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Towards a New Conceptual Model of AI-Enhanced Learning for College Students: The Roles of Artificial Intelligence Capabilities, General Self-Efficacy, Learning Motivation, and Critical Thinking Awareness

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Abstract: In the aftermath of the COVID-19 pandemic, college students have faced various challenges that could negatively impact their critical thinking abilities due to disruptions to education, increased stress and anxiety, less social interaction, and the advancement of distance learning relying more heavily on digital tools. With the increasing integration of AI technology across sectors, higher education institutions have deployed various AI capabilities for intelligent campuses and modernized teaching. However, how to fully utilize AI capabilities to promote students' thinking awareness on learning effectiveness is still not clear, as critical thinking is an essential skill set holding significant implications for college students' development. This research adopts the resource-based theory (RBT) to conceptualize the university as a unified entity of artificial intelligence (AI) resources. It aims to investigate whether AI capabilities can foster critical thinking awareness among students by enhancing general self-efficacy and learning motivation. In particular, it examines the causal relationships between AI capabilities, general self-efficacy, motivation and critical thinking awareness. Primary data was collected through a questionnaire administered to 637 college students. Structural equation modeling was employed to test hypotheses pertaining to causality. The results showed that AI capabilities could indirectly enhance students' critical thinking awareness by strengthening general self-efficacy and learning motivation, but the effect on critical thinking awareness was not significant. Meanwhile, general self-efficacy significantly affected the formation of learning motivation and critical thinking awareness. This indicates that AI capabilities are able to reshape the cognitive learning process, but its direct influence on thinking awareness needs to be viewed with caution. This study explored the role of AI capabilities in education from the perspective of organizational capabilities. It not only proves how AI facilitates cognition, but also discovered the important mediating role of general self-efficacy and motivation in this process. This finding explains the inherent connections between the mechanism links. Furthermore, the study expands research on AI capabilities research from the technical level to the educational field. It provides a comprehensive and in-depth theoretical explanation theoretically, guiding the practice and application of AI in education. The study is of positive significance for understanding the need for the future development of the cultivation of critical thinking awareness talents needed for future development through AI capabilities in education.

Keywords: AI capability; critical thinking awareness; general self-efficacy; learning motivation

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Citation: Jia, X.-H.; Tu, J.-C. Towards a New Conceptual Model of AI-Enhanced Learning for College Students: The Roles of Artificial Intelligence Capabilities, General Self-Efficacy, Learning Motivation, and Critical Thinking Awareness. *Systems* **2024**, *12*, 74. https://doi.org/10.3390/systems12030074

Academic Editor: José-Rodrigo Córdoba-Pachón

Received: 16 January 2024
Revised: 21 February 2024
Accepted: 21 February 2024
Published: 25 February 2024

1. Introduction

1.1. Background

In the aftermath of the COVID-19 pandemic, college students have encountered a range of difficulties and stressors, including alterations to their educational settings, heightened levels of anxiety, decreased opportunities for social engagement, and the emergence of mental health concerns [1–4]. These factors have the potential to detrimentally influence students' cognitive and emotional welfare, consequently impacting their capacity for critical thinking. In addition, the pandemic has compelled educational institutions to rapidly adapt to distance and online learning, thereby fostering the rapid development of digitalized teaching [5]. Educational institutions and educators have been compelled to innovate and integrate digital tools into their teaching practices to ensure the continuity of education during lockdowns and social distancing measures [6]. The emergence of big data and artificial intelligence (AI) has profoundly transformed management and pedagogical practices in higher education. Research demonstrates that AI can deliver personalized learning support and pinpoint learning difficulties to enhance academic progress [7]. Numerous studies have further illustrated the multifaceted applications of AI in education, including personalized instruction, autonomous learning, and intelligent campus environments [8,9]. Nevertheless, the integration of AI capabilities in higher education necessitates concerted efforts across departments. Per resource-based theory, the accumulation of strategic resources within an organization contributes to its core competitiveness [10]. Therein, universities can be construed as an amalgamation of AI resources, encompassing both hardware infrastructure and interdisciplinary collaboration skills. Given its extensive applications, AI is expected to profoundly reshape management approaches and pedagogies [11–13], thereby necessitating support from complementary technologies [7], as shown in Table 1. Currently, investigating the impact of AI capabilities on students' cognitive learning and motivation has become an important research area [12,14–16].

Table 1. Application of AI technology in education.

Scenarios of AI Education	AI-Related Technology
Assessment of students and schools	Adaptive learning methodologies and personalized learning approach, academic analytics
Grading and evaluation of papers and exams	Image recognition, computer-vision, prediction system
Personalized intelligent teaching	Data mining or Bayesian knowledge interference, intelligent teaching systems, learning analytics
Smart facilities	Facial recognition, speech recognition, virtual labs, A/R, V/R, hearing and sensing technologies
Online and mobile remote education	Edge computing, virtual personalized assistants, real-time analysis

Student participation and engagement in university governance and decision-making processes are increasingly recognized as pivotal for enhancing educational quality and institutional efficacy. Such involvement can yield positive outcomes, including increased participation, academic achievement, and development [17–20]. Integrating student perspectives aids in comprehending their needs, thereby informing responsive and student-centric policies and practices [21,22]. Promoting student participation helps foster ownership, responsibility, and empowerment, potentially enriching the educational experience. Students should systematically cultivate AI literacy to enable the transition from understanding AI capabilities to application [23,24]. This study elucidates the mechanisms facilitating AI adoption in education, yielding theoretical and practical implications.

While AI technology has brought about numerous advantages in education, the impact of AI capabilities on students' cognitive abilities, particularly on critical thinking, remains unclear [25–27]. Further comprehensive research is necessary to clarify the effects of AI capabilities. The factors affecting critical thinking are diverse [28], including general self-efficacy [29], learning motivation [30], cognition [31], emotional intelligence [32], and the environment [33]. Previous studies have shown that general self-efficacy and learning approaches play a crucial role in developing critical thinking skills [34]. Digital learning tools such as Google Classroom can also influence critical thinking through self-regulated learning and learning motivation [35,36]. General self-efficacy may alter learning goals and self-assessments [37]. Therefore, it is essential to investigate how AI capabilities impact critical thinking through these mediating variables. This study aims to enhance our understanding of how AI-enabled educational environments and AI capabilities shape critical thinking, and will provide both theoretical and practical implications.

The encouragement to learn, particularly intrinsic motivation, supports the cultivation of critical thinking awareness [38]. Additionally, a strong belief in one's abilities can boost enthusiasm for learning and cognitive skills, ultimately leading to improved academic performance [39]. Research has indicated that students with higher computer self-efficacy are more engaged in utilizing technology for tasks, suggesting a greater perceived proficiency in artificial intelligence [40,41]. These studies highlight the interconnections between these factors and emphasize the potential impact of learning motivation and general self-efficacy on students' critical thinking awareness. Therefore, given the potential relationships among artificial intelligence capabilities, general self-efficacy, critical thinking awareness, and learning motivation, it is valuable to further explore how artificial intelligence capabilities influence critical thinking awareness through general self-efficacy and learning motivation. This is the primary focus of the present study.

The study adopts an organizational perspective to examine universities and utilizes the resource-based theory (RBT) as its theoretical framework. RBT, as proposed by Penrose (1959) and Barney (1991), underscores the significance of internal resources and organizational capabilities, positing that an organization's unique and non-substitutable strategic resources form its core competencies [42,43]. In this context, the study considers universities' internal resources, such as AI data, algorithms, and application platforms, as valuable strategic assets. The management and integration of these resources are viewed as the core competencies and organizational capabilities of universities. By evaluating students' AI capabilities, the study systematically investigates how universities' integration of AI resources impact the development of students' critical thinking awareness. Drawing on RBT, the study examines the influence of AI capabilities on critical thinking awareness through general self-efficacy and learning motivation, as depicted in Figure 1. This approach provides a foundation for analyzing the relationship between AI capabilities in educational organizations and students' critical thinking awareness.

