



## Mediating roles of subjective norms and perceived usefulness in ai adoption: An examination of behavioral intention

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### Abstract

Artificial Intelligence (AI) in Indonesia is experiencing rapid growth, driven by national strategies, collaboration between industry and academia, and international investments. The 2020 National Strategy for AI highlights the importance of advancing AI while ensuring data security. A notable example of these efforts is Nvidia's planned AI school in Central Java, reflecting both local and global commitment to AI development. In the education sector, AI is increasingly integrated into learning, research, and administrative processes through technologies like chatbots, data analytics, and adaptive learning systems, signaling a significant transformation in educational practices. This research aims to examine whether factors such as AI literacy, and perceived usefulness of AI positively influence behavioral intention. The study involved 104 respondents, and the key findings are as follows, Attitude Toward Using AI does not have a significant or positive impact on behavioral intention, with a path coefficient of 33.7%. Confidence in Learning AI has no positive and no significant influence on behavioral intention, with a path coefficient of 13.9 %. Perceived Usefulness of AI has no positive but not significant effect, with a path coefficient of 2%. Subjective Norm has no positive and significant effect on behavioral intention, with a path coefficient of 20 %, though the p-value is  $< 0.05$ . AI Literacy shows a positive and significant influence on behavioral intention, also with a path coefficient of 29.6% and a p-value  $< 0.05$ . Collectively, these variables account for 70.7 % of the variance in behavioral intention, indicating a strong explanatory power (coefficient of determination). Additionally, the  $Q^2$  value for behavioral intention is 51%, reflecting a large level of predictive relevance.

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

### Introduction

Indonesia has seen significant advancements in artificial intelligence (AI) in recent years, driven by a range of government programs, partnerships between industry and academia, and investments from international tech giants. In 2020, the Indonesian government introduced the National Strategy for Artificial Intelligence (Stranas KA) to accelerate AI development and integration across various sectors. This strategy places a strong emphasis on data protection and privacy in AI implementation.

Collaborative efforts between companies and educational institutions have also emerged, such as the partnership between Indosat Ooredoo Hutchison and GoTo Gojek Tokopedia to create Sahabat-AI—an AI language model ecosystem tailored for the Indonesian language. Supported by AI Singapore, Tech Mahindra, and powered by Nvidia's AI Enterprise platform, Sahabat-AI is designed to support the creation of AI-driven applications that are sensitive to local cultural and linguistic contexts.

Furthermore, global tech firms have shown growing interest in Indonesia's AI landscape. Nvidia, for instance, is planning to establish a dedicated AI school in Central Java as part of its broader investment in multiple Indonesian cities. (Reuters, 2024) <sup>[29]</sup>,

The integration of artificial intelligence (AI) in higher education is expanding rapidly and playing an important role in transforming multiple educational functions. AI is being utilized to improve student learning experiences, support academic research, and streamline administrative and assessment processes. Key implementations of AI in the academic field include chatbots that assist students in

obtaining information, the use of data analytics to enhance teaching quality, and adaptive learning systems powered by AI to personalize instruction. These examples reflect the growing presence of AI technologies within higher education institutions.

### Literature Review

#### 1. AI Literacy

According to Ng *et al.* (2021) <sup>[25]</sup>, AI literacy encompasses the abilities needed to critically assess AI, communicate and collaborate effectively with AI systems, and leverage AI tools across various settings. Similarly, Long and Magerko (2020a) <sup>[22, 23]</sup>, delve into the competencies essential for AI literacy and educational design for AI. Laupichler *et al.* (2022) <sup>[21]</sup>, conducted a literature review on integrating AI literacy into higher and adult education. Ultimately, AI literacy can be understood as the skills that empower individuals to critically evaluate AI technologies, interact and cooperate efficiently with AI, and apply AI as a tool in online environments, at home, and professionally (Long & Magerko, 2020b) <sup>[22, 23]</sup>.

#### 2. Confidence of using AI

Chong *et al.* (2022) <sup>[8]</sup>, investigated how two types of human confidence—in AI and in oneself—evolve and impact decision-making. Their findings indicated that designers' confidence in AI agents shifted with poor AI performance but not with good performance. Interestingly, initial confidence levels were unaffected by AI accuracy; however, any subsequent change in accuracy, regardless of direction, led to a decrease in confidence (Chong *et al.*, 2023) <sup>[7]</sup>.

