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AI Dependency and Critical Thinking in Higher Education: A Life-Course Perspective on Ethical Awareness and Algorithmic Bias

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ABSTRACT

Purpose – The rapid adoption of artificial intelligence (AI) in higher education has transformed how students engage with learning tasks, raising concerns about dependency, ethical awareness, and algorithmic bias. From a life-course education perspective, early adulthood represents a critical developmental stage in which patterns of AI use may shape long-term critical thinking and lifelong learning dispositions. However, empirical studies integrating AI dependency, ethical awareness, and algorithmic bias awareness in relation to students' critical thinking remain limited. This study examines the effects of AI dependency, ethical awareness, and algorithmic bias awareness on university students' critical thinking skills in the context of Indonesian higher education.
Design/methods/approach – A quantitative cross-sectional design was employed. Data were collected from 110 undergraduate students across four universities in South Sulawesi, Indonesia, using purposive sampling. A validated questionnaire measured AI dependency, ethical awareness, algorithmic bias awareness, and critical thinking skills. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS.
Findings – The results indicate that all three variables significantly and positively influence students' critical thinking skills. Algorithmic bias awareness exhibits the strongest effect, followed by AI dependency and ethical awareness. These findings suggest that critical awareness of AI limitations contributes more substantially to critical thinking development than the intensity of AI use alone.
Research implications/limitations – The cross-sectional design limits causal interpretation, and the dominance of early-semester STEM students constrains generalizability. Potential moderating factors were not examined.
Originality/value – This study contributes to the literature on artificial intelligence in education by integrating ethical awareness and algorithmic bias awareness within a life-course framework, highlighting the central role of critical AI literacy in supporting sustainable critical thinking development in higher education.

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INTRODUCTION

The development of Artificial Intelligence (AI) has revolutionized education, particularly for students as frequent users of AI. Students use AI in a variety of activities, from searching for references and compiling scientific assignments to analyzing research data (Abbas, 2023). Although AI offers convenience and efficiency, excessive use has the potential to create dependency, which can reduce students' critical thinking skills. Furthermore, students' cognitive engagement in the learning process can decrease because they rely more on AI output than on their own analysis processes and also directly accept the results provided by AI without analyzing them (Firdaus & others, 2025). On the other hand, not all students are comfortable using AI; some also experience technological anxiety due to a lack of understanding and trust in AI. Low ethical awareness and a lack of understanding of the potential bias and validity of AI output can exacerbate these challenges. Less than 10% of higher education institutions worldwide have official guidelines for integrating AI safely and effectively into the learning process (Miao et al., 2023). These three factors dependence on AI, ethical awareness, and understanding of algorithmic bias are key challenges in developing students' critical thinking skills in the digital era, and therefore require further in-depth research in the context of higher education.

The use of Artificial Intelligence (AI) in education has significantly impacted students' critical thinking skills, influenced by three main aspects: dependence on AI, ethical awareness, and awareness of algorithmic bias. In Indonesia, AI adoption among students has grown rapidly, particularly following the emergence of generative platforms like ChatGPT, which are widely used for assignment writing and research.

The increased use of AI in learning can transform how students process information and make decisions, in accordance with The Digital Cognition Framework (Dewantara & Dewi, 2025), and encourage personalization of learning through Adaptive Learning Theory (Ifani et al., 2024). However, this ease of access triggers excessive dependence explained through the phenomenon of Cognitive Offloading (Dewantara & Dewi, 2025), where thinking processes are transferred to AI, thus reducing students' initiative to analyze and evaluate information independently, thereby decreasing critical thinking skills (Rohman & others, 2025).

Ethical awareness is an important factor in avoiding AI misuse, especially regarding risks of academic cheating, plagiarism, and ghostwriting that are difficult to detect by conventional software (Creswell & Creswell, 2018; Syahroni, 2022). Meanwhile, low awareness of algorithmic bias causes students to accept AI output without critical verification, even though AI systems can reinforce social prejudice due to unrepresentative training data and produce unfair assessments (Long & Magerko, 2020; Rohman & others, 2025). This indicates the need for research that focuses on how dependence on AI, ethical awareness, and algorithmic bias can affect students' critical thinking skills in Indonesia.

