EXPLORING HUMAN–AI DISTRIBUTED CRITICAL THINKING (HADCT): PILOT VALIDATION OF A CRITICAL THINKING SCALE WITH VIETNAMESE EFL LEARNERS

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Abstract: The increasing integration of Generative Artificial Intelligence (GenAI) in education has prompted renewed attention to how learners think and reason within AI-mediated environments. While prior studies have explored AI's potential to enhance reasoning and argumentation, few validated instruments capture the distinctive cognitive, metacognitive, and interactive processes underlying such engagement. Addressing this gap, this study develops and validates the Critical Thinking in GenAI-Assisted Learning Scale (CrTAI), a self-report instrument encompassing three dimensions: analytical reasoning, source verification, and metacognitive self-regulation. Data from 100 English-major undergraduates at a Vietnamese university demonstrates strong internal consistency (α =.93) and satisfactory construct validity (EFA: 63.8% variance explained; CFA: CFI = 0.96, TLI = 0.95, RMSEA = 0.07 [90% CI.03–.11], SRMR = 0.04). Drawing on these findings, the study advances Human–AI Distributed Critical Thinking (HADCT) as a reconceptualization of critical thinking that takes shape within a third space — a shared cognitive territory where human analytical judgement and metacognitive regulation intersect with AI-generated reasoning to co-construct understanding. The CrTAI therefore functions as both an assessment instrument and a conceptual lens, enabling evaluation of learners' critical engagement while also illuminating how such reasoning unfolds within the human–AI third space through analysis, verification, and reflective regulation.

Keywords: critical thinking, EFL, generative AI, instrument, Vietnamese

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The rapid integration of Generative Artificial Intelligence (GenAI) into education has transformed how students interact with information, raising concerns about its impact on critical thinking skills (Liu et al., 2025; Oliveira et al., 2025). On the one hand, AI-powered tools such as ChatGPT are widely used for tasks like argument construction, source evaluation, and problem-solving, offering new opportunities to enhance higher-order thinking (de la Puente et al., 2024; Zhou et al., 2024). However, research suggests that while AI can support analytical reasoning, it also poses risks of cognitive offloading and passive reliance on AI-generated content (Essien et al., 2024; Gerlich, 2025). The challenge lies in ensuring that students actively engage with AI outputs critically rather than accepting them uncritically.

Despite the growing interest in AI's role in education, existing assessments primarily rely on general critical thinking measures that do not account for the unique cognitive demands of

AI-enhanced learning environments. Well-established instruments such as the Watson–Glaser and Cornell Critical Thinking Tests (Watson & Glaser, 1980) and the California Critical Thinking Skills Test (Facione, 1990), for example, were developed for traditional reasoning contexts and overlook AI-specific dimensions such as source verification, bias detection, and self-regulation against cognitive offloading (e.g., Zhai et al., 2024). As a result, they may overestimate learners' analytical ability while underrepresenting potential risks of automation bias and uncritical acceptance of AI outputs.

To address this limitation, this study develops and validates a self-report scale designed to measure self-report critical thinking in GenAI-assisted learning. Existing conventional instruments while contributing valuable insights into participants' critical thinking may not fully capture the distinctive challenges and opportunities presented by GenAI tools. For example, a systematic review of GenAI in pedagogical practice by Xiaoyu et al. (2025) has noted that while such tools can promote generic critical thinking, they also raise distinct challenges such as bias, hallucinated outputs, and diminished independent reasoning. Zhou et al. (2024) found that self-regulation mediated the relationship between ease of use of GenAI tools and students' critical thinking, suggesting that regulatory dimensions differ when AI is involved.

The significance of this study lies in its potential to enhance educational practices and curriculum design in AI-integrated learning environments. Empirical studies have shown that integrating AI tools without explicit guidance may potentially lead to superficial engagement and cognitive dependence (Essien et al., 2024; Gerlich, 2025). A validated scale for assessing critical thinking in GenAI-assisted contexts could provide educators with a more reliable means of identifying students' AI-related critical thinking abilities and potential areas for improvement. Such a tool may also support the design of targeted pedagogical interventions aimed at strengthening learners' reasoning and evaluative skills when engaging with AI-generated content. Furthermore, the findings potentially contribute to the development of evidence-informed AI literacy frameworks, helping students to engage with AI outputs more critically rather than accepting them unreflectively. By addressing the current lack of contextualized assessment instruments, this study aims to lay an initial foundation for fostering critical thinking competencies that are increasingly important in an AI-mediated educational landscape.

What is Critical Thinking?

Critical thinking (CT) has been theorized through various frameworks, each emphasizing different dimensions and educational purposes. Within Bloom's Taxonomy, CT is situated among higher-order cognitive processes such as analysis, evaluation, and creation, illustrating its relevance to complex thinking tasks (Essien et al., 2024). The Watson–Glaser Critical Thinking Appraisal (Watson & Glaser, 1980) conceptualizes CT as a set of reasoning abilities, specifically inference, recognition of assumptions, deduction, interpretation, and evaluation of arguments, designed primarily for assessing decision-making and logical reasoning. In contrast, the California Critical Thinking Skills Test (CCTST) (Facione, 1990) expands the construct to include dimensions such as explanation, induction, and numeracy, aligning more closely with academic and professional problem-solving contexts. More recently, Imjai et al. (2025) has proposed a multidimensional model encompassing analytical skills, logical reasoning, evidence evaluation, and open-mindedness, offering a balanced view that integrates both cognitive and dispositional aspects of CT. Although these models differ in focus and intended application, they collectively emphasize core cognitive processes of CT, involving systematic inquiry, verification, and logical reasoning.

In educational contexts, fostering critical thinking is regarded as a fundamental goal, equipping students with the necessary skills to analyze arguments, assess evidence, and navigate complex real-world issues. In GenAI-assisted learning environments, these abilities are especially critical, as learners not only evaluate human-generated information but also scrutinize and verify AI-produced content. Developing such skills aligns with the aim of the present study, which seeks to measure and enhance learners' capacity to think critically, verify sources, and regulate their engagement with AI tools through the CrTAI scale.

