The Impact of AI Literacy on Undergraduate Autonomous Learning

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Abstract: This study explores the factors driving autonomous learning (AU) among undergraduate students in AI-enhanced education. It specifically examines the role of AI literacy (AI-L), critical thinking (CT), self-regulation (SR), and self-efficacy (SE). Data collected from Thai university students were analyzed using Structural Equation Modeling (SEM). The results show that AI-L demonstrated a strong and significant positive influence on all three mediating variables—SE (β = 0.99, t = 20.00), SR (β = 0.93, t = 18.53), and CT (β = 0.70, t = 7.30). SE exerted as the most powerful predictor of AU (β = 0.52, t = 6.38), while critical thinking had a smaller direct impact. The findings suggest that AI-L is a foundational competency that requires metacognitive support. Consequently, educators should utilize strategies like blended learning and reflective practice. These insights encourage a learner-centered approach to digital education, fostering future-ready, autonomous learners.

Keywords: AI literacy, Self efficacy, Self-regulation, Critical thinking, Autonomous learning, Self-directed learning

1. Introduction

Recently, global events and fast-moving technology have transformed education. As a result, there is a renewed focus on how AI literacy (AI-L) shapes a student's ability to learn independently.

While innovations such as blended learning and flipped classrooms have successfully enhanced students' general digital literacy (Latorre-Cosculluela et al., 2021, da Silva Negreiros et al., 2022) A critical area of inquiry is whether AI-L can effectively cultivate autonomous learning (AU)—a competency essential for lifelong learning and aligned with global policy frameworks like the Sustainable Development Goals (SDGs) and the UNESCO Institute for Lifelong Learning (UIL) (2024),While several studies have acknowledged that emerging technologies, including artificial intelligence (AI), can enhance autonomous learning (Intraboonsom, Darasawang and Reinders, 2020, Lai, 2019, Reinders, 2018, Ting, 2015, Papadakis et al., 2024) and foster other positive learning attributes such as self-regulation (Dragomir and Niculescu, 2020, Sinkkonen and Tapani, 2024), self-efficacy (Bewersdorff et al., 2025, Gupta and Jaiswal, 2025, Sun and Shi, 2024, Zhang et al., 2025b), and critical thinking (Lengua-Cantero et al., 2024, Nosratinia and Zaker, 2015, Yüce, 2023), there remains a notable gap regarding whether AI-L directly promotes autonomous learning, or whether its influence is mediated through variables such as self-regulation, self-efficacy, or critical thinking.

Addressing this gap is of significant importance, as autonomous learning enables students to take control of their educational journeys By identifying whether AI-L acts as a standalone skill or a foundational competency supported by mediating factors, this study contributes to the field of educational technology by deepening the theoretical and empirical understanding of AI-L that cultivate self-directed, future-ready learners.

1.1 Research Questions

RQ1. What are the factors influencing AU among undergraduate students?

RQ2. What are the relationships between AI-L, CT, SR, SE and AU among undergraduate students?

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RQ3. How do AI-L, CT, SR, and SE influence AU in university students?

RQ4. What is the most effective mediating factor in promoting AU among undergraduate students?

1.2 Research Objectives

This study aims to investigate the factors influencing autonomous learning among undergraduate students by employing SEM. The objectives of this study are as follows:

- To explore the factors influencing AU among undergraduate students
- To examine the relationships between AI-L, CT, SR, SE and AU among undergraduate students.
- To examine the influence of AI-L, CT, SR, and SE to AU in university students
- To identify the most effective mediating factor that promotes AU in undergraduate education.

2. Literature Review and Hypothesis Development

2.1 AI Literacy

AI Literacy (AI-L) refers to the ability to understand and use AI technology effectively. In this context, AI technology includes a diverse suite of technologies ranging from cognitive processing tools (such as Large Language Models- LLM) to specialized pedagogical support system (such as Intelligent Tutoring Systems, AI for image and video production, and Analytical AI). This proficiency encompasses having basic knowledge about AI, evaluating AI performance, assessing AI capabilities, limitations, as well as appropriately creating innovations using AI (Ng et al., 2021b, Ng et al., 2021a, Long and Magerko, 2020, Laupichler et al., 2022, Kandlhofer et al., 2016). In this study, AI-L was categorized into five distinct aspects based on various literature sources.

2.1.1 AI recognition

This includes the ability to distinguish between technological artifacts that use and do not use AI (Long & Magerko, 2020).

2.1.2 AI understanding

This is the ability to explain the concepts and functions of AI and machine learning (Aeri, 2021), along with an understanding of the fundamental principles of AI (Stolpe and Hallström, 2024)

2.1.3 AI leverage

This is the capacity to determine when it is appropriate to utilize AI and when to rely on human judgment and expertise (Long & Magerko, 2020). It also includes the ability to understand and interpret AI-generated outputs with an awareness of potential sources of error or bias (McCoy et al., 2020)

2.1.4 AI ethics

This is the ability to identify key ethical and moral issues related to AI (Long & Magerko, 2020). It also includes the disposition to uphold moral values and ethics in the use and development of AI technologies, along with a willingness to take responsibility for their consequences (Aeri, 2021). Furthermore, it involves an awareness of human-centered considerations (Ng et al., 2021a).