Previous research has discussed the impact of Artificial Intelligence (AI) on students' critical thinking skills, but most have focused on a single aspect and not integrated across multiple disciplines. Some studies have highlighted AI dependency and cognitive offloading. (Dewantara & Dewi, 2025; Ifani et al., 2024), while other studies emphasize ethical aspects without linking them to cognitive processes (Sukma & others, 2025). Other studies identify algorithmic bias, but have not empirically tested its impact on critical thinking (Rohman & others, 2025). This study fills this gap through a quantitative approach to examine the influence of dependence on AI, ethical awareness, and awareness of algorithmic bias on the critical thinking skills of students in higher education in Indonesia.

Despite growing literature on AI in education, previous studies have examined AI dependency (Dewantara & Dewi, 2025), ethical aspects (Sukma & others, 2025), and algorithmic bias (Robiul et al., 2023) separately. No prior study has integrated these three dimensions in Indonesian higher education using structural modeling. This study addresses this gap by examining how these factors simultaneously influence critical thinking skills through PLS-SEM analysis.

Based on the identified research gaps, a more comprehensive study of the impact of Artificial Intelligence (AI) use on students' critical thinking skills is crucial. This research is designed to provide insight into how reliance on AI, ethical awareness, and understanding of algorithmic bias simultaneously impact critical thinking skills in higher education settings. Furthermore, the research findings are expected to contribute to the development of policies and learning strategies that encourage the wise, ethical, and sustainable use of AI to improve students' critical thinking skills in the digital age.

Research Question:

1. Does dependence on Artificial Intelligence (AI) affect students' critical thinking skills?
2. Does ethical awareness in the use of Artificial Intelligence (AI) influence students' critical thinking skills?
3. Does awareness of algorithmic bias in Artificial Intelligence (AI) impact students' critical thinking skills?
4. Do the three variables of dependence on AI, ethical awareness, and awareness of algorithmic bias simultaneously have a significant effect on students' critical thinking skills?

METHOD

Research Design

The method used in this study is a quantitative method, namely a research method used to examine a specific sample using an instrument (Syahroni, 2022). This method is used because it can obtain numerical data that can be analyzed statistically. The research design used is a cross-sectional design , namely a research design that aims to collect data from respondents at a specific point in time to examine the relationship between variables without intervening (Creswell & Creswell, 2018).

Data collection technique

Participants in this study were active students from different universities in South Sulawesi who often use Artificial Intelligence (AI) in their academic work, such as looking for references, preparing assignments, and analyzing research data. The students were chosen because their use of AI is closely related to the study's purpose, which is to see how much and how often they use AI can influence their critical thinking abilities. The study included 110 students from four universities in South Sulawesi: Universitas Negeri Makassar, Universitas Hasanuddin, Universitas Islam Negeri Alauddin, and STIEM Bongaya. The selection of students was done using a purposive sampling method, which means choosing people based on certain conditions that match the study's goals (Gerlich, 2025). The requirements for being part of the study were: (1) being an active student, (2) having used AI at least once for academic tasks like writing assignments, searching for references, or analyzing data, and (3) being willing to complete the questionnaire on their own without any pressure. The data was collected through a questionnaire with closed-ended questions that used a five-point Likert scale. This questionnaire was designed to assess four main areas: how much students rely on AI, their awareness of ethical issues, their understanding of algorithmic bias, and their level of critical thinking skills.

Ethical Considerations

This study received ethical approval from the Research Ethics Committee of Universitas Negeri Makassar. All participants were informed about the study purpose and provided voluntary informed consent before participation. Data confidentiality and anonymity were maintained throughout the research process.

Instrument

This research instrument was developed through several stages. The first stage involved collecting instrument indicators adapted from various previous studies relevant to the research variables . The second stage involved developing statements based on the theoretical review and adaptation results, resulting in a total of 20 statement items representing four research variables: dependence on AI, ethical awareness, awareness of algorithmic bias, and critical thinking skills. Prior to distribution, the instrument underwent expert validation to assess the suitability of the content and clarity of each statement. All items were measured using a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree).

Table 1. Research Instruments

Variables	Variable Symbols	Statement	Reference
Dependence on AI	DOA	1-5	(Tian et al., 2024)
Ethical Awareness	EA	6-10	
Awareness of Algorithmic Bias	AOAB	11-15	
Critical thinking	CT	16-20	(Gerlich, 2025)

Procedure

This research will go through seven systematic stages. The first stage is preparation, including problem identification, formulation of the problem, and literature review to formulate research variables. The second stage is instrument development, namely the creation of a questionnaire based on indicators validated by expert judgment. The third stage is the distribution of the expert-validated questionnaire using Google Forms to several predetermined targets. The fourth stage is data collection, which has been distributed to 110 active students from various universities in South Sulawesi. The fifth stage is data processing and analysis, where the collected data is selected, then analyzed using descriptive and inferential statistical tests to examine the relationships between variables. The final stage is the preparation of the research report, which contains the results of the analysis, discussion, as well as conclusions and recommendations based on the research findings. For more detailed stages, see Figure 1 below.

