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Article

Beyond AI Use: How AI Literacy Is Linked to Critical Thinking through AI-Assisted Problem-Solving Ability and AI Reliance

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Abstract
With the widespread adoption of generative artificial intelligence in English as a Foreign Language (EFL) learning, helping learners use AI effectively to solve language-related problems while maintaining independent judgment and critical thinking has become a key issue in technology-enhanced language education. However, existing studies have largely focused on EFL learners' acceptance of AI, intentions to use it, and usage behaviors, offering limited explanations of how AI literacy shapes learners' interactions with AI and relates to critical thinking. To address this gap, the present study drew on self-regulated learning theory and adopted an explanatory sequential mixed-methods design. Questionnaire data from 450 university students with generative AI-assisted EFL learning experience were analyzed using structural equation modeling and bootstrapping. Subsequently, 20 participants selected through stratified purposive sampling took part in semi-structured interviews, which were analyzed thematically. Quantitative results showed that AI literacy was positively associated with AI-assisted problem-solving ability and indirectly associated with critical thinking through AI-assisted problem-solving ability and AI reliance. Thematic analysis further revealed how learners translated AI-related knowledge and skills into effective problem-solving practices and how different levels of cognitive control were associated with distinct patterns of AI use and cognitive outcomes. This study deepens the understanding of the internal cognitive mechanisms underlying EFL learners' adaptation to AI and provides practical implications for the systematic development of AI literacy and critical thinking in EFL education.

Keywords
AI-assisted problem-solving competence, AI literacy, AI reliance, critical thinking, mixed-methods design

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1 Introduction

The swift development of artificial intelligence (AI) is changing EFL learning settings (Chen et al., 2026; Liu & Fan, 2026; Teng & Shen, 2026; Wang et al., 2026; Yang & Yang, 2026; Zong & Yang, 2025), as well as the competences expected of learners in technology-enabled contexts. Unlike conventional digital tools, AI technologies can play a more active role in the learning process by generating text, providing feedback, and interacting with learners (H. Liu et al., 2026; Shen et al., 2026; Teng & Huang, 2026; Yao et al., 2025; Zhao & Yang, 2026). Previous research has shown that AI supports language learning through simulated communicative contexts, writing assistance, and feedback (Jiang et al., 2026; Lim & Darvin, 2026; Ren et al., 2026; Liu & Song, 2021; Xing & Teng, 2026; Yang & Yang, 2025; Zhang et al., 2025). However, the educational value of AI depends on learners' ability to understand, use, and critically evaluate AI-generated outputs (Deng et al., 2026; Fu et al., 2026; Yang, 2026).

Against this backdrop, AI literacy has become a key competence for learners in an increasingly AI-mediated world (Yang & Derakhshan, 2026). The concept was initially defined as an individual's ability to understand, use, and critically evaluate AI technologies. More broadly, however, AI literacy can be regarded as a cognitive resource that enables learners to engage meaningfully and effectively in human–AI interaction (Zhao & Shi, 2026). Viewed in this way, AI literacy extends beyond the mere use of digital technologies (Wu & Yang, 2025). It involves understanding how AI systems generate outputs, critically evaluating AI-generated information, and adapting AI use to task-specific requirements. According to Zhu and Kong (2026), AI literacy should extend beyond AI knowledge and tool use to include AI-assisted problem solving, effective interaction with intelligent systems, and responsibility for AI-assisted decisions. Critical assessment of AI-generated output is also important. Lim and Darvin (2026) further emphasised learners' capacity to analyze the assumptions, biases, and limitations of AI-generated content. It implies that AI literacy cannot be considered simply in terms of how often the technology is used but rather as a meta-competency that influences learners' attitudes toward AI.

Whether AI can meaningfully enhance learning depends largely on learners' ability to engage with it as a cognitive tool throughout the problem-solving process. Instead of using AI to get pre-formulated solutions, learners should use it to analyze problems, generate possible solutions, evaluate them, and integrate relevant information to produce high-quality outcomes (Lin et al., 2025). The available literature suggests that problem-solving with the assistance of AI is defined by the collaboration between learners and AI systems. Zhu and Kong (2026) argue that AI-assisted problem solving requires learners not only to operate AI tools but also to apply them critically, collaborate intentionally with intelligent systems, and take responsibility for their decisions. From the cognitive point of view, Guo et al. (2025) suggest the possibility for AI to act as the extended part of the cognitive system that assists in information processing and ideas formulation. Taken together, these findings indicate that generative AI has considerable potential to support the development of problem-solving competence in educational settings. Lim et al. (2025) found that, compared with traditional text-based contexts, AI-enhanced simulated environments significantly improved learners' problem-solving skills, helping them better understand problem scenarios and increasing their engagement in problem solving. In their study on EFL learners' AI-assisted writing processes, Liu et al. (2024) found that AI chatbots can help students develop writing ideas, generate textual content, and support information organisation in multimodal writing tasks. Nevertheless, the development of AI-assisted problem-solving ability depends on learners maintaining their agency. According to Guo et al. (2025), even though AI could be used to improve task completion, too much reliance on AI-driven thinking might reduce the independence of learners and cause technological dependency.

As AI becomes increasingly embedded in educational practice (Sozon et al., 2025; Wong et al., 2026), the relationship between learners and AI is evolving from straightforward tool use towards more complex forms of human–AI collaboration. As distinct from conventional technology use behavior, the concept of

AI reliance is associated with the acceptance, evaluation, and incorporation of AI-generated information or recommendations into problem solving and decision making. AI reliance should not be regarded as inherently negative. In fact, Hou et al. (2026) suggest that the outcomes of AI reliance depend on how reliance is regulated rather than on reliance itself. Appropriately calibrated reliance can foster beneficial interaction between human beings and AI, whereas reliance that lacks cognitive monitoring can impair the autonomy of learners. Klingbeil et al. (2024) found that blind trust in the recommendations provided by AI can give rise to over-reliance in the sense that users still follow recommendations even if there is contradictory evidence or the user does not agree with them. Cruz et al. (2026) identified the concepts of cognitive over-reliance and strategic reliance in the context of generative AI. Cognitive over-reliance is when the learner allows the AI to replace their cognitive function, while strategic reliance implies the usage of AI for increasing the efficiency of the task without losing control over the cognitive process and being responsible for it. Thus, AI reliance should be seen not only as a tendency to use AI frequently, but also as a way of evaluating, regulating, and integrating AI-generated information and solutions.

