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The influence of AI literacy, subjective norm, attitude, and perceived usefulness on behavioral intention to learn ai with the mediating role of confidence in learning AI

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Abstract
Artificial Intelligence (AI) development in Indonesia has been growing rapidly, supported by national strategic initiatives, strong collaboration between academia and industry, and increasing international investment. The National Strategy for Artificial Intelligence 2020 underscores the need to promote AI advancement while maintaining data protection. A significant illustration of this progress is Nvidia's plan to establish an AI school in Central Java, demonstrating both local and global dedication to AI growth. Within the education sector, AI has become increasingly embedded in teaching, research, and administrative operations through tools such as chatbots, data analytics, and adaptive learning platforms, signaling a major shift in educational paradigms.This study seeks to analyze whether factors such as AI literacy and perceived usefulness of AI positively affect behavioral intention. A total of 104 respondents participated in the research. The result finding that the confidence of learning AI and AI Literacy, Subjective Norm, Attitude Toward using AI, Perceived Usefullness of AI influence to Behavior Intention with value 90,7 %, and the most influence to behavior intention to learn AI is subjective norm, the second is attitude toward using AI, the third is perceived usefulness of AI, the fourth is AI literacy and finaly is confidence of learning AI.

Keywords: AI literacy, subjective norm, attitude toward using ai, perceived usefulness of ai, confidence of learning ai, behavior intention

Introduction

In recent years, Indonesia has made remarkable progress in the field of Artificial Intelligence (AI), driven by government-led initiatives, collaborations between academia and industry, and substantial investments from global technology companies. The launch of the National Strategy for Artificial Intelligence (Stranas KA) in 2020 marked a key milestone in accelerating AI adoption across various sectors, with a particular focus on ensuring data security and privacy in its application.

Joint initiatives between corporations and educational institutions have also gained momentum. One prominent example is the collaboration between Indosat Ooredoo Hutchison and GoTo Gojek Tokopedia to develop Sahabat-AI, an Indonesian-language AI ecosystem. Supported by AI Singapore and Tech Mahindra and powered by Nvidia's AI Enterprise platform, this project aims to foster the development of AI-based applications that are culturally and linguistically aligned with Indonesia's context.

Global technology companies have likewise demonstrated increased engagement in Indonesia's AI landscape. Nvidia, for example, has announced plans to establish a specialized AI school in Central Java as part of its broader investment strategy in several Indonesian cities (Reuters, 2024) [32].

The integration of AI in higher education is also expanding rapidly, reshaping multiple academic domains. AI technologies are now being employed to enhance student learning, facilitate research, and improve administrative efficiency. Key applications include AI-driven chatbots for student assistance, data analytics for improving teaching quality, and adaptive learning systems that personalize instruction reflecting the growing adoption of AI across educational institutions.

Literature Review

AI Literacy

According to Ng *et al*. (2021), AI literacy refers to a set of competencies that enable individuals to critically evaluate artificial intelligence, interact and collaborate effectively with AI systems, and utilize AI tools in diverse contexts. In a similar vein, Long and Magerko (2020a) [24, 25] emphasize the core skills necessary for fostering AI literacy and for designing educational frameworks that support AI understanding. Laupichler *et al*. (2022) [23] further expand on this by reviewing literature focused on incorporating AI literacy into higher and adult education. Collectively, these studies conceptualize AI literacy as the capability to critically assess AI technologies, engage and cooperate productively with AI, and apply AI applications effectively across digital, domestic, and professional domains (Long & Magerko, 2020b) [24, 25].

Confidence of using AI

Chong *et al*. (2022) [10] explored the evolution of two distinct forms of human confidence—confidence in AI systems and self-confidence—and their influence on decision-making. The study revealed that designers' confidence in AI fluctuated in response to poor AI performance but remained stable during periods of strong performance. Interestingly, initial confidence levels were not influenced by AI accuracy; however, any subsequent changes in performance, whether positive or negative, resulted in a reduction in confidence (Chong *et al*., 2023) [9]. Expanding upon Hu *et al*.'s (2019) dynamic trust model, Chong *et al*. (2023) [9]. proposed a confidence model that predicts these behavioral patterns based on prior experience, cumulative confidence, and bias. This framework applies to

both confidence in AI and self-confidence, with the experience component remaining stable, while confidence, accumulated confidence, and bias terms vary depending on whether the focus is directed toward AI systems or the individual (Long & Magerko, 2020b) [24, 25].