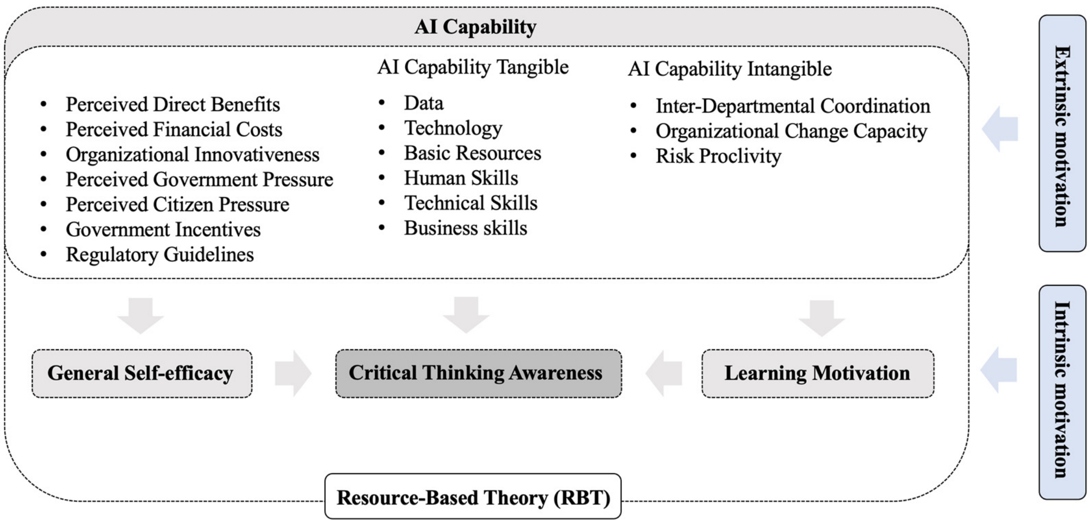

Figure 1. Research framework based on RBT theory.

1.2. Research Purpose and Significance

The purpose of this study is to explore how artificial intelligence (AI) capabilities influence the relationships among key learning variables and reveal the mechanism of its impact. The existing literature has verified that AI may affect learners' general self-efficacy and learning motivation, which in turn correlate with critical thinking awareness levels. However, how AI capabilities affect the above intermediary variables, and how these variables transmit influence remains unclear in current theoretical frameworks. To address this issue, this study takes AI resource integration capabilities in higher education as the entry point, viewing AI data, technologies, etc., as strategic organizational resources, and capability as the resource management level based on resource integration theory [44,45]. Under this theoretical framework, this study will examine whether the level of AI resources at a school can indirectly shape the relationships among key learning variables. In particular, this study will test the positive impacts of AI capabilities in universities on general self-efficacy and learning motivation, as well as the influence of transmission to critical thinking awareness. Model testing can elaborate the intrinsic mechanisms of AI impacts and enrich relevant theories. Meanwhile, the findings will also provide references for teaching management, such as optimizing AI-assisted teaching models. Overall, this study will thoroughly investigate the substantial roles of AI in education.

2. Relevant Research

2.1. AI Capability

The concept of artificial intelligence (AI) capabilities pertains to the capacity of AI systems to execute tasks typically requiring human intelligence. In contrast to the technological focus of artificial intelligence, AI capabilities center on the organizational and societal impacts of AI, emphasizing human-centered approaches in the Fourth Industrial Revolution to achieve sustainable development goals. Furthermore, the versatility of AI is evident in its diverse applications across various domains and scenarios, such as autonomous driving, healthcare, finance, and industrial robotics, showcasing its extensive capabilities and relevance [44]. AI's multifaceted functions have the potential to significantly influence education, with applications including personalized learning, adaptive assessment, and the integration of AI technologies into learning environments. Likewise, the role of AI in education has been extensively examined, with a focus on harnessing AI to enhance learning experiences and improve educational outcomes [7]. The utilization of AI technologies such as machine learning and natural language processing can foster personalized engagement and offer tailored educational experiences for students [45]. Additionally, the integration of AI in STEM education presents complex challenges in combining various AI technologies with educational elements to meet instructional and learning requirements [16]. AI-empowered e-learning has the potential to enhance personalization and learning outcomes, contributing to more effective educational settings [46]. The implementation of AI education in secondary school technology education has also been explored, emphasizing the significance of integrating AI with other disciplines and applying it to problem-solving processes [47]. Studies have indicated that AI can assist in identifying areas requiring improvement in educational infrastructure, pedagogical practices, and learning environments to enhance the quality of education [48]. The application of AI in middle and primary schools underscores the prevalence of AI education and its potential to nurture students' integrated thinking abilities [49].

In summary, this study refers to the definition of AI capabilities by Mikalef and Gupta (2021) [10] which specifically outlines universities' AI capabilities as encompassing tangible resources such as data, technologies, and infrastructure; human skills including technical and business expertise; and intangible resources such as cross-departmental coordination, organizational adaptability, and risk appetite. AI capabilities denote an organizations' abilities to leverage their AI-specific resources.

2.2. Critical Thinking Awareness

Critical thinking awareness has been widely recognized as fundamental for university students [50]. It is seen as an essential part of education at all levels, involving analyzing, evaluating, and resolving various challenges [51]. Critical thinking plays a crucial role in shaping students' learning, cognition, analysis, and decision-making [52,53]. Universities and employers have consistently emphasized the significance of critical thinking awareness as a foundational and necessary skill [54]. Research has also highlighted the relationship between first-year university students' critical thinking dispositions, perceived academic control, and academic performance, underscoring the importance of critical thinking awareness for academic success [55]. Furthermore, developing critical thinking awareness through academic reading is considered key to meeting the higher-order thinking requirements of 21st century students [56]. However, studies have shown that many college students are still inadequately prepared to think critically, indicating a need to integrate this skill into curricula more effectively. Overall, the substantial impact of critical thinking awareness in colleges underscores the importance of cultivating this skill in order to ensure students' academic and professional success. Therefore, educational institutions must continue emphasizing the development of critical thinking awareness to prepare students for future challenges.

2.3. General Self-Efficacy

The concept of general self-efficacy, which pertains to an individual's belief in their capacity to accomplish tasks and attain objectives, has been extensively examined within the university setting. Studies have demonstrated that general self-efficacy beliefs play a critical role in psychological adaptation, physical well-being, and strategies for behavioral change [57]. Furthermore, Bandura's (1995) research has underscored the influence of personal efficacy beliefs within sociocultural contexts, shaping the trajectories of individuals' lives [58]. Moreover, general self-efficacy has been shown to alleviate the impact of stressors on perceived stress among university students and forecast academic achievement [59]. A positive association has also been established between university students' physical activity and general self-efficacy, highlighting the role of general self-efficacy in managing academic procrastination [60]. Academic general self-efficacy is linked to various university outcomes, including academic performance and persistence [61,62]. It is also considered a predictive factor for the success of first-generation and ethnically diverse university students [63]. Furthermore, academic general self-efficacy is viewed as a significant indicator of success in high school education [64]. These findings underscore the importance of general self-efficacy in the academic sphere.

2.4. Learning Motivation

Learning motivation refers to the intrinsic and extrinsic factors that drive individuals to engage in and persist with learning activities. It plays a crucial role in shaping students' attitudes, behaviors, and academic performance. Various studies have explored the multifaceted nature of learning motivation and its impacts on educational outcomes. They emphasized the importance of students' motivation to learn, highlighting that it provides students with the mental focus and attention required for effective learning. This underscores the function of motivation in directing students' attention and effort towards completing learning tasks [65]. Moreover, discussions on the profound effects of motivation on student behavior showed that when students are motivated to learn, it generates learning interest. This demonstrates that motivation can influence the level of students' engagement with and interest in the learning process [66]. Additionally, significant and positive correlations were found between teaching styles, learning motivation, and academic achievement. This implies that motivation impacts not just students' attitudes, but also their academic performance [67]. Furthermore, the research distinguished between integrative and instrumental motivations, highlighting individuals' different reasons for learning a language. This distinction emphasizes the complexity of motivation and its various potential underlying factors [68]. In conclusion, learning motivation is a multifaceted construct that profoundly affects students' attitudes, behaviors, and academic achievement. It encompasses the intrinsic and extrinsic motivational factors that drive engagement in learning activities and shape learners' focus, interest, perseverance, and performance throughout the learning process.