Although AI can rapidly provide information and solutions, its outputs are not always accurate or credible. Hashemi and Ghanizadeh (2012) define critical thinking as a systematic reasoning process involving mental activities such as interpreting, analyzing, evaluating, and drawing conclusions. In educational contexts, critical thinking is closely related to learners' active regulation and deep cognitive processing. Mohammadi et al. (2023) found that cognitive strategies and metacognitive strategies in self-regulated learning can significantly predict learners' critical thinking ability. In digital environments, learners not only need to access information, but also need to judge the sources of information and evaluate their reliability. Fan et al. (2025) also noted that critical thinking is a multidimensional ability involving complex reasoning and reflective thinking, the core of which lies in comprehensive analysis and critical judgment of information. Therefore, learners' ability to maintain active evaluation and reflection in AI-enriched environments may be an important factor associated with critical thinking.

Although growing attention has been paid to AI literacy, AI use, and critical thinking in generative AI contexts, the mechanisms through which AI-assisted learning supports higher-order cognitive development remain insufficiently understood. Drawing on self-regulated learning theory, the present study adopts a mixed-methods design to investigate how AI literacy, AI-assisted problem-solving ability, and AI reliance are associated with critical thinking and to explore the cognitive processes underlying these relationships from learners' perspectives.

2 Literature Review

2.1 Theoretical foundation

Self-regulated learning theory perceives learning as a continuous process in which learners control their cognition, motivation, and behavior to attain the learning objectives through an active process and not as passive recipients of knowledge from the outside world (Zimmerman, 2000). Zimmerman's (2000) cyclical model comprises three interconnected phases: forethought, performance, and self-reflection. Forethought involves task analysis, goal setting, and strategic planning. Performance involves strategy implementation and self-monitoring, while self-reflection involves evaluating performance and adjusting subsequent learning. Pintrich (2000) further conceptualizes self-regulation as involving planning, monitoring, control, and reflection across cognition, motivation/affect, behavior, and context.

In AI-enabled learning settings, self-regulated learning theories serve as a strong theoretical basis for interpreting learner interactions with AI-based sources and possible implications of such an interaction on cognitive outcomes. Within this framework, AI literacy is primarily related to forethought because knowledge of AI capabilities and limitations can inform task analysis and strategic planning. AI-assisted problem-solving ability is more closely associated with performance regulation because learners

need to select strategies, evaluate AI-generated information, and integrate useful outputs into problem solving. AI reliance may reflect learners' monitoring and adjustment of AI use, whereas excessive or uncritical reliance may indicate insufficient regulation. Critical thinking, however, should not be regarded simply as the final outcome of this process. It may also shape learners' evaluation of AI outputs and their subsequent strategies and reliance. Accordingly, the proposed pathway from AI literacy to critical thinking through AI-assisted problem-solving ability and AI reliance represents one theoretically plausible regulatory pathway for empirical examination rather than a strictly linear representation of SRL.

2.2 AI literacy

AI literacy is commonly understood as a multidimensional competence that enables individuals to understand, use, and critically evaluate AI technologies. In addition to the knowledge that the learners have concerning the key concepts, functioning, and uses of AI, AI literacy also entails the ability of learners to utilize the technology for task completion, evaluate the output generated by AI, and recognize the wider ramifications of AI technologies (Zhong & Liu, 2025). Cruz et al. (2026) found that learners' AI literacy was associated with their understanding and use of generative AI. Together, these aspects give the learners the ability to comprehend and evaluate AI technologies in an appropriate manner (Heung et al., 2026). According to Cao and Mao (2026), AI literacy in the context of generative AI means that learners need more than just the operational skill of AI technologies. Learners are expected to understand how AI systems work, evaluate the output generated by the AI systems, and recognize the issues that can be encountered through the use of AI. Taken together, these studies suggest that the regulatory function of AI literacy lies not simply in knowing how AI works, but in informing learners' decisions about when, how, and for what purposes AI should be used and evaluated.

Despite previous efforts in defining and measuring AI literacy, the focus has largely been on understanding its components as well as the learners' AI knowledge and skills with relatively little focus on the behavioral manifestation of AI literacy. From an SRL perspective, AI literacy may provide the knowledge base for learners to decide when and how AI should be used, select appropriate AI-supported strategies, and evaluate whether AI-generated information is relevant to a task. Importantly, AI literacy should therefore be distinguished from AI-assisted problem-solving ability: the former provides AI-related knowledge and evaluative awareness, whereas the latter reflects how such resources are enacted during specific problem-solving tasks. AI-assisted problem solving can therefore be viewed as one way in which AI literacy is translated into observable regulatory behavior. To fill this gap, the present study examines the relationship between AI literacy and problem solving using AI and how it can help develop critical thinking skills among learners.

2.3 AI-assisted problem-solving ability

AI-assisted problem-solving ability emphasises whether learners can employ AI as a cognitive support tool to engage in problem analysis, information acquisition, solution generation, and other activities around specific tasks. This ability involves not only seeking answers, but also understanding and representing problems, applying solution strategies, and monitoring and regulating the problem-solving process (Luengo-Aravena et al., 2024). Generative AI-enhanced learning environments can provide learners with practical opportunities that approximate authentic problem situations through more dynamic and contextualised forms of interaction, thereby promoting the development of problem-solving ability (Lim et al., 2025). Similarly, Zheng et al. (2026) pointed out that AI-supported problem solving is not a simple process of information acquisition, but rather comprises multiple stages including problem understanding, problem representation, solution implementation, and critical reflection, during which learners need to continuously monitor and adjust their solution strategies throughout the interaction.

Collectively, these studies position AI-assisted problem solving as the situated enactment of regulatory strategies during task performance, rather than as another form of AI literacy.

These regulatory behaviors also provide a theoretical basis for linking AI-assisted problem solving with patterns of AI reliance. Through problem definition, evaluation of AI outputs, and adjustment of solution strategies, learners may adopt a more selective approach to deciding when AI input should be accepted, questioned, or supplemented by their own judgment. The key mechanism is therefore not greater AI use, but the regulation of how cognitive work is shared between learners and AI during problem solving. However, the reverse relationship is also theoretically possible because learners' existing reliance on AI may influence how they approach AI-assisted problem solving. Thus, the proposed ordering represents a theoretically specified pattern of association rather than the only possible sequence.

