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Does strategic generative AI learning in higher education trigger job anxiety? An experimental study

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ABSTRACT

Background: The use of AI-based instructional videos in higher education is rapidly expanding, offering greater convenience and potential benefits in the learning process. However, alongside these advantages, students are increasingly concerned about the possibility that AI may replace human roles, particularly in the context of future employment.

Purpose: This study aims to examine the effects of perceived ease of use (PEU), perceived benefits (PB), and knowledge of generative AI (KAI) on AI job replacement anxiety (REPLC), as well as to test the moderating role of KAI in these relationships. As part of its broader contribution, this study positions AI literacy as a strategic capability shaping workforce readiness.

Method: This study employs an explanatory quantitative approach using a quasi-experimental design involving 200 undergraduate students in Jakarta. Respondents were first exposed to an AI-generated lecture video before completing a questionnaire measured on a five-point Likert scale. Data were analysed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) with SmartPLS software.

Findings: The results indicate that PEU and PB are not significant with respect to KAI, while KAI has a positive and significant effect on such anxiety. In addition, KAI has a significant negative effect on PB and PEU. However, the moderating effects are not empirically supported. These findings highlight that AI literacy plays a critical role in shaping students' awareness of potential job disruption caused by AI technologies. Furthermore, AI literacy can be considered as a strategic competence to prepare students for digital transformation and future workforce issues.

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INTRODUCTION

The growing use of AI-based instructional videos in higher education emphasizes the importance of perceived ease of use (PEU) in shaping students' learning experiences. Students tend to accept technology when it is easy to operate and supports their learning needs (Chan & Hu, 2023). This ease is reflected not only in simple access to materials but also in how efficiently students can understand content delivered in a structured format (Christian et al., 2025). As a result, AI can reduce cognitive effort and make learning more manageable. Instructors also benefit from AI tools that simplify content production, improving both quality and accessibility of learning materials. However, challenges remain, such as reduced creativity due to overreliance on AI and concerns about content accuracy that still require human supervision. These challenges show that simplicity of use does not in itself lead to successful learning results. Therefore, it is essential to build AI literacy and adaptive policies that allow AI to be integrated responsibly and successfully in education.

In addition to convenience of use, PB has an important role in influencing students' adoption of AI-based educational videos. Students often recognize advantages such as faster access to information and improved efficiency in understanding complex materials (Pellas, 2023). AI-generated videos, especially those using avatars, can enhance engagement and simplify difficult concepts. Such benefits promote a more participatory and supportive learning environment. At the same time, positive attitudes and trust in AI further reinforce these perceptions (Chan & Hu, 2023). However, the perceived advantages are not without limitations. Concerns concerning quality and accuracy of content still matter and over-reliance on AI may lead to erosion of critical thinking skills in students. This suggests that benefits should be understood as supportive rather than transformative factors. Therefore, a balanced approach is necessary which integrates technology innovation with sound educational approaches.

Another important factor is knowledge of generative AI (KAI), which determines how effectively students can use AI-based learning tools. Students with a better understanding of how AI works are more likely to use it strategically and evaluate its outputs critically (Chan & Hu, 2023). This information helps their capacity to appraise the strengths and limitations of AI in learning environments. AI literacy, including ethical awareness and evaluation skills, also strengthens students' sense of control when interacting with technology (Zhang et al., 2025). As a result, students become more selective in using AI-generated content. However, limitations still exist, particularly in areas such as prompt design and the ability to interpret AI outputs effectively. Increased knowledge also raises awareness of risks, including bias and ethical concerns. Consequently, it is crucial to embed AI literacy into curricula and institutional policies to promote responsible use of technology

Previous studies consistently identify PEU use and PB as key determinants of AI acceptance in higher education (Acosta-Enriquez et al., 2024; Tian et al., 2024). These reasons explain students' readiness to accept AI tools, especially when the technology is seen as useful and easy to use. However, most existing research remains centred on behavioral intention, satisfaction, and adoption outcomes, rather than examining AI job replacement anxiety (REPLC) as a psychological consequence. As a result, the emotional and career-related implications of AI use among students are still underexplored. Some studies on AI-based learning, including video-based tools, emphasize usability and engagement but do not explicitly connect these perceptions with employment concerns (Christian, Pardede, Yulita, et al., 2024; Kamalov et al., 2023; Pellas, 2023). Meanwhile, research on AI-related job anxiety shows that students are aware of potential changes in job structures, yet this discussion is typically framed at a general level of AI exposure. This indicates that the specific experience of interacting with AI-generated lecture videos has not been sufficiently examined. Furthermore, although KAI has been linked to literacy, attitudes, and anxiety, its integrated role remains limited (Li et al., 2025). This disparity is notably visible in the empirical testing of its moderating impact. Despite the growing number of studies on AI acceptance in higher education, existing research remains largely concentrated on behavioral intention, satisfaction, and technology adoption outcomes. Limited attention has been given to the psychological implications of AI exposure, particularly AI job replacement anxiety emerging from direct interaction with AI-generated instructional media. Moreover, prior studies tend to examine AI literacy primarily as a factor influencing technology acceptance, rather than as a strategic cognitive capability shaping perceptions of future workforce disruption. This indicates a theoretical gap regarding how AI knowledge simultaneously influences technology evaluation and employment-related anxiety within digitally transformed educational environments.

From a strategic management perspective, it emphasizes the importance of aligning AI deployment with workforce preparation and the long-term development of human capital in institutions. Although prior studies generally report positive relationships between AI literacy and technology acceptance, findings regarding the psychological consequences of AI exposure remain inconsistent. Some studies argue that AI literacy reduces anxiety by increasing self-efficacy and perceived control, whereas others suggest that deeper knowledge heightens awareness of automation risks and labor market disruption. This inconsistency indicates the need for further empirical investigation, particularly within AI-based instructional environments where students directly interact with AI-generated learning media.

Based on these assumptions, this study examines the effects of perceived ease of use, perceived benefits, and knowledge of generative AI on AI job replacement anxiety among undergraduate students exposed to AI-based learning environments. In addition, the study investigates the moderating role of AI knowledge in shaping the relationships between technology perceptions and job-related anxiety. From a strategic management perspective, this research positions AI literacy not merely as a technological competency, but as a strategic capability associated with workforce readiness and long-term human capital development within higher education institutions. The present research, within a framework of strategic management, emphasizes the necessity of the alignment of technology innovation with the human resource readiness. The urgency is particularly relevant in major Indonesian cities such as Jakarta, where AI adoption in education is rapidly increasing. Accordingly, this research emphasizes not only technology acceptance but also the development of workforce readiness in response to digital transformation.