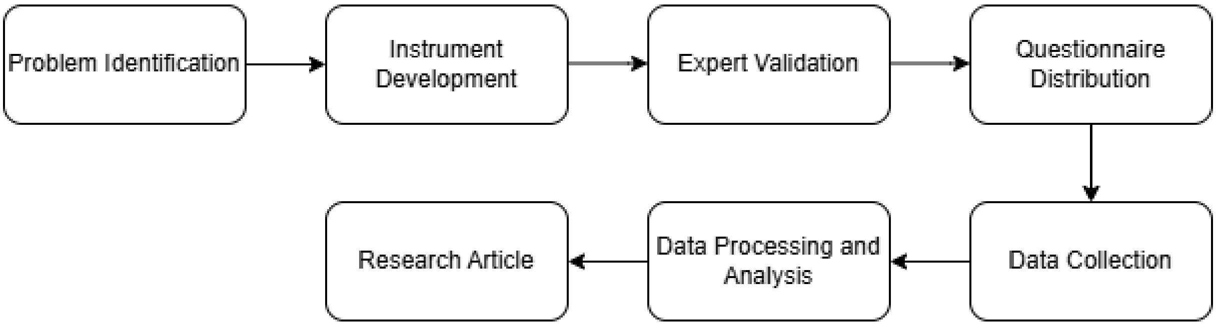

Figure 1. Research procedure

Data analysis

Data analysis in this study was conducted in two stages: descriptive analysis and inferential analysis. The first stage, descriptive analysis, was used to describe the characteristics of respondents such as gender, age, study program, semester, and frequency of use of Artificial Intelligence (AI) in academic activities. This analysis was conducted using Jamovi, using basic statistical techniques in the form of percentages, averages, medians, and minimum and maximum values to obtain an overview of the respondent profile and tendencies towards each research variable. The second stage was inferential analysis, which aimed to examine the relationships and influences between research variables. This analysis was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method through the SmartPLS application. This approach was chosen because it is capable of analyzing complex models with a relatively small sample size and data that does not have to be normally distributed. Through the combination of Jamovi and SmartPLS, this study can provide more comprehensive analysis results from both descriptive and inferential perspectives (Harahap, 2020).

Outer Model

In Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, an outer model evaluation is conducted to ensure that the indicators used are able to represent the construct validly and reliably (Holmes et al., 2023). The evaluation focuses on three aspects: convergent validity, discriminant validity, and construct reliability. Convergent validity is measured through outer loading (>0.70) and Average Variance Extracted (AVE >0.50) (Kasneci et al., 2023), while discriminant validity is tested using the Heterotrait-Monotrait Ratio (HTMT) criterion with HTMT values <0.85 . Construct reliability is assessed using Cronbach's Alpha and Composite Reliability (both >0.70) to ensure good internal consistency (Kasneci et al., 2023).

Inner Model

The inner model evaluates causal relationships between constructs according to the research hypothesis [18]. Path coefficients are calculated to determine the magnitude and direction of influence between variables, with values ranging from -1 to +1 (Kasneci et al., 2023) Significance testing is performed using a bootstrapping procedure with 5,000 subsamples (Holmes et al., 2023). Relationships are considered significant when T-Statistics exceed 1.65 and P-Values are below 0.05, indicating significance at the 95% confidence level (α = 0.05, one-tailed test).