Subjective Form

Ham *et al*. (2015) [14] examined the influence of two distinct forms of subjective norms in determining consumers' intentions to purchase green food products. Similarly, Niemiec *et al*. (2020) [29] distinguished among subjective, descriptive, and personal norms, emphasizing their respective roles in shaping conservation-related behaviors. Jermsittiparsert *et al*. (2023) [16] further investigated the relationship between subjective norms and the adoption of e-banking, highlighting the mediating role of perceived usefulness in this process. Building upon these perspectives, Walker *et al*. (2013) [36] conceptualized subjective norm as an individual's perception of social approval and support for engaging in a particular behavior, in conjunction with perceived behavioral control (PBC), which reflects one's perceived capability to execute that behavior.

Attitude Toward using AI

Hanoch and Wood (2024) note that public apprehension toward artificial intelligence (AI) remains prevalent, often influenced by demographic variables such as age and prior exposure to media portrayals of AI. Expanding on this, Koenig (2024) [22] identifies three dimensions of AI acceptance: user-centered technology acceptance, acceptance of delegation and automation, and societal-level technology adoption acceptance. Meanwhile, Grassini (2023) [13] concentrated on the development and validation of an AI Attitude Scale, designed to measure perceptions of AI's usefulness as well as its broader implications for society and humanity. Furthermore, Grassini (2023) [13] defines behavioral intention to use AI as an individual's willingness or readiness to engage with and utilize AI technologies.

Perceived Usefulness of AI

Klarin *et al*. (2024) [21] investigate the relationship between adolescents' executive function and their frequency and perceived usefulness of generative AI chatbots for schoolwork. Kim *et al*. (2024) [20] extend the Technology Acceptance Model (TAM) to examine the role of both utilitarian and hedonic values in the adoption of AI conversational agents. Furthermore, Sadriwala and Sadriwala (2022a) [33, 34] analyze the impact of perceived usefulness and ease of use of AI on marketing innovation. Ardiyanti and Susilowati (2024) [3] define perceived usefulness as a user's belief that a system can enhance time efficiency, increase productivity, and accelerate activities.

Behavioral Intention

Chao (2019) [7] proposed a predictive model to identify the key determinants influencing students' behavioral intentions toward adopting mobile learning (m-learning). In a related study, Unal and Uzun (2021) [35] analyzed quantitative data to explore the factors that shape university students' behavioral intentions to use Edmodo, a widely utilized educational social networking platform. Similarly, Chaveesuk *et al*. (2022) [8] investigated how perceived usefulness and perceived ease of use affect individuals' behavioral intentions to engage in mobile payment systems. Collectively, these studies align with the foundational definition of behavioral intention (BI) proposed by Warshaw and Davis (1985) [38], who describe it as the degree to which a person has consciously formulated a plan to perform or refrain from performing a particular future action.

AI Literacy has positively influence to Behavior Intention

Wang *et al*. (2024) [37] employed structural equation modeling and qualitative interviews to examine Chinese university students' adoption of generative AI. Their results revealed that AI literacy and subjective norms exert a positive influence on students' attitudes and perceived behavioral control toward generative AI, both of which serve as mediating factors in shaping their intention to use the technology. Similarly, Jang (2024) [15] explored determinants affecting South Korean university students' intention to adopt text-based generative AI tools. By extending the Unified Theory of Acceptance and Use of Technology (UTAUT) with the inclusion of AI literacy, a survey of 239 business students demonstrated that AI literacy, performance expectancy, and social influence significantly predict their intention to utilize such tools for learning purposes. In a related study, Du *et al*. (2024) [11] investigated the connection between AI literacy and teachers' behavioral intentions to engage with AI. Their findings indicate that AI literacy directly enhances teachers' motivation and willingness to participate in AI-related professional development activities. So the hypothesis is H1**:** AI Literacy has positively influence to Behavior Intention