2.4 AI reliance

AI reliance refers to the extent to which individuals incorporate AI-generated information, recommendations, or content into their own judgments and actions during cognitive activities or task completion (Hou et al., 2026). Rather, it concerns the degree to which they depend on AI to acquire knowledge, solve problems, and make decisions. Klingbeil et al. (2024) noted that over-reliance may arise when users' trust in AI recommendations exceeds the system's actual capabilities. AI reliance is therefore not inherently detrimental; its consequences depend largely on learners' ability to evaluate, verify, and regulate AI-generated outputs. As Cruz et al. (2026) argued, reliance is more likely to be productive when learners use AI as a cognitive aid rather than as a substitute for independent thought. From this perspective, appropriately calibrated AI reliance represents a form of human–AI collaboration grounded in autonomous judgment, rather than the passive acceptance of AI-generated conclusions. Accordingly, AI reliance is better understood as a multidimensional phenomenon rather than simply as a continuum from low to high dependence, because learners may display qualitatively different patterns of reliance during human-AI interaction.

However, previous research has focused mainly on the antecedents of AI reliance, with less attention to how different reliance patterns are related to learners' cognitive processes. The central conceptual issue is therefore not simply how much learners rely on AI, but how that reliance is regulated and how different reliance patterns relate to learners' own cognitive engagement. In particular, it remains unclear how selective or uncritical reliance on AI is associated with learners' evaluation, verification, and reflection, which are central to critical thinking.

2.5 Critical thinking

Critical thinking is widely understood as a higher-order cognitive capacity involving analysis, evaluation, reasoning, and reflection. At its core is the ability to form well-founded judgments about information, perspectives, and proposed solutions by applying relevant evidence and appropriate criteria (Hashemi & Ghanizadeh, 2012). In educational settings, this capacity is reflected in learners' ability to identify problems, consider alternative viewpoints, assess the quality of evidence, and critically examine their own reasoning. Fan et al. (2025) further conceptualised critical thinking as a multidimensional construct that encompasses both complex reasoning and reflective thought, emphasising learners' capacity to analyze information comprehensively and evaluate it critically. Although AI can quickly generate text, opinions, and solutions, the selection of reliable outputs still depends on learners' critical thinking. As Gerlach et al. (2025) emphasised, in digital information environments, learners need to develop critical digital literacy to identify and evaluate potential issues in digital information and to avoid uncritical acceptance of information. Consequently, in the generative AI environment, critical thinking is no longer merely a traditional capacity for logical analysis, but has become a key competence for learners

to regulate the relationship between humans and AI, evaluate AI-generated information, and maintain cognitive autonomy.

Taken together, the literature suggests a regulatory pathway in which AI literacy informs AI use, AI-assisted problem-solving ability reflects its enactment during task performance, and AI reliance reflects how learners regulate AI's contribution to their cognitive work. Although critical thinking may also shape subsequent AI reliance within the broader SRL process, the present study focuses on one theoretically specified indirect pathway from AI literacy to critical thinking through AI-assisted problem-solving ability and AI reliance. Given the cross-sectional nature of the data, this pathway is interpreted as a pattern of indirect associations rather than a causal or developmental sequence. Accordingly, the following research questions are proposed:

RQ1: How are AI literacy, AI-assisted problem-solving ability, and AI reliance sequentially associated with learners' critical thinking?

RQ2: How do learners experience AI reliance during AI-assisted problem solving, and how do they perceive its relationship with critical thinking?

3 Method

3.1 Participants

The research adopted an explanatory sequential mixed-methods research design. Participants for this research were drawn from five universities in northern China. During the quantitative stage, convenience sampling was applied, and students were invited to fill out an online questionnaire distributed through Wenjuanxing. Eligible participants were non-English-major undergraduates with prior experience using AI to support English learning. A total of 450 valid responses were obtained, with 86, 89, 90, 92, and 93 participants from the five universities, respectively, indicating a relatively balanced institutional distribution. Among the 450 participants, 239 were males (53.11%), and 211 were females (46.89%). In terms of age, 308 were aged between 18 and 20 years (68.44%), and 142 were aged between 21 and 23 years (31.56%). Regarding academic year distribution, first-year students represented the largest group (N = 197, 43.78%), followed by second-year students (N = 108, 24.00%), fourth-year students (N = 88, 19.56%), and third-year students (N = 57, 12.66%). The purpose of the study was communicated to the respondents, who provided their consent before filling out the questionnaire.

3.2 Instruments

Construct validity was assessed through confirmatory factor analysis (CFA). Model fit was evaluated using commonly used criteria, with χ^2/df values below 3 indicating good fit and values between 3 and 5 acceptable fit, CFI and TLI greater than 0.90, and RMSEA and SRMR lower than 0.08. Following Kline (2023), these indices were interpreted jointly rather than as rigid cutoff criteria.

3.2.1 AI literacy

AI literacy was measured using the scale created by Wang et al. (2023). The test includes four dimensions, namely awareness, use, evaluation, and ethics, all of which consist of three items each. Responses to the questions were given on a seven-point Likert scale from 1 (Strongly disagree) to 7 (Strongly agree). A sample item is "I can distinguish between smart devices and non-smart devices." The scale demonstrated satisfactory reliability in the present study, with Cronbach's α coefficients of 0.944 for the overall scale and 0.920, 0.899, 0.920, and 0.908 for the four subscales, respectively. In addition, the results of CFA indicated an acceptable model fit: $\chi^2/df = 1.871$, CFI = 0.991, TLI = 0.988, RMSEA = 0.044, and SRMR = 0.023.

3.2.2 AI-assisted problem-solving ability

Learners' AI-assisted problem-solving ability was measured using the Empowerment in Using Artificial Intelligence for Problem-Solving Scale developed by Kong et al. (2025). The scale consists of three dimensions: impact, self-efficacy, and meaningfulness, with 11 items in total. Participants responded to each item on a five-point Likert scale ranging from 1 ("Strongly disagree") to 5 ("Strongly agree"). A sample item is "I am good at solving problems with AI." The scale demonstrated satisfactory reliability in the current study, with a Cronbach's α of 0.932 for the overall scale. The reliability coefficients for the three dimensions were 0.890, 0.901, and 0.895, respectively. Furthermore, the results of CFA indicated satisfactory model fit: $\chi^2/df = 2.883$, CFI = 0.978, TLI = 0.971, RMSEA = 0.065, and SRMR = 0.032.

3.2.3 AI reliance

Learners' AI reliance was measured using the Scale of Reliance Behaviors during Human-AI Problem-Solving developed by Hou et al. (2025). The answers provided by the participants were measured on a five-point Likert scale, whereby 1 meant "Strongly disagree" while 5 meant "Strongly agree." The scale comprises four dimensions of reliance on generative AI: reflective, cautious, thoughtless, and collaborative use. Accordingly, AI reliance in the quantitative model was operationalised as an overall construct encompassing these four reliance behaviors rather than as a direct measure of strategic reliance. A sample question is "I critically read the content generated by generative AI." The scale demonstrated excellent internal consistency, with an overall Cronbach's α of 0.951. The Cronbach's α coefficients for the four dimensions were 0.890, 0.897, 0.897, and 0.903, respectively. Confirmatory factor analysis also indicated good construct validity, $\chi^2/df = 1.784$, CFI = 0.986, TLI = 0.982, RMSEA = 0.042, and SRMR = 0.025.