2.5. Research Hypothesis

The impact of AI on critical thinking has drawn attention from different fields [69]. Early research showed that AI has the potential to facilitate critical thinking skills by providing new perspectives [69]. Additionally, Muthmainnah et al. (2022) further demonstrated that AI can also enhance individual cognitive abilities [70]. In the future, AI may become an educational tool to alleviate its potential threats to education [71]. Research highlights the need to develop critical thinking, and AI has the potential to complement human cognition [57]. Moreover, Bustami (2018) validated that situational learning can enhance relevant skills [72]. Several studies showed AI outperforming humans on assessments or helping improve higher-order cognitive abilities [73]. However, it is imperative for higher education institutions to engage in thoughtful consideration of the challenges associated with integrating generative artificial intelligence tools into educational settings and academic curricula [74]. In retrospect, previous research focused primarily on how AI facilitates cognition, but has not clearly explored its impacts on critical thinking. Therefore, this study aims to investigate whether AI helps improve college students' critical thinking awareness [57]. To this end, a pre-liminary Hypothesis H1 is proposed:

H1: *AI capability has a positive impact on critical thinking awareness.*

While there is a lack of empirical evidence in the scholarly literature demonstrating the specific influence of artificial intelligence capability on the awareness of critical thinking, it is important to clarify that AI capability is being considered here as a potential resource rather than solely a technical tool. The potential for AI to enhance individual cognitive abilities has been supported in research [75]. Research suggests that educational institutions should effectively leverage AI to enhance critical thinking skills [57]. Artificial intelligence (AI) is enhancing student motivation in education through a variety of methods. Ling et al. (2022) discovered a positive correlation between the interactivity of AI tools and learner satisfaction [76]. Similarly, Farhan and Rofi'ulmuiz (2021) demonstrated that integrating emotional intelligence into AI has a significant positive influence on student motivation [77]. Jian et al. (2021) discussed how AI improves student learning abilities, consequently enhancing teaching effectiveness [56]. AI has been shown to increase classroom engagement in project-based learning settings [51,78] and stimulate learning motivation by providing immersive experiences through hologram technology [79]. Oudeyer (2017) and Popenici and Kerr (2017) emphasized the pivotal role of AI in fostering autonomous learning, curiosity, and intrinsic motivation, which are crucial elements for social learning and peer interactions [80,81]. The impact of AI in higher education has also been extensively researched [81], and the emerging field of AI in education (AIEd) is revolutionizing educational technologies [74,82]. These technologies have demonstrated their efficacy in emulating human decision-making processes to create effective learning environments [82,83]. Karampelas (2021) further confirmed the positive effects of online AI applications in increasing student engagement [83]. In summary, these references collectively support the constructive role of AI in enhancing student learning motivation. Consequently, a preliminary Hypothesis H2 is proposed:

H2: *AI capability has a positive impact on learning motivation.*

Earlier research has shown that artificial intelligence has positive impacts on improving individuals' general self-efficacy across different domains. Collaborating with and gaining trust in AI can enhance general self-efficacy [84,85]. Cultivating positive attitudes towards AI underscores the importance of general self-efficacy in fields like healthcare [86]. Monteiro et al. (2021) found that general self-efficacy is positively correlated with perceptions of AI trustworthiness [87]. These studies provide evidence that AI can improve individual general self-efficacy through various approaches. Relevant research has emphasized the need to consider self-efficacy factors when designing and applying AI technologies [7]. Li et al.'s (2022) study also showed AI capability can influence knowledge sharing and vitality within organizations [88]. However, whether university implementation of AI affects student general self-efficacy remains undetermined. Based on this, Hypothesis H3 is proposed to investigate the impacts of AI on general self-efficacy:

H3: *AI capability has a positive impact on general self-efficacy.*

Extensive research has examined the relationship between general self-efficacy and critical thinking awareness. According to Bandura's theory, general self-efficacy affects individual behavior [89]. Zahodne et al. (2015) indicated that personal efficacy beliefs can enhance cognitive performance through cognitive, emotional, and motivational processes [90]. General self-efficacy is associated with critical thinking awareness as part of higher-order thinking [91] because individuals need to have confidence in their own abilities to solve problems, make decisions, etc. [34]. Multiple studies [29,92–96] have corroborated the positive correlation between general self-efficacy and critical thinking awareness. Research has also shown general self-efficacy can moderate other influencing factors of critical thinking awareness [97,98]. Overall, the above studies support a positive impact of general self-efficacy on critical thinking awareness. This study intends to examine whether general self-efficacy still positively affects critical thinking awareness in the context of university AI in education, proposing Hypothesis H4:

H4: *General self-efficacy has a positive impact on critical thinking awareness.*

Academic research provides evidence supporting the positive influence of self-efficacy on the development of critical thinking awareness. In particular, a study has established a correlation between self-efficacy and critical thinking, indicating that individuals with greater self-efficacy in their academic abilities also exhibit higher levels of critical thinking awareness [99]. Additionally, another two teaching-related studies provided evidence that the "think-pair-share" model and project-based learning have been proven to influence students' critical thinking skills through their impact on self-efficacy [93,100]. General self-efficacy plays an important role in the learning process. Research has proven that general self-efficacy positively affects learning attitudes and motivation [101,102]. Building on this foundation, further studies found that general self-efficacy may inspire learning motivation by enhancing feelings of achievement and the pursuit of success [103]. The academic excellence of learners with high general self-efficacy is attributed to the close connection between general self-efficacy and motivation [14]. Teng et al. (2021) further elaborated that the ability of general self-efficacy to drive motivation lies in its shaping of students' interests [104]. In summary, the scholars above collectively outlined a framework of how general self-efficacy positively impacts various aspects of learning. It not only directly affects motivation, but also strengthens the learning experience through mechanisms like sense of growth. This guides us to integrate previous research results and understand the important position of general self-efficacy in teaching and learning. Therefore, the research Hypothesis H5 is proposed.

H5: *General self-efficacy has a positive impact on learning motivation.*

Research has demonstrated the positive impacts of learning motivation on critical thinking skills [105–107], and highlighted the importance of motivation in cultivating critical thinking dispositions oriented towards learning [108]. For instance, studies have found that students with high academic motivation are interested in problem-solving and critical thinking, leading to greater perfectionism and positive effects on their cognitive abilities and academic performance [109]. Learning motivation has a major influence on critical thinking skills [110,111]. Together, these studies provide robust evidence for the positive impacts of learning motivation on critical thinking skills. This supports the view that motivation plays a role in enhancing critical thinking capabilities in specific academic domains. In summary, these references indicate that nurturing students' proactivity can facilitate the development and strengthening of critical thinking skills, ultimately helping improve academic performance and problem-solving abilities. Therefore, the research Hypothesis H6 is proposed:

H6: *Learning motivation has a positive impact on critical thinking awareness.*

3. Research Methods and Hypothesis Model

3.1. Hypothesis and Model Construction

Drawing from the preceding discourse, this study developed a model. There are several factors, such as AI capability in the educational institution, general self-efficacy, and critical thinking awareness, that influence learning attitudes (Figure 2). The following hypotheses are proposed as follows:

H1: *AI capability has a positive impact on critical thinking awareness.*

H2: *AI capability has a positive impact on learning motivation.*

H3: *AI capability has a positive impact on general self-efficacy.*

H4: *General self-efficacy has a positive impact on critical thinking awareness.*

H5: *General self-efficacy has a positive impact on learning motivation.*

H6: *Learning motivation has a positive impact on critical thinking awareness.*

In summary, based on the above hypothetical analysis, the theoretical model proposed in this study is shown in Figure 2 below.