2.1.5 AI utilization

This is the ability to apply AI in addressing emerging and complex problems (Stolpe & Hallström, 2024), and the ability to select and utilize AI tools accurately and appropriately to enhance work efficiency (Chee, Ahn and Lee, 2024).

Educational strategies for AI-L are becoming more diverse, ranging from universal models to discipline-specific integration. Researchers like De Silva et al. (2024) and Kong et al. (2021) advocate for standalone courses designed to establish AI knowledge. De Silva et al. (2024) propose a "Universal AI Literacy Module" developed through human-centered co-design, focusing on four constructs: Foundational Knowledge, Problem Solving, Ethical Practice, and Entrepreneurship, which ensures a baseline of competence. Similarly, Kong et al. (2021) proposed a short, 7-hour standalone course designed to improve AI-L across diverse disciplines without requiring prior programming knowledge. In contrast to standalone models, Southworth et al. (2023) recommend embedding AI learning directly into specific fields of study rather than keeping it separate, such as "GeoAI" for geography, alongside broad certificates. Apart from curriculum structure, Xu et al. (2024) identified that smart classrooms—which incorporate diverse technologies such as AI, virtual reality, digital cameras, and interactive whiteboards to bridge the gap between online and offline learning—can drive successful AI learning. Challenging these competency-based views, Bearman and Ajjawi (2023) argue that instead of trying to teach students to understand how AI works (seeing inside the “black box”), students should learn to work with the "black box" by engaging in meaningful interactions with AI systems, interpreting the technology of AI within the contexts of its use.

2.2 Autonomous Learning

Autonomous Learning (AU) is a concept originating from language education. Started by Henri Holec (1979), who defined the term as "the ability to take charge of one's own learning" (p. 3). In his book titled "Self-instruction in Language Learning," Dickinson (1987) described AU as situations "in which a learner, with others or alone, is working without direct control of a teacher" (p. 5). Later, in 2007, David Little (2007) revisited the fundamentals. He defined autonomy as "the ability to take charge of one's own learning" (p.14), and argued that the concept doesn't have to be specifically applied to language learning in the field.

Early research by Benson and Voller (1997) and Blin (2004) highlighted how technology facilitates self-access and reinforces self-directed practice. Figura and Jarvis (2007) further noted that computer-based media helps learners develop a high-level awareness of their own learning strategies. This concept has expanded in the AI era; Alm (2024) found that Large Language Model tools, such as ChatGPT,allow learners to independently set goals, adjust strategies, and explore language. Similarly, Kalantzis and Cope (2025) proposed the "cyber-social literacy learning" framework, viewing AI as a key driver in creating collaborative human-AI learning spaces that significantly support learner agency and autonomy. However, the mere presence of technology does not automatically guarantee learning autonomy; it requires appropriate instructional design alongside the learner's critical thinking and metacognitive skills. Blin (2004) emphasized that technology only "increases" the opportunity for self-directed practice rather than ensuring it. In the context of AI, Alm (2024) and Kalantzis and Cope (2025) argue that true autonomy depends on the learner's ability to critically evaluate AI-generated content, engage in "intentional decision-making," and utilize effective feedback loops. Furthermore, Thorne (2024) raised concerns regarding academic integrity and inclusivity, suggesting that collaborative teaching strategies are necessary to prevent AI from obscuring the essential mechanisms of the learning process.

Ultimately, despite technological advancements, fostering autonomous learners must remain human-centered. Thorne (2024) asserted the irreplaceable value of human interaction in language learning, warning that AI usage must not diminish the role of the teacher. Meanwhile, Kalantzis and Cope (2025) viewed AI as a transformative force in learning structures but maintained that it should exist to "support, rather than replace, learner agency." The consensus from this research indicates that successful AI integration to promote learner autonomy requires a balanced synthesis of technological capabilities and the critical decision-making of both teachers and learners.

2.3 Self-efficacy

Bandura (1997) defined self-efficacy as the perception of one's capability to organize and execute tasks successfully. Rooted in Social Cognitive Theory, self-efficacy influences how individuals feel, think, and self-motivate. This construct is derived from four key sources: (1) mastery experiences, (2) vicarious experiences, (3) verbal or social persuasion, and (4) physiological and affective states.

Based on this concept, Johnson (2005) and Usher & Pajares (2008) investigated the structural relationships of these four factors with learners. They found that these factors influence behaviors affecting learners' academic success and their choice of major and career. This aligns with Zhou, Chen, and Hou (2022) and Xu, Li, and Yang (2024), who explained that self-efficacy has a positive relationship with self-regulation and motivation. In the context of language learners, those with high self-efficacy tend to use self-regulation strategies effectively, which in turn further stabilizes their self-efficacy. Additionally, Xu et al. (2024) found that self-efficacy plays a mediating role between self-regulated learning and learning engagement. Specifically, learners who self-regulate through communication with instructors and AI, and who perceive they can manage their learning in online environments or smart classrooms, develop confidence in their communication abilities, leading to increased learning engagement (Zhu et al., 2025). Thus, it is evident that self-efficacy has both direct and indirect influences on learning-related variables. As discovered by Honicke & Broadbent (2016) and Sun & Shi (2024), self-efficacy functions as a mediator influencing academic achievement and supporting active learning behaviors, both in higher education contexts (Honicke & Broadbent, 2016) and in offline and online learning environments (Sun & Shi, 2024).