3.2.4 Critical thinking

Critical thinking was measured using the scale developed by W. Liu et al. (2026). There are five components of the scale, namely systematic analyticity, open-mindedness, confidence in reasoning, reflective skepticism, and truth-seeking. The answers were rated from 1 (not at all like me) to 5 (very much like me). An example of one of the items is as follows: "I like to organize evidence before forming an opinion." The scale demonstrated satisfactory reliability, with an overall Cronbach's α of 0.958 and coefficients of 0.892, 0.853, 0.899, 0.910, and 0.918 for the five dimensions, respectively. The construct validity of the scale was confirmed by the following fit indices: $\chi^2/df = 2.320$, CFI = 0.967, TLI = 0.961, RMSEA = 0.054, and SRMR = 0.027.

3.3 Data collection

Participants first provided demographic information and subsequently completed four validated measurement instruments. To reduce potential common method bias, responses were collected anonymously, and different response formats were used across the measures. Participants were also informed that there were no right or preferred answers. In the second phase, semi-structured interviews were conducted immediately after the questionnaire phase to further explain the quantitative findings and explore learners' experiences of AI-supported English learning. Stratified purposive sampling was used to select participants according to high, medium, and low score levels across the four focal constructs. A total of 20 students were invited, and all agreed to participate. Each interview lasted approximately 40–50 minutes and was conducted in English. With participants' consent, the interviews were audio-recorded and transcribed verbatim.

3.4 Data analysis

To answer RQ1, the quantitative data were analyzed using SPSS 27 and AMOS 24 software. Descriptive statistics and Pearson correlation analyses were conducted first to examine the relationships among AI literacy, AI-assisted problem-solving ability, AI reliance, and critical thinking. As a diagnostic assessment of common method bias, Harman's single-factor test was conducted using all measurement items. Next, CFA was performed to evaluate the validity of the measurement model. After an acceptable measurement model had been established, structural equation modeling (SEM) with maximum likelihood estimation was conducted to examine the proposed structural model and serial indirect pathway. The statistical significance of the indirect effects was assessed through bootstrapping with 2,000 resamples and 95% bias-corrected confidence intervals.

For RQ2, a reliability-oriented thematic analysis was conducted on the semi-structured interview transcripts, with reference to the six phases proposed by Braun and Clarke (2006). Meaning units expressing a coherent idea were used as the coding units, and an initial codebook was developed and refined through pilot coding. Two coders independently coded the interview transcripts and subsequently compared their coding decisions, resulting in an intercoder agreement of 84.78%. Disagreements were discussed until consensus was reached.

4 Results

4.1 Quantitative results

Harman's single-factor test was conducted as a diagnostic assessment of common method bias. The first unrotated factor accounted for 35.782% of the total variance, below the commonly used 50% threshold, suggesting that no single factor dominated the covariance among the measures.

Table 1 presents the descriptive statistics and correlations among the four study variables. The skewness values ranged from −0.698 to −0.445, and the kurtosis values ranged from −0.805 to −0.068, indicating no substantial departures from normality.

The correlation analysis showed that all four variables were significantly and positively correlated with one another ($p < 0.01$). Specifically, AI literacy was significantly positively correlated with AI-assisted problem-solving ability ($r = 0.408$), AI reliance ($r = 0.376$), and critical thinking ($r = 0.407$). AI-assisted problem-solving ability was also significantly positively correlated with AI reliance ($r = 0.554$) and critical thinking ($r = 0.540$). In addition, AI reliance was significantly positively correlated with critical thinking ($r = 0.536$).

Table 1
Descriptive Statistics and Correlations

Variables	M	SD	Skewness	Kurtosis	1	2	3	4
1. AI literacy	3.80	1.15	-0.445	-0.068	-			
2. Ability	3.36	0.94	-0.585	-0.805	0.408**	-		
3. AI reliance	3.32	0.89	-0.649	-0.621	0.376**	0.554**	-	
4. Critical thinking	3.31	0.87	-0.698	-0.512	0.407**	0.540**	0.536**	-

Note: ** $p < 0.01$; Ability=AI-assisted problem-solving ability

Figure 1 presents the confirmatory factor analysis model for the four latent variables. The model fit indices were as follows:: $\chi^2/df = 1.464$, CFI = 0.964, TLI = 0.962, RMSEA = 0.032, SRMR = 0.040.