Subjective Norm has positively influence to Behavior Intention

Frans Warmanto M.B. (2005) [12] found that although subjective norms did not have a significant effect on the intention to share knowledge, both attitude and perceived behavioral control exhibited significant positive influences. Similarly, Ali Maskur *et al*. (2020) [1] reported that in the context of customers' intention to obtain Micro People's Business Credit (KUR), subjective norms were not significant predictors, whereas perceived behavioral control had a positive and significant impact. In contrast, Bella Risca Monica *et al*. (2019) [4] identified a significant relationship between subjective norms and the intention of housewives at risk of HIV to access Voluntary Counseling and Testing (VCT) services, along with the influence of knowledge and perceived behavioral control. So the hypothesis is H2: Subjective Norm has positively influence to Behavior Intention

Attitude toward using AI has positively influence to Behavior Intention

Yeunhee Kwak (2022) [39] explored the influence of AI ethical awareness, attitude toward AI, AI-related anxiety, and self-efficacy on nursing students' willingness to adopt artificial intelligence technologies. In a related study, Jiao and Cao (2024a) [17, 18] investigated designers' adoption of AI-assisted design (AIAD) by integrating the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) to identify the factors shaping their behavioral intention to utilize AIAD tools. Furthermore,

Odai *et al*. (2024) [30] employed a Likert-scale approach to measure participants' attitudes toward generative AI and their behavioral intention to use it within academic settings, ultimately analyzing the interrelationship between these two constructs. So the hypothesis is H3: Attitude toward using AI has positively influence to Behavior Intention

Perceived usefulness of AI has positively influence to Behavior Intention

Jiao and Cao (2024b) [17,18] discovered that designers' behavioral intention to adopt AI-assisted design (AIAD) increases when they perceive greater benefits from its use, highlighting that demonstrating AI's practical value is essential for promoting adoption. In a similar vein, Sadriwala and Sadriwala (2022b) [33,34] identified a significant positive relationship between the perceived usefulness of AI and marketing innovation, which subsequently influences individuals' intention to utilize AI technologies. Likewise, Jo (2022) emphasized both the direct and indirect effects of perceived usefulness on users' intention to continue using AI-based personal assistants, reinforcing its pivotal role in shaping sustained user engagement and long-term behavioral intention. So the hypothesis is H4: Attitude toward using AI has positively influence to Behavior Intention So the hypothesis is H4: Perceived usefulness of AI has positively influence to Behavior Intention

AI literacy has positively influence to Confidence of Learning AI

Several recent studies consistently demonstrate that AI literacy has a positive influence on individuals' confidence in learning AI. Bewersdorff *et al*. (2024) [5] found that university students with higher AI literacy levels exhibit stronger self-efficacy and confidence in understanding and applying AI concepts, emphasizing that knowledge of AI fundamentals enhances learners' perceived competence. Similarly, Alt *et al*. (2025) [2] in Smart Learning Environments reported that students' technical and practical dimensions of AI literacy significantly and positively affect their AI self-efficacy, suggesting that familiarity with AI tools builds confidence in learning and experimentation. Supporting these findings, Li, Deng, and Chen (2025) introduced the 'A-factor' framework, showing that individuals with stronger AI literacy perform better and demonstrate greater trust and confidence when collaborating with AI systems. Collectively, these studies highlight that strengthening AI literacy not only enhances understanding but also fosters psychological readiness and confidence to engage in AI learning and application. So the hypothesis is H5: AI literacy has positively influence to Confidence of Learning AI.

Confidence of Learning AI has positively influence to Behavior Intention

Pratama (2024) [24] examined the influence of individuals' attitudes toward artificial intelligence (AI) on both their initial adoption and continued use of AI in performing routine tasks. The results indicated that a positive attitude toward AI significantly enhances an individual's intention to utilize the technology. Similarly, Ma (2024) investigated the impact of human confidence calibration within AI-assisted decision- making contexts. The findings showed that when human confidence is accurately calibrated, it not only enhances the overall performance of human–AI collaborations but also promotes a more rational and balanced reliance on AI systems. So the hypothesis is H6: Confidence of Learning AI has positively influence to Behavior Intention.