The novelty of this research lies in integrating AI job replacement anxiety into the technology acceptance framework through direct exposure to AI-generated instructional videos within a higher education context. Unlike prior studies that primarily focus on adoption intention or learning satisfaction, this study emphasizes the psychological consequences of AI interaction, particularly employment-related anxiety. In addition, knowledge of generative AI is positioned not only as a direct explanatory variable but also as a strategic cognitive capability associated with workforce preparedness and human capital adaptability in the era of digital transformation.

AI Job Replacement Anxiety

REPLC represents students' concerns that AI technologies may replace human roles in the workplace, particularly when AI-based lecture videos demonstrate that certain teaching activities can be automated. Theoretically, this construct can be explained through technology displacement theory and career identity theory, which suggest that individuals experience anxiety when technological advancements threaten professional identity and roles traditionally perceived as uniquely human (Kai et al., 2026; Mohamed et al., 2025). Within the AI anxiety framework, this form of anxiety constitutes an emotional dimension that can inhibit technology acceptance, even when its benefits are acknowledged (Christian, Nan, et al., 2024; Kai et al., 2026). Empirical evidence indicates that students recognize the advantages of AI while simultaneously expressing concerns about job opportunities and shifting professional demands (Chan & Hu, 2023), and that positive attitudes toward AI can coexist with fears of human labor displacement (Amiri et al., 2024). Moreover, AI literacy plays a dual role by reducing anxiety through increased perceived control, while also heightening awareness of automation risks (Klimova & Pikhart, 2025). This anxiety has been shown to hinder AI acceptance in educational contexts (Kai et al., 2026) and is reinforced by broader concerns regarding job displacement (Jackson et al., 2024; Mohamed et al., 2025; Pellas, 2023; Preiksaitis & Rose, 2023). In the Indonesian context, this phenomenon is increasingly relevant as the digitalization of higher education occurs alongside uncertainty in graduate labor markets. From a strategic management perspective, this anxiety can be understood as a form of perceived strategic risk associated with future job uncertainty and the evolving structure of workforce competencies.

Perceived Ease of Use

PEU indicates students find AI-powered educational films easy to access, understand and use with not too many technological challenges. From the perspective of the TAM theory, PEU is a key determinant influencing users' attitudes and intentions toward technology adoption (Al-Adwan et al., 2023; Chan & Hu, 2023; Zhang et al., 2025). Within the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) framework, this construct is conceptualized as effort expectancy, which explains that ease of use increases the likelihood of technology adoption (Acosta-Enriquez et al., 2024; Cortez et al., 2024). Empirical studies indicate that prior experience, AI training, and access to digital devices strengthen students' positive attitudes toward AI-generated video content (Pellas, 2023), and contribute to higher user satisfaction (Alshammari & Babu, 2025). However, extended TAM models suggest that emotional factors, such as AI-related anxiety, may weaken the influence of ease of use on technology acceptance (Kai et al., 2026). Furthermore, ease of use can generate ambivalent perceptions, as students simultaneously recognize the long-term implications of AI on employment (Chan & Hu, 2023). The literature also highlights that AI literacy may reduce job-related anxiety through increased self-efficacy (Klimova & Pikhart, 2025; Kwak et al., 2022; Li et al., 2025), although concerns about overreliance persist (Lin & Chen, 2024). The simplicity of using AI in the educational context in Indonesia is closely associated with the issue of readiness for future work. From a strategic management perspective, PEU primarily reflects operational efficiency rather than directly shaping perceptions of long-term career risk. Then, the following hypothesis put forward: **H1:** PEU has a significant effect on REPLC.

Perceived Benefits

PB is conceptualized as the amount to which students perceive concrete advantages of using AI-based lecture videos, such as efficiency, personalization, and a better understanding of learning material. Within the TAM and UTAUT2 frameworks, PB align with the concepts of perceived usefulness or performance expectancy, which serve as primary predictors of technology acceptance (Acosta-Enriquez et al., 2024; Al-Adwan et al., 2023; Dahri et al., 2024). From the perspective of Social Exchange Theory (SET), individuals evaluate technology usage based on a cost–benefit trade-off, including perceived risks (Shrivastava, 2025). Empirical evidence shows that students view AI as a tool that enhances productivity and access to learning (Chan & Hu, 2023), while also increasing engagement and facilitating the understanding of complex concepts (Lin & Chen, 2024; Malakul, 2025; Pellas, 2023). However, according to Protection Motivation Theory (PMT), PB may compete with perceived threats, meaning that benefits do not necessarily reduce anxiety (Shrivastava, 2025). This is reflected in findings where students continue to worry about the impact of AI on future employment (Klimova & Pikhart, 2025), even when they recognize its advantages (Kai et al., 2026; Yuan et al., 2025). The benefits of AI in expanding access to education coexist with concerns about the relevance of future workforce competencies. Therefore, the benefits of AI are not only understood as operational efficiencies in learning but also as sources of strategic value creation that may enhance institutional competitiveness. Nonetheless, these PB tend to be short-term and operational, and may not provide long-term strategic reassurance regarding career sustainability. In this regard the following hypothesis can be formulated: **H2:** PB have a significant effect on REPLC.

Knowledge of Generative AI

KAI refers to students' level of understanding regarding how AI works, including its functionalities, benefits, risks, and ethical implications in learning contexts. Theoretically, this construct is grounded in the AI literacy perspective within a TPB–TAM hybrid framework, where AI knowledge shapes attitudes, subjective norms, and perceived behavioural control toward technology use (Zhang et al., 2025). In addition, AI literacy functions as a cognitive factor that enhances self-efficacy and individuals' ability to critically evaluate technological outputs (Li et al., 2025). Empirical findings indicate that higher AI knowledge improves PEU and fosters more positive attitudes toward technology (Chan & Hu, 2023; Chan & Lee, 2023), while also strengthening effort expectancy within the UTAUT2 framework (Tang et al., 2025). while also strengthening effort expectancy within the UTAUT2 framework (Chan & Zhou, 2023; Fan et al., 2025), although this relationship is not always linear and is influenced by trust and contextual factors. At the same time, AI literacy increases awareness of risks such as bias, accuracy limitations, and ethical concerns (Hardie et al., 2026; Kamalov et al., 2023; Preiksaitis & Rose, 2023). Within a risk–benefit framework, AI knowledge strengthens individuals' evaluation of both opportunities and threats (Shrivastava, 2025). Regarding job-related anxiety, AI literacy demonstrates an ambivalent effect, as it can reduce anxiety through increased perceived control while simultaneously heightening awareness of automation risks (Amiri et al., 2024; Klimova & Pikhart, 2025). In the Indonesian context, variations in students' digital literacy make these effects highly contextual. From a strategic management perspective, KAI can be viewed as a strategic capability that enables individuals to critically assess technological opportunities and risks within dynamic environments. On this basis, the following possibilities are proposed: **H3:** KAI has a significant effect on REPLC; **H4:** KAI has a significant effect on PB; and **H5:** KAI has a significant effect on PEU.