Generative AI and Critical Thinking

With the rise of GenAI, including ChatGPT and other AI-powered text generators, researchers have begun examining the impact of AI on students' critical thinking skills. AI-driven tools have been recognized for their potential to enhance analytical reasoning, particularly by facilitating structured argumentation, evidence evaluation, and error detection. In their experimental study, de la Puente et al. (2024) examined the effectiveness of using AI to support students' debating sessions. The experimental group that used AI assistance demonstrated stronger conceptual understanding as well as greater improvement in critical thinking and debating skills compared with the control group. AI models can generate diverse perspectives, prompting students to engage with multiple viewpoints, refine their reasoning, and critically assess AI-generated outputs. These affordances suggest that AI can function as a scaffold for higher-order thinking when learners are able to actively interrogate and regulate their interaction with the tool, an aspect central to the analytical reasoning and metacognitive dimensions captured in the present study's CrTAI scale.

Studies have shown that GenAI in structured pedagogical designs can significantly improve students' ability to construct arguments, recognize logical fallacies, and critically evaluate evidence. In a study involving Vietnamese EFL undergraduate and graduate students, Cong-Lem et al. (2025) demonstrated the effectiveness of a 90-minute intervention workshop in enhancing participants' ability to recognize biases and inaccuracies in ChatGPT-generated output, thereby fostering their critical thinking skills in engaging with AI tools. Similarly, Drushlyak et al (2025) demonstrated that verifying the correctness of AI-generated solutions fostered preservice mathematics teachers' critical thinking skills. Such findings highlight the constructive potential of AI when learners are guided to verify and evaluate AI outputs, a process closely aligned with the source verification component of this study's instrument.

Despite these benefits, several challenges have been identified. One major concern is cognitive offloading, where students could potentially become over-reliant on AI-generated responses instead of engaging in independent critical thinking (Gerlich, 2025). A systematic review by Zhai et al. (2024) suggests that when students passively accept AI-generated outputs without questioning their accuracy or logical coherence, their ability to evaluate information critically may decline over time, which can also lead to errors in task performance. Additionally, AI models are known to hallucinate information, generating responses that appear plausible but are factually incorrect (Cong-Lem et al., 2024). These risks reinforce the importance of cultivating metacognitive self-regulation in AI-mediated learning, a core dimension of the CrTAI scale that addresses learners' awareness of their cognitive reliance on AI tools.

Ethical considerations also play a role in the AI-critical thinking debate. The uncritical acceptance of AI-generated content can lead to bias reinforcement, misinformation spread, and ethical dilemmas related to authorship and academic integrity (Humphreys, 2025; Wise et al., 2024). As GenAI continues to be integrated into education, researchers argue that explicit instruction in AI literacy, teaching students how GenAI models work, their limitations, and their biases, is essential for ensuring that AI supports rather than erodes critical thinking skills (Beninger et al., 2025; Cong-Lem et al., 2025).

The advent of GenAI tools has prompted scholars to examine the role of metacognition and self-regulatory capacity in learners' engagement with these technologies. Lee et al. (2024) found that self-regulated learning (SRL) was positively associated with students' higher-order thinking skills, suggesting that the ability to plan, monitor, and evaluate one's own thinking supports deeper reasoning in AI-enhanced contexts. Similarly, Shen and Teng (2024) demonstrated that learners with stronger self-regulatory capacity achieved higher scores on interpretation, analysis, and evaluation tasks and exhibited greater critical engagement in GenAI-assisted writing. These findings collectively highlight the importance of Metacognitive Self-Regulation (MSR), the reflective process through which learners monitor, evaluate, and adjust their reliance on AI tools, to ensure that AI use enhances rather than replaces independent reasoning.

In summary, CT in GenAI-assisted learning involves a combination of analytical, evaluative, and self-regulatory skills that enable learners to engage thoughtfully with AI-generated content. It requires the capacity to interpret and reason through complex information, verify the credibility and relevance of algorithmically produced outputs, and regulate one's cognitive reliance on AI tools. Accordingly, informed by a synthesis of existing scholarship on critical thinking within GenAI-mediated learning, this study focuses on three core dimensions: *Analytical Reasoning*, which reflects learners' ability to identify logical inconsistencies and assess the soundness of AI-generated arguments; *Source Verification and Evaluation*, which concerns the appraisal of information accuracy and credibility; and *Metacognitive Self-Regulation*, which encompasses reflective monitoring and adaptive control of AI use. Together, these dimensions capture the multifaceted nature of critical thinking necessary for ensuring that AI serves as a catalyst rather than a substitute for human reasoning.

Generative AI, Critical Thinking, and EFL Learning

In English as a Foreign Language (EFL) education, the integration of GenAI tools has expanded opportunities for English language skills, idea generation, personalized feedback, and adaptive language practice (e.g., Abdelhalim & Alsehibany, 2025; Alberth, 2023; Almusharraf et al., 2025). Beyond facilitating linguistic development, these tools have drawn attention to their potential influence on critical thinking, a higher-order cognitive skill integral to academic writing, reading comprehension, and argumentation. Yet, growing research reveals a tension between GenAI's capacity to scaffold analytical engagement and its risk of encouraging cognitive dependence or reduced reflective reasoning (e.g., Hong et al., 2025; Liu et al., 2025).

Research on GenAI-assisted writing indicates that GenAI tools can support EFL students in developing English language skills, structured arguments, refining their reasoning, and expanding their lexical resources (Abdelhalim & Alsehibany, 2025; Almusharraf et al., 2025). Yang and Lin (2025), drawing on interview data and interaction logs with Chinese EFL learners, found that students leveraged GenAI's affordances to generate ideas, solve linguistic problems, and engage in translanguaging practices such as using their mother tongue to enhance comprehension and output quality. Almusharraf et al. (2025) found that GenAI chatbots positively influenced EFL students' writing self-efficacy, satisfaction, and behavioural intention, with self-efficacy and satisfaction mediating the link between AI use strategies and continued engagement. These findings suggest that GenAI tools can foster learners' confidence and positive attitudes toward second language writing, particularly among digitally literate university students.

Grounded in Vygotsky's sociocultural theory, Abdelhalim and Alsehibany (2025) examined the impact of integrating ChatGPT into classroom instruction to enhance EFL learners' vocabulary learning and retention. Using a quasi-experimental mixed-methods design, they found that students who practiced vocabulary interactively with ChatGPT significantly outperformed those receiving traditional instruction in productive vocabulary knowledge and overall achievement. Qualitative findings further revealed learners' positive perceptions of ChatGPT as a motivating, scaffolded, and context-rich tool that supported deeper lexical engagement.