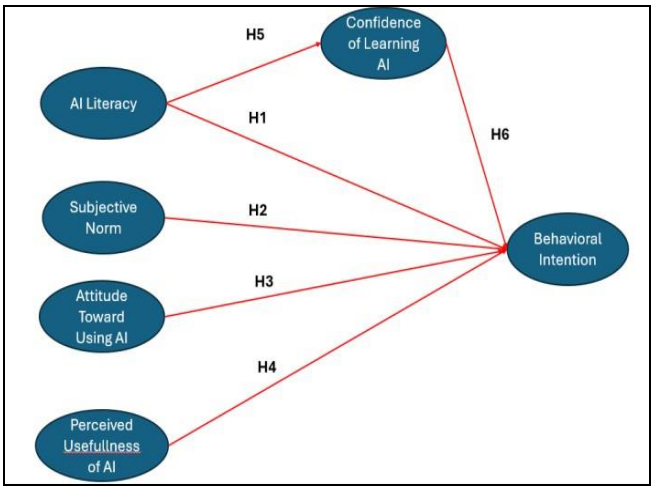

Fig 1: Conceptual Framework

For data analysis, this research utilizes Partial Least Squares Structural Equation Modeling (PLS-SEM), specifically with SmartPLS version 3.2.9. The PLS-SEM approach involves two main components: the outer model and the inner model. The outer model focuses on the connections between indicators and their corresponding latent variables. This step ensures the quality of the measurement model by assessing the reliability and validity of the indicators for the measured variables, as noted by Hair *et al*. (2019). Conversely, the inner model serves as the structural model. It evaluates the overall quality of the entire research model by analyzing the significance of relationships between different constructs, typically through a path coefficient analysis.

Outer Model

When analyzing data with PLS-SEM, the outer model is crucial for evaluating the reliability and validity of the measured indicators, as detailed by Hair *et al*. (2019). This assessment happens in several steps. First, individual indicators are checked, requiring an outer loading value greater than 0.708. Next, the construct reliability is confirmed by ensuring both Cronbach's alpha and composite reliability results exceed 0.7. Following this, construct validity is established if the average variance extracted (AVE) is higher than 0.5. Finally, discriminant validity is assessed using the heterotrait-monotrait ratio (HT/MT), which must be below 0.9 to meet the criteria.

Inner Model

The inner model in PLS-SEM represents the structural relationships between latent variables within a study. To assess this model, the first step involves checking the Variance Inflation Factor (VIF) to detect multicollinearity, ideally with values below 3. Hair *et al*. (2019) note that VIF values between 3 and 5 suggest potential multicollinearity, while values exceeding 5 indicate a critical state. Next, the coefficient of determination, or R^2, is examined. This value, ranging from 0 to 1, indicates how well the PLS-SEM

model explains the relationships Hypothesis testing is a crucial phase, using bootstrapping to determine the relationships and significance between variables. This study employs a one-tail method to test for positive influences, with a significance level of 0.05 and infinite degrees of freedom, setting the T-Table value at 1.645. If the calculated T-value from bootstrapping exceeds 1.645, it indicates a positive influence. Alternatively, a P-value below 0.05 also signifies a significant relationship between variables.

Variable Operationalization

Table 1: Operationalization of Variable

Variable	Definition	Operationalization of Variable		
AI Literacy	a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace. (Long & Magerko, 2020b) [24,25]	I understand why AI technology needs big data	AL1	(Chai *et al*., 2020) [4]
		I know the processes through which deep learning enables AI to perform voice recognition tasks	AL2	
		I understand how AI technology optimizes the translation output for online translation.	AL3	
		I understand how AI assistant such as SIRI or Hello Google handles human-computer interaction	AL4	
		I know how AI can be used to predict possible outcomes through statistics	AL5	
		I understand how computers process image to produce visual recognition	AL6	
Confidence of Learning AI	The model predicts the dynamics of human confidence based on experience, accumulated confidence, and bias (Jermsittiparsert *et al*., 2023) [16]	I feel confident that I will do well in the AI classes	CL1	(Chai *et al*., 2020) [4]
		As I am taking the AI classes; I believe that I can succeed if I try hard enough.	CL2	
		I have fun using AI technology	CL3	
		I am confident I can learn the basic concepts about AI taught in the lessons.	CL4	
		I am confident I can understand the most complex material presented by the instructor in the AI classes.	CL5	
Subjective Norm	is defined as the perceived social acceptance and support for the behaviour; and perceived behavioural control (PBC), which refers to one's perceived ability to perform the behaviour. (Walker *et al*., 2013) [36]	My classmates feel that it is necessary to learn about AI technology	SN1	(Chai *et al*., 2020) [4]
		My parents support me to learn about AI technology	SN2	
		Most people I know think that I should learn about AI technology	SN3	
Attitude Toward using A	Subjective norm is defined as is defined as the perceived social acceptance and support for the behaviour; and perceived behavioural control (PBC), which refers to one's perceived ability to perform the behaviour. (Walker *et al*., 2013) [36]	Using AI technology is pleasant.	AT1	(Chai *et al*., 2020) [4]
		I find using AI technology to be enjoyable	AT2	
		I have fun using AI technology	AT3	
Perceived Usefulness of AI	perceived usefulness is a user's belief that the system is able to increase time efficiency, increase productivity and speed up activities. (Ardiyanti & Susilowati, 2024)	Using AI technology enables me to accomplish tasks more quickly	PU1	(Chai *et al*., 2020) [4]
		Using AI technology enhances my effectiveness	PU2	
		Using AI technology improves my performance	PU3	
		Using AI technology increases my productivity.	PU4	
Behavioral Intention	Behavior intention (BI) is defined as the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior. (Warshaw & Davis, 1985) [38]	I will continue to learn AI technology in the future	BI1	(Chai *et al*., 2020) [4]
		I will keep myself updated with the latest AI applications	BI2	
		I plan to spend time in learning AI technology in the future	BI3	
		I will pay attention to emerging AI applications	BI4	