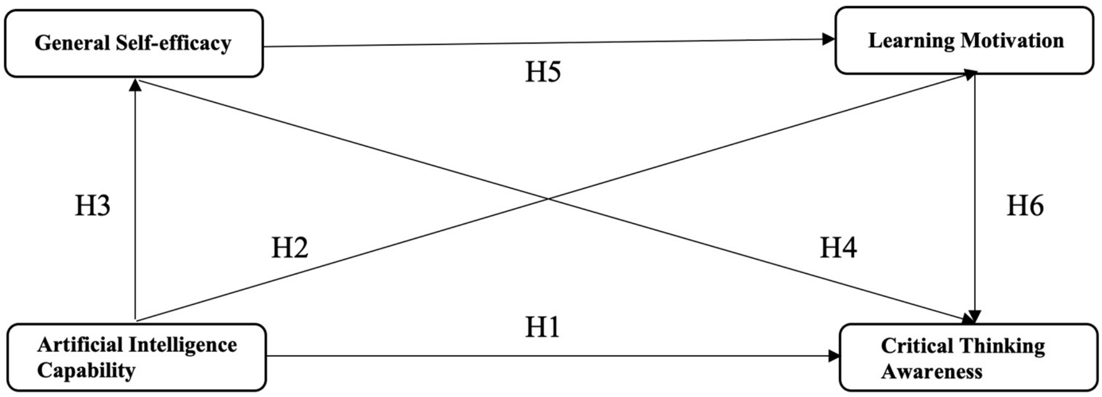

Figure 2. Hypothetical model.

3.2. Design of Questionnaire

The questionnaire items in this study were designed based on the research topic and with reference to the relevant literature, as shown in Appendix A. Table 2 provides the constructs, codes, questions, and sources of the scales.

To ensure the reliability and validity of the measurement scales, this study selected mature scale items and made appropriate adjustments to the questions based on efficient research scenarios. With reference to relevant research by scholars, AI capabilities were measured with 45 questions [45,112], critical thinking awareness with 6 questions [113,114]; general self-efficacy included 10 question items [115,116]; learning motivation comprised 7 questions [117]. In summary, the total number of questions in this study's scale was 61. The questions discussed in this paper were scored using a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). The sources of the scales are summarized in Table 2.

Table 2. The sources of the scales.

Scale	Number	Sources
AI Capability Scale	38	[48,114]
Critical Thinking awareness Scale	6	[114,115]
General Self-Efficacy Scale	10	[116,117]
Learning Motivation	7	[118]

3.3. Research Methodology

The research methodology of this study comprises six sequential steps: the literature review, formulation of research hypotheses, data collection, design and validation of questionnaires, statistical analysis, and discussion of results.

Initially, a comprehensive review of the existing literature pertaining to AI capability, general self-efficacy, learning motivation, and critical thinking awareness was conducted to gain an understanding of the current state of research. Subsequently, six research hypotheses were developed based on the findings of the literature review. Given the utilization of the structural equation modeling (SEM) in this study, which necessitates data collection and statistical analysis, questionnaire surveys were employed to gather data for subsequent statistical analysis. The sources of the questionnaire data are elaborated upon in Section 3.4. In the section pertaining to questionnaire design and validation, the fourth step, the reliability of the questionnaires was ensured, as the three scales utilized in this study are established and validated, thereby providing a dependable foundation for statistical analysis. The fifth step, statistical analysis, encompasses six methods: descriptive analysis, reliability analysis, confirmatory factor analysis, structural equation modeling (SEM), and regression analysis. The final step involves the discussion of results, where the research hypotheses are deliberated upon in light of the statistical findings. The research procedures are visually depicted in Figure 3.

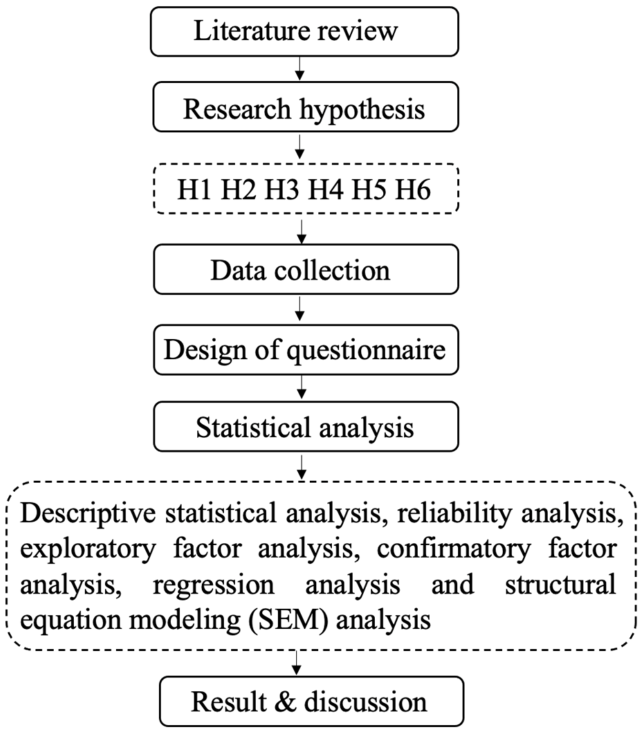

Figure 3. Research steps.

3.4. Data Collection

In order to ensure the validity of the sample, this study selected university students in Taiwan as the survey participants. The Ministry of Education in Taiwan has implemented a comprehensive AI education strategy, encompassing AI learning at all educational levels, in response to the widespread integration and application of AI technologies in universities across the country. In 2022, the Ministry of Education introduced the "Overall Promotion Strategy for AI and Emerging Science and Technology Education". Additionally, the Taiwan AI Labs Excellence Research Center was established by the National Science Council to facilitate government agency integration and international collaboration, thereby fostering the rapid development of an AI ecosystem. Furthermore, universities in Taiwan have actively introduced AI-related courses and partnered with technology companies to cultivate AI talent in various fields such as business, medicine, and engineering. Consequently, Taiwanese universities have made notable advancements in AI education and implementation. The selection of university students in Taiwan as the sample population is intended to ensure the credibility of the research.

4. Research Data Analysis and Result

4.1. Reliability Analysis and Validity Tests

In this questionnaire, reliability and validity were evaluated using Cronbach's alpha coefficient as well as the corrected item-total correlation coefficient (CITC) consisting of two correlation coefficients and three examination criteria. As indicated in Table 3, the Construct-Item Total Correlation (CITC) for all constructs exceeded 0.4. The exclusion of specific items did not yield a substantial improvement in the reliability coefficient, and the Cronbach's alpha coefficient surpassed 0.6 [109]. Consequently, the internal consistency among the questionnaires and scales utilized in this study was deemed to be strong [118,119], thereby facilitating subsequent analysis.

Table 3. Results of reliability analysis.

Item	Mean	Std. Deviation	CITC	Cronbach's α If Item Deleted	Cronbach's α
AIC1	5.143	1.060	0.603	0.963	0.964
AIC2	5.102	1.118	0.622	0.963	
AIC3	5.127	1.126	0.625	0.963	
AIC4	5.129	1.249	0.670	0.962	
AIC5	5.061	1.234	0.629	0.963	
AIC6	4.989	1.260	0.641	0.963	
AIC7	4.733	1.405	0.577	0.963	
AIC8	5.118	1.172	0.630	0.963	
AIC9	5.600	1.088	0.556	0.963	
AIC10	5.564	1.039	0.592	0.963	
AIC11	5.578	1.037	0.543	0.963	
AIC12	5.248	1.098	0.567	0.963	
AIC13	5.454	1.031	0.568	0.963	
AIC14	5.396	1.080	0.613	0.963	
AIC15	5.567	1.000	0.594	0.963	
AIC16	4.914	1.166	0.545	0.963	
AIC17	5.358	0.986	0.545	0.963	
AIC18	5.666	1.009	0.510	0.963	
AIC19	5.383	1.037	0.580	0.963	
AIC20	5.449	1.014	0.630	0.963	
AIC21	5.466	1.064	0.623	0.963	
AIC22	5.342	1.083	0.677	0.962	
AIC23	4.956	1.206	0.594	0.963	
AIC24	5.118	1.182	0.663	0.962	
AIC25	5.268	1.072	0.656	0.962	
AIC26	5.190	1.067	0.687	0.962	
AIC27	5.256	1.100	0.696	0.962	