Furthermore, the concept of self-efficacy has expanded into the dimension of confidence in technology use, as explored by Wang & Chuang (2024), Mah & Groß (2024), Chen, Liu & Liu (2024), and Bewersdorff et al. (2025), who studied AI self-efficacy among both learners and instructors. The confidence of learners or instructors in their own ability to understand and use AI effectively serves as a crucial condition linking knowledge, attitudes, and actual usage experience with behavioral outcomes regarding AI use for learning and teaching. Wang and Chuang (2024) examined AI self-efficacy in terms of technological skills, comfort, and human-AI interaction, linking these to motivated learning behaviors. Meanwhile, Bewersdorff et al. (2025) found that AI self-efficacy is related to AI-L, attitudes, and AI usage. In the context of second language learning, Chen and Liu (2024) found that AI self-efficacy positively impacts attitudes, AI usage for language learning, and the reduction of AI anxiety. Additionally, Mah and Groß (2024) found among faculty members that AI self-efficacy correlates with the level of AI adoption in teaching; instructors with positive attitudes and perceived benefits of AI are better able to translate self-efficacy into actual classroom practice.

2.4 Critical Thinking

Critical thinking (CT) has been increasingly recognized as a foundational element in fostering autonomous learning, particularly in higher education contexts. Rezaee and Saleh (2025) describe CT as a purposeful, reflective process shaped by context, culture, and personal experience, aimed at enhancing reasoning, self-awareness, and judgment. Calma and Davies (2025) emphasize CT role in informed decision-making, especially in managerial contexts, while Rivas, Saiz, and Ossa (2022) conceptualize CT as a reasoning-based, problem-solving process geared toward achieving effective outcomes. Other definitions highlight CT as a cognitive skill for logical analysis (Razak et al., 2022), a multifaceted process for understanding and interpreting information (Tathahira, 2020), and a quality of thought that improves communication and engagement with diverse perspectives (Campo et al., 2023, Meneses, Pashchenko and Mikhailova, 2023, Zhang, 2022).

Across literature, CT is consistently linked to the development of Autonomous Learning (AU). Research demonstrates that CT enhances learners' capacity for self-direction, decision-making, and metacognitive reflection. Yüce (2023) identifies CT as a significant predictor of AU ($\beta = .66$, $p < 0.001$), while Nosratinia and Zaker (2015) emphasize how CT allow learners to take responsibility for their learning and manage their progress more effectively. Kravchenko et al. (2023) further support this view by demonstrating that CT development improves communication, analysis, synthesis, and reflection skills, which arecritical components for successful self-study in higher education. Similarly, Lengua-Cantero et al. (2024) highlight how CT fosters self-regulation and deeper understanding, which are essential for navigating the demands of modern education. Horváth (2007) and Iqbal & Akbar (2021) also argue that CT enables learners to plan, assess, and reflect on their goals and learning processes, promoting greater independence and ownership of learning outcomes. Moreover, the integration of critical and creative thinking is increasingly seen as vital, particularly in earlier educational stages. Varías and Callao (2022) propose that a combined model of critical and creative thinking within AU frameworks enhances students' problem-solving abilities and overall educational experience.

Researchers often disagree on whether CT is a general personality trait or a skill tied to specific subjects (Black, 2007). Some scholars argue that CT consists of general skills that can be used in many different areas of life. For example, Dunne (2015) suggests that CT is a way of "being" in the world that combines reasoning with self-reflection and action. Similarly, Bailin (1998) describes it as a process based on universal values like clarity and accuracy, which work across all subject divisions. From this perspective, an ideal critical thinker is someone who has developed a "critical spirit" or a general habit of mind that guides their behavior in all situations. In contrast, other viewpoints suggest that CT is a skill for specific tasks that cannot exist without a particular subject like science or history. One major argument from Black & Dunne (Black, 2007, Dunne, 2015) is that thinking is always "thinking about something," which makes CT conceptually empty if it is not used within a specific field. Even those who see CT as a general ability acknowledge that a person still needs specific knowledge to use these skills well in a particular context (Facione, 1990). For instance, someone may have the mental skills to think critically, but they still need background information to make a good judgment about a complex medical or technical problem. Ultimately, how well a person thinks often depends on their level of experience in a certain area.

2.5 Self-regulation

Self-regulation (SR) is a construct in understanding how individuals manage their cognitive, emotional, and behavioral processes to achieve learning goals. Posner and Rothbart (2000) highlight the complexity of SR, noting its deep connections to volition, genetic predispositions, and social experiences.

