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From Literacy to Intention: The Mediating Role of Perceived Usefulness in AI Adoption Behavior

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ABSTRACT

Artificial intelligence (AI) development in Indonesia, reinforced by the National AI Strategy and programs such as Sahabat AI involving Indosat Ooredoo Hutchison, GoTo, and Nvidia, has reshaped both economic and educational sectors. Within universities, AI tools like chatbots, adaptive systems, and academic analytics are altering how Generation Z learns and makes financial decisions. Nevertheless, financial literacy continues to be the main factor guiding students in evaluating risks and opportunities. Recent studies indicate that although AI enhances accessibility, investment behaviors are still largely influenced by literacy, financial attitudes, and digital skills. This research aims to examine whether factors such as AI literacy, and perceived usefulness of using AI positively influence behavioral intention to make investment. The study involved 127 respondents derived from post graduate medical student, and the key findings are as follows, Perceived Usefulness, the largest contributing factor ($\beta = 0.346$), followed by Subjective Norm ($\beta = 0.306$), Financial Literacy ($\beta = 0.264$), attitude of using AI ($\beta = 0.117$), and AI Literacy ($\beta = 0.059$) and R^2 of Behavior Intention is 70.7% . These results emphasize that students' perception of AI usefulness is shaped primarily by their emotional and cognitive attitudes, how enjoyable and beneficial they believe AI and by social encouragement. Once again, knowledge alone about AI (AI literacy) does not directly translate into perceiving it as useful. Students' enthusiasm, openness, and social exposure to AI-related applications are far more decisive in enhancing perceived usefulness.

Keyword: AI Literacy, Financial Literacy, Subjective Norm, Attitude of Using AI, Perceived Usefulness of Using AI, Behavior Intention

INTRODUCTION

The rapid development of artificial intelligence (AI) in Indonesia, marked by the National AI Strategy (New Zeland Foreign Afair and Trade, 2023) and initiatives such as Sahabat-AI supported by Indosat Ooredoo Hutchison, GoTo, and Nvidia, has significantly influenced social and economic sectors, including finance and education. In higher education, AI applications such as chatbots, adaptive learning, and academic analytics not only shape the learning environment of Generation Z but also affect how students approach decision making in financial investment from the post graduate medical student . At the same time, financial literacy has become a crucial determinant of students' ability to evaluate investment risks and opportunities, providing the foundation for rational and well-informed choices. Recent empirical studies in Indonesia highlight that while technological progress offers new tools, investment decisions among Gen Z are strongly driven by financial literacy, financial attitudes, and digital financial capabilities, with AI acting as a facilitator rather than a substitute for financial knowledge (Susanto et al., 2025). Thus, the intersection of AI integration and financial literacy plays a strategic role in shaping the investment behavior of young investors, particularly university students in Indonesia, as they navigate increasingly complex and technology-driven financial markets (Tubastuvi et al., 2024).

2. LITERATURE REVIEW

2.1 AI Literacy

According to (Ng et al., 2021) this article explores AI literacy as a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool in various contexts. Meanwhile, according to (Long & Magerko, 2020) discusses the competencies required for AI literacy and design considerations for AI education, (Laupichler et al., 2022) reviewed the literature on the integration of AI literacy in higher education and adult education. AI Literacy can be defined as 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. (Lopus et al., 2019)

2.2 Financial Literacy

Financial literacy is increasingly recognized as a foundational capability that shapes household well-being and market outcomes in today's digitized financial ecosystem. A large meta-analysis of 76 randomized experiments shows that financial education has clear, causal, and economically meaningful effects on both financial knowledge and downstream behaviors, underscoring the policy value of scalable education programs (Cakici & Zaremba, 2022) Beyond traditional literacy, evidence from India indicates that digital financial literacy and financial inclusion each raise financial well-being, with inclusion exerting the strongest effect after addressing endogeneity, highlighting complementary roles for access and skills (Kamble, P. A., Mehta, A., & Rani, 2024). At the market level, cross-country analysis finds that populations with higher financial literacy experience faster FinTech market growth, implying that financial knowledge catalyzes adoption of new financial technologies (AlSuwaidi & Mertzanis, 2024). New cross-OECD evidence further shows that tertiary education and human development indicators are positively associated with financial literacy and behaviors, while inequality and household debt are negatively associated—pinpointing macro-institutional levers that complement micro-level education initiatives (Nogueira et al., 2025)