Table 2: Construct Reliability

	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Ai literacy	0,853	0,901	0,697
Attitude toward using ai	0,935	0,958	0,885
Behavior intention	0,912	0,939	0,795
Confidence of learning ai	0,816	0,915	0,843
Perceived usefullness of ai	0,864	0,917	0,788
Subjective norm	0,890	0,932	0,820

All Cronbach alpa has > 0,05, and composite reliabity has > 0,7, so it has reliable all construct, so it has already reliable (Hair *et al*., 2019)

Table 3: Inner VIF

	Ai literacy	Attitude toward Using AI	Behavior intention	Confidence of learning Ai	Perceived usefulness of Ai	Subjective norm
Ai literacy						
Attitude Toward using ai	0,683					
Behavior intention	0,845	0,899				
Confidence of Learning AI	0,599	0,557	0,595			
Perceived usefullness of AI	0,558	0,716	0,776	0,612		.
Subjective norm	0,857	0,696	0,958	0,640	0,597	

All VIF has < 5, so it has reliable all construct, so it has already valid (Hair *et al*., 2019).

Table 4: R Squared is moderate, based on (Hair *et al*., 2019)

	R-square	R-square adjusted
Behavior intention	0,907	0,890
Confidence of learning AI	0,269	0,246

Result

PLS-SEM Result

The most semester is in fourth semester with value 39.4 % and 64.4 % is female.