Figure 1
CFA Model

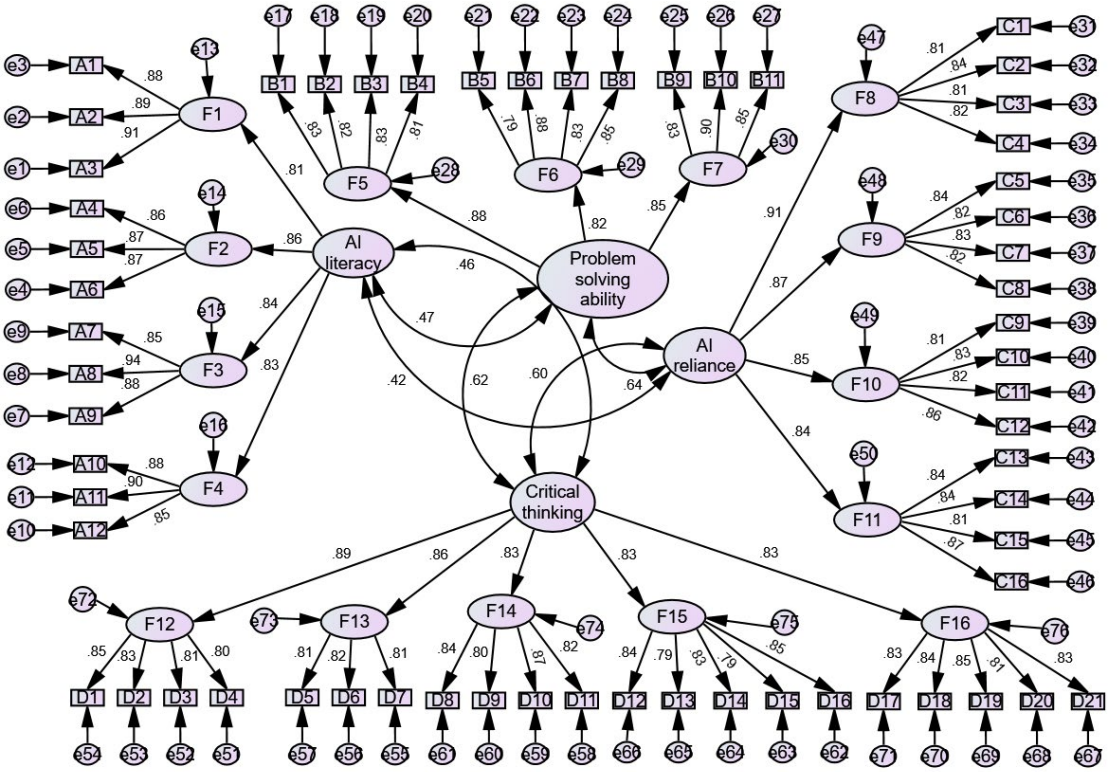


Table 2 presents the results of composite reliability, convergent validity, and discriminant validity assessments for the study variables. The CR values for AI literacy, AI-assisted problem-solving ability, AI reliance, and critical thinking were 0.977, 0.963, 0.972, and 0.978, respectively. The AVE values were 0.778, 0.702, 0.687, and 0.681, respectively, all exceeding the recommended threshold of 0.50 and indicating satisfactory convergent validity (Hair et al., 2019). Regarding discriminant validity, the diagonal values represent the square roots of AVE (0.882, 0.838, 0.829, and 0.825), which were greater than the correlations with other constructs. The HTMT values ranged from 0.397 to 0.589, below the recommended threshold of 0.85, further supporting discriminant validity.

Table 2
Reliability, Convergent Validity, and Discriminant Validity

Construct	CR	AVE	1	2	3	4
1. AI literacy	0.977	0.778	**0.882**	0.433	0.397	0.427
2. Ability	0.963	0.702	0.474	**0.838**	0.589	0.569
3. AI reliance	0.972	0.687	0.419	0.639	**0.829**	0.562
4. Critical thinking	0.978	0.681	0.457	0.618	0.602	**0.825**

Note: Diagonal values in bold are the square roots of AVE. Values below the diagonal are latent inter-construct correlations estimated from the CFA model, and values above the diagonal are HTMT ratios.

Figure 2 presents the structural model proposed in this study and the path relationships among the latent variables, while Table 3 further reports the results of the structural model analysis. Table 3 reports the standardised coefficients together with bias-corrected 95% bootstrap confidence intervals. The results showed that AI literacy was significantly and positively associated with AI-assisted problem-solving ability ($\beta = 0.474$, $p = 0.001$). Further analysis revealed that AI-assisted problem-solving ability was

significantly and positively associated with AI reliance (β = 0.568, p = 0.001). Meanwhile, AI reliance was significantly and positively associated with critical thinking (β = 0.318, p = 0.001). In addition, AI literacy was significantly and positively associated with critical thinking (β = 0.164, p = 0.003) and AI reliance (β = 0.150, p = 0.014). AI-assisted problem-solving ability was also significantly and positively associated with critical thinking (β = 0.337, p = 0.001).

Figure 2
The Finalized SEM Model

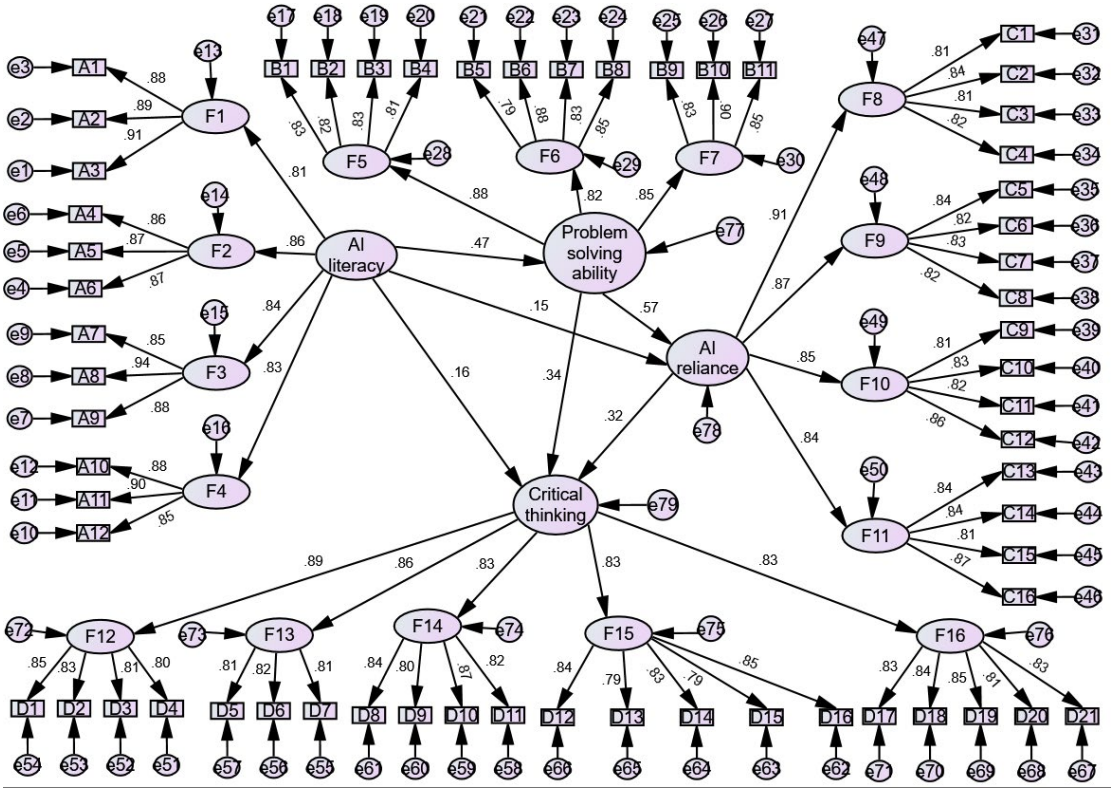


Table 3
Path Analysis

Path	Standardised β	95% BC Bootstrap CI	Bootstrap p
AL → AB	0.474	[0.358, 0.575]	0.001
AB → AR	0.568	[0.439, 0.696]	0.001
AL → AR	0.150	[0.030, 0.281]	0.014
AR → CT	0.318	[0.154, 0.494]	0.001
AL → CT	0.164	[0.057, 0.271]	0.003
AB → CT	0.337	[0.178, 0.494]	0.001

Note: AL=AI literacy; AB= AI-assisted problem-solving ability; AR=AI reliance; CT=Critical thinking; BC = bias-corrected.