While early work often focused on observable behaviors, recent research emphasizes self-regulated learning (SRL) as a dynamic and self-directed process in which learners actively control their educational journey. SRL involves setting goals, selecting strategies, monitoring progress, and reflecting on outcomes—actions driven by internal motivation and belief systems (Blackmore et al., 2021, Higgins, Frankland and Rathner, 2021, Dragomir and Niculescu, 2020, Tadesse et al., 2022, Sinkkonen and Tapani, 2024, Boruchovitch, Simão and Frison, 2023). Zimmerman (2002) outlines this process as a cyclical model comprising forethought, performance, and self-reflection stages, each reinforcing learners' metacognitive awareness and strategic adaptability. Through consistent engagement with SRL processes, learners enhance their autonomy by taking initiative, exercising control over their learning, and making independent decisions. Thus, SR not only improves academic outcomes but also plays a critical role in fostering autonomous learning and preparing students for sustained, lifelong learning.

Based on the literature review, this study proposed the following framework and hypothesis as depicted in Figure 1

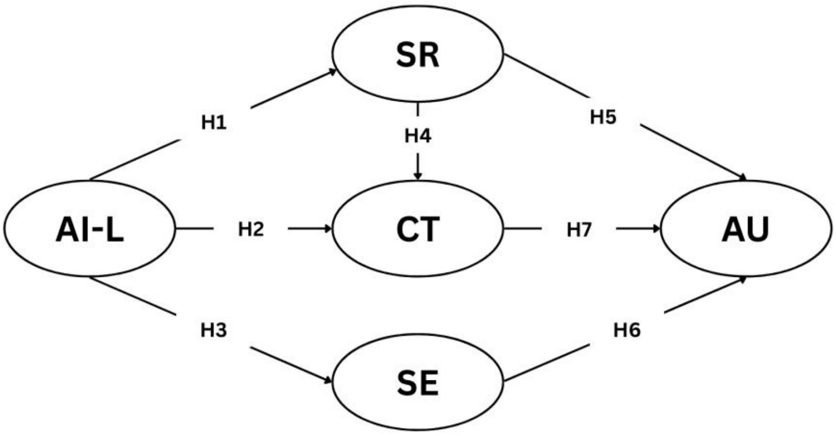


Figure 1: Research model of the study

Hypothesis

The following hypothesis is formulated in this study:

H1: AI positively influences SR, which in turn promotes AU among undergraduate students.

H2: AI positively influences CT, which in turn promotes AU among undergraduate students.

H3: AI positively influences SE, which in turn promotes AU among undergraduate students.

H4: SR positively influences CT, which in turn promotes AU among undergraduate students.

H5: SR positively influences AU among undergraduate students.

H6: SE positively influences CT, which in turn promotes AU among undergraduate students.

H7: CT positively influences AU among undergraduate students.

3. Research Methodology

3.1 Population and Sample Group

The population of this study consists of undergraduate students enrolled in Thai universities. The sample comprises 512 students from diverse academic disciplines—namely Health Sciences, Technology, Engineering, and Social Sciences—across more than 20 universities in Thailand. A convenience sampling method was employed for participant selection. The sample size for conducting SEM was determined based on the recommendation by Hair et al.(2010), resulting in a total of 477 participants, with approximately 9 samples allocated per parameter.

3.2 Research Instrument

The research instrument implemented in this study is a survey questionnaire in an online format. The questionnaire consisted of two parts. Part 1 collected demographic information of the participants, such as age, gender, and department along with their experiences with various types of AI-powered learning tools to understand their background composition. Part 2 of the questionnaire comprised a series of statements designed to examine participants' CT, AI, SR, SE, and their capacity for AU. The participants were asked to rate their agreement with each statement using 5-point Likert scale items ranked from "Strongly agree" (5) to "Strongly disagree" (1). This section of the questionnaire comprised a total of 23 items designed to assess each construct within the research model. Specifically, five items measured AI, five AU, four evaluated CT, four addressed SR, and four measured SE.

3.3 Data Analysis

The proposed research model underwent statistical analysis using SPSS (version 25), and LISREL (8.80) software. The analysis consisted of two stages. In the first stage, Confirmatory Factor Analysis (CFA) was conducted to assess the representativeness of the latent construct with each variable and to assess the fitness of the research model to the actual data to confirm the hypothesized factor structure. The second stage involved conducting a SEM path analysis to examine the causal relationships among the proposed variables. Model fit was evaluated using several indices, including the Comparative Fit Index (CFI), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), and the Root Mean Square Error of Approximation (RMSEA). According to Hair et al. (2010) an excellent model fit is indicated when the CFI, GFI, and AGFI values exceed 0.95, and the RMSEA value is below 0.05.

4. Results and Findings

4.1 Demographic Profile

The study participants in Figure 2 consisted of 512 respondents, 132 (25.8%) are male, 345 (67.4%) are female and another 35 (6.8%) identified as LGBTQ. Participants came from diverse faculties, with 251 (49.0%) from health sciences, 188 (36.7%) from social sciences, 62 (12.1%) from engineering, and 11 (2.2%) from physical sciences. Additionally, 508 participants (99.2%) reported prior use of Generative AI, while the remaining 4 participants (0.8%) did not.

