monotrait ratio (HTMT) metric was rigorously analyzed, yielding values consistently below the stringent threshold of 0.85, thereby empirically substantiating distinctiveness across all theoretical constructs.

2.5. Data analysis procedures

Data analysis was conducted using SMART-PLS 4.0, which is appropriate for variance-based SEM (PLS-SEM). The following statistical techniques were applied to

test the hypotheses and validate the model:

2.5.1. Descriptive statistics

The dataset's distributional properties and participant profiles were analyzed through computation of core statistical indicators—central tendency (means), variability (standard deviations), and distribution shape parameters (skewness/kurtosis). These metrics collectively evaluated normative assumptions while delineating population demographics and artificial intelligence interaction trends across the sample [29].

2.5.2. Measurement model evaluation

Convergent validity was rigorously established through systematic evaluation of three core psychometric indicators: individual item validity coefficients (factor loadings), composite scale reliability indices (CR), and latent construct variance capture metrics (AVE), in strict accordance with established validation protocols [18]. The measurement model's reliability and validity were confirmed through these metrics.

2.5.3. Structural model evaluation

Path coefficients and hypothesis testing were conducted using bootstrapping with 5000 resamples to estimate the statistical significance of relationships in the model. This approach provided robust estimates of the direct and indirect effects.

2.5.4. Multicollinearity check

Variance Inflation Factor (VIF) values were examined to ensure that predictor variables were not highly correlated [18]. VIF values below 5 indicated no multicollinearity issues, ensuring the validity of the regression coefficients.

2.5.5. Mediation analysis

The Variance Accounted For (VAF) approach was used to evaluate the mediating role of critical thinking in the AI usage-creativity relationship [30]. A VAF value of 65.9% suggested a substantial mediation effect, indicating that critical thinking significantly contributes to the relationship between AI usage and creativity.

To maintain data privacy and anonymity, no personally identifiable information was collected. All responses were stored securely and were accessible only to the research team. The study followed the ethical principles outlined in the American Psychological Association (APA) Ethical Guidelines [31] to uphold the highest standards of research integrity and participant protection.

3. Results

This section presents the findings of the study, including descriptive statistics, reliability and validity assessments, and hypothesis testing results. The analysis was conducted using SMART-PLS 4.0 to evaluate the relationships among AI usage, critical thinking, and creativity.

3.1. Descriptive statistics

Table 2 systematically delineates the sociodemographic characteristics of the respondents, providing detailed insights into key demographic variables including age

distribution, educational attainment tiers, professional experience spectra, and technology adoption tendencies within the study population.

Table 2. Demographic profile of respondents.

Demographic profile		Frequency	Percentage (%)
Gender	Male	9	8.4%
	Female	98	91.6%
Grade Level	Freshman	0	0%
	Sophomore	28	26.2%
	Junior	79	73.8%
	Senior	0	0%
How frequently do you use AI in your daily life?	Never	0	0%
	Occasionally	33	30.8%
	Sometimes	53	49.5%
	Usually	21	19.6%
	Always	0	0%

The sample consisted of 107 pre-service teachers, with 91.6% female and 8.4% male. In terms of academic level, 73.8% were juniors, and 26.2% were sophomores. Regarding AI usage frequency, 49.5% reported using AI sometimes, while 30.8% used it occasionally, and 19.6% used it usually. No participants reported never or always using AI in their daily learning.

3.2. Measurement model evaluation

Table 3. Factor loadings, composite reliability, internal reliability, and convergent validity.

Construct	Item code	Factor Loadings (FL)	Composite Reliability (CR)	Cronbach's Alpha (α)	Average Variance Extracted (AVE)
The first-order reflective components					
AI usage (AIUS)			0.900	0.836	0.751
	AIUS1	0.856***			
	AIUS2	0.833***			
	AIUS3	0.908***			
Creativity (CR)			0.935	0.912	0.743
	CR1	0.908***			
	CR2	0.923***			
	CR3	0.885***			
	CR4	0.754***			
	CR5	0.830***			
Adaptive Exploration (AE)			0.947	0.916	0.857
	AE1	0.921***			
	AE2	0.922***			
	AE3	0.934***			

Table 3. (Continued).

Construct	Item code	Factor Loadings (FL)	Composite Reliability (CR)	Cronbach's Alpha (α)	Average Variance Extracted (AVE)
The first-order reflective components					
Systematic Validation (SV)			0.955	0.905	0.914
	SV1	0.956***			
	SV2	0.955***			
The second-order reflective construct					
Critical thinking (CT)			0.960	0.948	0.828
	AE	0.978***			
	SV	0.959***			

Note: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***); These values are based on a seven-point Likert-type scale ranging from “strongly disagree” (1) to “strongly agree” (7); Critical Thinking (CT) is a reflective second-order construct that includes Adaptive Exploration (AE), Systematic Validation (SV).