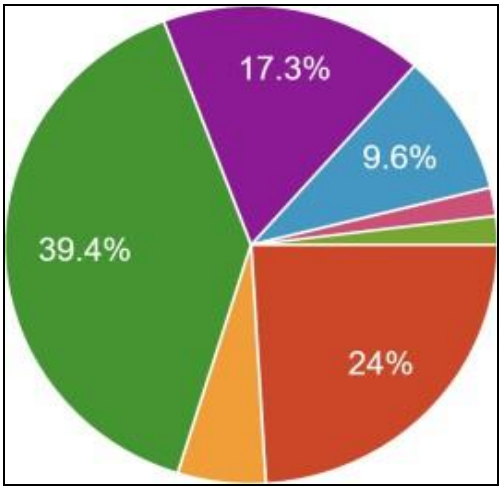

Fig 2: Semester

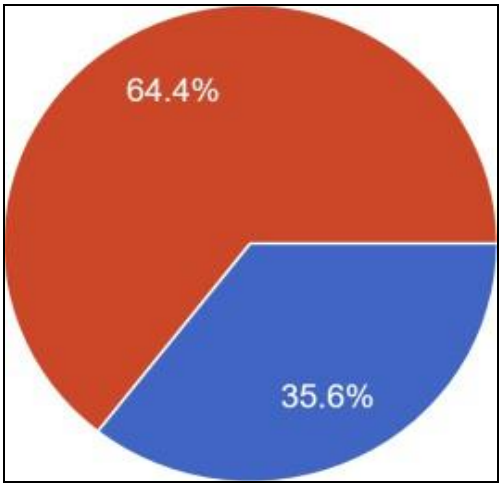

Fig 3: Female

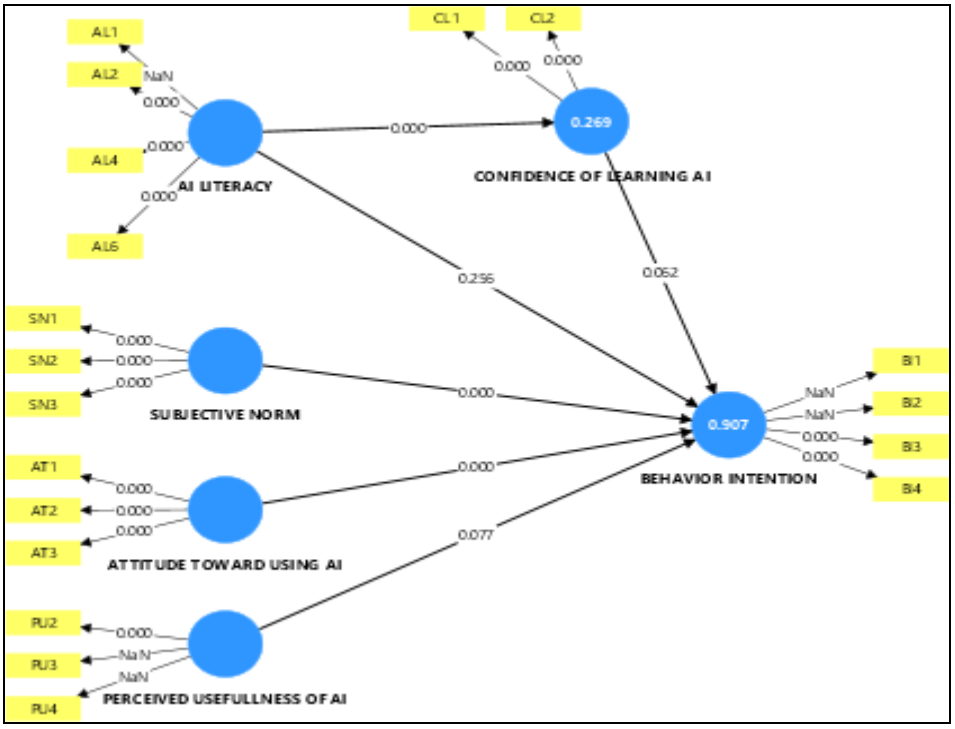

Fig 2: Outer Loading Table 5. Bootstrapping

Table 5: Bootstrapping

	Original sample (O)	T statistics (|O/STDEV|)	P values	Result
Ai literacy -> behavior intention	0,098	0,656	0,256	Not Supported
Ai literacy -> confidence of Learning AI	0,518	3,706	0,000	Supported
Attitude toward using ai -> Behavior intention	0,381	3,309	0,000	Supported.
Confidence of learning AI -> Behavior intention	-0,110	1,539	0,062	Not Supported
Perceived usefullness of AI -> Behavior intention	0,201	1,426	0,077	Not. Supported
Subjective norm -> behavior Intention	0,500	3,818	0,000	Supported

All hypothesis has t statistic > 1.65 and p values has < 0.05, so AL-> BI and SN-> PU has positive influence and has significant.

Discussion

The bootstrapping results presented in Table 5 provide an overview of the hypothesized relationships among variables related to the behavioral intention to use Artificial Intelligence (AI). Out of the six hypothesized paths, three are supported while the other three are not. This indicates that although certain factors significantly influence behavioral intention toward AI usage, some expected relationships do not hold statistically. The results highlight the complexity of behavioral determinants in the adoption of AI technologies, suggesting that cognitive, affective, and social elements contribute differently to individuals' intentions.

The path coefficient between AI Literacy and Behavioral Intention ($\beta = 0.098$, $t = 0.656$, $p = 0.256$) is not statistically significant, indicating that AI literacy alone does not directly influence individuals' intention to use AI. This result suggests that simply possessing knowledge or awareness about AI may not be sufficient to drive behavioral intention. In other words, being literate in AI does not necessarily translate into a motivation to engage with or adopt AI technologies, unless supported by other psychological or contextual factors such as confidence, perceived usefulness, or social influence.