Building on Hu *et al.*'s (2019) dynamic trust model, Chong *et al.* (2023)<sup>[7]</sup>, developed a confidence model that predicts these dynamics based on experience, accumulated confidence, and bias. This model applies to both confidence in AI and self-confidence. While the experience term remains constant, the confidence, accumulated confidence, and bias terms adjust depending on whether the focus is on AI or oneself (Long & Magerko, 2020b)<sup>[22, 23]</sup>.

### 3. Subjective Form

Ham *et al.* (2015)<sup>[13]</sup>, specifically analyze the role of two types of subjective norms in shaping the intention to buy green food. Niemiec *et al.* (2020)<sup>[26]</sup>, differentiate between subjective, descriptive, and personal norms and discuss their impact on conservation behavior. Jermstittiparsert *et al.* (2023)<sup>[15]</sup>, explore how subjective norms affect the adoption of e-banking, particularly through their influence on perceived usefulness. Ultimately, Walker *et al.* (2013)<sup>[13]</sup>, define subjective norm as the perceived social acceptance and support for a behavior, alongside perceived behavioral control (PBC), which is an individual's perceived ability to perform that behavior.

### 4. Attitude Toward using AI

Hanoch and Wood (2024) observe that many people are quite apprehensive about AI's potential, a sentiment often linked to demographic factors like age and prior media exposure. Koenig (2024)<sup>[20]</sup>, further categorizes AI acceptance into three types: user-centered technology acceptance, delegation and automation acceptance, and societal technology adoption acceptance. Meanwhile, Grassini (2023)<sup>[12]</sup>, focused on developing and validating an AI attitude scale that assesses the perceived utility and potential impact of AI on society and humanity. Grassini (2023)<sup>[12]</sup>, also defines behavioral intention to use AI as an individual's willingness to utilize the technology

### 5. Perceived Usefulness of AI

Klarin *et al.* (2024)<sup>[19]</sup>, investigate the relationship between adolescents' executive function and their frequency and perceived usefulness of generative AI chatbots for schoolwork. Kim *et al.* (2024)<sup>[18]</sup>, 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)<sup>[30]</sup>, analyze the impact of perceived usefulness and ease of use of AI on marketing innovation. Ardiyanti and Susilowati (2024)<sup>[2]</sup>, define perceived usefulness as a user's belief that a system can enhance time efficiency, increase productivity, and accelerate activities.

### 6. Behavioral Intention

Chao (2019)<sup>[5]</sup>, developed a model to predict the elements that drive students' behavioral intention to use mobile learning (m-learning). Unal and Uzun (2021)<sup>[31]</sup>, investigated the factors influencing college students' behavioral intention to use Edmodo, a popular educational social networking site, by analyzing quantitative responses. Similarly, Chaveesuk *et al.* (2022)<sup>[6]</sup>, examined variables, including perceived usefulness and ease of use, that impact the behavioral intention to use mobile payments. Ultimately, Warshaw and Davis (1985)<sup>[34]</sup>, define behavioral intention (BI) as the extent to which an individual has consciously planned to perform, or not perform, a specific future action.

### 7. AI Literacy influence to Behavior Intention

Wang *et al.* (2024)<sup>[33]</sup>, used structural equation modeling and interviews to analyze Chinese university students' adoption of generative AI. Their findings indicate that AI literacy and subjective norms positively impact students' attitudes and perceived behavioral control toward generative AI, which in turn mediates their intention to use the technology. Similarly, Jang (2024)<sup>[24]</sup>, investigated the factors influencing South Korean university students' intention to use text-based generative AI tools. By modifying the Unified Theory of Acceptance and Use of Technology (UTAUT) with AI literacy, a survey of 239 business students revealed that AI literacy, performance expectations, and social influence significantly affect their intention to use these tools for learning. Finally, Du *et al.* (2024) explored the relationship between AI literacy and teachers' behavioral intentions to learn about AI. Their research showed that AI literacy directly influences teachers' willingness to engage in various AI-related professional learning activities.

### 8. Confidence of Learning AI to Behavior Intention

Pratama (2024)<sup>[28]</sup>, investigated how individuals' attitudes toward AI influence their initial and continued use of AI for routine tasks. The analysis revealed that a positive attitude toward AI significantly increases the intention to use the technology. Ma (2024) explored the role of human confidence calibration in AI-assisted decision-making. This research demonstrated that properly calibrated human confidence can improve the performance of human-AI teams and foster a more rational reliance on AI.