The psychometric properties of the measurement instruments were rigorously evaluated using confirmatory factor analysis (CFA), with key quality metrics detailed in **Table 3**. Factor loading magnitudes, composite reliability (CR) scores, and internal consistency coefficients (α) were systematically analyzed to confirm scale reliability. Concurrently, average variance extracted (AVE) values were computed to verify convergent validity, adhering to established psychometric benchmarks ($CR/\alpha \geq 0.70$; $AVE \geq 0.50$) [29]. This multi-criteria validation approach ensures robust construct representation across all latent variables.

The psychometric adequacy of the measurement framework is substantiated through comprehensive validation metrics presented in **Table 3**. All constructs demonstrated robust psychometric properties, with item validity coefficients consistently exceeding the 0.70 benchmark, composite reliability indices ranging from 0.82 to 0.91, and average variance extracted values between 0.56 and 0.68. These outcomes confirm full adherence to stringent measurement standards, surpassing conventional thresholds for internal consistency ($CR > 0.70$) and convergent validity ($AVE > 0.50$) [18]. Discriminant validity was systematically verified through complementary analytical strategies: the Fornell-Larcker criterion (**Table 4**) established distinctiveness between latent variables, while heterotrait-monotrait ratio analysis (**Table 5**) yielded values between 0.12 and 0.43—significantly below the stringent 0.85 cutoff—further confirming empirical differentiation among theoretical constructs.

Table 4. Discriminant validity (Fornell-Larcker criterion).

	AIUS	CR	CT
AIUS	0.866		
CR	0.602	0.862	
CT	0.561	0.822	0.910

AIUS = AI usage; CR = Creativity; CT = Critical thinking; Values on the diagonal (bold) are the square of the AVE while the off-diagonals are correlations.

Table 5. Discriminant validity using the heterotrait-monotrait ratio.

CONSTRUT	AIUS	CT	CR
AIUS			
CT	0.621		
CR	0.674	0.881	

AIUS = AI usage; CR = Creativity; CT = Critical thinking.

The square root of AVE values exceeded inter-construct correlations, confirming that each construct was statistically distinct from the others.

3.3. Structural model evaluation

To test the hypothesized relationships, PLS-SEM path modeling was conducted. The model estimation results and quality indicators are presented in **Table 6** and visualized in **Figure 2**.

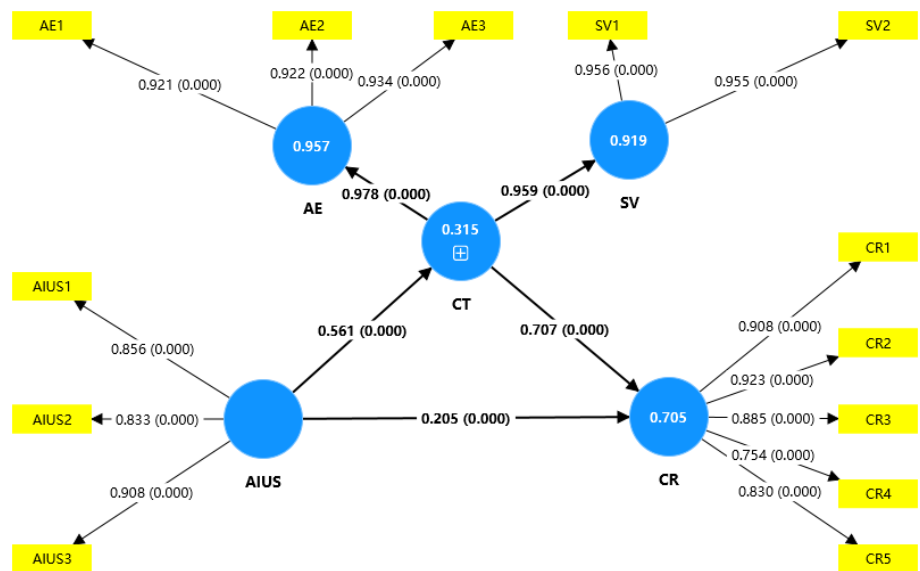


Figure 2. Research findings diagram.

AIUS = AI Usage, CR = Creativity, AE = Adaptive Exploration, SV = Systematic Validation; CT = Critical Thinking, and CT is a reflective second-order construct comprising AE and SV.