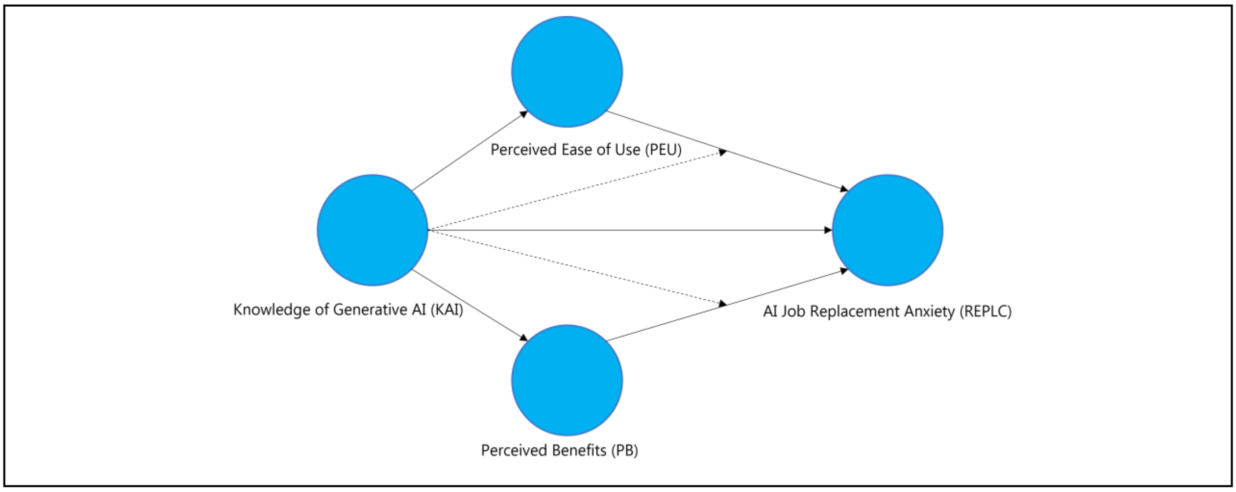
Furthermore, KAI is shown as a moderating variable that could strengthen or weaken the associations between PEU, PB, and REPLC. Within the UTAUT2 framework, AI literacy acts as an enabling factor that enhances the effect of effort expectancy on technology acceptance (Acosta-Enriquez et al., 2024; Cortez et al., 2024). From a risk–benefit trade-off perspective integrating SET and PMT, knowledge plays a critical role in determining how individuals balance PB and risks (Shrivastava, 2025). The literature suggests that AI literacy can reduce anxiety through increased self-efficacy (Laupichler et al., 2024; Li et al., 2025; Türk et al., 2025), but may also heighten awareness of job displacement risks (Chan & Hu, 2023; Wang et al., 2024). Additionally, PB of AI often coexist with job-related anxiety (Amiri et al., 2024; Yuan et al., 2025), reinforcing the relevance of testing moderating effects. In the Indonesian context, variations in AI literacy among students make these moderating effects highly contextual and potentially non-linear. Then, the following hypotheses are proposed: **H6:** KAI moderates the effect of PEU on REPLC, and **H7:** KAI moderates the effect of PB on REPLC.

METHODS

This study uses an explanatory quantitative method, with a quasi-experimental design, to investigate the causal link between constructs within a conceptual model involving cognitive, affective, and perception-based dimensions of AI technology (as illustrated in research framework in Figure 1). In addition, the study integrates a media-based experimental technique, in which respondents are first exposed to an AI-generated learning video that must be watched prior to completing the questionnaire, enabling a more contextual and experience-based measurement of perceptions. The sample consists of 200 undergraduate students in Jakarta, selected using purposive sampling with the criterion of having prior experience with online or digitally mediated learning. The sample size is sufficient to meet the minimal criteria for PLS-SEM analysis which is ten times the number of indicators (Hair et al., 2021). Jakarta was selected due to its role as a major educational and technological hub in Indonesia, with a significant amount of adoption of artificial intelligence and digital learning convergence, thus providing a relevant and representative empirical context. Jakarta represents one of Indonesia's most digitally connected urban educational environments, where undergraduate students are increasingly exposed to AI-based technologies in both academic and non-academic settings. Undergraduate students were chosen because they are in a transitional phase toward the workforce, making them more sensitive to REPLC. This context also reflects a strategically relevant digital transformation environment, where students are actively exposed to technological innovations in education.

The research workflow is initiated by the presentation of a stimulus in the form of a ±1-minute AI-based lecture video from the "Research Methods" course, delivered by an AI-generated avatar, with visuals created using Gemini AI and audio synchronized through sync.so. The video opens with the greeting, "Welcome to the Research Methods class!", followed by a brief explanation of the lecture topic: "In this video, we will discuss Research Design, specifically focusing on valid and effective data collection methods. This includes survey, interview, and observation techniques, which are essential to ensure the validity of your research findings." The video then provides an interactive prompt through a Q&A invitation: "Please feel free to submit your questions via the provided email if anything is unclear," and concludes with the closing statement, "Enjoy the session!". This script was intentionally designed to be concise and structured, to make it believable for powered by artificial intelligence lecture delivery. It is vital to point out that the purpose of this script is not to assess students' academic ability, but rather to assess students' views of clarity, the convenience of use, and the PB of information transmitted by AI-based learning medium.

Figure 1.
Research Framework



Following exposure to the stimulus, participants were required to complete a questionnaire using a five-point Likert scale, adapted from established instruments (Chan & Hu, 2023; Li et al., 2025; Wang et al., 2022; Wang & Wang, 2022). The questionnaire was distributed between July and September 2025. Table 1 presents the operational variables employed in this investigation. Data analysis was conducted using SmartPLS through two main stages: outer model evaluation to assess convergent validity (loading factor > 0.70; AVE > 0.50) and construct reliability (Composite Reliability > 0.70), and inner model evaluation to examine structural relationships among variables using R^2, Q^2, and bootstrapping results ($t > 1.96$; $p < 0.05$). Indicators that did not match the required thresholds were eliminated and reanalysed to check the robustness of the model.