### 9. Subjective Norm to Behavior Intention

Frans Warmanto MB (2005)<sup>[10]</sup>, found that while subjective norms didn't significantly impact the intention to share knowledge, both attitudes and behavioral control had a significant positive effect. Similarly, Ali Maskur *et al.* (2020)<sup>[1]</sup>, reported that for customers' intention to borrow Micro People's Business Credit (KUR), subjective norms were not significant, but perceived behavioral control had a positive and significant influence. In contrast, Bella Risca Monica *et al.* (2019)<sup>[3]</sup>, discovered a significant relationship between subjective norms and the intention of housewives at risk of HIV to access Voluntary Counseling and Testing (VCT) services, alongside their knowledge and perceived behavioral control.

### 10. Attitude toward using AI to Behavior Intention

Yeunhee Kwak (2022)<sup>[35]</sup>, identified how AI ethical awareness, attitude toward AI, anxiety, and self-efficacy impact nursing students' willingness to adopt AI. Jiao and Cao (2024a)<sup>[16]</sup>, examined designers' adoption of AIAD by applying the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) to analyze the factors influencing their behavioral intention to use AIAD. Lastly, Odai *et al.* (2024)<sup>[27]</sup>, used a Likert scale to measure respondents' attitudes toward generative AI and their behavioral intention to use it in an academic context, ultimately assessing the relationship between these two aspects.

### 11. Perceived usefulness of AI to Behavior Intention

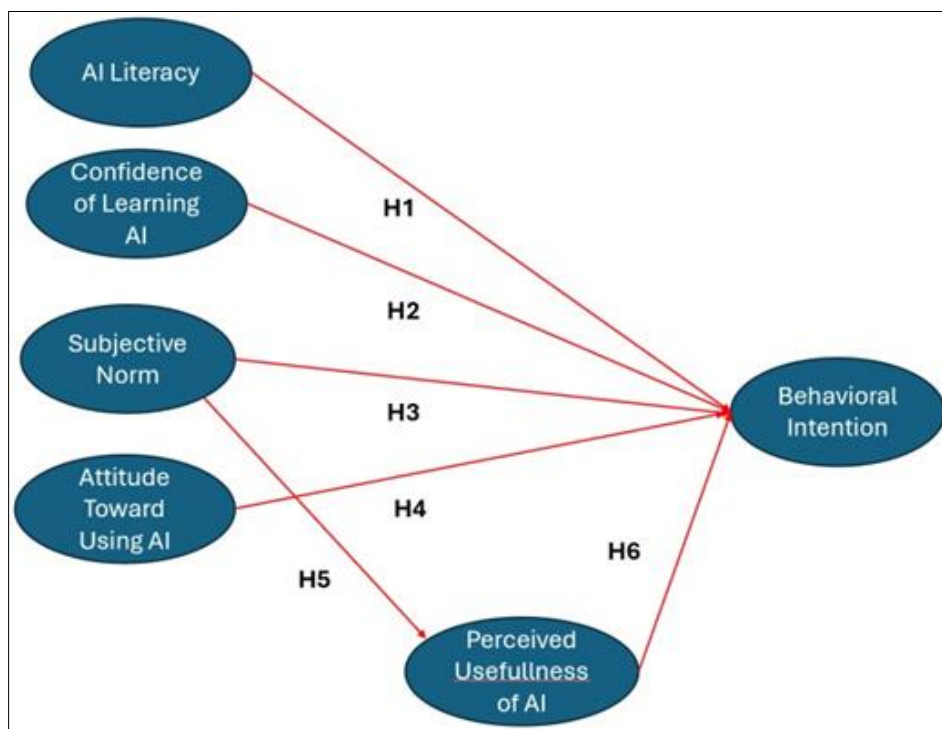
Jiao and Cao (2024b)<sup>[16]</sup>, found that when designers perceive greater benefits from using AIAD, their behavioral

intention to use it increases. This suggests that demonstrating the practical advantages of AI is key to encouraging its adoption. Similarly, Sadriwala and Sadriwala (2022b) <sup>[30]</sup>, showed a significant positive link between the perceived usefulness of AI and marketing innovation, which in turn influences the intention to use AI. Finally, Jo (2022) emphasized the direct and indirect impact of perceived usefulness on users' intention to continue using AI-based personal assistants, underscoring its importance in shaping longterm user behavior.