Conversely, the relationship between AI Literacy and Confidence of Learning AI is strongly supported ($\beta = 0.518$, $t = 3.706$, $p < 0.001$). This finding indicates that individuals with higher AI literacy tend to have greater confidence in their ability to learn and use AI-related tools. This aligns with previous research emphasizing the importance of foundational literacy in reducing technological anxiety and enhancing self-efficacy. Hence, AI literacy serves as a critical enabler that fosters positive learning attitudes toward AI technologies.

The path from Attitude Toward Using AI to Behavioral Intention is also significant ($\beta = 0.381$, $t = 3.309$, $p < 0.001$), supporting the notion that positive attitudes toward AI use strongly predict the intention to adopt it. This result corroborates the Technology Acceptance Model (TAM), which emphasizes the role of attitude as a mediating variable between beliefs and behavioral intention. When individuals perceive AI as beneficial, interesting, or valuable, they are more likely to intend to use it in their personal or professional contexts.

The relationship between Confidence of Learning AI and Behavioral Intention is not supported ($\beta = -0.110$, $t = 1.539$, $p = 0.062$). Although confidence is generally assumed to enhance behavioral intention, this finding implies that confidence alone may not guarantee a willingness to use AI. One possible explanation is that confident individuals may still have reservations or perceive external barriers, such as ethical concerns, complexity, or institutional support, which weaken the direct translation of confidence into intention. This finding invites further investigation into mediating or moderating factors.

Interestingly, Perceived Usefulness of AI does not show a significant relationship with Behavioral Intention ($\beta = 0.201$, $t = 1.426$, $p = 0.077$). This contradicts the core assumption of TAM, where perceived usefulness is usually a strong predictor of intention. The result may suggest that users' behavioral intentions toward AI are influenced more by affective or normative factors rather than by purely utilitarian considerations. In other words, individuals might decide to use AI not necessarily because they find it useful, but because of attitudes or social norms encouraging AI engagement.

Finally, the path from Subjective Norm to Behavioral Intention is significant and positive ($\beta = 0.500$, $t = 3.818$, $p < 0.001$), indicating that social influence plays a key role in shaping individuals' intention to use AI. When peers, colleagues, or authority figures support AI usage, individuals are more likely to form favorable behavioral intentions. This finding highlights the cultural and organizational dimensions of AI adoption, suggesting that policy interventions, leadership endorsement, and community awareness can substantially strengthen AI acceptance and behavioral readiness.

Conclusion

This study concludes that individuals' behavioral intention to use Artificial Intelligence (AI) is influenced by a combination of attitudinal and social factors rather than purely cognitive or utilitarian dimensions. Among the six hypothesized relationships, three were found to be significant: AI Literacy → Confidence of Learning AI, Attitude Toward Using AI → Behavioral Intention, and Subjective Norm → Behavioral Intention. These results demonstrate that while knowledge and understanding of AI can enhance learning confidence, the actual intention to adopt AI is more strongly driven by positive attitudes and perceived social expectations.

From a theoretical perspective, the findings partially support the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). While attitude and subjective norms emerged as strong predictors of behavioral intention, perceived usefulness did not have a significant influence.

This suggests that the traditional assumption that usefulness drives adoption may not fully apply to AI, a technology often surrounded by uncertainty and ethical concerns. Instead, affective and normative components play a more decisive role, indicating that emotional readiness and social encouragement are key elements in promoting AI adoption.

Practically, the study implies that initiatives to promote AI adoption should not only focus on improving technical literacy but also on shaping positive perceptions and supportive social environments. Educational programs,

workplace training, and public campaigns should aim to increase confidence in learning AI while simultaneously fostering favorable attitudes and emphasizing social endorsement. Future research is encouraged to explore mediating and moderating factors—such as trust in AI, perceived risk, or institutional support—that could further explain the complex relationship between literacy, confidence, and behavioral intention in diverse cultural and professional settings.

The result finding that the confidence of learning AI and AI Literacy, Subjective Norm, Attitude Toward using AI, Perceived Usefullness of AI influence to Behavior Intention with value 90,7 %, and the most influence to behavior intention to learn AI is subjective norm, the second is attitude toward using AI, the third is perceived usefulness of AI, the fourth is AI literacy and finaly is confidence of learning AI.

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