Recent empirical research has started to illuminate how GenAI tools shape EFL learners' CT, highlighting both their potential benefits and the challenges they pose. For instance, Hong et al. (2025) found that structured integration of GenAI in EFL writing led to significant gains in analytical depth, evaluative judgment, and metacognitive reflection when scaffolded through the GenAI-CT framework. However, Liu et al. (2025), in a systematic review, reported that while roughly two-thirds of studies highlight GenAI's positive role in fostering CT, many also warn of over-reliance and diminished independent reasoning without proper guidance.

The reviewed studies above underscore both the promise and the complexity of using GenAI in EFL education. While evidence points to GenAI's potential to enhance linguistic development, engagement, and certain aspects of higher-order reasoning, existing findings also reveal inconsistent outcomes and a lack of standardized, validated instruments for measuring learners' critical thinking in AI-mediated contexts. This gap highlights the need for a context-sensitive, psychometrically sound self-report scale that can capture how students analyze, verify, and regulate their cognitive engagement with AI tools in language learning environments.

The Need for Validated Self-Report Scales in GenAI-assisted Critical Thinking Assessment

While existing studies highlight the potential of GenAI in fostering critical thinking (e.g., de la Puente et al., 2024; Drushlyak et al., 2025), a major limitation in current research is the lack of standardized, validated scales specifically designed to assess self-reported critical thinking in GenAI-assisted learning environments. As discussed in the previous sections, studies relying on generic critical thinking assessments, such as the Watson-Glaser Critical Thinking Appraisal (e.g., de la Puente Pacheco et al., 2025), may not fully capture the AI-specific cognitive processes involved in analyzing, verifying, and regulating engagement with AI-generated content. Yang et al. (2025) argue that in the newly emerging GenAI-assisted learning environment, the success and effectiveness of learning with such tools also depend critically on the ability to assess learners' psychological and cognitive processes as they interact with them.

To date, few validated, self-report instrument have been developed specifically for GenAI-assisted learning contexts (Oliveira et al., 2025; Su et al., 2025), suggesting a need for a psychometrically robust scale that capture how learners engage in analytical reasoning, source evaluation, and metacognitive self-regulation when interacting with AI-generated information. For instance, Su et al. (2025), in their scoping review, identified a notable lack of empirical studies providing evidence for the validity and reliability of instruments used to assess AI literacy, within which critical thinking is often conceptualized as a core component (Drajati et al., 2025; e.g., Meng et al., 2025). Developing such a scale would enable researchers and educators to systematically assess critical thinking development, identify areas for intervention, and design evidence-based AI-integrated curricula that actively promote higher-order cognitive skills.

METHOD

Participants

The study recruited undergraduate students enrolled in GenAI-assisted learning environments across multiple disciplines. A total of 100 participants took part in the pilot phase. The participants were selected based on their prior exposure to AI tools in learning, ensuring relevance to the study's focus on critical thinking in AI-enhanced education. Demographic information, including age, year of study, major, GPA, and AI usage experience, was collected to explore potential differences in critical thinking skills (see Table 1).

Instrument Development

The development of the CrTAI was grounded in Facione's (1990) seminal theoretical framework, which conceptualizes critical thinking as a multifaceted construct comprising core cognitive skills and the metacognitive disposition to use them. This framework was selected for its comprehensiveness and widespread validation in educational contexts (e.g., Payan-Carreira et al., 2022). However, to address the unique cognitive demands of GenAI-assisted learning identified in contemporary literature, we combined and adapted Facione's (1990) critical thinking dimensions with findings from recent empirical studies on critical thinking in Generative AI–assisted learning contexts (e.g., Essien et al., 2024; Shen & Teng, 2024) to formulate three overarching constructs particularly relevant to AI interaction: Analytical Reasoning, Source Verification and Evaluation, and Metacognitive Self-Regulation.

Several items in the CrTAI scale were adapted from Imjai et al.'s (2025) Critical Thinking subscale, which captures essential cognitive dimensions of critical thinking such as analytical skills, logical reasoning, evidence evaluation, and open-mindedness. However, the original items were designed for general academic reasoning, whereas the present study required items relevant to GenAI-assisted learning contexts where students must interpret, verify, and regulate their engagement with AI-generated information. Therefore, the items were systematically reviewed and reworded to incorporate AI-related cognitive processes and metacognitive awareness.

For example:

- The original Imjai et al.'s (2025) item "You consistently analyse complex data and always identify the relationships between different data sets" was adapted to "I can identify logical inconsistencies in AI-generated responses (AR1)", shifting the focus from generic data analysis to reasoning within AI outputs.
- "You always verify the accuracy and the sources of information before using it" became "I always verify the sources of information provided by AI tools before using them (SE1)", reflecting source evaluation within AI-mediated information retrieval.
- The original item on open-mindedness, "You are willing and interested in experimenting with new problem-solving methods that you have never tried before," inspired the creation of metacognitive self-regulation items such as "I reflect on how much I rely on AI tools and adjust my approach when necessary (MSR1)", extending the construct toward self-monitoring and cognitive control in AI use.

Beyond the adaptation of items from Imjai et al. (2025), the third dimension, Metacognitive Self-Regulation, was developed based on seminal works on metacognition (Facione, 1990; Lai, 2011) and supported by recent empirical findings emphasizing reflective regulation in GenAI use (Essien et al., 2024; Shen & Teng, 2024; Zhai et al., 2024). These items were designed to capture learners' awareness of over-reliance, reflection on AI influence, and evaluation of cognitive independence after using AI tools. For example, one item states: "I pause to consider whether I'm critically engaging with AI-generated content or passively accepting it," illustrating how the scale operationalizes reflective monitoring of cognitive stance during AI use.

A 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used to capture varying degrees of agreement with each item. The initial item pool underwent expert review to assess content validity, ensuring that the items appropriately measured AI-specific critical thinking.

Data Collection

The data were collected through an online survey using Google Forms, administered during class sessions to ensure high participation rates. Students were given time to complete the survey in a controlled environment, minimizing external distractions.