Table 3. *Cont.*

Item	Mean	Std. Deviation	CITC	Cronbach's α If Item Deleted	Cronbach's α
AIC28	5.245	1.131	0.695	0.962	0.964
AIC29	5.411	1.014	0.663	0.962	
AIC30	5.316	1.094	0.683	0.962	
AIC31	5.176	1.093	0.682	0.962	
AIC32	5.174	1.240	0.726	0.962	
AIC33	5.157	1.170	0.674	0.962	
AIC34	5.235	1.171	0.691	0.962	
AIC35	5.385	1.146	0.697	0.962	
AIC36	4.829	1.235	0.634	0.963	
AIC37	5.154	1.111	0.629	0.963	
AIC38	5.122	1.158	0.708	0.962	
CTA1	5.617	1.054	0.557	0.786	0.812
CTA2	5.571	1.011	0.587	0.780	
CTA3	5.543	1.011	0.583	0.780	
CTA4	5.630	1.070	0.627	0.770	
CTA5	5.403	1.068	0.506	0.798	
CTA6	5.392	1.014	0.580	0.781	
GSE1	5.482	1.035	0.550	0.904	0.907
GSE2	4.969	1.196	0.619	0.901	
GSE3	4.782	1.326	0.671	0.898	
GSE4	5.030	1.178	0.712	0.895	
GSE5	4.867	1.213	0.738	0.893	
GSE6	5.265	1.093	0.651	0.899	
GSE7	5.259	1.088	0.701	0.896	
GSE8	5.262	1.084	0.658	0.898	
GSE9	5.270	1.056	0.658	0.898	
GSE10	4.887	1.253	0.715	0.895	
LM1	5.606	1.006	0.642	0.819	0.846
LM2	5.625	1.021	0.647	0.818	
LM3	5.708	0.936	0.654	0.818	
LM4	5.804	0.997	0.627	0.821	
LM5	5.619	1.058	0.567	0.830	
LM6	5.504	1.004	0.513	0.838	
LM7	5.667	1.050	0.577	0.829	

4.2. Exploratory Factor Analysis

In this research, an exploratory factor analysis was performed using SPSS 26.0 to evaluate the unidimensionality of the constructs. The principal component analysis was utilized to extract new factors with eigenvalues greater than 1 for each dimension, as indicated in Table 4. The resulting Kaiser–Meyer–Olkin (KMO) values were all above 0.70, and the Bartlett test significance was found to be $p < 0.05$, suggesting that the data was suitable for factor analysis [120,121]. For each construct, only one new factor was extracted, explaining over 70% of the total variance, with eigenvalues greater than 1 [122], indicating satisfactory validity [123].

Table 4. Discriminant validity for the measurement model.

	AIC	CTA	GSE	LM
AIC	0.687			
CTA	0.519	0.695		
GSE	0.510	0.380	0.746	
LM	0.568	0.684	0.373	0.695

Furthermore, the correlation matrix revealed partial correlations between the items, rejecting the null hypothesis of an identity matrix. Therefore, exploratory factor analysis was deemed appropriate [124]. Notably, all item communalities exceeded 0.5, and factor loadings were above 0.6, aligning with the emergence of a single factor for each construct and demonstrating the interrelationships between items measuring the same dimension in accordance with recommended standards [123]. In summary, these findings provided sufficient evidence for the unidimensionality of all measurement constructs.

4.3. Confirmatory Factor Analysis

This study utilized confirmatory factor analysis (CFA) to assess the convergent and discriminant validity of each construct. Initially, the focus was on examining convergent validity. In the CFA model, all items exhibited factor loadings exceeding 0.5, and the ratio of coefficient estimates to standard errors was statistically significant ($p < 0.05$), aligning with measurement standards. Items with standardized loadings below 0.6 and lower factor loadings were eliminated, including AIC1, AIC7, AIC9, AIC10, AIC11, AIC12, AIC13, AIC14, AIC15, AIC16, AIC17, AIC18, AIC19, AIC20, AIC23, CTA1, CTA5, CTA6, GSE1, GSE2, GSE8, GSE9, LM6, and LM7. Ultimately, the composite reliability (CR) for each construct exceeded 0.6 [125], and the average variance extracted (AVE) was above 0.36 [126]. As indicated in Table 5, the first-order CFA model demonstrated a good fit for the data [127]. Based on the aforementioned analysis, the questionnaire data in this study exhibited strong convergent validity.

Discriminant validity was evaluated in accordance with Fornell and Larker's criteria [126], which stipulate that if the square root of the average variance extracted (AVE) for each construct exceeds the correlation coefficients between constructs, the model demonstrates sufficient discriminant validity. The findings indicated that all diagonal values surpassed off-diagonal values in this investigation, indicating that each construct displayed strong discriminant validity, as illustrated in Table 5. Consequently, additional analysis was deemed necessary.

Table 5. CFA validity of convergence.

Item	Un Std. Estimate	Std. Estimate	Std. Error	Z(CR)	Sig.	AVE	CR
AIC2	1.000	0.648	-	-	-	0.471	0.953
AIC3	1.012	0.651	0.068	14.895	0.001		
AIC4	1.182	0.686	0.076	15.572	0.001		
AIC5	1.103	0.647	0.074	14.822	0.001		
AIC6	1.136	0.653	0.076	14.936	0.001		
AIC8	1.011	0.625	0.070	14.375	0.001		
AIC21	0.912	0.621	0.064	14.298	0.001		
AIC22	1.005	0.673	0.066	15.314	0.001		
AIC24	1.082	0.663	0.071	15.132	0.001		
AIC25	0.966	0.648	0.065	14.929	0.001		
AIC26	1.029	0.699	0.067	15.819	0.001		
AIC27	1.085	0.715	0.069	15.983	0.001		
AIC28	1.105	0.708	0.061	15.093	0.001		
AIC29	0.926	0.661	0.067	16.162	0.001		
AIC30	1.083	0.717	0.067	16.159	0.001		
AIC31	1.082	0.717	0.067	16.159	0.001		
AIC32	1.316	0.769	0.077	17.121	0.001		
AIC33	1.161	0.719	0.072	16.203	0.001		
AIC34	1.184	0.732	0.072	16.448	0.001		
AIC35	1.162	0.735	0.070	16.496	0.001		
AIC36	1.150	0.675	0.075	15.355	0.001		
AIC37	1.009	0.658	0.067	15.035	0.001		
AIC38	1.182	0.740	0.071	16.585	0.001		

Table 5. *Cont.*

Item	Un Std. Estimate	Std. Estimate	Std. Error	Z(CR)	Sig.	AVE	CR
CTA2	1.000	0.663	-	-	-	0.483	0.737
CTA3	1.057	0.660	0.074	14.335	0.001		
CTA4	1.166	0.697	0.079	14.768	0.001		
GSE3	1.000	0.727	-	-	-	0.556	0.882
GSE4	0.945	0.739	0.049	19.300	0.001		
GSE5	0.987	0.787	0.050	19.567	0.001		
GSE6	0.741	0.797	0.046	16.209	0.001		
GSE7	0.788	0.665	0.045	17.359	0.001		
GSE10	0.982	0.769	0.052	18.855	0.001		
LA1	1.000	0.731	-	-	-	0.483	0.823
LA2	1.009	0.727	0.059	17.107	0.001		
LA3	0.906	0.712	0.054	16.765	0.001		
LA4	0.914	0.674	0.058	15.886	0.001		
LA5	0.897	0.624	0.061	14.708	0.001		

4.4. Results of the Structural Equation Model

In order to evaluate the theoretical framework, a structural equation model was developed using AMOS. Path analysis was performed on each latent variable using Amos 24 statistical software to investigate their impacts. Maximum likelihood estimation was employed with 2000 bootstrap runs to establish 95% confidence intervals during the computation. The model fit indices were as follows: c2/df (2.972), RMSEA (0.053), CFI (0.903), PGFI (0.760), SRMR (0.047), all falling within optimal ranges, as presented in Table 6. These findings indicated that all model fit indices met the recommended criteria [127]. The outcomes of the path analysis are detailed in Table 7 and Figure 4. According to prior studies, path coefficient values ranging from 0.1 to 0.3 indicated low levels of influence, 0.3 to 0.5 denoted moderate levels of influence, and 0.5 to 1.0 represented high levels of influence [128]. As illustrated in Figure 3, a structural model is provided. The model fit results demonstrated that each construct displayed positive correlations with other constructs.

Table 6. Adaptability of SEM.

Common Indices	×2	df	×2/df	PGFI	CFI	PNFI	RMSEA	SRMR
Judgement criteria	-	-	<3	>0.5	>0.9	>0.5	<0.10	<0.08
CFA value	1851.624	623	2.972	0.760	0.903	0.806	0.053	0.047

Table 7. Regression coefficients.