Table 4 presents the results of the mediation effect analysis. The bootstrap analysis showed that the 95% confidence intervals for all three indirect effects did not include zero, indicating that all mediating pathways were statistically significant. Specifically, AI literacy showed a significant positive indirect association with critical thinking through AI-assisted problem-solving ability. AI literacy also showed a significant indirect association with critical thinking through AI reliance. In addition, AI-assisted problem-solving ability and AI reliance formed a significant serial indirect pathway between AI literacy

and critical thinking. Among the three indirect pathways, the specific indirect association through AI-assisted problem-solving ability was the largest. The serial pathway showed an intermediate magnitude, whereas the pathway through AI reliance alone was the smallest, indicating that statistical significance did not imply equal substantive importance across the three pathways. The total association between AI literacy and critical thinking was also statistically significant.

Table 4
Bootstrap Results for Unstandardized Indirect and Total Effects.

Parameter	Estimate	95% CI [Lower, Upper]	*p*
Indirect effect			
AL→AB→CT	0.121	[0.066,0.205]	0.001
AL→AR→CT	0.036	[0.008,0.092]	0.008
AL→AB→AR→CT	0.065	[0.033,0.114]	< 0.001
Total effect			
AL→CT	0.345	[0.251,0.443]	0.001

Note: AL=AI literacy; AB= AI-assisted problem-solving ability; AR=AI reliance; CT=Critical thinking

4.2 Qualitative results

The qualitative thematic analysis identified three interrelated themes of AI-assisted English learning: Blind Trust Awakening, Strategic Interaction Reconfiguration, and Synergistic Autonomy Integration. Participants described recognising AI's limitations, adjusting their interaction and problem-solving strategies, and developing more regulated forms of human–AI collaboration while maintaining independent judgment. As shown in Figure 3, the nine first-order codes were organised into three themes, which were further grouped into two higher-order categories: Adaptive Trust Evolution and Sovereign Partnership. Adaptive Trust Evolution encompasses Blind Trust Awakening and Strategic Interaction Reconfiguration, highlighting how learners evaluate AI reliability and regulate their interaction strategies. Sovereign Partnership corresponds to Synergistic Autonomy Integration and highlights a collaborative mode of AI use in which learners draw on AI support while retaining autonomous judgment and regulatory control.

The theme of "Blind Trust Awakening" captures learners' gradual shift from largely accepting AI-generated outputs to recognising the limitations of AI and evaluating its reliability more critically. During the early stages of AI use, participants were often drawn to its speed, convenience, and linguistic fluency, viewing it primarily as a means of obtaining answers quickly and completing learning tasks efficiently. Participant 1 recalled, "*In the beginning, I often trusted AI responses and rarely questioned whether the information was completely accurate.*" This unquestioning trust began to change when learners encountered inaccurate or contextually inappropriate AI-generated content. For example, after a teacher identified an AI-recommended expression as unsuitable for a particular context, Participant 1 came to recognise that, although AI could offer useful suggestions, it could not replace the learner's own judgment of linguistic appropriateness. Other participants similarly observed that AI-generated summaries and explanations, while helpful for improving task efficiency, sometimes omitted important arguments, oversimplified complex ideas, or discouraged deeper engagement with the original material. As Participant 3 explained, "*I was receiving information but not truly processing it.*" Following these experiences, participants reported adopting more reflective and selective strategies. Participant 3, for instance, began reading source texts independently and used AI mainly to clarify difficult concepts, while verifying AI-generated information against textbooks, academic literature, and personal understanding. This pattern helps explain the positive quantitative associations involving AI literacy, AI reliance,

and critical thinking: awareness of AI's limitations appeared to encourage monitoring and evaluation, whereas uncritical acceptance could restrict deeper information processing. From an SRL perspective, this theme reflects the emergence of error awareness and self-monitoring, as learners began to recognise discrepancies between AI outputs, task requirements, and their own understanding. However, because the quantitative measure captures overall AI reliance rather than strategic reliance alone, the positive coefficient should not be interpreted as direct evidence that reflective or strategic reliance improves critical thinking. The qualitative findings instead indicate that learners' reliance experiences may include reflective, selective, and monitored forms.

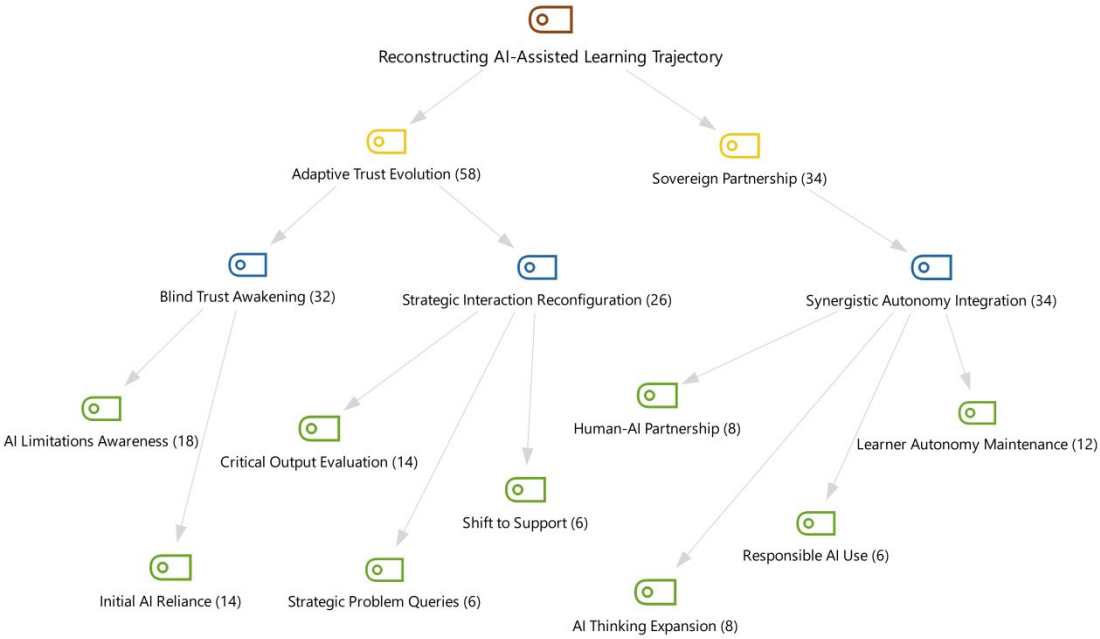
The theme of "Strategic Interaction Reconfiguration" captures how learners began to modify their questioning practices, task sequences, and information-evaluation strategies after becoming aware of AI's limitations. As Participant 2 explained, "*Before interacting with AI, I tried to identify my specific difficulties.*" Rather than asking AI to generate an essay introduction directly, the participant used it to assess the clarity of the argument and the coherence of the paragraph structure. The resulting suggestions were then compared with the participant's own ideas before any revisions were adopted. Strategic interaction, therefore, is not defined by more frequent AI use. Instead, it involves integrating AI purposefully into different stages of problem solving, including problem identification, comparison of possible solutions, and evaluation of outcomes. In SRL terms, these behaviors reflect adaptive strategy use and performance control, as learners adjusted how they engaged with AI in response to task demands and ongoing monitoring. Through this process, AI shifts from functioning as a substitute for task completion to serving as a resource that supports learners' reasoning and decision making. This theme offers further insight into the quantitative findings, particularly the significant positive effect of AI literacy on AI-assisted problem-solving ability and the positive effects of AI-assisted problem-solving ability on both AI reliance and critical thinking. Learners who possess a clearer understanding of AI's functions and limitations appear better able to define problems, formulate appropriate prompts, evaluate the relevance of AI-generated responses, and determine whether those responses are suitable for particular tasks.