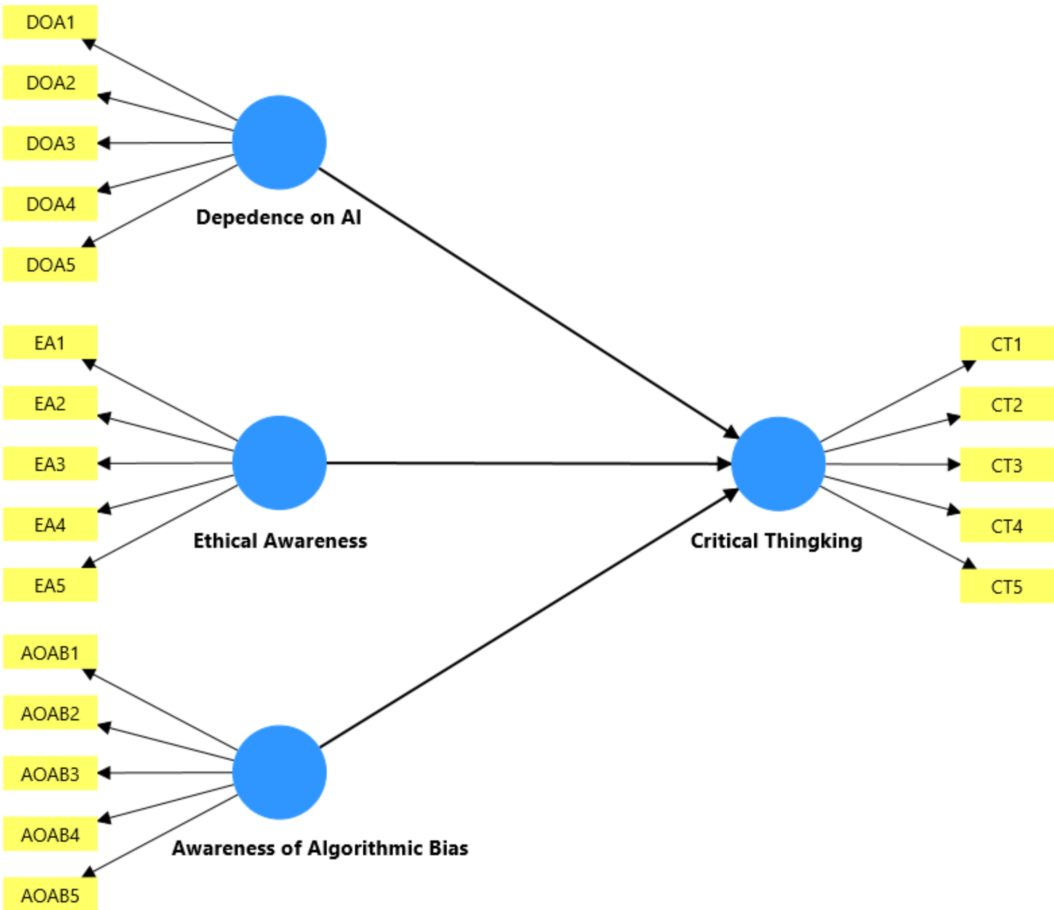

Figure 2. Structural Model of Research

Research Hypothesis

Based on the structural model in Figure 2, the research hypothesis is:
H1: Dependence on AI affects Critical Thinking Skills
H2: Ethical awareness influences critical thinking skills
H3: Awareness of Algorithmic Bias influences Critical Thinking Skills

RESULTS AND DISCUSSION

Respondent Characteristics

The total number of respondents for this study consisted of 110 respondents. The demographic information of the respondents is summarized in the table below, which includes information regarding gender, age, semester, academic year, major (STEM/Non-STEM), and frequency of technology use for learning .

Table 2. Demographic Characteristics of Respondents

Category	Description	Percentage
Gender	Man	34.5%
	Woman	65.5%
Age	17 years	0.9%
	18 years	8%
	19 years	66.4%
	20 years	17.7%
	21 years	4.4%
	22 years	1.8%
	23 years	0.9%
Semester	I	6.4%
	III	84.5%
	V	1.8%
	VII	7.3%
Class	2022	8.2%
	2023	0.9%
	2024	84.5%
	2025	6.4%
Major	STEM	71.8%
	Non-STEM	28.2%
Frequency of Technology Use for Learning	Every day	84.5%
	3-5 times a week	11.8%
	1-2 times a week	2.7%
	Seldom	0.9%

Based on Table 2, the respondents in this study showed a nearly balanced distribution between genders, with a female predominance (65.5%). Respondents' ages ranged from 17 years (0.9%), 18 years (8%), 19 years (66.4%), 20 years (17.7%), 21 years (4.4%), 22 years (1.8%), and 23 years (0.9%), reflecting the active student population at the university. The majority of respondents were from the third semester (84.5%) and the class of 2024 (84.5%), indicating a focus on early-year students who are actively engaged in the learning process. The distribution of majors shows a dominance of STEM students (71.8%), which is relevant to the context of research on the use of AI technology in learning. In terms of frequency of technology use, the majority of respondents use technology for learning every day (84.5%), indicating a high level of familiarity with digital platforms.