2.3 Subjective Form

This study analyzes the role of two types of subjective norms in shaping the intention to purchase green food. (Ham et al., 2015) This article discusses the differences between subjective norms, descriptive norms, and personal norms, and their impact on conservation behavior. (Niemiec et al., 2020) This study explores the role of subjective norms in e-banking adoption, emphasizing how subjective norms influence behavioral intentions through perceived usefulness. (Jermsittiparsert et al., 2023). Subjective norm is defined as is defined as the perceived social acceptance and support for the behavior; and perceived behavioral control (PBC), which refers to one's perceived ability to perform the behavior. (Walker et al., 2013)

2.4 Attitude Toward using AI

According to (Grassini, 2023) In this research The study found that gender is a significant predictor of attitudes toward AI, with female participants showing lower scores than male participants.There are three type of AI acceptance such as user-centered technology acceptance, delegation and automation acceptance, and societal technology adoption acceptance. (Koenig, 2025)The scientific literature broadly suggests that artificial intelligence (AI) has the potential to be a valuable asset in education, fulfilling various roles that can improve both the learning and teaching experience (Grassini, 2023) define behavioral intention to use AI as how much an individual is willing to use.

2.5 Perceived Usefulness of AI

This study perceived usefulness of generative AI for schoolwork among students who reported its usage, the majority indicated infrequent use, with 37.9% using it rather seldom and 46.6% using it very seldom (Klarin et al., 2024). According to (Kim et al., 2021) Based on initial findings, people tend to have more favorable views of functional AI than social AI. The study suggests that this is because functional AI is seen as more useful, and this perception of usefulness, in turn, leads to more positive attitudes and a stronger sense of realism about the technology (Sadriwala & Sadriwala, 2022). On the this journal the benefits of digital competence felt by accounting students in higher education are able to provide perceived usefulness benefits (Alfi Ardiyanti & Endah Susilowati, 2024).

2.6 Behavioral Intention

In the field of technology adoption, behavioral intention is a key predictor of whether an individual will actually use a new system or technology. This concept, rooted in the Theory of Planned Behavior, refers to the subjective probability that a person will engage in a specific behavior (Ajzen, 1991). Several recent studies highlight the critical role of behavioral intention in predicting the use of new technologies, including artificial intelligence. For instance, a study by (Dwivedi et al., 2019) found that users' intention to use AI-based services was a strong predictor of their actual adoption, influenced by factors such as perceived usefulness and ease of use. Similarly, a study on AI in healthcare by Sun et al. (2022) revealed that healthcare professionals' behavioral intention to use AI-powered diagnostic tools was significantly influenced by their trust in the technology and the perceived benefits. Furthermore, research by (Arora et al., 2023), demonstrated that positive attitudes toward AI and strong behavioral intentions to use it were critical for successful integration of AI tools in business operations. These findings are echoed in a meta-analysis by (Aini et al., 2025), which concluded that behavioral intention consistently emerges as the most powerful determinant of technology use across various contexts, from consumer products to organizational systems.

2.7 AI Literacy influence to Behavior Intention

Recent empirical studies consistently show that AI literacy significantly influences behavioral intention to adopt AI tools in education and learning contexts. (Jang, 2024) extended the UTAUT model and found that AI literacy, along with performance expectancy and social influence, strongly predicts students' intention to use generative AI for learning. Similarly, (Du et al., 2024) demonstrated that AI literacy indirectly shapes teachers' intention to learn AI, mediated through AI ethics awareness, perceptions of AI for social good, and self-efficacy, highlighting the ethical and motivational pathways of adoption. Adding to this, a 2025 study on Palestinian university students confirmed that AI literacy positively affects generative AI acceptance, even after controlling for 21st-century skills, showing its broad and direct impact across diverse contexts (Salhab & Aboushi, 2025). Collectively, these findings underscore AI literacy as a vital determinant of behavioral intention, enhancing both competence and confidence in AI adoption.

2.8 AI Literacy influence to Perceived Usefulness of AI

Ng et al. (2021) reviewed AI literacy frameworks and emphasized that higher literacy equips individuals to better evaluate AI's benefits, thereby increasing perceived usefulness in decision-making and learning (Ouyang & Jiao, 2021). (Jang, 2024) tested an extended UTAUT model with 239 students and found that AI literacy significantly enhances perceived usefulness of text-based generative AI, which in turn predicts intention to use such tools in education (Jang, 2024). Similarly,(Ke et al., 2025) conducted structural equation modeling with university students and confirmed that AI literacy is a direct positive predictor of perceived usefulness, mediated by performance and effort expectancies. Together, these studies demonstrate that AI literacy not only builds competence but also strengthens the belief that AI is useful, which is critical for broader adoption.