Relationship	Un Std.	Std.	S.E.	C.R.	*p*-Value	Hypotheses	Support
AIC ⇒ CTA	0.056	0.06	0.049	1.125	0.260	H1	No
AIC ⇒ GSE	0.739	0.546	0.067	11.085	0.001	H2	Yes
AIC ⇒ LM	0.594	0.585	0.057	10.329	0.001	H3	Yes
GSE ⇒ CTA	0.060	0.088	0.03	1.97	0.049	H4	Yes
GSE ⇒ LM	0.083	0.110	0.035	2.352	0.019	H5	Yes
LM ⇒ CTA	0.721	0.795	0.064	11.265	0.001	H6	Yes

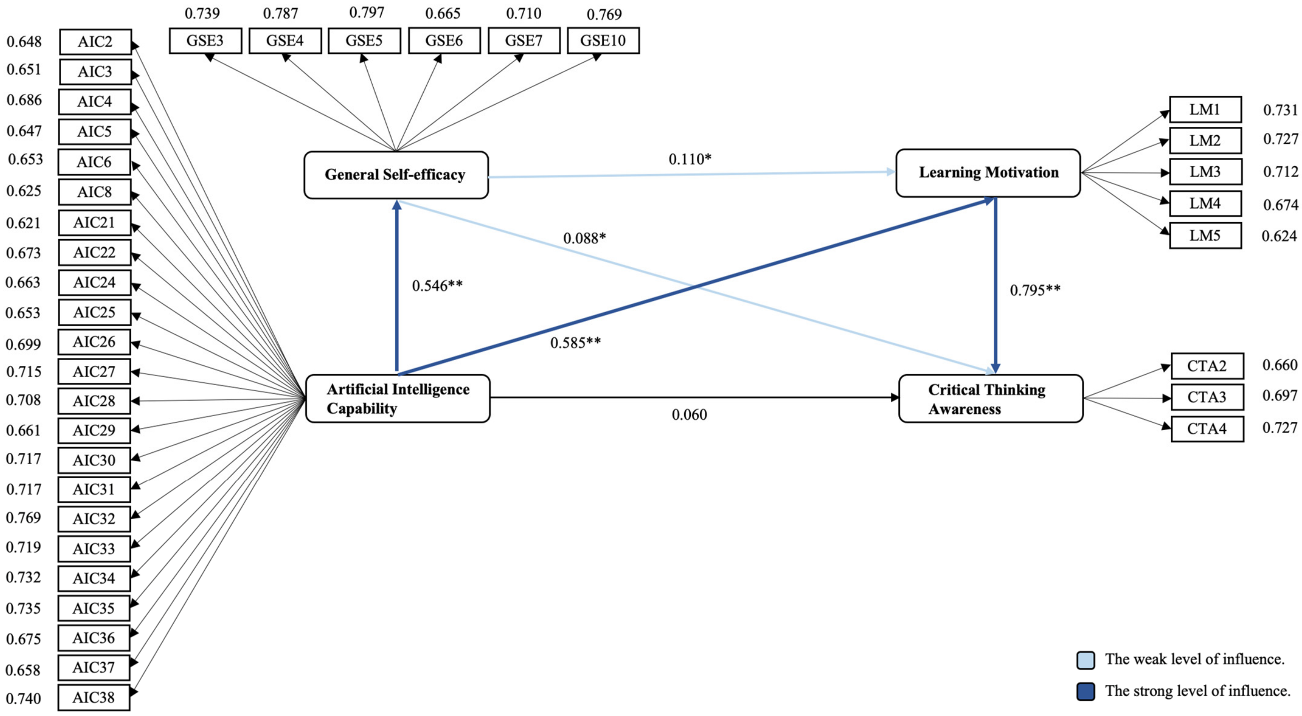

Figure 4. Results of the structural equation model. (* $p < 0.05$; ** $p < 0.001$).

4.5. Analysis of Mediation Effects

Based on the research framework of this study, the analysis of mediating effects should employ a serial mediation analysis. The mediating effects were examined using the Bootstrap sampling method with 1000 iterations. The results indicate that for the mediating path 'AIC ⇒ LM ⇒ CTA', the 95% confidence interval does not include the value of 0 (95% CI: 0.255–0.352), suggesting the presence of this mediating effect. Similarly, for the mediating path 'AIC ⇒ GSE ⇒ CTA', the 95% confidence interval does not include the value of 0 (95% CI: 0.050–0.130), indicating the existence of this mediating effect. Furthermore, the analysis of the serial mediating effects path reveals that for the path 'AIC ⇒ LM ⇒ GSE ⇒ CTA', the 95% confidence interval does not include the value of 0 (95% CI: 0.010–0.038), demonstrating the presence of this mediating effect path. The summary of effect analysis process is shown in Table 8, and the analysis of mediation effects is shown in Table 9.

Table 8. Summary of effect analysis process.

Item	Path	Effect	SE	t	*p*-Value	LLCI	ULCI
Direct effect	AIC ⇒ CTA	0.110	0.038	2.898	0.004	0.036	0.185
	AIC ⇒ LM	0.542	0.031	17.388	0.000	0.481	0.603
	AIC ⇒ GSE	0.472	0.042	11.115	0.000	0.389	0.555
Indirect effect	LM ⇒ GSE	0.220	0.044	4.951	0.000	0.133	0.308
	LM ⇒ CTA	0.582	0.037	15.673	0.000	0.510	0.655
	GSE ⇒ CTA	0.192	0.033	5.904	0.000	0.128	0.256
Total effect	AIC ⇒ CTA	0.539	0.035	15.309	0.000	0.470	0.608

Table 9. Analysis of Mediation Effects.

Item	Effect	Boot SE	Boot LLCI	Boot ULCI	z	*p*-Value
AIC ⇒ LM ⇒ CTA	0.316	0.024	0.255	0.352	13.024	0.000
AIC ⇒ GSE ⇒ CTA	0.091	0.020	0.050	0.130	4.574	0.000
AIC ⇒ LM ⇒ GSE ⇒ CTA	0.023	0.007	0.010	0.038	3.230	0.001

5. Discussions

5.1. The Insignificant Impact of Artificial Intelligence Capabilities on Critical Thinking Awareness

H1 is invalidated. The findings of H1 suggest that despite the widespread integration of AI capabilities in academic institutions, its actual influence on students' critical thinking awareness has been relatively minimal. While AI applications primarily focus on enhancing efficiency and resource management, it is essential to thoroughly assess their substantive contributions to improving students' abilities for in-depth analysis and logical reasoning [71,129]. Although the adoption of AI in administrative and educational settings aims to enhance efficiency and automate processes, the direct impact of such efficiency gains on students' critical thinking awareness is uncertain [130,131]. Critical thinking awareness goes beyond rapid information processing, and requires skills for independent thought, comprehensive understanding, and sound judgment [69,70]. While AI excels at analyzing extensive data, this primarily involves inputting information. In contrast, critical thinking awareness involves deep evaluation, reasoning, and critique of information, which rely not only on AI but also on learning, reflection, and practical experience [131]. During the COVID-19 pandemic, a reduction in interaction and an excessive reliance on digital teaching may have a negative impact on students' development of critical thinking skills and inquiry spirit [132]. As the long-term effects of the COVID-19 pandemic on learning and student development become apparent, an overreliance on digital technology in learning may fail to cultivate critical thinking awareness. Relevant authorities should take targeted measures to enhance critical thinking awareness in the educational system following the transformation of this unprecedented public health crisis.

In conclusion, despite the advantages of AI, its impact on enhancing students' critical thinking awareness is none. Further research should focus on developing students' profound analytical abilities alongside improving efficiency.