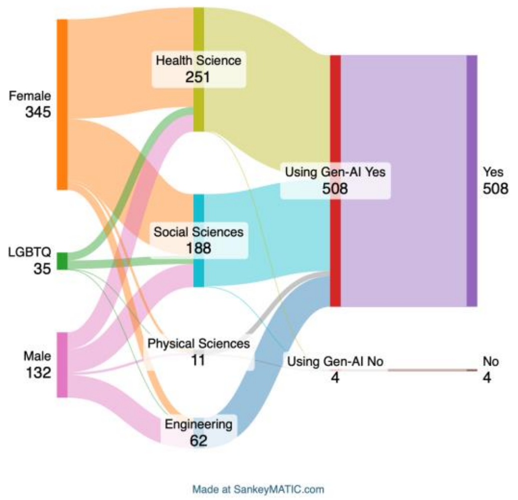


Figure 2: Demographic statistics of the participants

Figure 3 illustrates the usage frequency of generative AI among 508 experienced participants. A total of 150 participants (29.6%) reported using AI 1–3 times per week, followed closely by 145 participants (28.5%) who used it more than six times per week. Additionally, 130 participants (25.6%) used AI 4–6 times per week, 64 participants (12.6%) used it 1–3 times per month, and 19 participants (3.7%) reported using AI less than once per month. Regarding access, most participants—452 (89.0%)—relied on free services, while a smaller portion, 48 participants (9.4%), paid for access either through per-use fees or subscriptions. The remaining 8 participants (1.6%) received access through organizational support.

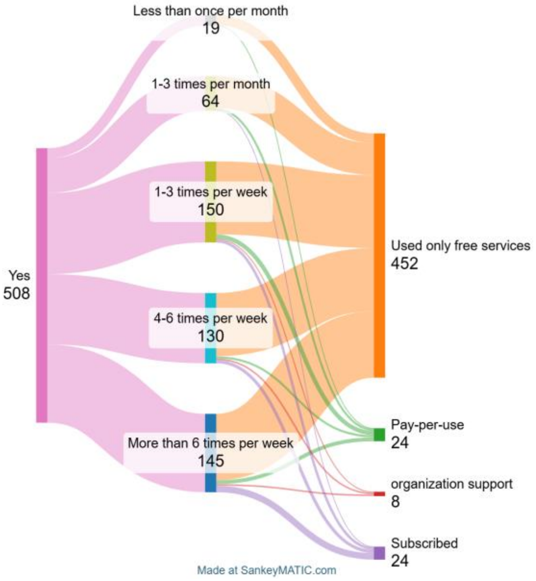


Figure 3: AI usage frequency and type of service

4.2 Measurement Model

In evaluating the measurement model, all constructs demonstrated acceptable to excellent levels of model fit. The SR construct showed a good fit, with a Chi-Square value of 4.84 (df = 2), RMSEA of 0.053, SRMR of 0.008, and fit indices including CFI and GFI at 1.00, and AGFI at 0.98. Similarly, SE construct exhibited strong model fit, reflected by a Chi-Square of 4.00 (df = 3), RMSEA of 0.026, SRMR of 0.005, and perfect values for CFI, GFI (1.00), and a high AGFI of 0.98. AI construct also indicated a good fit with a Chi-Square of 5.58 (df = 2), RMSEA of 0.05, SRMR of 0.01, and high indices (CFI = 0.99, GFI = 0.99, AGFI = 0.97). CT showed an excellent fit with a Chi-Square of 0.23 (df = 1), RMSEA of 0.00, SRMR of 0.002, and perfect CFI and GFI values (1.00), along with AGFI of 0.99. Lastly, AU displayed strong model fit indicators, including a Chi-Square of 1.18 (df = 2), RMSEA of 0.00, SRMR of 0.004, and perfect CFI and GFI scores (1.00), with AGFI at 0.99.

Table 1 presents psychometric properties of five latent constructs measured by multiple items, including their means (M), standard deviations (SD), skewness (SK), kurtosis (KU), factor loadings (FL), and key validity and reliability indices (Cronbach's alpha, Construct Reliability, and Average Variance Extracted). In summary, the measurement model shows strong psychometric validity across all constructs. AI, CT, SE, SR and AU. Each demonstrates high factor loadings, excellent construct reliability (CR > 0.70), and solid average variance extracted (AVE > 0.50). Although AI-L has slightly lower factor loadings and AVE (0.597), it still meets acceptable standards, indicating sound measurement quality overall. Correlation analyses were also applied within the scope of studying the connection between AI, CT, SR, SE and AU, as depicted in Table 2:

Table 1: Descriptive statistics of the measurement model

Construct	Items	Questions	M	SD	SK	KU	FL	α	CR	AVE
AU	AU1	I can set learning goals on a daily, weekly, or long-term basis to support my own learning.	3.66	0.94	-.455	.092	0.82	0.931	0.744	0.935
	AU2	I plan methods and manage my time effectively to achieve learning success.	3.75	0.90	-.400	-.075	0.87			

Construct	Items	Questions	M	SD	SK	KU	FL	α	CR	AVE
	AU3	I am capable of self-regulated learning without relying on others.	3.81	0.90	-.450	-.023	0.86			
	AU4	I can select learning styles, techniques, and technologies that suit my personal needs.	3.90	0.90	-.521	-.061	0.87			
	AU5	I am able to self-assess in order to improve the effectiveness of my learning.	3.84	0.89	-.390	-.196	0.89			
CT	CT1	I am able to analyze information in detail to understand and draw conclusions.	3.79	0.87	-.450	.226	0.81	0.925	0.902	0.698
	CT2	I can use reasoning to compare opinions or experiences to support well-informed decisions.	3.86	0.88	-.552	.276	0.86			
	CT3	I am capable of establishing criteria to assess importance or value.	3.80	0.87	-.499	.332	0.84			
	CT4	I can apply reasoning and skills to find solutions to various problems.	3.89	0.89	-.527	.127	0.83			
SR	SR1	I can select and apply strategies to enhance effective learning.	3.83	0.89	-.586	.539	0.80	0.923	0.913	0.723
	SR2	I am intrinsically motivated to set goals, engage in learning, persevere through challenges, and	3.83	0.87	-.412	.065	0.86			

Construct	Items	Questions	M	SD	SK	KU	FL	α	CR	AVE
		believe in my own abilities.								
	SR3	I can adapt and improve my learning strategies based on feedback and self-reflection.	3.81	0.90	-.414	-.027	0.86			
	SR4	I actively participate in collaborative learning with others in the classroom.	3.88	0.95	-.675	.355	0.88			
SE	SE1	I have sufficient knowledge to independently solve complex problems in learning or work.	3.74	0.85	-.324	.100	0.77	0.938	0.926	0.715
	SE2	I believe that my existing skills enable me to succeed in both simple and challenging tasks.	3.83	0.87	-.441	.075	0.89			
	SE3	I can plan and manage my work effectively to achieve set goals.	3.87	0.89	-.478	.010	0.88			
	SE4	Even when facing obstacles, I remain confident in my ability to find solutions.	3.88	0.88	-.513	.167	0.88			
	SE5	I am confident in my capacity to develop diverse knowledge and skills to meet future challenges	3.88	0.87	-.455	.020	0.80			
AI	AI1	I can identify which technologies utilize AI.	3.50	1.00	-.247	-.304	0.73	0.895	0.880	0.597
	AI2	I am able to explain the basic principles of how AI works.	3.280	1.00	.000	-.460	0.67			

Construct	Items	Questions	M	SD	SK	KU	FL	α	CR	AVE
	AI3	I can analyze the advantages and limitations of AI.	3.69	0.92	-.433	.106	0.83			
	AI4	I am aware of ethical issues (e.g., bias, privacy) and potential societal impacts arising from AI use.	3.86	0.96	-.543	-.094	0.82			
	AI5	I can apply AI tools (e.g., ChatGPT, AI image generators) appropriately to different types of tasks.	3.94	0.96	-.758	.330	0.80			

Table 2: Inter-construct correlation

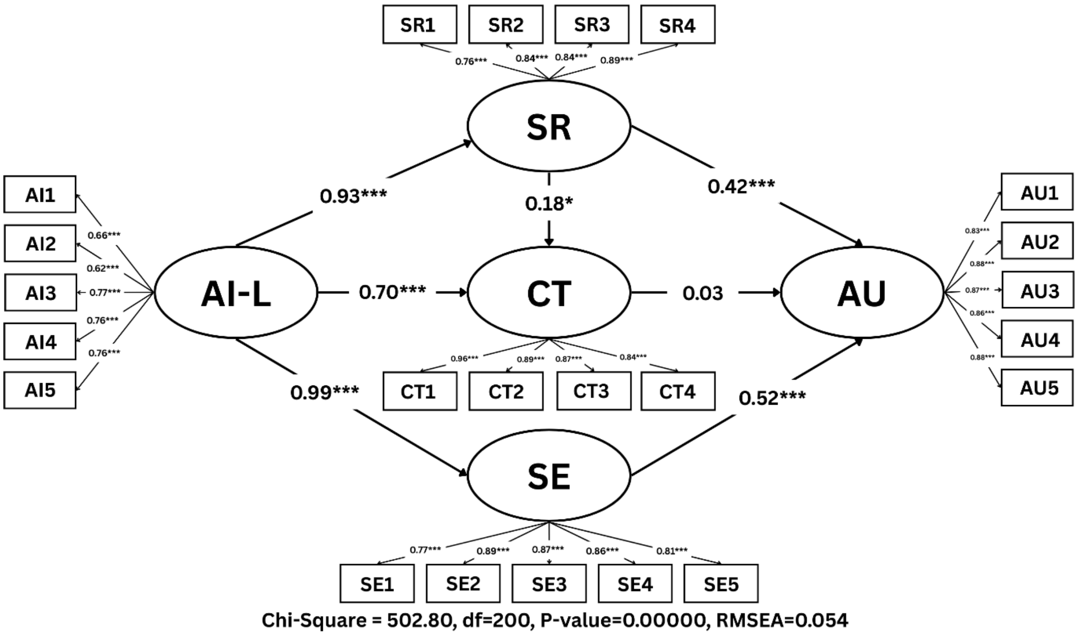
	AI-L	SR	SE	CT	AU
AI-L	1				
SR	.494	1			
SE	.549	.055	1		
CT	.213	.708	.575	1	
AU	.768	.490	.885*	.698	1