Outer Model

Convergent Validity and Construct Reliability

Convergent validity and construct reliability were tested to ensure that the indicators used were able to adequately measure the latent constructs. The test results are presented in Table 3.

Table 3. Results of Convergent Validity and Construct Reliability Tests

Construct	Indicator	Outer Loading	Cronbach's Alpha	Rho_A	Composite Reliability	AVE
Dependence on AI	DOA1	0.793	0.901	0.917	0.926	0.716
	DOA2	0.880				
	DOA3	0.844				
	DOA4	0.860				
	DOA5	0.852				
Ethical Awareness	EA1	0.819	0.878	0.885	0.910	0.670
	EA2	0.837				
	EA3	0.840				

	EA4	0.775				
	EA5	0.822				
Awareness of Algorithmic Bias	AOAB1	0.784	0.897	0.902	0.924	0.708
	AOAB2	0.887				
	AOAB3	0.816				
	AOAB4	0.873				
	AOAB5	0.843				
Critical thinking	CT1	0.860	0.888	0.897	0.918	0.691
	CT2	0.841				
	CT3	0.886				
	CT4	0.797				
	CT5	0.769				

All indicators demonstrated outer loading values exceeding 0.70, indicating adequate construct measurement [19]. All constructs met the recommended thresholds: Cronbach's Alpha >0.70, rho_A >0.70, Composite Reliability >0.70, and AVE >0.50. Specifically, Dependence on AI showed outer loadings of 0.793-0.880 (AVE=0.716); Ethical Awareness showed 0.775-0.840 (AVE=0.670); Awareness of Algorithmic Bias showed 0.784-0.887 (AVE=0.708); and Critical Thinking showed 0.769-0.886 (AVE=0.691). These results confirm good internal reliability and convergent validity (Holmes et al., 2023).

Overall, the AVE values for all constructs were above 0.50, indicating that each construct was able to explain more than 50% of the variance of its indicators (Sarstedt et al., 2021) The Cronbach's Alpha , rho_A, and Composite Reliability values for all constructs exceeded the recommended threshold of 0.70, thus confirming the good internal reliability of this research instrument (Hair, 2021).

Discriminant Validity

Discriminant validity was tested to ensure that each construct was empirically distinct from the other constructs. The test was conducted using the Heterotrait-Monotrait Ratio (HTMT) criterion, with the results presented in Table 4.

Table 4. Results of the Discriminant Validity Test (HTMT)

	Critical thinking	**Ethical Awareness**	**Awareness of Algorithmic Bias**
Ethical Awareness	0.609		
Awareness of Algorithmic Bias	0.694	0.756	
Dependence on AI	0.476	0.328	0.392

The results of the discriminant validity test using the Heterotrait-Monotrait Ratio (HTMT) criterion show that all HTMT values are below the recommended threshold of 0.85. The highest HTMT value is 0.756 between Ethical Awareness and Awareness of Algorithmic Bias, which is still far below the critical limit. This can be explained because both constructs are conceptually related in the context of critical awareness of the use of AI, but can still be distinguished empirically. The HTMT value between Critical Thinking and Awareness of Algorithmic Bias is 0.694, between Critical Thinking and Ethical Awareness is 0.609, while the lowest HTMT value is between Dependence on AI and Ethical Awareness at 0.328.

The use of HTMT as a discriminant validity criterion was chosen because this method is more robust and sensitive in detecting discriminant validity problems compared to the traditional Fornell-Larcker criterion (Henseler et al., 2015). All HTMT values below 0.85 confirm that discriminant validity is met, which means each construct in the model can be well distinguished from other constructs and measures different concepts (Hair, 2021). With the fulfillment of convergent validity, construct reliability, and discriminant validity, the measurement model in this study is declared valid and reliable for further analysis.

Inner Model

Hypothesis Testing

After the measurement model was declared valid and reliable, the next stage was testing the structural model to evaluate the causal relationships between constructs according to the research hypotheses. Testing was conducted using the bootstrapping method with 5,000 subsamples. The results of the hypothesis testing are presented in Table 5.