The theme of "Synergistic Autonomy Integration" describes a stage at which learners incorporate AI into their learning in a sustained and purposeful manner while retaining control over their own reasoning, judgment, and decision-making. Participant 10 explained, "AI works best when combined with human thinking. AI can provide different perspectives and expand possible solutions, but humans still need to evaluate and make decisions." In complex tasks such as group presentations, this participant used AI to generate ideas, organise information, and identify weaknesses in arguments, while relying on discussion with classmates to determine which suggestions were worth adopting.

Within this collaborative arrangement, AI reliance was no longer viewed simply as reliance, but as a flexible and regulated form of learning. As Participant 5 observed, "I believe AI reliance is not necessarily negative. The key issue is whether learners maintain their own judgment during the process." Synergistic autonomy integration therefore does not require learners to minimise their use of AI. Rather, it involves drawing on AI support while preserving control over learning goals, processes, and outcomes. From an SRL perspective, this theme reflects reflective evaluation and the maintenance of learner-held regulatory control while AI is incorporated as an external cognitive resource. This theme helps explain the positive AR→CT association and the AL→AB→AR→CT serial indirect pathway, while also suggesting that the role of reliance may differ depending on whether learners retain evaluative control. This theme provides qualitative insight into one form of AI reliance observed among participants, but it should not be taken to mean that the positive quantitative coefficient specifically represents strategic reliance. When learners engage with the multiple explanations and possible solutions generated by AI, they must assess the reliability of the information, consider its relevance to the task, and decide whether it should be accepted, modified, or rejected. Such evaluative activity may strengthen comparison, critical judgment, and independent decision-making.

Taken together, the interview findings help explain the quantitative pathways. Strategic Interaction Reconfiguration most directly informs the AL→AB and AB→CT pathways, whereas Synergistic Autonomy Integration provides insight into the AB→AR→CT pathway. Blind Trust Awakening, in contrast, suggests that uncritical acceptance may limit deeper processing. These qualitative themes should be interpreted as explanations of the observed cross-sectional associations rather than evidence of score changes or a fixed temporal sequence.

Figure 3
Thematic Map



5 Discussion

5.1 AI-assisted problem-solving pathway

The present study found a significant positive indirect association between AI literacy and critical thinking through AI-assisted problem-solving ability. This result can be interpreted through the lens of self-regulated learning theory. In this process, AI-assisted problem-solving ability is associated with behaviors such as identifying and representing problems, comparing AI-generated information, and monitoring the solution process, which are also central to critical thinking. This finding echoes the work of Luengo-Aravena et al. (2024), who pointed out that digital skills involve not only technical operations but also the capacity to search, analyze, evaluate, and integrate information in digital environments, and that problem-solving itself requires problem understanding, strategy use, and metacognitive monitoring. Their study also found that learners with lower digital skills tended to evaluate online collaborative problem-solving processes less favourably. Meanwhile, Zheng et al. (2026) found that GenAI-enhanced multi-agent support can improve learners' collaborative problem-solving performance and ability by promoting problem identification, process monitoring, strategy adjustment, and reflection.

Notably, the indirect pathway through AI-assisted problem-solving ability was the largest of the three indirect pathways. This relative advantage suggests that problem-solving ability may be the more prominent mechanism in the present model, although the magnitude of the indirect association remains insufficient to support claims of a strong educational effect. From an SRL perspective, this may be because problem-solving ability reflects more proximal regulatory behaviors, such as problem

identification, strategy selection, monitoring, comparison, and output evaluation, which closely engage the analytical and evaluative processes involved in critical thinking.

The Strategic Interaction Reconfiguration theme helps contextualise this pathway. In SRL terms, it reflects adaptive strategy use and performance control. This finding is consistent with the study by Mohammadi et al. (2023), whose results showed that cognitive and metacognitive strategies can significantly promote critical thinking; their interview findings also indicated that learners, through goal setting, self-questioning, process monitoring, and outcome evaluation, are able to analyze materials more deeply and solve learning problems. The present study further extends this mechanism to the context of AI-assisted English learning, suggesting that high-quality human-AI interaction does not depend on the frequency of AI use, but on whether learners can engage in strategic questioning and output evaluation.

5.2 AI reliance pathway

A significant positive indirect association through AI reliance was identified between AI literacy and critical thinking. However, the AL→AR coefficient was comparatively small ($\beta = .150$), suggesting that AI literacy was related to AI reliance only to a limited extent relative to the other structural paths. Consistent with this pattern, the indirect pathway through AI reliance alone was also the smallest of the three indirect pathways. According to self-regulated learning theory, in AI-supported learning contexts, learners with higher AI literacy are more likely to understand the functional boundaries of AI and decide, based on task demands, when to turn to AI and which outputs are worth adopting. This interpretation resonates with the findings of Hou et al. (2026), who distinguished GenAI reliance into reflective, cautious, collaborative, and thoughtless use, and found that critical thinking interventions could reduce learners' passive acceptance of AI-generated content. Therefore, the positive association observed for the overall AI reliance construct should not be interpreted as evidence that strategic reliance alone benefits critical thinking. Rather, the qualitative findings suggest that learners may experience AI reliance in different ways, including more reflective and monitored forms. These qualitative distinctions should be viewed as possible refinements of the overall quantitative construct rather than as distinct forms of reliance directly measured by the SEM, and they require further quantitative validation.