**Correlation is significant at the 0.05 level (2-tailed)*

4.3 Structural Model: Goodness of fit Statistics and Hypothesis Testing

As depicted in Figure 4, The SEM analysis revealed that the model fits the data well, with strong indices such as CFI (0.99), RMSEA (0.054), and SRMR (0.026). Although GFI (0.92) and AGFI (0.89) were slightly below ideal thresholds, they remained within acceptable ranges. A key finding was the significant influence of AI-L on all three mediators—SE (β = 0.99), SR (β = 0.93), and Critical Thinking (β = 0.70)—indicating that greater AI proficiency is closely linked to stronger self-directed learning capacities and analytical skills. Among predictors of AU, SE had the strongest direct effect (β = 0.52) whereas SR and CT did not show significant contributions to the development of AU.

The SEM analysis confirms hypotheses H1 through H6, demonstrating that AI has a significant influence on SE, SR and CT. Additionally, significant paths were observed from SE to AU and from SR to AU. In contrast, hypothesis H7 is not supported, indicating no significant relationship between CT and AU, as illustrated in Table 3.



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

Figure 4: Results of Structural Equation Model

Table 3: Structural Equation Modelling results of the proposed model

Hypothesis	Standardized Solution	Results
H1: AI-L → SR	0.93***	Supported
H2: AI-L → CT	0.70***	Supported
H3: AI-L → SE	0.99***	Supported
H4: SR → CT	0.18*	Supported
H5: SR → AU	0.42***	Supported
H6: SE → AU	0.52***	Supported
H7: CT → AU	0.03	Not supported

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

5. Discussion and Implications

One of the most significant findings of this study is the strong impact of AI-L on SE, which in turn significantly predicts AU. Students who develop a foundational knowledge of AI-L concepts and tools gain confidence in using AI effectively, reducing anxiety and enhancing their belief in their ability to succeed. This supports Bandura's (1997) theory that that succeeding at tasks strengthens self-efficacy, which later confirmed by Chen et al. (2024) and Zhang et al. (2025). The strong impact of AI-L on SE also reinforces the importance of equipping students with essential AI knowledge to boost self-confidence and learning autonomy (Bewersdorff et al., 2025; Gupta & Jaiswal, 2025). To translate these findings into practice, educators should add basic AI lessons to all subjects, using flexible learning plans that fit each major. The use of AI-enabled assessment tools, digital credentials, and faculty development programs, including hands-on workshops and case-based training, can further support effective implementation, as suggested by Mah and Groß (2024).

The study also highlights the role of AI-L in fostering SR, which contributes to the development of AU. As students engage with AI tools for the purpose of education such as intelligent tutoring systems and generative AI—they are prompted to make decisions, monitor progress, and assess outputs, all of which reinforce SR. This aligns with research on flipped and blended learning (Yoon, Hill and Kim, 2021, Latorre-Cosculluela et al., 2021), which supports student autonomy and metacognitive skill development. Educators are encouraged to adopt models like the MOOC-based flipped classroom (Pérez-Sanagustín et al., 2021) or the FCM-AI integration (Zhu et al., 2025) to promote deeper learning and critical reflection. Additionally, the proceedings from the 3L-Person 2024 workshop (Papadakis et al., 2024) support this connection. The Person-oriented Approach central to the workshop highlights how AI-enhanced ICT tools can support individualized learning paths. Specifically, research within this volume demonstrates that such environments can foster a culture of independence through formative assessment and promote successful professional self-realization by developing digital competencies in immersive environments.