For the main study, the data were collected from a larger sample of 100 participants to evaluate the scale's psychometric properties. The survey was administered online, and participants provided informed consent before completing the questionnaire. The survey included demographic questions, AI usage background, and the CrTAI scale.

Data Analysis

The validity and reliability of the CrTAI were examined through three complementary psychometric methods: internal consistency analysis, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA). These procedures provided a comprehensive evaluation of the scale's reliability and structural validity. Internal consistency was first assessed using Cronbach's alpha (α), with values of $\geq .70$ considered acceptable, and item–total correlations examined to ensure each item contributed meaningfully to its subscale.

Preliminary normality checks indicated that item means ranged from 3.07 (AR1) to 3.51 (SV2, SV4, META4), with standard deviations between 0.86 (AR2) and 1.12 (SV2). Skewness (−0.55 to −0.83) and kurtosis (−0.11 to 0.86) values were within the acceptable range ($|\text{skew}| \leq 1$; $|\text{kurtosis}| \leq 1$), suggesting approximate univariate normality (Kline, 2023). Mardia's multivariate kurtosis (5.47, critical ratio = 1.82) indicated a mild departure from multivariate normality; thus, CFA models were estimated using the robust maximum likelihood (MLR) method with Yuan–Bentler scaled χ^2 and robust fit indices (CFI, TLI, RMSEA), which are recommended when multivariate normality assumptions are violated (Brown, 2015; Yuan & Bentler, 2000).

EFA was then conducted to explore the factor structure, allowing correlations between theoretically related dimensions. The Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity confirmed sampling adequacy. Items with loadings $\geq .40$ were retained, while those with cross-loadings or weak contributions were considered for removal. The total variance explained by the extracted factors was examined to ensure that the scale captured core components of critical thinking in GenAI-assisted learning.

The resulting structure was further tested through CFA using the same robust MLR estimator. Model fit was evaluated using CFI, TLI, RMSEA, and SRMR, applying accepted thresholds (CFI/TLI >.90; RMSEA, SRMR <.08). Standardized factor loadings were inspected to confirm item–construct alignment, and modification indices were applied only when theoretically justified.

FINDINGS AND DISCUSSION

Findings

Participants' AI-Usage Background

The study sample consisted of 100 EFL students majoring in English language at a public university in Vietnam, with demographic information collected on gender, year of study, AI usage frequency, AI knowledge, and age to provide context for their engagement with GenAI-assisted learning.

The gender distribution indicated that the majority of the participants were female (75%), while male participants comprised 25% of the sample. This gender imbalance aligns with trends in language studies, where female enrolment tends to be higher. Regarding year of study, most participants were first-year students (83%), with smaller representations from Year 2 (7%), Year 3 (7%), and Year 4 (2%), while one participant was a postgraduate student. The predominance of first-year undergraduate students suggests that many respondents are at an early stage of their academic journey, which may impact their familiarity with AI tools and critical thinking development.

Table 1 summarizes the demographic and AI-related background characteristics of the participants, highlighting their gender distribution, study year, AI usage frequency, AI knowledge levels, and age statistics.

Table 1. Background Characteristics of Participants (N = 100)

Variable	**Category**	**Frequency (n)**	**Percentage (%)**
Gender	Female	75	75.0
	Male	25	25.0
Year of Study	Postgraduate	1	1.0
	Year 1	83	83.0
	Year 2	7	7.0
	Year 3	7	7.0
	Year 4	2	2.0
AI Usage Frequency	Daily	8	8.0
	Frequently	42	42.0
	Occasionally	45	45.0
	Rarely	5	5.0
AI Knowledge	No Knowledge	2	2.0
	Basic Understanding	49	49.0
	Moderate Understanding	40	40.0
	Advanced Understanding	8	8.0
	Expert Knowledge	1	1.0
Age	Minimum	18	-
	Maximum	30	-
	Mean (SD)	19.02 (1.81)	-

In terms of AI usage frequency, 8% of the students reported using AI daily, 42% frequently, 45% occasionally, and 5% rarely. The high proportion of frequent and occasional users (87%) indicates that most participants have some level of engagement with AI tools, making them relevant subjects for studying AI-related critical thinking skills. Similarly, when asked about AI knowledge, 49% of the students identified as having a basic understanding, 40% as having a moderate understanding, and 8% as having an advanced understanding, while only 1% reported expert-level knowledge and 2% indicated no knowledge of AI. These findings suggest that while most students have some familiarity with AI, relatively few possess high-level expertise, which may influence how they critically evaluate AI-generated content.

The age of the participants ranged from 18 to 30 years, with a mean age of 19.02 (SD = 1.81). These demographic findings provide essential context for interpreting the results of the CrTAI. Given the varying levels of AI knowledge and usage experience among the participants, future research should explore how AI literacy influences students' self-reported critical thinking skills and whether educational interventions can further support critical engagement with AI-generated content.

Descriptive Statistics of CrTAI

The descriptive statistics for the CrTAI highlight the three core dimensions that distinguish this instrument from existing critical thinking assessments, Analytical Reasoning (AR), Source Verification and Evaluation (SV), and Metacognitive Self-Regulation (MSR). Unlike the traditional tools such as the California Critical Thinking Skills Test (CCTST; Facione, 1990) or Imjai et al.'s (2025) general CT scale, which focus primarily on generic analytical or evaluative reasoning, the CrTAI captures learners' AI-specific engagement, how they analyze, verify, and regulate their cognitive interaction with AI-generated information.

The descriptive results show that the participants generally exhibit a moderate-to-high level of agreement with the scale items, indicating active engagement in these AI-specific critical thinking processes (see Table 2). The mean scores ranged from 3.07 (AR1) to 3.51 (SV2, SV4, MSR4), suggesting that learners tend to perceive themselves as reflecting critically on AI-generated content rather than accepting it uncritically. The standard deviations ranged from 0.86 (AR2) to 1.11 (SV2), indicating a reasonable level of response dispersion.