**12. Subjective Norm to Perceived Usefulness of AI**

The influence of social pressure, or subjective norms, on an individual's perception of AI's usefulness is a significant area of research. For instance, a study by Wang *et al.* (2023) within the context of e-commerce AI explicitly found that subjective norms directly influenced both perceived usefulness and perceived ease of use. This suggests that if an individual's important social circle—be it colleagues,

friends, or family—perceives an AI tool as beneficial, it can directly enhance that individual's own belief in its utility and ease of use. This highlights how shared social endorsements can shape an individual's assessment of AI's practical value. Further research reinforces this connection. Ye *et al.* (2019), in their study on public acceptance of AI in medical settings, revealed a multifaceted relationship where subjective norms significantly influenced the intention to use AI devices, with perceived usefulness acting as a mediating factor. This indicates that social expectations can indirectly lead to a stronger perception of AI's benefits, which then drives adoption. Similarly, an *et al.* (2023) observed that both perceived usefulness and subjective norms significantly explained English teachers' behavioral intention to use AI tools. While this study directly links subjective norms to intention, the underlying premise of technology acceptance models suggests that social influence often operates by fostering a collective understanding of an AI tool's practical advantages, thereby bolstering its perceived usefulness.



**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.

**1. 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.

**2. 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<sup>2</sup>, 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.

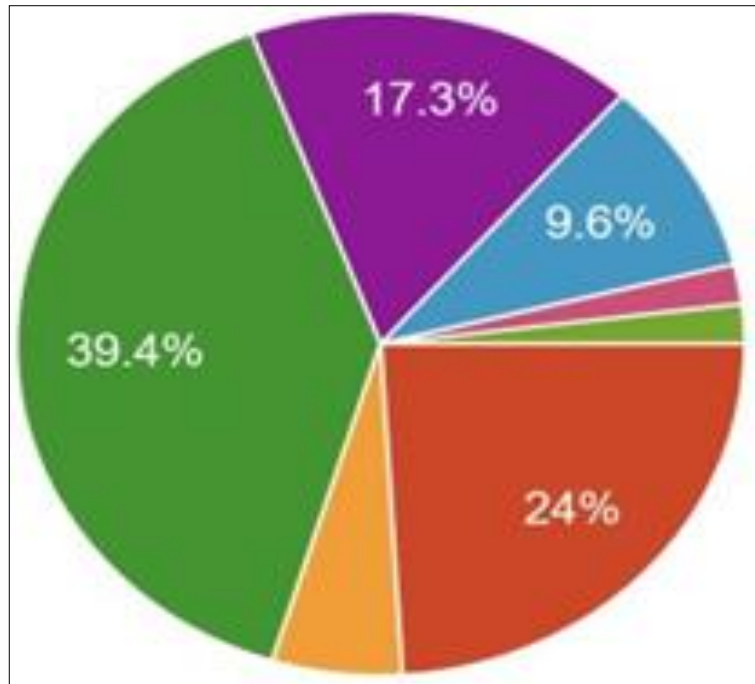
### 3. Variable Operationalization

**Table 1:** Operationalization of Variable

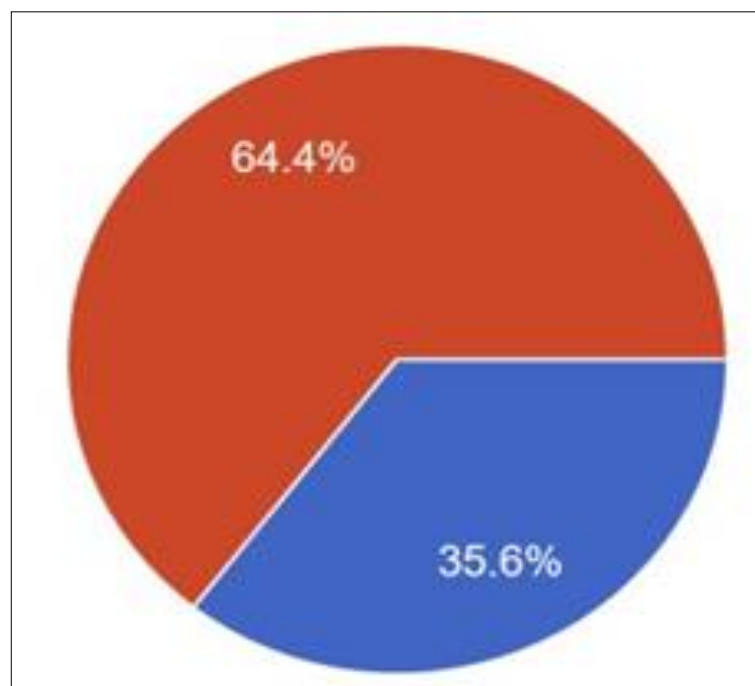
Variable	Definition	Operationalization of Variable		
AI Literacy	a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace. (Long & Magerko, 2020b)	I understand why AI technology needs big data	AL1	(Chai <i>et al.</i> , 2020)
		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 Learning AI of	The model predicts the dynamics of human confidence based on experience, accumulated confidence, and bias. (Jermsittiparsert <i>et al.</i> , 2023)	I feel confident that I will do well in the AI classes	CL1	(Chai <i>et al.</i> , 2020)
		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 <i>et al.</i> , 2013)	My classmates feel that it is necessary to learn about AI technology	SN1	(Chai <i>et al.</i> , 2020)
		My parents support me to learn about AI technology	SN2	
		Most people I know think that I should learn about AI technology	SN3	
Attitude using AI Toward	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 <i>et al.</i> , 2013)	Using AI technology is pleasant.	AT1	(Chai <i>et al.</i> , 2020)
		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 <i>et al.</i> , 2020)
		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)	I will continue to learn AI technology in the future	BI1	(Chai <i>et al.</i> , 2020)
		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	