RESULT AND DISCUSSION

Participants Profile

Based on the participants profile (Table 2). Most of the participants were female with 113 individuals (56.50%), while male respondents totalled 87 individuals (43.50%). In terms of age, the sample was dominated by students aged 20 years (54.50%), followed by those aged 21 years (29.00%),

Tabel 1.
Operationalization of Variables

Variable (Construct)	No.	Indicator
PEU; adapted from Chan & Hu (2023); Li et al., (2025)	1	AI-based lecture videos facilitate the learning process.
	2	It's simple to gain knowledge how to use AI-powered lecture videos to comprehend course materials.
	3	AI-based lecture videos are practical tools for supporting understanding and completing academic tasks.
	4	Students understand that AI-based lecture videos can deliver complex academic content effectively when properly managed.
	5	Students recognize the importance of ensuring the accuracy of explanations in AI-based lecture videos.
KAI; adapted from Chan & Hu (2023); Li et al., (2025)	6	Students know that AI-generated lecture films can be altered to stay relevant to specific course content.
	7	Students recognize that AI can be used to make instructional videos which give balanced and objective explanations.
	8	Students see how current sources can be combined with AI-enabled instructional films to improve contextual relevance.
	9	Students comprehend the ability to use methodologies that integrate social and cultural variables to supplement AI-based teaching videos.
	10	AI-based lecture videos help improve understanding of course materials.
	11	AI-based lecture videos provide additional explanations for topics not fully covered in class.
PB; adapted from Chan & Hu (2023); Li et al., (2025)	12	AI-based lecture videos support learning needs that may not be fully addressed in face-to-face lectures.
	13	AI-based lecture videos offer additional support for independent learning outside class hours.
	14	The process of learning becomes easier by learning through AI-based lecture videos.
	15	The use of AI-based lecture videos supports the development of skills within a specific field of study.
	16	Students know that AI technology might replace certain human positions in education or work.
REPLC; adapted from Wang & Wang, (2022); Wang et al., (2022)	17	Students recognize that the use of AI in education may influence the demand for educators or professionals.
	18	Students understand that AI-based technologies may affect future job dynamics.
	19	Students recognize that AI development may change the types of skills required in the future workforce.
	20	Students understand that widespread AI adoption may increase job competition for individuals who do not adapt to technological changes.

with smaller proportions aged 22 (9.00%), 23 (6.50%), and 24 (1.00%), indicating a relatively homogeneous sample within the early undergraduate stage. Regarding academic background, most respondents were from Management, Economics, and Business programs (55.00%), followed by Communication (25.00%) and Language studies (20.00%). Furthermore, respondents' level of knowledge regarding the use of AI in learning tended to be moderate to high, with the majority selecting scores of 3 (39.00%) and 4 (43.00%), and a smaller proportion selecting 5 (15.50%). This distribution suggests that most respondents possess a reasonably good understanding of AI within the context of higher education learning environments.

Tabel 2.
Participants Profile

Profile		Freq	%
Gender	Female	113	56.50%
	Male	87	43.50%
Age	20	109	54.50%
	21	58	29.00%
	22	18	9.00%
	23	13	6.50%
	24	2	1.00%
Study Program	Management, Economics, and Business	110	55.00%
	Communication	50	25.00%
	Language Studies	40	20.00%
Level of Knowledge of AI in Learning (Scale 1 = Very Low to 5 = Very High)	1 (Very low)	2	1.00%
	2	3	1.50%
	3	78	39.00%
	4	86	43.00%
	5 (Very high)	31	15.50%

Outer Model Evaluation

The outcomes of the outer model assessment using the PLS algorithm (Table 3) indicate that that every construct analysed in this study conform to the required requirements of validity and reliability in PLS-SEM analysis. In terms of convergent validity, all indicators demonstrate loading factor values above the minimum score of 0.70, including KAI (0.832–0.896), PB (0.750–0.966), PEU (0.822–0.920), and REPLC (0.790–0.892), confirming that all indicators are valid. Also, the AVE values of all the constructs are greater than 0.50, specifically KAI (0.748), PB (0.748), PEU (0.738), and REPLC (0.708), indicating strong convergent validity across constructs.

From a reliability perspective, every construct has Cronbach's Alpha values over 0.70 (KAI = 0.701; PB = 0.712; PEU = 0.827; REPLC = 0.861), demonstrating acceptable reliability.

These findings are further supported by Composite Reliability values that also exceed 0.70 (KAI = 0.856; PB = 0.854; PEU = 0.894; REPLC = 0.906), indicating strong internal consistency. Therefore, the validity and reliability of every construct in the research model are confirmed.

Tabel 3.
PLS-algorithm

Construct / Item	LF	CA	CR	AVE
Construct: KAI	-	0.701	0.856	0.748
Item: KAI3	0.832	-	-	-
Item: KAI4	0.896	-	-	-
Item: PB	-	0.712	0.854	0.748
Item: PB1	0.966	-	-	-
Item: PB5	0.750	-	-	-
Construct: PEU	-	0.827	0.894	0.738
Item: PEU1	0.920	-	-	-
Item: PEU2	0.831	-	-	-
Item: PEU3	0.822	-	-	-
Construct: REPLC	-	0.861	0.906	0.708
Item: REPLC2	0.805	-	-	-
Item: REPLC3	0.892	-	-	-
Item: REPLC4	0.875	-	-	-
Item: REPLC5	0.790	-	-	-

**LF=Loading Factor (>0.7); CA=Cronbach's Alpha (0.7); CR=Composite Reliability (>0.7); AVE=Average Variance Extracted (>0.5); **Items not included in the table have been eliminated.*

Explaining the Evaluation of Inner Model

The outcomes of the inner model assessment based on the R-square values indicate that the construct of REPLC has an R^2 value of 0.089 (Adjusted R^2 = 0.066), suggesting that the exogenous variables only 8.9% of the variance in job replacement anxiety, which falls into the weak category. The PB construct shows an R^2 value of 0.045 (Adjusted R^2 = 0.040), reflecting a very limited power of the predictor variables on PB. Similarly, PEU has an R^2 value of 0.078 (Adjusted R^2 = 0.073), which is also considered weak. The relatively low explanatory power of the model may indicate that AI job replacement anxiety is influenced by broader external and contextual factors beyond technology perception variables alone. In the context of Jakarta's highly competitive labor market and rapidly evolving digital economy, students may develop employment-related concerns through exposure to societal narratives regarding automation, workforce disruption, and future career uncertainty. Variables such as career adaptability, perceived employability, self-efficacy, institutional support, and socio-economic background may therefore play a more substantial role in shaping AI-related job anxiety and should be considered in future investigations.