Across dimensions, the Analytical Reasoning (AR) items reveal that students demonstrate moderate levels of agreement in their ability to identify inconsistencies and reasoning patterns in AI responses. The Source Verification and Evaluation (SV) items show slightly stronger agreement, implying comparatively greater attentiveness to verifying the accuracy and credibility of AI-generated information. The Metacognitive Self-Regulation (MSR) items display slightly higher means overall, suggesting growing awareness of how learners monitor and adjust their reliance on AI tools.

The skewness values (−0.63 to −0.83) indicate that responses are slightly skewed toward agreement, while kurtosis values near zero confirm that the data distribution approximates normality. Collectively, these findings demonstrate satisfactory score distribution and provide preliminary support for the CrTAI's theoretical intent: to measure how learners reason, verify, and self-regulate in AI-mediated contexts.

Table 2. Descriptive Statistics for CrTAI Scale (N = 100)

Item	Mean (M)	Standard Deviation (SD)	Range	Skewness	Kurtosis
AR1	3.07	0.95	1-5	-0.63	-0.08
AR2	3.31	0.86	1-5	-0.63	0.81
AR3	3.48	1.07	1-5	-0.59	-0.02
AR4	3.37	1.00	1-5	-0.78	0.35
SV1	3.32	1.06	1-5	-0.66	-0.11

Item	Mean (M)	Standard Deviation (SD)	Range	Skewness	Kurtosis
SV2	3.51	1.11	1-5	-0.74	0.05
SV3	3.32	1.02	1-5	-0.55	0.10
SV4	3.51	1.03	1-5	-0.74	0.36
MSR1	3.29	0.96	1-5	-0.80	0.75
MSR2	3.39	0.87	1-5	-0.83	0.86
MSR3	3.33	0.89	1-5	-0.68	0.53
MSR4	3.50	0.99	1-5	-0.68	0.44

Reliability Analysis and Internal Consistency

Reliability and internal consistency were high across all subscales and for the overall 12-item CrTAI (see Table 3). The overall 12-item scale demonstrated excellent internal reliability (Cronbach's α =.93, McDonald's ω =.94), indicating that the CrTAI items cohered well with the three theorized dimensions, namely Analytical Reasoning, Source Verification, and Metacognitive Self-Regulation, with high internal consistency prior to confirmatory testing.

Table 3. Reliability and Convergent Validity Indices of the CrTAI

Subscale	Cronbach's α	McDonald's ω
Analytical Reasoning	0.91	0.91
Source Verification	0.89	0.89
Metacognitive Self-Regulation	0.86	0.87
Overall Scale (12 items)	0.93	0.94

Exploratory Factor Analysis

The suitability of the dataset for factor analysis was confirmed using Bartlett's Test of Sphericity and the Kaiser–Meyer–Olkin (KMO) measure. Bartlett's test yielded $\chi^2(66) = 926.12$, $p < .001$, indicating that the correlation matrix was not an identity matrix and therefore appropriate for factor analysis. The KMO value of 0.90 further indicated excellent sampling adequacy (Kaiser, 1974).

EFA was conducted on the initial 12 items using principal axis factoring with oblimin rotation to allow for correlated factors. An oblique rotation was selected because the three theorized dimensions, Analytical Reasoning, Source Verification, and Metacognitive Self-Regulation, were expected to be conceptually interrelated. The sample was adequate (KMO =.90; Bartlett's $\chi^2(66) = 926.12$, $p < .001$). The three-factor solution was consistent with theoretical expectations, explaining 63.8% of the total variance, with all items loading above.40 on their intended factors and no substantial cross-loadings. The factor correlations ranged from .50 to .70, supporting related yet distinct components of critical thinking in GenAI-assisted learning (see Table 4). This initial EFA informed subsequent model refinement and CFA.

Table 4. Pattern Matrix for the CrTAI (PAF, Oblimin Rotation; Loadings <.40 Suppressed)

Item	AR	SV	MSR	h²
AR1	.78			.61
AR2	.87			.70
AR3	.80			.65
AR4	.49			.55
SV1		.75		.59
SV2		.87		.67
SV3		.65		.54
SV4		.50		.48
MSR1			.43	.40
MSR2			.67	.55
MSR3			.58	.49
MSR4			.71	.59

Note: Loadings below.40 are suppressed for clarity.

Overall, the EFA results provide robust empirical support for the theoretically expected three-factor structure of the CrTAI. The extracted factors, Analytical Reasoning, Source Verification, and Metacognitive Self-Regulation, represent distinct yet interrelated dimensions of critical thinking in AI-mediated learning, warranting subsequent validation through CFA.

Confirmatory Factor Analysis

Prior to confirmatory testing, the CrTAI item pool was refined through an iterative, data-informed exploratory factor analytic procedure. Item retention and removal were guided by both psychometric evidence and theoretical coherence to ensure that the remaining items adequately represented the three hypothesized dimensions, Analytical Reasoning, Source Verification, and Metacognitive Self-Regulation, while maintaining conceptual and structural integrity of the construct.

Specifically, the refinement process followed three principles:

1. Bayesian Information Criterion (BIC) was used to identify whether removing an item improved overall model parsimony and fit.
2. Items with weak loadings (<.45), cross-loadings (>.30), or Heywood-like issues (loadings > 1.0) were considered for removal.
3. Each latent factor was required to retain at least three items, a psychometric standard to ensure factor identification, stability, and adequate construct representation (Hair et al., 2020; Kline, 2023).

Across three pruning iterations, three items, including AR1, SV1, and MSR1, were removed because they either contributed to local misfit or displayed inconsistent loadings, without meaningfully strengthening the factorial structure. Their exclusion improved model parsimony (ΔBIC ≈ 200–230) and yielded a nine-item solution with balanced coverage across dimensions:

- Analytical Reasoning: AR2, AR3, AR4
- Source Verification: SV2, SV3, SV4
- Metacognitive Self-Regulation: MSR2, MSR3, MSR4

This refined model was then tested through CFA using robust maximum likelihood estimation (MLR) with Yuan–Bentler scaled χ^2 corrections, given mild non-normality in the data. Although preliminary reliability was assessed using the original 12 items (α =.93, ω =.94), CFA-based refinement produced a more parsimonious and theoretically coherent 9-item scale. The final version retains three items per dimension (AR, SV, MSR), each with strong loadings (.74–.90) and satisfactory convergent validity. All reported CFA fit values refer to this final 9-item model.