A noteworthy observation from our study is that AI usage does not strongly CT, nor does CT significantly influence AU. The relationship between CT and AI-L is complex and context-dependent, leading to mixed results depending on whether CT is seen as a result of using AI or a requirement for acquiring AI competency. Gerlich (2025) and Zhou et al. (2024) found that high trust in AI, particularly among younger users or consumers of paid AI services, often leads to cognitive offloading and hinders critical reflection. In contrast, Hornberger et al. (2023) frame CT as a core component of AI competence. This has been empirically confirmed via Confirmatory Factor Analysis ($X^2/df = 2.54$) that critical interpretation and technical knowledge are driven by the same latent literacy capability. In summary, there is a strong connection if CT is seen as a skill needed to understand AI. However, if it is seen as a result of using AI, the connection is inconsistent and depends on other factors like the user's age and the type of service.Another point worth discussing is the weak relationship between CT and AU which interpret that having higher-order thinking does not guarantee autonomous learning. This finding contrasts with previous research, where scholars have agreed that CT and AU share a strong relationship (Campo et al., 2023, Kravchenko et al., 2023, Yüce, 2023). Typically, learners with higher CT tend to be more self-directed. Similarly, it is well-established that autonomous learners often possess better higher-order thinking skills than those who rely on others for their learning. We suggest that the context of using AI as a "learning companion" explains this discrepancy. Even if students develop CT (mainly to critique AI's output) through this process, this might not translate into self-directed learning because they may perceive using AI as relying on an external source. Therefore, even learners with high CT might assess themselves as "reliant on AI" when they use these tools. Recent research highlights the negative effects of relying too heavily on AI. Zhang et al. (2025a) found that excessive dependence causes a decline in independent thinking skills, which leads to reduced autonomy. Similarly, Aljuraid (2025) noted that heavy reliance affects professionals, such as clinicians, by diminishing their sense of control which can lead to a loss of identity. Furthermore, Tian and Zhang (2025) explain that relying on AI promotes cognitive offloading which weakens their ability to think independently over time. These findings are important for teachers who want to apply this research in the classroom. It suggests that teachers, in cooperation with their institutions and faculties, should set clear boundaries for AI usage. By defining what level of use is acceptable, educators can help students feel more self-directed. This approach encourages students to become confident and responsible learners, without feeling that they are relying too heavily on AI.

It must be acknowledged that a debate is still being held by researchers about whether CT should be conceptualized as a domain-specific skill or as a transferable attribute applicable across diverse disciplines. For the purposes of this study, CT was scoped to a generalized predisposition shaped by a learner's formative upbringing and learning experiences. Because of this, specific types of CT, like the logic that is needed to write AI prompts or the skills that are learned from using AI tools over time, were not tested. It is therefore suggested that the link between CT and AU might be different if it were studied as a skill for specific tasks, rather than the general habit that was used for this work.

6. Conclusion

This study aimed to explore the factors influencing CT among undergraduate students, with a particular focus on the roles of AI-L, CT, SR, and SE. Through structural equation modeling (SEM). AI-L was found to have a significant and robust positive effect on all three mediating variables—SE ($\beta = 0.99$, $t = 20.00$), SR ($\beta = 0.93$, $t = 18.53$), and CT ($\beta = 0.70$, $t = 7.30$). Among the predictors of AU, SE emerged as the most influential factor ($\beta = 0.52$, $t = 6.38$), highlighting how important it is for academic achievement. These findings offer valuable implications for promoting AI-L, particularly through pedagogical models such as blended learning and flipped classrooms, both of which are well-documented for enhancing self-regulatory behaviors and learner confidence.

While critical thinking showed a relatively smaller direct effect on academic outcomes, its presence remains crucial in shaping comprehensive AI-L. It is important to design classes where students learn to check AI outputs for errors instead of relying on them completely. By linking AI-L to metacognitive skills, this study broadens the scope of e-learning research. It suggests that AI-powered learning tools must be paired with reflective instruction and ongoing feedback. This approach helps educators design student-centered curricula that foster true autonomy and digital readiness.

7. Limitation and Suggestion for Future Studies

This study contains limitations that may influence the interpretation of the data. Therefore, researchers should approach our findings with caution. The first limitation concerns the study context. We conducted this research among Thai undergraduate students within a specific educational and cultural setting. The second limitation involves reliance on self-report methods. This approach might introduce subjective bias, as participants may inaccurately assess their own skills. Consequently, generalizing these findings to other populations requires careful consideration.

To build upon the findings of this research, we recommend that future studies further explore the relationship between critical thinking, AI usage, and autonomous learning. As noted, evidence regarding this relationship remains contradictory across the literature. Additionally, there is a growing need for research focused on the development of curricula and instructional designs within specific subject areas. These pedagogical interventions should aim to enhance self-efficacy through the cultivation of AI-L, meeting the demands of 21st-century education in an AI-driven world.

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Declaration of AI use: This manuscript involved the use of AI Writing Assistants (Grammarly) and Generative AI (Google Gemini) solely for the purpose of language editing and grammar refinement. The content, ideas, structure, and interpretations presented in the article are entirely the author's original work. AI assistance was limited to improving clarity, coherence, and academic style without altering the substantive meaning of the text.

Ethics Statement: This study strictly adheres to the ethical guidelines established by Chulalongkorn University, Thailand. All respondents recruited for the questionnaire were adults aged 18 years or older and participated on a purely voluntary basis. Prior to data collection, participants were fully briefed on the research objectives and the intended use of the findings. Informed consent was obtained from all respondents before they accessed the questionnaire, confirming their understanding of the study's nature. To protect participant privacy, all responses have been anonymized, and respondents were informed of their right to withdraw from the study at any stage. Furthermore, the researcher declares that there are no known conflicts of interest associated with any organization.

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