Table 5. Hypothesis Testing Results

Hypothesis	Track	Path Coefficient	T-Statistics	P-Values	Decision
H1	Dependence on AI → Critical Thinking	0.233	1,657	0.049	Accepted
H2	Ethical Awareness → Critical Thinking	0.196	1,909	0.028	Accepted
H3	Awareness of Algorithmic Bias → Critical Thinking	0.414	2,901	0.002	Accepted

The results of the hypothesis testing indicate that the three hypotheses proposed in this study are accepted. The first hypothesis (H1) which states that dependence on AI influences students' critical thinking skills is accepted with a path coefficient of 0.233, T-Statistics of 1.657 (>1.65), and P-Values of 0.049 (<0.05). The second hypothesis (H2) which states that ethical awareness influences students' critical thinking skills is also accepted with a path coefficient of 0.196, T-Statistics of 1.909, and P-Values of 0.028. The third hypothesis (H3) which states that awareness of algorithmic bias influences students' critical thinking skills is accepted with a path coefficient of 0.414, T-Statistics of 2.901, and P-Values of 0.002, indicating the strongest influence among the three variables.

All T-Statistic values exceed 1.65 and P-Values are less than 0.05, indicating that the relationship between the variables is statistically significant at the 95% confidence level (Hair, 2021). Positive path coefficient values for all three hypotheses indicate that reliance on AI, ethical awareness, and awareness of algorithmic bias have a positive influence on students' critical thinking skills.

The Impact of AI Dependence on Critical Thinking Skills

The results showed that reliance on AI had a positive and significant effect on students' critical thinking skills, with a path coefficient of 0.233 (p=0.049). This finding indicates that the use of AI in academic activities contributes positively to the development of students' critical thinking skills. These positive results demonstrate that AI can function as a tool that complements, rather than replaces, students' critical thinking processes.

This finding aligns with the concept of Adaptive Learning Theory , which states that AI technology can personalize learning according to students' individual needs, which in turn can increase cognitive engagement and higher-order thinking skills (Rohman & others, 2025). In the context of the Digital Cognition Framework, digital technology can change the way students process information and make decisions, enabling them to use technology as an extension of their cognitive abilities (Holmes et al., 2023). Large language models such as ChatGPT have great potential to support learning if used with a proper understanding of their limitations and capabilities (Kasneci et al., 2023).

Recent studies from 2023-2024 provide nuanced perspectives on this relationship. While (Kasneci et al., 2023) demonstrated that large language models can enhance learning when students maintain critical awareness, (Gerlich, 2025) warns that excessive cognitive offloading to AI tools could impact society's future critical thinking capabilities if not managed wisely. The positive effect observed in this study (β=0.233) likely stems from contextual factors when students possess adequate digital literacy and use AI strategically while remaining aware of its limitations, AI functions as a cognitive complement rather than substitute, thereby supporting rather than undermining critical thinking development.

Excessive dependence on AI can reduce critical thinking skills through the phenomenon of cognitive offloading , where students tend to delegate the thinking process to AI (Ifani et al., 2024). Cognitive offloading can lead to a decrease in students' initiative to analyze and evaluate information independently (Dewantara & Dewi, 2025). Recent research has found empirical evidence that smartphones are used to replace thinking processes, which can reduce available cognitive capacity (Barr et al., 2015). Reliance on AI tools could impact the future of society's critical thinking skills if not managed wisely (Gerlich, 2025).

These differences in results are likely due to the context in which AI is used and the students' digital literacy levels. When students possess adequate digital literacy and use AI as a strategic learning tool, while being aware of its limitations, it can have a positive impact on their critical thinking skills. Conversely, passive and uncritical use can lead to cognitive decline.

The Influence of Ethical Awareness on Critical Thinking Skills

Ethical awareness has a positive and meaningful impact on critical thinking skills, with a patcoefficient of 0.196 (p=0.028). This means that being aware of ethical issues related to using AI helps students think more critically. Ethical awareness doesn't just make students accept what AI produces without question it also encourages them to check if the information is true, accurate, and ethically sound.

These results match with other studies that say ethical awareness is key to stopping the wrong use of AI in school settings (Sukma & others, 2025). Schools and colleges need to create clear and complete rules to keep academic honesty in the age of AI. They should also make sure that teaching students how to use AI ethically is a regular part of their learning (Cotton et al., 2023). When students understand the ethical sides of AI, they become more careful when looking at AI-generated results, which makes their learning better overall (Sullivan et al., 2023).