Model Fit Indices

CFA indicated a good model fit (see Table 5). The Comparative Fit Index (CFI =.972) and Tucker–Lewis Index (TLI =.959) both exceeded the .95 criterion, demonstrating excellent fit. The Root Mean Square Error of Approximation (RMSEA =.074, 90% CI [.033,.108]) and Standardized Root Mean Square Residual (SRMR =.041) were within acceptable thresholds, supporting the adequacy of the three-factor model. The reliability and convergent validity were also satisfactory, with composite reliability (CR) ranging from .86 to .90 and the average variance extracted (AVE) ranging from .67 to .75, surpassing recommended benchmarks (Fornell & Larcker, 1981).

Table 5. Model Fit Indices for CFA

Fit Index	Value	Acceptable Threshold
χ^2 (24, N = 100)	36.97	—
CFI	0.97	> 0.90 (Good)
TLI	0.95	> 0.90 (Good)
RMSEA	0.07 (90% CI [.033,.108])	< 0.08 (Acceptable)
SRMR	0.04	< 0.08 (Good)
BIC	2003.26	—

Note: Estimation method = Robust Maximum Likelihood (MLR); fit statistics are based on the Yuan–Bentler scaled χ^2 correction.

Standardized Factor Loadings

All retained items loaded significantly on their respective latent constructs (p <.001), confirming strong associations between the observed variables and their theoretical dimensions (see Table 6). The standardized factor loadings ranged from .74 to .89, all exceeding the .70

benchmark for practical significance (Hair et al., 2020). These results provide further evidence of the convergent validity of the CrTAI.

Table 6. Standardized Factor Loadings from CFA

Item	Factor 1: Analytical Reasoning	Factor 2: Source Verification	Factor 3: Metacognitive Self-Regulation
AR2	0.74	—	—
AR3	0.85	—	—
AR4	0.86	—	—
SV2	—	0.90	—
SV3	—	0.83	—
SV4	—	0.87	—
MSR2	—	—	0.84
MSR3	—	—	0.89
MSR4	—	—	0.74

Note: All standardized loadings are statistically significant (p <.001).

These loadings provide strong empirical evidence that each item contributes meaningfully to its respective construct. The balanced representation of the three items per factor also supports the theoretical coherence and psychometric stability of the three-factor model.

Inter-Factor Correlations with Significance Levels

The CFA results reveal strong positive correlations among the three latent dimensions of the CrTAI, suggesting that analytical reasoning, source verification, and metacognitive self-regulation are interrelated yet empirically distinguishable aspects of critical thinking in GenAI-assisted learning (see Table 7).

Table 7. Inter-Factor Correlation Matrix with Significance Levels

Factors	1. Analytical Reasoning	2. Source Verification	3. Metacognitive Self-Regulation
1. Analytical Reasoning	1.00	.83**	.81**
2. Source Verification	-	1.00	.83**
3. Metacognitive Self-Regulation	-	-	1.00

*Note: **p <.001. Values are standardized correlations between latent factors from CFA (MLR estimation).*

The correlations between Analytical Reasoning and Source Verification (r =.83, p <.001), Analytical Reasoning and Metacognitive Self-Regulation (r =.81, p <.001), and Source Verification and Metacognitive Self-Regulation (r =.83, p <.001) indicate strong and statistically significant inter-factor relationships. These findings suggest that students who critically analyze

AI-generated outputs tend to also verify their credibility and engage in reflective monitoring of their cognitive reliance on AI tools.

Although these correlations are high, they remain below .90, providing evidence for discriminant validity and suggesting that the three constructs are conceptually related yet empirically distinct. This pattern supports the theoretical proposition that effective critical thinking in GenAI-assisted learning entails an integrated engagement of analytical, evaluative, and metacognitive processes.

Discussion

This study has developed and provided empirical support for CrTAI, a self-report instrument designed to measure students' engagement in critical thinking processes when interacting with GenAI tools in educational settings. The scale was administered to 100 English-major undergraduates at a public university in Vietnam, and its psychometric properties were rigorously evaluated through internal consistency reliability, EFA, and CFA.

The analyses identified a three-factor, nine-item structure encompassing Analytical Reasoning (AR2–AR4), Source Verification (SV2–SV4), and Metacognitive Self-Regulation (MSR2–MSR4). The findings confirm that the CrTAI captures a coherent three-factor structure comprising Analytical Reasoning, Source Verification, and Metacognitive Self-Regulation. Both exploratory and confirmatory analyses were consistent with this theoretical model, with fit indices indicating an overall good model fit (CFI =.96, TLI =.95, RMSEA =.07). All items loaded strongly on their intended constructs (standardized loadings ≈.74–.90), indicating that each subscale reliably represents a distinct aspect of AI-related critical thinking.

The internal consistency of the scale is also high ($\alpha \approx .93$), while moderate-to-strong inter-factor correlations ($r = .81$–$.83$, $p < .001$) suggest that these dimensions are closely connected yet empirically distinguishable. Together, these results provide converging evidence that effective critical thinking in GenAI-assisted learning involves the integration of analytical, evaluative, and self-regulatory processes, lending support to the theoretical coherence and construct validity of the CrTAI.

Overall, the CrTAI demonstrates strong psychometric quality and theoretical consistency. It offers a psychometrically sound measure for assessing how learners critically engage with AI-generated content by analyzing information, verifying sources, and regulating their cognitive reliance on AI tools.

Comparison with Literature and Contribution of the Study

The findings contribute to the growing discourse on AI and critical thinking by addressing a crucial gap in assessment methodologies. While existing research has provided valuable insights into how AI influences cognitive engagement, much of this work relies on non-validated or generic CT instruments. For instance, Lee et al. (2025) conducted a large-scale survey with 319 knowledge workers to explore how generative AI affects users' cognitive effort and confidence in critical thinking. Although theoretically informed by Bloom's taxonomy, their study relied on self-reported perceptions rather than a validated scale, revealing that higher confidence in AI correlated with reduced critical thinking effort. Similarly, Brazão and Tinoca

(2025) employed a qualitative case study with higher education students to examine the evolution of critical questioning in AI-mediated dialogues. While their five-level questioning framework provided valuable insights into learners' reflexivity and metacognitive growth, it was exploratory and not grounded in a validated assessment instrument.