In general, the results imply that the model is able to explain the direction of relationships among variables, its explanatory power remains relatively low, indicating the potential influence of additional variables not included in the model. From a broader perspective, this outcome indirectly highlights the importance of other strategic factors—such as career readiness, labor market perceptions, and institutional strategies—might perform a more substantial role in explaining students' REPLC within the context of digital transformation in higher education.

Tabel 4.

R-Square

Construct	R Square	R Square Adjusted
REPLC	0.089	0.066
PB	0.045	0.04
PEU	0.078	0.073

The multicollinearity assessments (Table 5) indicate that all Variance Inflation Factor (VIF) values, (outer VIF at indicator level and inner VIF at construct level) are less than the crucial value of 3.3. The outer VIF values range from 1.334 to 3.043, with the highest value still within an acceptable tolerance level, suggesting no serious multicollinearity issues among the indicators. Similarly, the inner VIF values are relatively low (e.g., 1.107 and 1.865), indicating the absence of high correlations among predictor constructs within the structural model. Thus it may be inferred that the study's framework is free from multicollinearity problems and is suitable for further interpretation and hypothesis testing.

Tabel 5.
Variance Inflation Factor (VIF)

<table>
<tr><th rowspan="2">Item</th><th rowspan="2">Outer VIF Value</th><th colspan="4">Inner VIF Value</th></tr>
<tr><th>REPLC</th><th>KAI</th><th>PB</th><th>PEU</th></tr>
<tr><td>KAI3</td><td>1.334</td><td rowspan="2">1.107</td><td rowspan="2">-</td><td rowspan="2">1.000</td><td rowspan="2">1.000</td></tr>
<tr><td>KAI4</td><td>1.334</td></tr>
<tr><td>PB1</td><td>1.441</td><td rowspan="2">1.865</td><td rowspan="2">-</td><td rowspan="2">-</td><td rowspan="2">-</td></tr>
<tr><td>PB5</td><td>1.441</td></tr>
<tr><td>PEU1</td><td>2.057</td><td rowspan="3">1.865</td><td rowspan="3">-</td><td rowspan="3">-</td><td rowspan="3">-</td></tr>
<tr><td>PEU2</td><td>1.903</td></tr>
<tr><td>PEU3</td><td>1.753</td></tr>
<tr><td>REPLC2</td><td>1.770</td><td rowspan="4">-</td><td rowspan="4">-</td><td rowspan="4">-</td><td rowspan="4">-</td></tr>
<tr><td>REPLC3</td><td>3.043</td></tr>
<tr><td>REPLC4</td><td>2.864</td></tr>
<tr><td>REPLC5</td><td>1.658</td></tr>
</table>

The findings of the discriminant validity assessment using the HTMT criterion (Table 6) indicate the fact that the inter-construct standard indices are less than the conservative score of 0.90. The greatest score is observed in the PB and PEU relationship, at 0.871, which is still in the permissible range. Other construct relationships exhibit lower values, such as the relationship between KAI and REPLC at 0.352, as well as relatively small values involving moderating effects. These findings suggest that each construct in the model demonstrates adequate discriminant validity and is empirically distinct in measuring different conceptual domains. Thus, the discriminant validity of the the assessment framework is confirmed.

Tabel 6.

Heterotrait-monotrait ratio (HTMT)

Construct	REPLC	KAI	Moderating Effect 1	Moderating Effect 2	PB	PEU
REPLC	-	-	-	-	-	-
KAI	0.352	-	-	-	-	-
Moderating Effect 1	0.130	0.013	-	-	-	-
Moderating Effect 2	0.130	0.061	0.774	-	-	-
PB	0.086	0.267	0.290	0.282	-	-
PEU	0.084	0.350	0.356	0.303	0.871	-

The outcomes of predictive relevance test in Q^2 (Table 7) show all of which constructs possess Q^2 values above 0, meaning that the framework has sufficient power to predict. REPLC has Q^2 value of 0.499, reflecting strong predictive relevance, while PEU, with a Q^2 value of 0.462, is also considered high. Meanwhile, PB (0.278) and KAI (0.244) demonstrate moderate predictive relevance. At the indicator level, all the Q^2 values are also positive, indicating the good overall predictive relevance of the model. Therefore, despite the relatively low R^2 values, the model still demonstrates the ability to predict endogenous variables empirically.

The outcomes of the structural path (illustrated in Table 8) demonstrate the empirical evidence for all hypotheses is not complete. H1, which examines the effect of PEU on REPLC, is not shown to be significant ($\beta = -0.015$; $t = 0.121$; $p = 0.904$), and therefore the hypothesis is not supported. This outcome is consistent with previous literature suggesting that the ease of using AI technologies primarily contributes to increased acceptance and intention to use, but does not directly reduce anxiety related to job displacement (Acosta-Enriquez et al., 2024; Kai et al., 2026). Furthermore, a number have demonstrated that even when AI systems are perceived as easy to use, concerns regarding employment implications persist, as such concerns are more closely linked to broader perceptions of AI's impact at a macro level rather than its functional attributes (Chan & Hu, 2023; Klimova & Pikhart, 2025).

Tabel 7.

Q^2

Indicator	SSO	SSE	Q^2 (=1-SSE/SSO)
KAI3	200	151.598	0.242
KAI4	200	150.914	0.245
PB1	200	148.975	0.255
PB5	200	139.747	0.301
PEU1	200	102.371	0.488
PEU2	200	104.908	0.475
PEU3	200	115.248	0.424
REPLC2	200	113.096	0.435
REPLC3	200	80.784	0.596
REPLC4	200	84.096	0.58
REPLC5	200	122.799	0.386
Construct			
REPLC	800	400.774	0.499
KAI	400	302.512	0.244
PB	400	288.722	0.278
PEU	600	322.528	0.462

**SSO=Sum of Squares Observations; SSE=Sum of Squares Errors*

Tabel 8.