The Impact of Awareness of Algorithmic Bias on Critical Thinking Skills

Awareness of algorithmic bias had the strongest and most important effect on critical thinking skills, with a path coefficient of 0.414 (p=0.002). This shows that when students understand the limits of AI systems and the possibility of bias in their outputs, they are more likely to think critically about the information given by AI. This awareness helps students not just accept AI results without thinking, but instead question and check if the information is accurate and trustworthy.

These findings are highly relevant to research highlighting that AI systems can reinforce social prejudice due to unrepresentative training data (Robiul et al., 2023). AI can produce unfair judgments when its training data is biased or unrepresentative (Rohman & others, 2025). AI literacy is defined as a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool, with an understanding of algorithmic bias being a key component of AI literacy (Long & Magerko, 2020).

The strong influence of awareness of algorithmic bias compared to the other two variables suggests that this aspect is a key component in developing critical thinking skills in the AI era. This is likely due to the fact that awareness of algorithmic bias is directly linked to evaluation and analysis skills, which are at the heart of critical thinking. When students understand that AI is not an absolute source of truth and can produce biased information, they naturally develop a healthy skepticism and the skills to critically evaluate information. Awareness of how algorithms work influences how individuals make decisions, indicating the importance of understanding algorithmic mechanisms in developing critical thinking skills (Tian et al., 2024).

The substantially stronger effect of algorithmic bias awareness (β=0.414) compared to AIdependency (β=0.233) and ethical awareness (β=0.196) warrants theoretical explanation. Understanding algorithmic bias requires metacognitive awareness the ability to evaluate the evaluation tool itself which represents a higher-order thinking skill (Long & Magerko, 2020). When students recognize that AI systems can produce biased outputs due to flawed training data or algorithmic design, they develop epistemic vigilance that prevents uncritical acceptance of information (Tian et al., 2024) . This metacognitive skill transfers directly to critical thinking abilities, as both require questioning assumptions and evaluating evidence quality (Sarstedt et al., 2021). In contrast, while AI dependency and ethical awareness are important, they may influence critical thinking through more indirect behavioral pathways rather than fundamental cognitive restructuring.

CONCLUSION

This study demonstrates that AI dependency, ethical awareness, and algorithmic bias awareness all play significant roles in shaping university students' critical thinking skills. Among these factors, awareness of algorithmic bias emerges as the strongest predictor, indicating that students' ability to critically evaluate the limitations and potential biases of AI systems is more influential than the mere intensity of AI use. Ethical awareness and AI dependency also contribute positively, suggesting that when AI is used reflectively and responsibly, it can function as a cognitive support rather than a substitute for independent thinking.

From a life-course education perspective, these findings highlight early adulthood as a formative stage in which students develop enduring patterns of interaction with AI that may influence their lifelong learning dispositions. Developing critical AI literacy—particularly awareness of algorithmic bias—supports epistemic vigilance and higher-order thinking skills that are essential for sustainable learning across the lifespan. Rather than restricting AI use, higher education institutions should prioritize pedagogical strategies that foster critical engagement, ethical reflection, and informed skepticism toward AI-generated outputs.

Theoretically, this study extends research on artificial intelligence in education by integrating AI dependency, ethical awareness, and algorithmic bias awareness into a unified explanatory framework grounded in life-course learning. Methodologically, the use of PLS-SEM enables the simultaneous examination of these interrelated constructs. However, the cross-sectional design, sample homogeneity, and absence of moderating variables limit the generalizability of the findings. Future research should adopt longitudinal designs, conduct multi-group analyses across academic disciplines and educational stages, and incorporate variables such as AI literacy, self-regulated learning, and digital epistemic beliefs to further advance understanding of AI-supported lifelong and life-course education.

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AUTHOR CONTRIBUTION STATEMENT

JNP contributed to the conceptualization of the study, literature review, and drafting of the original manuscript. MAH was responsible for instrument development, data collection, and preliminary data processing. MA conducted the statistical analysis using PLS-SEM and interpreted the empirical results. AA provided theoretical supervision, methodological validation, and critical revisions of the manuscript.

AI DISCLOSURE STATEMENT

The authors used ChatGPT solely as a language-support tool for grammatical refinement, clarity improvement, and structural editing during manuscript preparation. All substantive scholarly activities including research design, theoretical framework development, data collection, statistical analysis, interpretation of findings, and conclusion formulation were performed entirely by the authors. The authors critically reviewed and edited all AI-assisted content and take full responsibility for the originality, accuracy, and integrity of the published work.

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