The Blind Trust Awakening theme further contextualises this positive quantitative association. From an SRL perspective, it reflects self-monitoring and trust calibration when AI output conflicts with task requirements or prior knowledge. This finding resonates with the work of Klingbeil et al. (2024), who found that individuals may still adopt AI suggestions even when these suggestions conflict with contextual information and their own judgments, suggesting that blind trust can easily lead to over-reliance. Their study also underscores the importance of AI literacy and trust calibration. The present study further suggests that, in AI-assisted English learning, direct encounters with AI errors and limitations may be associated with trust calibration and more critical and deliberate judgment.

The Synergistic Autonomy Integration theme provides a complementary perspective, suggesting that productive AI reliance may involve continued AI use under learner-held evaluative control. This finding echoes the study by Hashemi and Ghanizadeh (2012), which showed that learners can develop reflective and critical thinking by interpreting information, weighing evidence, identifying hidden assumptions, and being exposed to multiple perspectives. The present study further extends this process to the context of AI-assisted English learning, emphasizing the combination of AI support and learners' autonomous judgment, thereby forming a human-AI relationship that is both collaborative and cognitively controlled. Together, these themes suggest that the positive quantitative association involving AI reliance is contextually heterogeneous and may depend on how learners monitor, evaluate, and regulate their engagement with AI.

5.3 Serial pathway

The serial mediating pathway from AI literacy to critical thinking via AI-assisted problem-solving ability and AI reliance was statistically significant. Its magnitude fell between the problem-solving-only and AI-reliance-only pathways, suggesting that the serial pathway adds to the overall pattern of indirect associations but is not the dominant pathway in the model. This result can be interpreted through self-regulated learning theory: AI literacy may be associated with learners' selection of appropriate AI usage strategies, which may in turn be reflected in problem-solving competencies such as problem identification, solution comparison, and output evaluation. From an SRL perspective, the incorporation of AI into problem solving may also involve monitoring, verification, and adjustment of AI outputs, although these regulatory behaviors should not be assumed to represent the quantitative AI reliance construct itself. This finding echoes the work of Mohammadi et al. (2023), whose results indicated that cognitive and metacognitive strategies can directly promote critical thinking, while other learning factors may also exert indirect effects through these strategies, suggesting that higher-order cognitive outcomes often emerge from continuous self-regulatory processes. The present study thus further suggests that AI literacy is more likely to be associated with critical thinking when accompanied by effective problem-solving practices and patterns of AI reliance.

Taken together, the two datasets suggest that this serial pathway may reflect an interconnected set of regulatory activities rather than a fixed developmental sequence. The qualitative findings therefore help specify the possible mechanisms and conditions underlying the statistical relationships rather than merely reproducing them.

This study makes three main theoretical contributions. First, the research explains the indirect pathways through which AI literacy is associated with critical thinking. The findings suggest that AI literacy may be reflected in learners' ability to interact critically with AI through problem recognition, strategy selection, and outcome evaluation. Second, the study extends self-regulated learning theory to AI-assisted English learning by identifying that self-regulation is not limited to internal cognitive and behavioural strategies but also involves the selection and adjustment of AI as an external cognitive tool. Conventional SRL models primarily focus on how learners regulate their own cognition and behaviour, but they give less attention to how regulatory control is managed when an adaptive external system participates directly in task performance. The present findings suggest that regulation in AI-assisted learning may also involve distributing cognitive responsibility to AI, reclaiming that responsibility when necessary, and evaluating whether AI input should be accepted, modified, or rejected. Finally, the study provides a better understanding of the concept of AI reliance by showing that AI reliance should not be equated with over-reliance and that the qualitative findings suggest potentially heterogeneous reliance experiences that require further quantitative validation.

This paper suggests three implications for pedagogy in terms of practice. Firstly, for learners displaying Blind Trust Awakening, instruction should emphasise structured error-detection and source-comparison activities. Instructors can provide students with responses that are inaccurate, biased, or poorly reasoned and then ask them to validate the information provided, consult other sources, and decide whether to accept, modify, or reject the response. Secondly, for learners beginning to reconfigure their interactions with AI, tasks should encourage justification, alternative solutions, and verification. In particular, students can be tasked with defining a problem by themselves, using iterative prompts to suggest different solutions, comparing them, and arriving at evidence-based conclusions. Thirdly, for learners demonstrating greater autonomy, instruction should preserve productive human-AI collaboration while ensuring that final judgment remains with the learner. For example, they can be asked to describe the function of AI in the assignment and explain how they assessed and modified its output. Consequently, assessment would cover problem analysis, evidence, output validation, and reasoning behind students' actions.

6 Conclusion

This study examined the relationships among AI literacy, AI-assisted problem-solving ability, AI reliance, and critical thinking. The quantitative findings showed significant direct and indirect associations among these constructs, including a positive association between AI reliance and critical thinking. The qualitative findings identified three interrelated themes of AI engagement: Blind Trust Awakening, Strategic Interaction Reconfiguration, and Synergistic Autonomy Integration. Within the present AI-assisted English learning context, the results suggest that the value of AI lies not in accepting AI-generated material without criticism but in critically analysing and interacting with AI-generated content. In general, AI literacy was associated with critical thinking through AI-assisted problem-solving ability and AI reliance. The positive quantitative association involving AI reliance should be interpreted at the level of the overall construct, while the qualitative findings indicate that learners may experience reliance in different forms.

However, this paper has several limitations. Firstly, the quantitative part of the study relied on cross-sectional data, which limits causal and temporal interpretations of the observed relationships. In future research, longitudinal designs could examine whether and under what conditions learners move between or return to different patterns of AI engagement, while experimental designs could further clarify causal relationships among the variables. In addition, because the study used convenience sampling and involved non-English-major undergraduates with prior AI-assisted English learning experience from five universities in northern China, the findings should not be generalised to Chinese university students or other educational contexts without further evidence. Possible residual institution-level clustering should also be considered when interpreting the results. Secondly, this paper heavily relied on self-reported data from surveys and semi-structured interviews that can be affected by issues such as social desirability and recollection. Because the four quantitative constructs were assessed through self-report questionnaires completed by the same participants, shared method variance may also have inflated some of the observed associations. Including behavioral evidence, such as interaction logs between the learners and the AI systems as well as performance logs and classroom observations, will add objectivity to future studies. Lastly, patterns of AI use and reliance may vary across generative AI systems, task types, and educational contexts, and their transferability should be examined in future research.

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