Path Coefficients

Path	OS	STDEV	T Statistics	P Values	H	Remark
PEU → REPLC	-0.015	0.127	0.121	0.904	H1	NS
PB → REPLC	-0.044	0.127	0.346	0.729	H2	NS
KAI → REPLC	0.252	0.073	3.444	0.001	H3	S
KAI → PB	-0.211	0.1	2.118	0.035	H4	S
KAI → PEU	-0.278	0.073	3.835	0.000	H5	S
Moderating Effect 1 → REPLC	0.078	0.121	0.639	0.523	H6	NS
Moderating Effect 2 → REPLC	0.033	0.124	0.263	0.792	H7	NS

**OS=Original Sample; STDEV=Standard Deviation; NS=Not Supported; S=Supported.*

In examining the relationship between PB and REPLC (REPLC), the results reveal a non-significant effect (β = -0.044; t = 0.346; p = 0.729), reflecting that the hypothesis is not supported. This finding is in line with other research that have noted the "double-edged perception" phenomenon, where students are aware of the benefits of AI, while still experiencing anxiety about potential job displacement (Chan & Hu, 2023; Lin & Chen, 2024).

Furthermore, several studies indicate that PB do not necessarily reduce anxiety, as the advantages of AI may actually increase awareness of its capability to replace human roles (Peng Yang et al., 2025; Yaşar & Karagucuk, 2025).

A different pattern emerges when analysing the influence of KAI on REPLC, where a positive and significant effect is observed ($\beta = 0.252$; $t = 3.444$; $p = 0.001$), supporting the hypothesis. This outcome reinforces the argument that greater levels of AI knowledge among students, the higher the level of awareness of the potential risks of job disruption (Amiri et al., 2024; Chan & Hu, 2023). However, the literature also presents mixed evidence, suggesting that in certain contexts, AI knowledge may reduce anxiety by enhancing self-efficacy and perceived control (Klimova & Pikhart, 2025; Li et al., 2025), indicating that this relationship is inherently complex and context-dependent.

With regard to the effect of KAI on PB, the findings indicate a significant but negative relationship ($\beta = -0.211$; $t = 2.118$; $p = 0.035$), confirming the hypothesis. This finding directs that increased AI knowledge does not necessarily enhance PB; instead, it may reduce them as students become more critical of AI's limitations. This outcome is consistent with research suggesting that individuals with higher AI literacy tend to be more aware of risks, biases, and limitations, leading to more realistic evaluations of benefits (Francis et al., 2025; Preiksaitis & Rose, 2023). However, some studies report a positive relationship between knowledge and PB, particularly when AI is perceived as a supportive learning tool (Chan & Hu, 2023; Heil et al., 2025), indicating that this relationship reflects a dynamic process of critical evaluation toward technology.

Turning to the relationship between KAI and PEU, the results show an important adverse impact ($\beta = -0.278$; $t = 3.835$; $p = 0.000$), confirming the hypothesis. It implies that students with an elevated AI knowledge level might think that the AI is less straightforward to use because they are more conscious complexity and limitations. This aligns with studies showing AI literacy increases awareness of usage challenges, such as the need to critically evaluate outputs and develop effective prompting skills (Chan & Hu, 2023; Zhao et al., 2025). However, some research report that AI knowledge can enhance PEU by increasing familiarity and experience for users alongside the technology (Acosta-Enriquez et al., 2024; Tang et al., 2025), suggesting that this relationship is non-linear and context-dependent.

When assessing the first moderating effect on REPLC, shown to be non-significant ($\beta = 0.078$; $t = 0.639$; $p = 0.523$), hence the hypothesis is rejected. This result suggests that the moderating variable in the model cannot empirically strengthen or weaken the primary relationship. This is similar with prior evidence which suggests that moderating effects, particularly those related to AI literacy or perception, are not consistently supported in AI-based educational circumstances (Kai et al., 2026; Mohamed et al., 2025). Moreover, several studies emphasize that the relationships among these variables tend to be direct or mediated rather than moderated, suggesting that the influence of knowledge or perception may operate through alternative mechanisms rather than interaction effects.

Similarly, the second moderating effect on REPLC was additionally discovered to be not significant ($\beta = 0.033$; $t = 0.263$; $p = 0.792$), which means the hypothesis is not supported. This finding further underlines the lack of statistical support for the hypothesized moderating role in the model. Previous literature similarly suggests that although moderation effects—particularly those involving AI literacy or beliefs about AI— exist yet existing literature provide minimal empirical data, which is inconsistent (Chan & Hu, 2023; Li et al., 2025). Therefore, this inference points out a desire to continue theoretical development to explore more robust and context-specific moderating mechanisms in explaining REPLC.

Operational Ease versus Strategic Anxiety: Why Usability Does Not Reduce Job Concerns

Contrary to initial expectations, the findings for H1 suggest that PEU does not significantly influence REPLC. This result suggests that the ease of using AI-based lecture videos is not a sufficiently strong factor to shape students' concerns about future job displacement. Conceptually, this occurs because ease of use operates at a functional level, whereas job anxiety is rooted in psychological and structural considerations. Prior studies consistently show that simplicity of usage is more important than anxiety reduction in promoting technology adoption (Acosta-Enriquez et al., 2024; Almulla, 2024; Elnaem et al., 2025; Kai et al., 2026; Mohamed et al., 2025). Students can still feel anxiety even if the technologies are seen as easy to use since they are aware of long-term labor market repercussions (Chan & Hu, 2023; Klimova & Pikhart, 2025). The dominance of item PEU1 ("facilitates learning activities") reinforces that respondents primarily focus on practical benefits rather than career implications. Within the TAM concept, PEU acts as an antecedent of attitude formation but does not directly explain emotional responses such as anxiety (Al-Adwan et al., 2023; Zhang et al., 2025). Similarly, at UTAUT2, effort expectancy is more closely related to behavioral intention than to perceived risk, making its link to anxiety indirect (Acosta-Enriquez et al., 2024; Cortez et al., 2024). These contrasting findings suggest that the relationship between technology perception and AI-related anxiety is highly contextual and may depend on differences in digital exposure, labor market competitiveness, educational environment, and students' perceptions regarding the future relevance of human competencies in increasingly automated workplaces. Moreover, the AI anxiety framework emphasizes that anxiety is primarily driven by perceived threats rather than usability factors (Christian, Pardede, Gularso, et al., 2024; Kai et al., 2026). From a Jakarta context, students are already accustomed to user-friendly technologies, reducing the salience of ease of use as a trigger for job-related concerns. This finding highlights that ease-of-use functions as an operational enabler rather than a strategic determinant of perceived career risk.