2.9 Subjective Norm to Perceived Usefulness of AI

(Al-Emran, 2025) examined higher education adoption of AI and found that subjective norm positively affects perceived usefulness, as peer and instructor support enhance beliefs in AI's value. According to (Jang, 2024) extended the UTAUT model in a study of Korean business students and confirmed that social influence, as a proxy for subjective norm, boosts perceived usefulness of generative AI for learning, reinforcing the importance of peer expectations. Similarly, (Le et al., 2020) used structural equation modeling with university students and showed that subjective norm directly predicts perceived usefulness, mediated by performance expectancy and effort expectancy. Collectively, these findings indicate that when significant others endorse AI use, individuals are more likely to perceive AI as useful, driving stronger acceptance and adoption.

2.10 Financial Literacy influence to Behavior Intention

Financial literacy is a strong determinant of behavioral intention in financial decision-making. For instance, (Alomari & Abdullah, 2023) examined that performance expectancy, effort expectancy, social influence, security, and awareness positively impact on behavioral intention to use Cryptocurrency. (Dwiprasetyo et al., 2025) analyzed millennials' investment choices in Indonesia and confirmed that financial literacy positively influences behavioral intention to invest, mediated by attitude toward investment. More recently, (Afiqah, 2022) studied university students in Malaysia and demonstrated that financial literacy enhances behavioral intention to use fintech applications, particularly through perceived ease of use and trust. Together, these findings suggest that financial literacy not only improves knowledge but also strengthens confidence and motivation, thereby shaping positive behavioral intentions toward financial products and technologies.

2.11 Financial Literacy influence to Perceived Usefulness of AI

Financial literacy shapes how useful people perceive AI-driven finance. In a 2024, (Bhatia et al., 2024). show financial literacy and trust significantly raise perceived usefulness (PU) of robo-advisory services, strengthening downstream adoption intentions. Complementing this, a 2024 conference study on e-wallets reports digital financial literacy positively predicts Perceived Usefulness, implying that financially savvy users more readily see value in AI-enabled financial apps. However using Bank of Italy microdata,(Aristei & Gallo, 2025.) find higher objective FL can substitute for robo-advice, which may temper perceived usefulness of automated advice for some investors.

2.11 Attitude to Using AI influence to Perceived Usefulness of AI

(Al-Emran, 2025) investigated AI adoption in higher education and found that a positive attitude toward AI directly improves PU, reflecting students' readiness to integrate AI into learning. (Jang, 2024) extended the UTAUT model with Korean business students and confirmed that favorable attitudes toward generative AI strengthen perceptions of its usefulness for academic tasks. Similarly, (Ke et al., 2025) employed structural equation modeling with university students and showed that attitude toward AI significantly predicts PU, reinforcing that positive evaluations of AI tools amplify their perceived value in education Collectively, these studies highlight attitude as a key psychological driver of PU in AI adoption.

2.12 Attitude to Using AI influence to Behavior Intention

(Al-Emran, 2025) examined higher education adoption and showed that a positive attitude toward AI significantly predicts BI, underscoring its motivational role in technology acceptance. (Jang, 2024) studied Korean business students with an extended UTAUT model and found that favorable attitudes toward generative AI tools directly enhance BI for learning purposes. Likewise, (Ke et al., 2025) applied structural equation modeling and confirmed that attitude toward AI is one of the strongest predictors of BI, mediating effects of performance and effort expectancies. Together, these findings highlight that individuals' evaluative stance toward AI is a central driver of their willingness to adopt and integrate AI technologies.

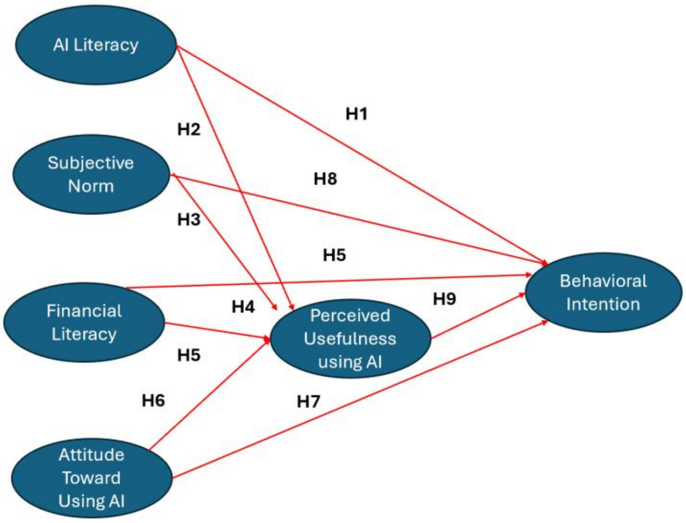
2.13 Subjective Norm to Behavior Intention

(Al-Emran, 2025) examined AI adoption in higher education and found that SN significantly predicts BI, indicating that social pressure from peers and instructors drives intention to use AI. (Jang, 2024) extended the UTAUT model with business students and confirmed that SN, captured through social influence, directly enhances BI to adopt generative AI for learning Similarly, (Ke et al., 2025) applied structural equation modeling among university students and revealed that SN remains a strong antecedent of BI, mediated partly by performance expectancy and perceived usefulness.