Unlike general critical thinking assessments, the CrTAI scale was designed to more closely reflect critical thinking processes that may occur within AI-enhanced learning environments. In contrast to traditional CT instruments which often overlook the distinctive cognitive demands of engaging with AI-generated information, such as evaluating algorithmic credibility, verifying potentially biased outputs, or reflecting on one's reliance on automated assistance, the CrTAI tentatively captures these emerging aspects through three theoretically and empirically supported dimensions, including Analytical Reasoning, Source Verification and Evaluation, and Metacognitive Self-Regulation. The study provides empirical findings to support existing cognitive dimensions discussed in CT theories (e.g., Facione, 1990; Lai, 2011; Watson & Glaser, 1980) and more recent empirical research (e.g., Imjai et al., 2025; Li & Liu, 2021). Specifically, analytical reasoning and source evaluation and verification reflect well-established cognitive CT constructs, whereas the metacognitive self-regulation dimension aligns with self-reflection as identified by Li and Liu (2021) in their taxonomy of CT skills in EFL contexts.

Theoretical Contribution: A Conceptual Framework of Human-AI Distributed Critical Thinking

The theoretical contribution of this study lies in reconceptualizing CT within GenAI-assisted learning environments as Human–AI Distributed Critical Thinking (HADCT) (see Figure 1). This reconceptualization has emerged through the theoretical framing and empirical insights derived from the validation of the CrTAI. While traditional models of CT (e.g., Facione, 1990; Lai, 2011; Watson & Glaser, 1980) have conceptualized thinking as an individual cognitive process involving analysis, inference, and evaluation, the findings of this study point to a more distributed and interactive form of reasoning that unfolds in human–AI partnerships. HADCT thus extends the scope of CT beyond individual cognition, emphasizing the reciprocal interplay between human analytical agency and AI-generated input in shaping critical reasoning.

In this reconceptualization, CT is viewed as a multi-layered construct comprising cognitive, metacognitive, and distributed reasoning dimensions. At the cognitive level, learners engage in analytical reasoning and evaluative judgment when assessing AI-generated outputs. At the metacognitive level, they monitor, regulate, and reflect upon their reliance on and interaction with AI tools. At the distributed level, they participate in a form of co-reasoning, a human–AI cognitive partnership in which understanding and decision-making are dynamically co-constructed through iterative interaction with AI-generated content. Evidence from the CrTAI responses supports this theorization: items such as "I compare multiple sources to confirm the accuracy of AI-generated outputs" (SE2) and "I reflect on how much I rely on AI tools and adjust my approach when necessary" (MSR1) capture processes of verification and regulation, while "After using AI tools, I evaluate whether my conclusions are genuinely my own or influenced by the AI" (MSR3) reflects critical self-awareness in distributed reasoning contexts.

These patterns suggest that CT in GenAI-assisted contexts is best understood not as a purely internal cognitive act, but as a relational and distributed process that integrates cognitive evaluation, metacognitive regulation, and human–AI co-reasoning. The resulting HADCT framework conceptualizes this synthesis as occurring within a '*human-AI third space*', a socio-technological zone where cognition is neither exclusively human nor machine-driven, but collaboratively enacted. This perspective aligns with Vygotskian notions of mediated cognition (Vygotsky, 1978, 1987) and resonates with theories of distributed cognition (Hutchins, 1995) and third-space learning (Gutiérrez, 2008), all of which emphasize the co-construction of knowledge across human, cultural, and technological systems. Within this view, HADCT positions critical thinking as a *shared, emergent, and adaptive* process, fundamental to learning and reasoning in AI-enhanced environments.

While HADCT foregrounds analytical reasoning, source evaluation, and metacognitive regulation, it is important to recognise that these processes are not typically operated as purely cognitive acts. Judgement, verification, and reflective control are often intertwined with affective orientations, such as curiosity, confidence, doubt, or mild apprehension, which can either energise or dampen learners' engagement with AI-generated content (e.g., Gonsalves, 2024; Hassen, 2025). In this sense, the human–AI third space of distributed reasoning described here remains cognitive in architecture, yet lived through emotional stance, meaning that critical thinking in AI-mediated contexts is better understood as both analytically and affectively inflected rather than strictly rational.

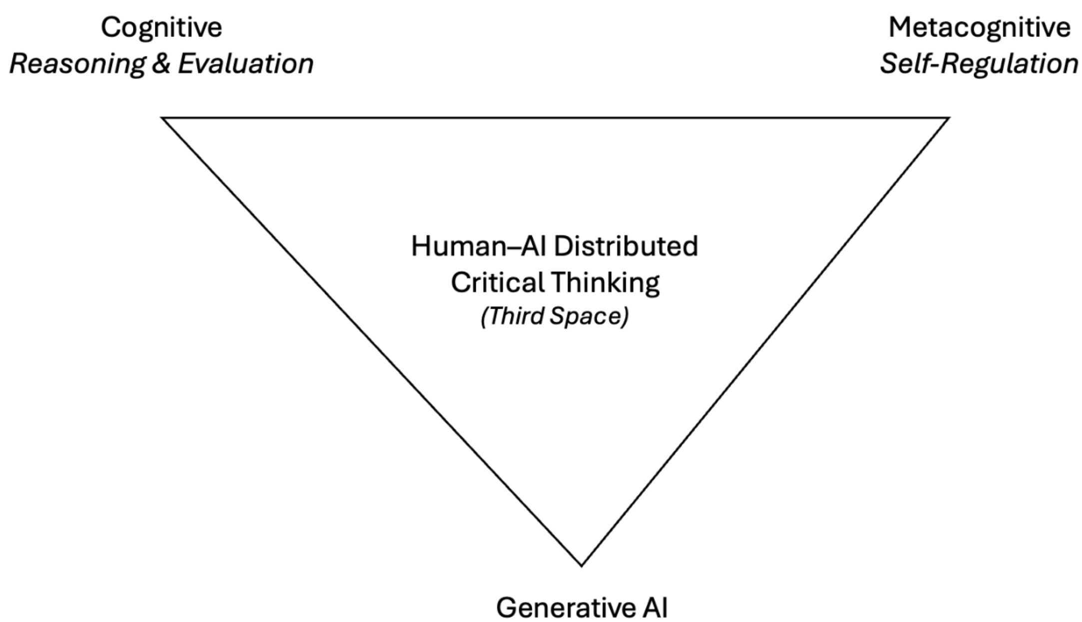

Figure 1. A Conceptual Framework of Human-AI Distributed Critical Thinking (HADCT)