The Double-Edged Nature of AI Benefits: When Advantage Does Not Alleviate Anxiety

A different perspective emerges from the findings of H2, where PB are also found to have no significant effect on REPLC. This result confirms the presence of ambivalence, in which the perceived advantages of AI do not automatically alleviate concerns about job displacement. Existing literature suggests that benefits such as efficiency and productivity can coexist with anxiety regarding automation (Chan & Hu, 2023; Lin & Chen, 2024; Peng Yang et al., 2025; Yaşar & Karagucuk, 2025; Yuan et al., 2025). In some cases, PB may even heighten awareness of AI's capabilities to replace human roles (Chan & Hu, 2023; Kai et al., 2026). The dominance of item PB1 ("helps in understanding course material") indicates that students emphasize short-term academic gains rather than long-term career implications. According to Social Exchange Theory (SET), individuals simultaneously evaluate benefits and costs, meaning that perceived advantages do not necessarily reduce perceived risks (Shrivastava, 2025). Furthermore, Protection Motivation Theory (PMT) explains that perceived threats can remain dominant even when benefits are high, especially if the threat is personally relevant (Shrivastava, 2025). This aligns with the notion of double-edged technology perception, where technology is viewed as both an opportunity and a threat (Klimova & Pikhart, 2025). In Jakarta, students actively use AI for learning efficiency but remain aware of intense labor market competition, limiting the anxiety-reducing effect of PB. Thus, PB tend to be tactical rather than strategic in nature and are insufficient to mitigate concerns related to long-term career sustainability. This finding extends existing models by demonstrating that the interaction between PB and psychological responses cannot be inherently linear.

AI Knowledge as a Strategic Awareness Driver of Job Displacement Anxiety

H3 demonstrates an important insight that KAI has a considerable favorable effect on REPLC. This finding shows that more comprehension improves students' awareness of technological risks, including potential job displacement. Empirical evidence supports that AI knowledge enhances awareness of automation and labor market disruption (Amiri et al., 2024; Chan & Hu, 2023; Hwang & Wu, 2025; Mohamed et al., 2025; Wang et al., 2024). However, other studies report contrasting results, suggesting that AI literacy can reduce anxiety through increased self-efficacy (Klimova & Pikhart, 2025; Laupichler et al., 2024; Li et al., 2025). From a strategic capability perspective, KAI reflects a cognitive resource that enables individuals to sense and interpret technological changes, thereby shaping their readiness to face uncertainty. In this context, AI literacy can be interpreted not only as technological knowledge, but also as a strategic intangible capability that enables students to adapt to rapidly changing workforce demands and digital transformation environments. This perspective aligns with the Resource-Based View, where knowledge-based competencies serve as key drivers of sustained advantage, and with capability theory, which emphasizes the role of adaptive capacities in responding to environmental uncertainty. The dominance of item KAI4 ("understanding accuracy") highlights that critical awareness of AI outputs triggers reflections on associated risks. Within the AI literacy framework (TPB–TAM hybrid), knowledge enhances evaluative capacity, including the identification of risks and limitations (Zhang et al., 2025). Additionally, technology displacement theory suggests that awareness of AI capabilities intensifies perceived threats to professional identity (Kai et al., 2026). This aligns with career identity theory, where individuals begin questioning the relevance of human roles in future professions. Students with a greater level of digital literacy in Jakarta are more exposed to the discussion of AI and future jobs and are more sensitive to the possibility of automation. Therefore, AI knowledge emerges as a strategic capability that strengthens awareness of technological disruption and its implications for workforce structures. From a strategic management perspective, this reinforces the role of AI literacy as an intangible asset that enhances individuals' ability to anticipate external environmental changes. Collectively, these findings indicate that AI literacy operates not only as a technological understanding mechanism, but also as a strategic cognitive capability that shapes how students interpret opportunities, risks, and future workforce uncertainty associated with artificial intelligence adoption in higher education.

From Optimism to Critical Evaluation: The Negative Reframing of AI Benefits

A contrasting pattern is observed in H4, where KAI significantly affects PB, but with a negative direction. This suggests that increased knowledge leads students to evaluate AI more critically, thereby reducing PB. Prior studies indicate that higher AI literacy is connected with increased awareness of the technology's biases and limitations, as well as risks associated with the technology (Ahmed et al., 2024; Francis et al., 2025; Hardie et al., 2026; Kamalov et al., 2023; Preiksaitis & Rose, 2023). Conversely, other research reports a positive relationship when AI is mostly seen as a learning endorse tool (Chan & Hu, 2023; Malakul, 2025; Navarrete et al., 2025; Pellas, 2023; Yan & Qianjun, 2025). The dominance of item KAI3 ("understanding complex content delivery") indicates that students increasingly assess the quality of AI outputs. Within the risk–benefit framework, higher knowledge strengthens risk evaluation, which can reduce PB (Shrivastava, 2025). In UTAUT2, experience and literacy may shift perceptions from optimistic to more realistic evaluations (Acosta-Enriquez et al., 2024). This is also consistent with cognitive elaboration theory, where knowledgeable individuals process information more critically. Students with higher exposure to AI tend to recognize trade-offs rather than viewing the technology uncritically. In Jakarta, where digital exposure is relatively high, this critical evaluation becomes more pronounced. Consequently, AI knowledge not only enhances technical understanding but also promotes strategic evaluation of the value and limitations of technology.

Understanding Complexity: How AI Knowledge Redefines Perceived Ease of Use

Further analysis of H5 reveals that KAI significantly influences PEU, but in a negative direction. This indicates that greater knowledge leads students to perceive AI as more complex rather than simpler to use. Existing studies suggest that AI literacy enhances evaluative skills but also increases awareness of operational challenges (Chan & Hu, 2023; Pham et al., 2025; Shen et al., 2025; Wu et al., 2025; Zhao et al., 2025). On the other hand, some research finds that familiarity and experience can increase PEU (Acosta-Enriquez et al., 2024; Fan et al., 2025; Han et al., 2025; Khlaif et al., 2025; Tang et al., 2025). The dominance item (KAI5) ("understanding content relevance") suggests that students focus on contextual and qualitative aspects rather than usability alone. In the UTAUT2, the increase in literacy leads to higher expectations about the functioning of the system. The evaluation of ease of use becomes more critical (Acosta-Enriquez et al., 2024). Additionally, cognitive load theory explains that deeper understanding may increase perceived complexity. This is consistent with the expertise reversal effect where more expert users are more critical of low-fidelity systems. In Jakarta, frequent exposure to AI tools makes students aware that effective use requires advanced skills such as prompting and output evaluation. These findings indicate that knowledge transforms ease of use from a simplistic perception into a more nuanced and critical assessment.