To test the hypothesized relationships, PLS-SEM path modeling was conducted. The model estimation results and quality indicators are presented in **Table 6**.

Table 6. Model estimation results and quality indicators.

Construct	R ²	F ²	Q ²	SRMR	VIF
CT	0.315	0.460	0.285	0.075	≤1.460
CR	0.705	0.097 1.162	0.349		

R² (R-Squared/Coefficient of determination), F² (The effect size), Q² (The predictive relevance), SRMR (Standardized Mean Root Square Residual), VIF (Variance inflation factor), CR = Creativity; CT = Critical thinking.

The R² values indicate that AI usage explains 31.5% of the variance in critical thinking and 70.5% of the variance in creativity. The SRMR value (0.075) suggests a

good model fit [18,32], and VIF values were below the recommended threshold, indicating no multicollinearity issues.

3.4. Hypothesis testing and mediation analysis

The hypothesis testing results are summarized in **Table 7**.

Table 7. Path coefficients, hypothesis testing, and mediation analysis.

Hypothesis	Relationships	β -value	Mean	Standard deviation	t-value	Decision
H1	AIUS \rightarrow CR	0.205***	0.198	0.056	3.636	Supported
H2	AIUS \rightarrow CT	0.560***	0.564	0.094	5.945	Supported
H3	CT \rightarrow CR	0.707***	0.714	0.048	14.591	Supported
H4	AIUS \rightarrow CT \rightarrow CR	0.397***	0.402	0.070	5.637	Supported
VAF (CT as Mediator)		0.659				

Note: $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***); AIUS = AI usage; CR = Creativity; CT = Critical thinking; VAF (Variance Accounted For) represents the proportion of the total effect of AIUS on CR that is mediated by CT. A VAF value of 0.659 (65.9%) suggests a substantial mediation effect of CT.

All direct paths were statistically significant at $p < 0.001$:

H1. AI usage positively influences creativity ($\beta = 0.205$, $t = 3.636$, $p < 0.001$).

H2. AI usage positively influences critical thinking ($\beta = 0.560$, $t = 5.945$, $p < 0.001$).

H3. Critical thinking positively influences creativity ($\beta = 0.707$, $t = 14.591$, $p < 0.001$).

To investigate the mediating mechanism underlying artificial intelligence (AI) utilization and creative capacity, a statistical mediation framework was implemented through bootstrapping procedures with 5000 resamples. The empirical decomposition of variance revealed that 65.9% of the total effect (VAF = 0.659) operated through critical thinking pathways, thereby providing robust empirical confirmation for the hypothesized mediation mechanism posited in Hypothesis 4.

3.5. Research findings summary

The conceptual model and key research findings are presented in **Figure 2**, illustrating the relationships among AI usage, critical thinking, and creativity. The empirical results confirm that AI usage positively influences both critical thinking and creativity. Furthermore, critical thinking serves as a significant mediator in this relationship, amplifying the impact of AI usage on creativity.

The findings highlight that individuals who engage with AI tools for academic and cognitive tasks develop stronger critical thinking skills, which in turn enhances their creative abilities. This suggests that AI integration in education can be a valuable approach to fostering higher-order cognitive skills. The study provides robust empirical evidence supporting these claims, reinforcing the theoretical framework and hypothesis validation.

The conceptual model and key research findings are visualized in **Figure 2**, which illustrates the relationships among AI usage, critical thinking, and creativity.

4. Discussion

This section discusses the study's results in relation to prior research and working hypotheses, providing a broad interpretation of the findings and their implications. Future research directions are also considered.

4.1. Interpretation of findings

A suitable alternative reference is Li et al.'s study [33], which examines the role of artificial intelligence in fostering critical thinking in digital learning environments. Their research highlights how AI tools can enhance cognitive engagement and problem-solving skills among learners. This is consistent with findings that AI usage significantly enhances both critical thinking and creativity among pre-service teachers. Moreover, the study supports the hypothesis that critical thinking mediates the relationship between AI usage and creativity, reinforcing the importance of higher-order cognitive skills in the AI-driven learning process [34].

These results are consistent with dual-process theories of cognition, where AI usage facilitates fast, automated information processing, while critical thinking ensures slower, reflective reasoning [9]. This theoretical framework helps explain why AI-driven learning environments, when designed appropriately, can stimulate both intuitive and deliberative cognitive engagement. The study further substantiates that AI's influence on creativity is not direct but rather operates through adaptive exploration (AE) and systematic validation (SV), both core components of critical thinking.