5.2. The Significant Impact of Artificial Intelligence Capabilities on General Self-Efficacy

The support for H2 confirms the significant impact of AI capabilities on students' overall self-confidence. The implementation of AI in universities has effectively improved administrative and teaching efficiency [130,131], which may have a positive psychological impact on students by increasing their general self-efficacy and making them feel more capable of handling academic challenges [74,88]. However, understanding the mechanisms behind the enhancement of general self-efficacy requires more understanding. General self-efficacy depends not only on the performance of technology, but also on students' adaptability to AI and their active engagement in learning [88,133]. Additionally, particularly in academic settings, it is crucial to thoroughly assess the potential drawbacks of AI automation, including heightened reliance and diminished cultivation of fundamental academic competencies. Improper use of generative AI has the potential to erode students' overall confidence and the effectiveness of traditional education. Therefore, institutions of higher education must conscientiously consider the integration of emerging technologies such as generative AI, ensuring that they enhance student learning by reinforcing critical thinking, research capabilities, writing proficiency, and intellectual independence [134]. In conclusion, the complex impact of AI on university students' general self-efficacy necessitates an assessment of technology efficiency, student involvement, and potential negative effects.

5.3. The Significant Impact of Artificial Intelligence Capabilities on Learning Motivation

H3 has been confirmed, indicating that the widespread use of AI capabilities has had a noticeable impact on students' motivation to learn in today's university setting. This influence is evident not only in providing personalized learning experiences, but also in various aspects such as interactivity, real-time feedback, and customization and improvement of resource management in teaching and learning environments [133–136]. These customized learning environments may better stimulate students' motivation to learn, as they perceive the alignment between learning content and their individual needs. Additionally, the interactivity and real-time feedback facilitated by AI applications can offer personalized pacing and error correction, allowing students to experience their learning progress more immediately [137,138]. Such immediate feedback mechanisms can enhance students' self-efficacy and consequently boost their motivation to learn. Furthermore, the use of technologies like virtual classrooms and augmented reality in education creates more captivating and immersive learning experiences [138,139]. These engaging environments can encourage students to participate more actively in learning activities, increasing their motivation. However, there are also potential concerns, such as excessive reliance on technology potentially weakening students' initiative [140,141], and unequal access to technology leaving some students unable to fully benefit. Factors contributing to technology access inequality include the digital divide, unequal distribution of tech devices and internet connectivity, and imbalanced allocation of educational resources. Therefore, while promoting the integration of AI in universities, it is important to balance technology with humanity and ensure fairness and inclusiveness while enhancing students' motivation to learn.

5.4. The Significant Impact of General Self-Efficacy on Learning Motivation and Critical Thinking Awareness

H4 and H5 have been found to have a positive impact on the motivation and critical thinking awareness of university students, demonstrating the influence of general self-efficacy. This influence is evident in various ways. Firstly, general self-efficacy reflects an individual's confidence in completing specific tasks [58]. This confidence directly enhances motivation for learning, as students believe that their efforts will lead to success. Secondly, the study indicates that general self-efficacy supports the development of critical thinking awareness. Students with high self-efficacy are more likely to take on challenges [142], and they have greater confidence in processing and evaluating information. This confidence enables active analysis and critique of ideas rather than passive acceptance. Additionally, general self-efficacy is closely related to emotional states [96], as positive emotions enhance motivation [98]. Confident students tend to develop positive emotions, further motivating their participation, improving their understanding, and enhancing their critical thinking awareness. It is important to note that building general self-efficacy involves various processes such as family, teaching methods, and social support [14,143]. Therefore, educational institutions should implement diverse strategies to ensure that students receive adequate encouragement throughout their learning in order to cultivate strong general self-efficacy, which in turn strengthens motivation and critical thinking awareness.

Based on the statistical analysis of the mediating effects, it can be inferred that self-efficacy and learning motivation play a mediating role between artificial intelligence capability and critical thinking awareness. It is important to note that in the path analysis, the statistical data indicates that the research findings demonstrate that learning motivation and self-efficacy constitute a partially mediated model. Specifically, AIC $\Rightarrow$ CTA exhibits a direct effect, while AIC $\Rightarrow$ GSE, LM $\Rightarrow$ GSE, and LM $\Rightarrow$ CTA demonstrate indirect effects. However, in the structural equation model, the path AIC $\Rightarrow$ CTA is not significant, indicating a marginally significant relationship. Rigorously speaking (or conservatively speaking), this implies that a fully mediated effect is more reasonable for this mediation model.

The COVID-19 pandemic has necessitated the rapid adoption of digital education and distance learning, impacting students' learning experiences and critical thinking abilities. However, it has also brought about some positive changes, such as increased independence and adaptability in the learning environment [4]. Some students have demonstrated resilience and coping strategies in response to the challenges posed by the pandemic [144]. Furthermore, the pandemic has led to changes in students' motivation and learning behavior, with students showing a greater appreciation for the impact of offline courses on their motivation compared to online courses, suggesting that offline courses may be more effective in promoting learning motivation. This may have implications for their critical thinking awareness [145]. Therefore, in the post-pandemic era, there is a call to advocate for offline courses as the primary means of instruction, while also gradually improving the impact of past predominantly online teaching backgrounds on students' learning motivation. In addition, as universities gradually deploy AI capabilities, in conjunction with the findings of this study on the mediating role of self-efficacy and learning motivation, it further suggests the need to focus on enhancing students' learning motivation and self-efficacy in the post-pandemic era. This will not only help restore students' declining learning motivation, but also enable students to effectively utilize AI capabilities to enhance their critical thinking awareness.

5.5. The Significant Impact of Learning Motivation on Critical Thinking Awareness

H6 is confirmed, indicating that a positive influence of learning motivation on critical thinking awareness. Previous research has demonstrated that increased motivation for learning is associated with higher levels of critical thinking, whereas decreased motivation for learning is linked to lower levels of critical thinking [35], meanwhile, intrinsic learning motivation drives student engagement in academic activities [146,147]. When students are interested and motivated to learn, they actively participate in class, engage in additional reading, and enthusiastically join discussions. This proactive approach helps them to better handle learning challenges, persist in reaching their goals, and develop solutions. These persistent efforts deepen their understanding of the subject matter and enhance their problem-solving skills [148,149]. This proactive attitude fosters critical thinking, enabling deeper consideration of issues, challenging existing perspectives, and raising thought-provoking questions. Furthermore, the significance of critical thinking skills and learning motivation in fostering innovative learning is highlighted [145]. Research indicates that learning motivation is closely associated with autonomous learning. Eager students take the initiative to seek out resources and explore new concepts, rather than simply completing assigned tasks. This proactive approach nurtures independent thinking, allowing students to develop more mature critical thinking skills during the learning process.

However, Suherman et al. (2021) found no significant impact of learning motivation on critical thinking skills [150]. This finding appears to be an outlier compared to the majority of references that support a positive influence of learning motivation on critical thinking. In summary, a comprehensive review of the literature demonstrates a strong consensus regarding the positive impact of learning motivation on critical thinking. Evidence from various studies in the field of education consistently supports the notion that higher levels of learning motivation are associated with an enhancement of critical thinking awareness. The college could regularly organize learning sharing sessions, allowing students to showcase the methods and experiences gained during project-based learning processes, thereby deriving encouragement from successful outcomes. This practice is conducive to enhancing learning motivation and bolstering general self-efficacy. Additionally, schools could periodically conduct surveys to gather student needs, understanding the difficulties and obstacles encountered during the learning process. Timely addressing of student inquiries, provision of personalized guidance, and assistance in establishing stronger learning beliefs could contribute to the enhancement of critical thinking skills. By demonstrating attention and respect for each student, the institution could elevate their learning engagement and sense of achievement, consequently fostering critical thinking awareness.

6. Conclusions and Suggestions

6.1. Theoretical Implications

This research utilizes the Resource Based View to consider colleges as AI resource units and presents a model that explains the impact of AI capabilities on educational development. Through quantitative analysis, the study confirms the hypotheses. The findings indicate that integrating AI capabilities in colleges could improve overall self-efficacy, motivation for learning, and awareness of critical thinking. Additionally, AI capabilities could indirectly promote critical thinking awareness by boosting general self-efficacy and learning motivation. By extending AI research from technology to education, this study offers theoretical insights that contribute to understanding the potential influence of AI capability in an educational organization on students' self-efficacy, learning motivation, and critical thinking awareness in education. In the era of the pandemic, the reliance of students on digital technologies such as AI poses potential risks for undermining critical thinking. Therefore, in the post-pandemic context of deploying artificial intelligence in higher education, enhancing students' motivation for learning and their general self-efficacy could have a positive impact on students' awareness of critical thinking.