Figure 1 illustrates the conceptual framework of HADCT, which conceptualizes critical thinking as a dynamic, multi-layered process situated within the third space. At the cognitive level, learners engage in reasoning and evaluation processes such as analyzing arguments, verifying evidence, and drawing conclusions. At the metacognitive level, they monitor, regulate, and reflect upon their reliance on and engagement with AI-generated information. GenAI functions as a mediating agent that interacts with these human processes, enabling distributed forms of reasoning and reflection that transcend individual cognition. The intersection of these three components represents a hybrid reasoning space, neither purely human nor purely artificial, where critical thinking is collaboratively constructed and adaptively negotiated within AI-enhanced learning environments. The inverted triangle symbolizes the emergence of HADCT as an integrative third space, arising from the interplay between cognitive reasoning, metacognitive regulation, and GenAI mediation.

Implications for Pedagogical Practices and Research

The CrTAI scale has important implications for teaching, learning, and AI literacy development. Educators can use the scale to assess students' AI-related critical thinking abilities, providing insights into their self-perceived analytical reasoning, source evaluation skills, and metacognitive regulation when engaging with AI-generated content. These insights can help instructors identify students who may over-rely on AI outputs without critical engagement, allowing for the design of targeted interventions that emphasize active questioning and verification strategies. Additionally, the scale can serve as a diagnostic tool in AI literacy programs, helping institutions develop curricula that promote higher-order thinking rather than passive GenAI usage.

Future research should extend the validation of the CrTAI scale across different educational contexts and disciplines to determine its generalizability. Additionally, studies could explore how self-reported critical thinking skills align with objective performance-based assessments, examining whether students' self-perceptions correspond to actual engagement with AI-generated content in real-world tasks. Further validation efforts should also investigate the scale's predictive validity, assessing whether CrTAI scores correlate with academic achievement, AI literacy levels, and broader digital literacy competencies.

By providing a validated, AI-specific self-report assessment, this study lays the foundation for evidence-based approaches to GenAI integration in education. As GenAI continues to shape learning environments, it is essential to equip students with the ability to critically engage with AI-generated content, fostering independent, reflective, and responsible learners in an GenAI-driven world.

CONCLUSION

This study has conducted a pilot validation of CrTAI scale, developed to measure students' self-reported engagement with analytical reasoning, source verification, and metacognitive self-regulation in generative AI–assisted learning environments. Administered to 100 EFL undergraduates at a public university in Vietnam, the instrument has demonstrated strong internal consistency and satisfactory construct validity through exploratory and confirmatory factor analyses. The findings suggest that the CrTAI scale offers a valuable, context-sensitive tool for capturing the multifaceted ways in which learners cognitively and metacognitively engage with AI-generated content. Psychometrically supported instruments such as this are critical for advancing empirical research on AI-enhanced learning, enabling more systematic examination of learners' reasoning, verification, and self-regulation processes across contexts.

Building on these empirical insights, the study contributes theoretically by advancing a reconceptualization of critical thinking as HADCT, a framework that situates reasoning within a dynamic third space co-constructed by human cognition, metacognition, and AI mediation. This perspective extends beyond traditional, human-centered accounts of critical thinking, highlighting how analytical judgment and reflective regulation emerge through reciprocal human–AI interaction. By integrating psychometric validation with conceptual theorization, the study bridges a methodological gap between measurement and theory, offering a foundation for understanding critical thinking as both an individual and distributed cognitive phenomenon in GenAI-assisted learning environments.

Nevertheless, several limitations should be acknowledged. The reliance on self-reported data may not fully reflect learners' authentic cognitive engagement, and the cross-sectional design restricts causal inference regarding AI use and critical thinking development. Furthermore, while the CrTAI instrument was grounded in established theoretical constructs and statistically validated, further research is needed to test its generalizability across diverse educational, linguistic, and cultural contexts. Finally, as the sample was limited to 100 EFL university students, future studies should explore how HADCT manifests across different learner populations and over extended learning trajectories.

In sum, this study provides both a psychometrically supported instrument and a theoretically grounded framework for examining critical thinking in AI-mediated contexts. Together, these contributions mark an important step toward understanding how humans and AI co-construct reasoning, reflection, and evaluative judgment within the evolving landscape of distributed cognition.

Declaration of Generative AI Use in the Writing Process

During the preparation of this work, the author used ChatGPT-5 to assist with language editing, clarity improvement, and stylistic refinement. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the final version of the manuscript.

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Conflict of Interest Disclosure

The author has no competing interests to disclose.

Ethics Approval Statement

Although Dalat University does not have a formal human research ethics committee, this study was conducted in accordance with established ethical standards for educational research. All participants were informed about the study's purpose, confidentiality, and voluntary participation, and provided electronic informed consent prior to data collection.

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APPENDIX

Appendix 1. Final Version of the Critical Thinking in GenAI-assisted Learning Scale (CrTAI)

The validated 9-item CrTAI measures three interrelated dimensions of critical thinking in GenAI-assisted learning: Analytical Reasoning, Source Verification, and Metacognitive Self-Regulation. Each item is rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Dimension	Item Statement
Analytical Reasoning (AR)	I critically analyze AI-generated outputs to distinguish between valid arguments and unsupported claims.
	When using AI tools, I consider multiple perspectives before accepting any conclusions.
	I evaluate whether AI-generated conclusions are based on sound reasoning and evidence.
Source Verification and Evaluation (SE)	I compare multiple sources to confirm the accuracy of AI-generated outputs.
	I frequently question whether AI-generated content might be biased or incomplete.
	When presented with AI-generated conclusions, I seek out additional evidence from independent, credible sources.
Metacognitive Self-Regulation (MSR)	I pause to consider whether I'm critically engaging with AI-generated content or passively accepting it.
	After using AI tools, I evaluate whether my conclusions are genuinely my own or influenced by the AI.
	I periodically question the extent to which AI tools have shaped my thinking process.