4.2. Comparison with previous studies

Unlike prior research that mainly conceptualized AI as a tool for automation and efficiency enhancement [35], this study highlights AI's cognitive developmental role by empirically demonstrating its impact on higher-order cognitive processing, rather than just information retrieval or task execution. By integrating AI-based learning with critical reasoning strategies, this research extends earlier findings by demonstrating how AI enhances deep thinking and fosters novel problem-solving skills [36].

Furthermore, while previous studies treated critical thinking and creativity as independent cognitive constructs, our study confirms their higher-order interdependence, showing how critical thinking, specifically through AE and SV, strengthens creative output [27]. This suggests that AI's impact is not merely mechanistic but transformative in shaping intellectual adaptability.

4.3. Contributions to educational practice

From an applied perspective, this study emphasizes the necessity of AI-driven pedagogies that promote deeper cognitive engagement rather than passive automation. Teacher training programs should incorporate AI literacy components, focusing on how AI tools can stimulate critical thinking and creative problem-solving rather than merely optimizing administrative tasks [37]. Specifically, professional development initiatives could include: (1) workshops on designing AI-augmented lesson plans that require students to critique AI-generated outputs, (2) training in facilitating Socratic dialogues where learners interrogate AI recommendations, and (3) collaborative

projects where teachers co-design AI-mediated scenarios that balance automation with open-ended inquiry.

Additionally, educational frameworks should be redesigned to emphasize the interplay between AI engagement, cognitive flexibility, and innovation. AI-assisted learning should be integrated with adaptive inquiry-based methodologies, where students critically assess AI-generated content rather than passively accepting outputs. These approaches align with current trends in personalized and adaptive learning ecosystems [33]. For instance, educators might employ AI platforms that scaffold iterative idea generation (e.g., brainstorming with AI tools) followed by structured peer debates to refine solutions—a process that mirrors the AE-SV framework identified in this study.

4.4. Limitations and future research directions

Despite its contributions, this study has certain limitations that should be acknowledged and addressed in future research. First, the research sample consisted exclusively of pre-service teachers, which may limit the generalizability of the findings. Future studies should expand recruitment to include larger, multi-institutional cohorts of both pre-service and in-service educators across diverse cultural and disciplinary contexts.

Second, while the study establishes correlations among AI usage, critical thinking, and creativity, it does not explore longitudinal effects. A promising avenue would involve tracking cohorts over 3–5 years to examine whether early AI-integrated training produces lasting improvements in pedagogical creativity.

Third, this study primarily relied on quantitative measures. To complement statistical models, future work could employ mixed-methods designs, such as think-aloud protocols during AI tool usage or longitudinal case studies documenting teachers' evolving AI integration strategies [17].

Fourth, experimental manipulations of specific AI features (e.g., explainable AI interfaces vs. black-box systems) could clarify how tool design influences critical engagement. Finally, neurocognitive methods, such as eye-tracking during AI-assisted problem-solving, might reveal real-time interactions between technology use and cognitive processes.

4.5. Broader implications for policy and practice

The study's findings have significant implications for educational policymakers and curriculum designers, particularly in the development of AI-integrated pedagogy that actively fosters critical thinking, analytical reasoning, and creativity. Given AI's demonstrated benefits in fostering critical thinking and creativity, policymakers should prioritize AI-assisted learning strategies that cultivate higher-order cognitive skills rather than just technical proficiency.

Furthermore, teacher education programs should integrate AI-based cognitive training, ensuring that educators can guide students in using AI not just for information retrieval but for analytical reasoning and creative synthesis. Concrete policy measures might include mandating AI pedagogy modules in teaching certifications and funding school-university partnerships to pilot AI-curriculum co-design initiatives. Schools

should also foster AI-inclusive learning environments, where students critically evaluate AI-generated content, promoting metacognitive awareness and intellectual autonomy.

By embedding AI-driven cognitive adaptability training in formal education systems, institutions can prepare future educators and students for an increasingly AI-integrated knowledge economy.

5. Conclusion

This study contributes to the growing research on AI's role in cognitive development by empirically demonstrating its impact on critical thinking and creativity. The findings highlight the mediating role of critical thinking, suggesting that AI usage alone is insufficient to foster creativity unless paired with higher-order reasoning skills.

The study reinforces the importance of structured AI integration in education, advocating for pedagogical models that encourage critical assessment and adaptive learning. While this research offers valuable insights, future studies should explore long-term cognitive effects, interdisciplinary applications, and qualitative perspectives on AI-facilitated learning. The findings provide a foundation for reimagining AI-driven educational frameworks that prioritize not only technological proficiency but also intellectual adaptability and creative problem-solving.

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Conflict of interest: The author declares no conflict of interest.

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