**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

**Table 2:** Construct Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AL	0,807	0,824	0,873	0,632
AT	0,869	0,890	0,918	0,789
BI	0,914	0,914	0,940	0,795
CL	0,862	0,867	0,907	0,709
PU	0,933	0,939	0,952	0,833
SN	0,805	0,811	0,884	0,718

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

**Table 3: Inner VIF**

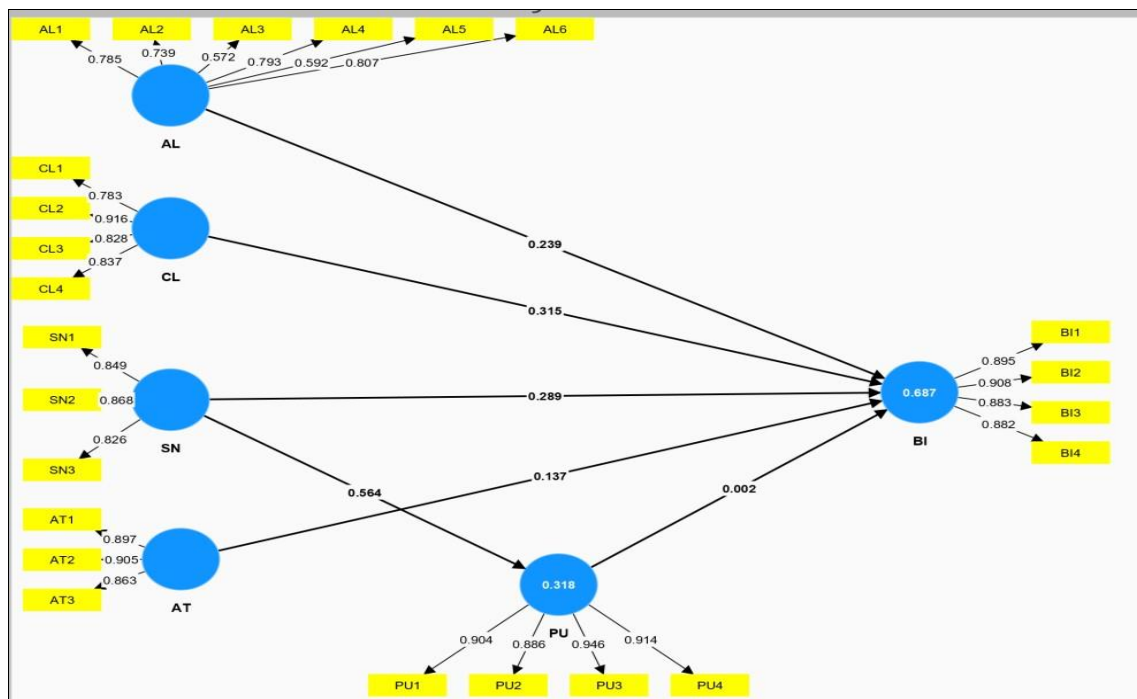
	AL	AT	BI	CL	PU	SN
AL			2,688			
AT			3,156			
BI						
CL			1,626			
PU			2,488			
SN			3,836		1,000	