Collectively, these studies highlight the power of social influence in encouraging AI adoption.

2.14 Perceived Usefulness of Using AI influence to Behavior Intention

(Upadhyay et al., 2022) analyzed AI adoption in organizations and found Perceived Usefulness to be a direct and significant driver of BI, highlighting its role in shaping managers' willingness to embrace AI (doi:10.1016/j.ijinfomgt.2020.102380). (Jang, 2024) tested an extended UTAUT model with business students and confirmed that Perceived Usefulness of generative AI for learning is a major determinant of BI, reinforcing the central role of utility beliefs in adoption. Likewise, (Ke et al., 2025) used structural equation modeling with university students and showed that Perceived Usefulness strongly influences behavior intention, mediating the effects of performance expectancy and subjective norm. Collectively, these findings underscore Perceived Usefulness as a cornerstone of AI acceptance models.



For data analysis, the research employs the PLS-SEM (Partial Least Squares Structural Equation Modeling) analysis method using SmartPLS version 3.2.9. The PLS-SEM analysis consists of two models: the outer model and the inner model. The outer model examines the relationship between indicators and their respective latent variables. It assesses the reliability and validity of the measured variables' indicators, ensuring the measurement model's quality (Hair et al., 2019). On the other hand, the inner model represents the structural model, which evaluates the overall quality of the research model by examining the significance of relationships between constructs, typically through path coefficient analysis.

3.1. Outer Model

Berdasarkan Hair et al. (2019), evaluasi outer model dilakukan dengan menguji reliabilitas dan validitas indikator yang diukur. Uji reliabilitas dilakukan secara bertahap. Pertama, indikator pada variabel laten diperiksa dengan ketentuan nilai outer loading harus lebih besar dari 0,708. Kedua, reliabilitas konstruk diuji melalui perhitungan Cronbach's alpha dan composite reliability, dengan nilai yang disyaratkan di atas 0,7. Selanjutnya, validitas konstruk ditentukan melalui average variance extracted (AVE), yang harus melebihi 0,5. Terakhir, uji validitas diskriminan dilakukan dengan menganalisis heterotrait-monotrait ratio (HT/MT), di mana nilainya harus berada di bawah 0,9 agar terpenuhi.

3.2. Inner Model

Menurut Hair et al. (2019), inner model atau model struktural menggambarkan hubungan antar variabel laten dalam suatu penelitian. Tahap pertama dilakukan dengan mengecek variance inflation factor (VIF) guna mengetahui adanya multikolinearitas. Nilai VIF yang baik adalah di bawah 3, sedangkan rentang 3–5 mengindikasikan potensi multikolinearitas, dan nilai di atas 5 menunjukkan kondisi kritis. Selanjutnya, tahap kedua adalah menilai koefisien determinasi (R^2) yang berada pada rentang 0–1, di mana semakin mendekati angka 1, semakin baik kemampuan model PLS-SEM dalam menjelaskan variabel. R^2 dengan nilai 0,75 dianggap kuat, 0,5 moderat, dan 0,25 lemah. Tahap ketiga adalah meninjau Q^2 atau predictive relevance untuk mengukur kemampuan prediktif model. Apabila Q^2_predict < 0, berarti model tidak memiliki daya prediksi. Dengan demikian, ketiga langkah ini digunakan untuk menilai kualitas model secara menyeluruh.

Pengujian hipotesis merupakan tahap paling krusial dalam penelitian ini. Pada tahap ini dilakukan bootstrapping untuk menilai hubungan serta signifikansi antar variabel. Uji hubungan dapat dilakukan dengan metode satu arah (one-tail) atau dua arah (two-tail). Metode one-tail menunjukkan adanya pengaruh positif antar variabel. Penelitian ini menggunakan tingkat signifikansi 0,05 dengan derajat kebebasan tak terbatas, sehingga nilai T-tabel untuk one-tail adalah 1,645. Selanjutnya, hasil perhitungan T dari bootstrapping dibandingkan dengan T-tabel. Jika nilai T hitung lebih besar dari 1,645, maka dapat diartikan terdapat pengaruh positif. Sementara itu, dilihat dari nilai P-Value, hubungan antar variabel dinyatakan signifikan apabila nilai yang diperoleh kurang dari 0,05.