Limits of Moderation: Why AI Knowledge Does Not Shape Ease–Anxiety Linkages

The findings related to H6 demonstrate that KAI does not moderate the association between PEU and REPLC. This suggests that AI literacy, although important, is not strong enough to alter how ease of use influences anxiety. Prior literature indicates that moderation effects involving AI literacy are often inconsistent and rarely significant (Elnaem et al., 2025; Kai et al., 2026; Laupichler et al., 2024; Mohamed et al., 2025; Türk et al., 2025). This is consistent with some studies suggest that relationships among variables are more likely to be mediated rather than moderated (Li et al., 2025). Within the TPB–TAM hybrid framework, AI literacy primarily acts as a direct determinant of attitudes and perceived behavioural control rather than as a moderating variable (Zhang et al., 2025). Additionally, the AI anxiety framework emphasizes that perceived threats, rather than cognitive factors like ease of use, are the main drivers of anxiety (Kai et al., 2026). This explains why the interaction effect is statistically insignificant. In Jakarta, the relatively homogeneous level of digital literacy among students may reduce variability, weakening potential moderation effects. Therefore, AI knowledge appears to function more as a direct explanatory factor than as a conditional variable.

Independent Pathways: Decoupling AI Benefits and Job Anxiety Beyond Moderation

Finally, the data for H7 suggest that KAI does not modulate the link between PB and REPLC. This suggests that PB and anxiety operate relatively independently, regardless of students' level of AI knowledge. Existing literature supports the coexistence of PB and anxiety without strong interaction effects (Amiri et al., 2024; Chan & Hu, 2023; Peng Yang et al., 2025; Yaşar & Karagucuk, 2025; Yuan et al., 2025). Furthermore, studies highlight that AI literacy tends to act as a direct predictor rather than a moderating factor (Chan & Lee, 2023; Klimova & Pikhart, 2025; Kwak et al., 2022; Li et al., 2025; Lin & Chen, 2024). From a Social Exchange Theory perspective, benefits and risks are evaluated in parallel, meaning that moderation effects may not necessarily emerge (Shrivastava, 2025). Protection Motivation Theory also suggests that perceived threats can stand independently of PB. This helps explain the non-significant moderation effect. Students in Jakarta, regardless of their level of expertise, may understand the benefits of AI while at the same time being concerned about employment competitiveness. These outcomes suggest that AI in education should be integrated into a wider human capital plan that may boost learning efficiencies and develop the adaptive competencies that will be required to meet future labor problems.

CONCLUSION

This study successfully addressed its primary objective of examining how perceived ease of use, perceived benefits, and knowledge of generative AI influence AI job replacement anxiety within AI-based learning environments among undergraduate students in Jakarta. The findings of this study show that in the case of AI-based video learning, students' anxiety regarding potential job replacement is not directly influenced by functional aspects of technology such as PEU and PB, but rather their degree of comprehension of the technology itself plays a major role. This finding strengthens the perception that managing technological innovation in institutions of higher learning should be viewed as part of a long-term strategic effort to build human capital competitiveness. The results further highlight that the cognitive dimension, represented by knowledge of generative AI, plays a central role in fostering critical awareness of AI's implications for future employment, with greater amounts of AI literacy being linked with stronger perceptions of potential threats. From a theoretical standpoint, this work contributes to the TAM view by considering job-related anxiety to be a psychological consequence of human–AI interaction. In the same time, the results show that more knowledge does not necessarily lead to more favourable attitudes towards technology but may lead to more critical assessments of advantages and ease of use, with a trade-off between technological optimism and risk awareness. Therefore, our work supports the development of AI acceptance models in educational institutions by include REPLC as a significant psychological result, particularly when dealing with the setting of AI-powered educational settings. Conceptually, these outcomes emphasize the importance of achieving strategic alignment between technological innovation and human resource capability development in navigating digital transformation within higher education.

The consequences of this study show that higher education institutions should not only work on improving access, usability and PB of AI in learning, but also actively manage students' AI literacy and psychological preparation for changes in the labor market. Practically, institutions need to design AI implementation strategies that go beyond improving learning efficiency, incorporating the development of adaptive competencies, ethical awareness, and career preparedness in the digital era. The findings suggest the significance of balancing technology adoption with the reinforcement of humanistic ideals in education in the Indonesian socio-cultural environment so that AI is positioned as a complementing tool that enhances rather than takes over the function of human beings. From a Resource-Based View (RBV), AI literacy represents a valuable, rare, and difficult-to-imitate intangible resource that contributes to long-term individual competitiveness. Moreover, drawing on capability theory, this knowledge can be understood as a dynamic capability that allows individuals to continuously adapt, reconfigure skills, and respond strategically to technological disruptions in the labor market.

Future research is recommended to develop more comprehensive models by integrating external variables including employment prospects, self-efficacy, and career readiness, as well as examining cross-generational and cross-cultural differences to enhance generalizability. Future studies are encouraged to examine additional moderating variables, such as gender differences, prior AI experience, digital exposure intensity, and disciplinary background, to provide a more nuanced understanding of AI job replacement anxiety within higher education environments. Furthermore, AI implementation in education should be framed as part of an integrated institutional strategy that not only prioritizes learning efficiency but also strengthens students' long-term career readiness. From a human capital strategy perspective, higher education institutions are encouraged to adopt learning approaches that simultaneously integrate technological competencies and strategic awareness of AI's broader implications. Therefore, strengthening workforce readiness should be positioned as a key strategic agenda within technology-driven higher education policies. From a policy perspective, higher education institutions are encouraged to integrate AI literacy programs into curricula not only to improve technological competencies, but also to strengthen students' adaptive career readiness, critical thinking, and psychological preparedness toward future workforce transformation driven by artificial intelligence.

DECLARATIONS

Author Contribution

Gularso, K., Conceptualization, Methodology, Editing and Visualization; **Christian, M.,** Writing - Review & Editing, Software, Methodology, Formal analysis; **Nan, G.,** Editing, Visualization, Resources, Supervision; **Jiancheng, L.,** Visualization, Resources, Project administration, Supervision.

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Conflict of Interest

The authors disclose no conflict of interest.

Declaration of AI Use

This study utilized Gemini AI for generating instructional video content, sync.so for audio synchronization (as mentioned above), and ChatGPT to assist in refining wording and improving the clarity of language in the manuscript.

Data Availability

Data supporting the findings of this study are accessible from the corresponding author upon reasonable request, subject to participant confidentiality and research ethics considerations.

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