6.2. Practical Implications

The practical implications could be seen in three main areas:

(1) Enhancing students' general self-confidence. This research demonstrates that AI could have a positive impact on college students' general self-confidence. Colleges could regularly host AI project exhibitions for students to present and exchange experiences, fostering success and greater confidence. Administrators could also regularly survey students using AI tools to gather their needs and provide prompt feedback, making students feel valued and enhancing their general self-confidence.

(2) Using AI to boost learning motivation through personalized teaching. Colleges could gather performance and interest data and utilize AI to analyze learning patterns, creating tailored plans for each student, for example, assigning topics based on students' interests to stimulate enthusiasm. Additionally, creating interactive course materials, using AI for real-time Q&A, assessing progress, and timely encouragement of students to enhance their engagement. Hosting interdisciplinary seminars could also spark curiosity and improve motivation.

(3) AI capabilities could enhance critical thinking awareness through general self-confidence and motivation. Colleges could develop programs that integrate AI to analyze learning and provide immediate feedback to help students understand their progress, thereby building confidence. In other words, college students who possess elevated levels of general self-efficacy and motivation for learning are likely to demonstrate improved performance in critical thinking awareness. The application of artificial intelligence (AI) technology for monitoring educational achievements, identifying shortcomings in critical thinking, and implementing tailored corrective measures will provide educators with actionable insights to gain a comprehensive understanding of students' skill mastery and to implement specific improvements.

6.3. Limitations and Future Research

The subsequent constraints may guide prospective research endeavors:

(1) Owing to the influence of various cognitive variables, including genetic factors, the present study did not account for the genetic impact and instead focused solely on investigating the effects of motivational variables, such as general self-efficacy and learning motivation, on critical thinking awareness. Consequently, future research endeavors may seek to complement these findings by considering the influence of genetic factors.

(2) The proposed path model in the article (CFl = 0.903) is marginally accepted as it maintains some non-significant or marginally significant relationships. Overall, while the model fit is preliminarily validated, caution should be exercised in interpreting the results due to the uncertainty in the strength of some relationships, and they should not be considered definitive. Future research should replicate and verify the study to establish more stable mechanisms of influence among variables in the proposed path model.

(3) This study examines the relevance of Reinforcement Learning Theory (RBT) to the topic, but it has not been fully utilized. RBT emphasizes positive reinforcement to influence motivation and behavior, which may explain the relationship between motivation and critical thinking. Further research is needed to validate the applicability of RBT in this field. Future studies could be based on RBT assumptions or comparative theoretical frameworks. While it is currently difficult to draw definitive conclusions,

RBT provides a perspective for subsequent work, such as how reinforcement affects beliefs and how task learning activities influence critical thinking. Overall, this study lays the groundwork for a more in-depth exploration of RBT, but there is a need for a more systematic application and comparative evaluation of its outcomes.

(4) Future research endeavors could compare the impacts of AI across various disciplines, thereby furnishing comprehensive references for diverse subject applications.

Author Contributions: Conceptualization, J.-C.T. and X.-H.J.; methodology, X.-H.J.; writing—original draft preparation, X.-H.J.; writing—review and editing, J.-C.T. and X.-H.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are contained within the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. The questionnaire of the research.

Construct	Coding	Item
AI capability	AIC1	Our instructors possess the ability to comprehend the challenges we encounter in our learning process and provide guidance on utilizing AI to address these issues.
	AIC2	Sufficient time is allocated by the school for the completion of AI-related learning projects.
	AIC3	The institution has explored or implemented cloud-based services for data processing and the operation of AI and machine learning.
	AIC4	The school furnishes the necessary hardware (such as CPUs and GPUs) to support our AI learning and projects.
	AIC5	The school has invested in network infrastructure (e.g., campus network) that facilitates efficient collaboration, characterized by high speed and low latency.
	AIC6	The school supports our use of multiple computers to handle substantial AI data.
	AIC7	The school provides cloud services such as Tencent Cloud and Baidu Cloud to enable various AI capabilities.
	AIC8	The school offers scalable cloud data storage for our AI learning.
	AIC9	The school places emphasis on fostering teamwork.
	AIC10	The school prioritizes cultivating shared objectives.
	AIC11	The school values collaborative division of labor.
	AIC12	The school emphasizes cultivating a unified understanding.
	AIC13	The school emphasizes fostering mutual comprehension.
	AIC14	The school emphasizes cultivating the sharing of information.
	AIC15	The school emphasizes fostering the sharing of resources.
	AIC16	We are capable of anticipating the conflicting emotions that may arise among peers due to changes brought about by AI learning.
	AIC17	We consider streamlining learning and workflow processes.
	AIC18	We recognize the need for gradual adaptation when learning new concepts.
	AIC19	We are able to elucidate to our peers the significance of learning AI.
	AIC20	We are willing to proactively adjust our learning methods for the sake of AI education.
	AIC21	Our class teacher is supportive of our AI learning endeavors.
	AIC22	Our instructor demonstrates a clear understanding of the appropriate applications of AI.
	AIC23	Within our class, we are unafraid to take on high-risk AI projects, recognizing their potential for significant returns.
	AIC24	In our class, we are willing to boldly attempt and complete the AI tasks assigned by our teacher.
	AIC25	When it comes to AI learning, we proactively engage to achieve the best outcomes.
	AIC26	The school teaches us how to acquire various forms of unstructured data for AI analysis.

Table A1. *Cont.*

Construct	Coding	Item
AI capability	AIC27	We are instructed on how to integrate data from different sources in various formats.
	AIC28	The school encourages us to connect with real-world scenarios, integrating practical data with theoretical knowledge.
	AIC29	We are encouraged to share our AI learning achievements with our peers.
	AIC30	Our teachers educate us on the rapid preparation and cleansing of AI data.
	AIC31	We are taught how to extract valuable data at different granularities as needed.
	AIC32	Our AI course instructors demonstrate strong leadership abilities.
	AIC33	The teachers can anticipate our needs in AI learning and proactively design the curriculum.
	AIC34	The teachers are adept at organizing our AI learning activities.
	AIC35	The AI instructors are deeply committed and take the lead in learning AI knowledge.
	AIC36	The school provides sufficient financial support for AI learning projects.
	AIC37	Our AI learning groups are adequately sized and have well-organized divisions of labor.
	AIC38	The school is open to hearing students' suggestions on how to utilize AI to improve teaching.
Critical thinking awareness	CTA1	During the process of learning, I engage in critical thinking to assess the accuracy of the knowledge acquired.
	CTA2	During the process of learning, I evaluate the value of new information or evidence presented to me.
	CTA3	During the process of learning, I endeavor to comprehend the content learned from various perspectives.
	CTA4	During the process of learning, I assess different opinions to determine their rationality.
	CTA5	During the process of learning, I am able to discern which information is credible and trustworthy.
	CTA6	During the process of learning, I will identify facts that are supported by evidence in the learning process.
General self-efficacy	GSE1	When I exert my best efforts, I consistently demonstrate the ability to resolve issues.
	GSE2	Despite opposition from others, I possess the capability to attain my desired outcomes.
	GSE3	For me, maintaining ideals and achieving objectives comes effortlessly.
	GSE4	I am confident in my ability to effectively manage unexpected situations.
	GSE5	With my intellect, I am certain that I can navigate unforeseen circumstances.
	GSE6	By exerting the necessary effort, I am assured of my capacity to address the majority of challenges.
	GSE7	I am able to confront difficulties calmly, as I trust in my problem-solving abilities.
	GSE8	When faced with a challenge, I typically identify several potential solutions.
	GSE9	In times of trouble, I am usually able to devise various coping strategies.
	GSE10	Regardless of the circumstances, I am adept at handling any situation that arises.
Learning attitude	LA1	I find the study of courses to be both engaging and valuable.
	LA2	I am eager to acquire more knowledge and gain further insights into the content of the courses.
	LA3	I believe that investing time in learning about course-related subjects is worthwhile.
	LA4	I consider mastering courses to be crucial for my personal development.
	LA5	Understanding the relationship between courses and the living environment is significant to me.
	LA6	I actively seek out additional information to enhance my understanding of the courses.
	LA7	I believe that the study of courses is essential for everyone.

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