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**

	R-square	R-square adjusted
BI	0,707	0,664
PU	0,318	0,300

based on (Hair *et al.*, 2019)



**Fig 2. Outer Loading**

**Table 5: Bootstrapping**

	Path Coefficient	T statistics	P values	Result
AL -> BI	0,337	1,834	0,033	Supported
AT -> BI	0,139	0,678	0,249	Not Supported
CL -> BI	0,329	1,458	0,072	Not Supported
PU -> BI	0,002	0,008	0,497	Not Supported
SN -> BI	0,200	0,899	0,184	Not Supported
SN -> PU	0,564	3,802	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**

AI Literacy (AL) as a Direct Driver of Behavioral Intention (BI): The finding that AI Literacy (AL) significantly influences Behavioral Intention (BI) (Path Coefficient = 0.337, T-statistic = 1.834, P-value = 0.033) is a crucial insight. This suggests that as individuals' understanding and competency with AI increase, their willingness or intention to engage in the specific behavior (e.g., use an AI tool, adopt an AI-driven approach) also significantly improves. This underscores the importance of educational initiatives

and training programs aimed at enhancing AI literacy to foster adoption.

Subjective Norms (SN) as a Strong Antecedent of Perceived Usefulness (PU): A highly significant relationship is observed between Subjective Norms (SN) and Perceived Usefulness (PU) (Path Coefficient = 0.564, T-statistic = 3.802, P-value = 0.000). This indicates that the perceived social pressure or the belief that important others (peers, colleagues, leaders) endorse or value a particular system or behavior strongly influences an individual's perception of its

usefulness. If one's social environment emphasizes the benefits of a technology or practice, individuals are much more likely to see it as useful. This highlights the powerful role of social influence and normative beliefs in shaping utilitarian perceptions.

Lack of Direct Impact on Behavioral Intention for Attitude (AT), Confidence Level (CL), Perceived Usefulness (PU), and Subjective Norms (SN): Interestingly, the results indicate that Attitude (AT), Confidence Level (CL), Perceived Usefulness (PU), and Subjective Norms (SN) do not directly or significantly influence Behavioral Intention (BI) in this specific model (all P-values > 0.05).

The non-significant direct effect of Perceived Usefulness (PU) on BI (Path Coefficient = 0.002, P-value = 0.497) is particularly noteworthy. In many technology acceptance models (e.g., TAM), perceived usefulness is often a primary predictor of behavioral intention. Its non-significance here suggests that while subjective norms strongly shape perceived usefulness, perceived usefulness itself may not be the direct driving force for behavioral intention in this context. This could imply a more complex mediation or the presence of other unmeasured variables that more directly influence BI.

The non-significant direct effect of Subjective Norms (SN) on BI (Path Coefficient = 0.200, P-value = 0.184) also merits attention. While SN significantly impacts PU, its direct link to BI is not supported. This reinforces the idea that SN's influence on BI might be fully or partially mediated through other constructs (such as PU, though PU itself was not directly significant to BI in this model).

The non-significant impact of Attitude (AT) and Confidence Level (CL) on BI also points to the possibility that in this specific behavioral context, direct emotional disposition or self-assuredness may not be the primary drivers of action compared to AI literacy.

## Conclusion

**Prioritize AI Literacy Initiatives:** For successful adoption of AI-related behaviors, investing in programs that genuinely enhance AI literacy appears to be a highly effective strategy. This goes beyond mere exposure to AI and involves developing a deeper understanding and practical skills.

**Leverage Social Influence for Perceived Usefulness:** To increase the perceived usefulness of new AI systems or practices, strategies should focus on fostering positive subjective norms. This could involve showcasing peer success stories, endorsements from opinion leaders, or creating community-driven initiatives that highlight the benefits.

**Re-evaluating Traditional Models:** The unexpected non-significance of perceived usefulness and attitude as direct predictors of behavioral intention suggests that the specific context of this study might deviate from assumptions made by traditional technology acceptance models. Future research should explore potential mediating effects or other contextual factors that could explain these non-significant direct paths. For instance, the influence of perceived usefulness on BI might be fully mediated by another variable not included in the direct path.

**Deeper Dive into Mediation:** It would be beneficial to explicitly test for indirect effects (mediation). For example, does SN indirectly influence BI *through* PU, even if the direct path from PU to BI is not significant? This could uncover more nuanced relationships.

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