3.2 Variable Operationalization

Variable	Definition	Operationalization of Variable		
AI Literacy	a set of competencies that enable 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 realize that AI technology relies on large amounts of data.	AL1	(Chai et al., 2020)
		I understand how deep learning processes enable AI to carry out voice recognition.	AL2	
		I know the way AI systems refine translation results in online translators.	AL3	
		I understand how digital assistants like SIRI or Google Assistant manage interactions between humans and computers.	AL4	
		I am aware that AI can apply statistical methods to forecast potential outcomes.	AL5	
		I understand how computers analyze images to generate visual recognition.	AL6	
Financial Literacy	is a measure of the degree to which one understands key financial concepts and possesses the ability and confidence to manage personal finances through appropriate, short- term decision-making and sound, long-range financial planning, while mindful of life events and changing economic conditions. (Remund, 2010)	I understand the basic concepts of digital financial systems (e.g. e-banking, e-wallet, digital investment).	FL1	(Choung et al., 2023)
		I know how digital financial platforms work and how they differ from traditional financial services.	FL2	
		I can explain the benefits and risks of using digital financial services.	FL3	
		I am familiar with new digital financial technologies such as blockchain.	FL4	
		I am aware of the various digital financial services available in my country (e.g. GoPay, OVO, DANA, ShopeePay).	FL5	
		I regularly follow information or updates about new digital financial services.	FL6	
		I know which financial institutions offer digital financial products that are safe and regulated by authorities.	FL7	
		I can identify the main functions of popular digital financial platforms.	FL8	
		I can easily transfer money using digital banking apps or e-wallets.	FL9	
		I am confident in conducting online transactions, such as paying bills or shopping through digital platforms.	FL10	
		I know how to check transaction history or account balance using digital tools.	FL11	
		I can compare digital financial products (e.g. loan or investment apps) before using them.	FL12	
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)	My classmates consider learning AI technology to be important.	SN1	(Chai et al., 2020)
		My parents encourage me to study AI technology.	SN2	
		Most people around me think I should gain knowledge about AI technology.	SN3	
Attitude Toward using AI	Subjective norm is defined as is defined as the perceived social acceptance and support for the behaviour; and	Using AI technology feels pleasant.	AT1	(Chai et al., 2020)
		I find interacting with AI technology to be enjoyable.	AT2	

	perceived behavioural control (PBC), which refers to one's perceived ability to perform the behaviour.(Walker et al., 2013)			
		I have fun when I use AI technology.	AT3	(Chai et al., 2020)
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)	AI technology helps me finish tasks more efficiently.	PU1	
		AI technology improves my effectiveness in completing work.	PU2	
		AI technology contributes to better performance.	PU3	
		AI technology makes me more productive.	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 intend to keep learning AI technology in the future.	BI1	(Chai et al., 2020)
		I will stay updated with new AI applications.	BI2	
		I plan to dedicate time to study AI technology in the future.	BI3	
		I will pay attention to the development of upcoming AI applications.	BI4	

RESULT

PLS-SEM Result

The most semester is in fourth semester with value 32.8 % and 67.2 % is female.

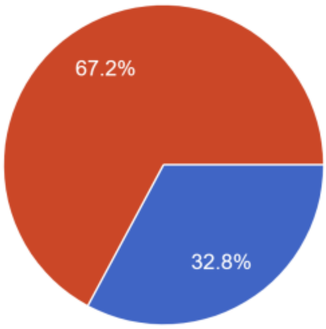


Figure 2. Female

Table 2. Construct Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI LITERACY	0.838	0.846	0.902	0.755
ATTITUDE TO USING AI	0.857	0.859	0.913	0.778
BEHAVIOR INTENTION	0.796	0.804	0.868	0.622
PERCEIVED USEFULLNESS TO USING AI	0.895	0.899	0.927	0.760
financial literacy	0.705	0.772	0.827	0.615
subjective norm	0.747	0.758	0.856	0.664

All Cronbach alpa 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

	AI LITERACY	ATTITUDE TO USING AI	BEHAVIOR INTENTION	PERCEIVED USEFULLNESS TO USING AI	financial literacy	subjective norm
AI LITERACY						
ATTITUDE TO USING AI	0.501					
BEHAVIOR INTENTION	0.527	0.718				
PERCEIVED USEFULLNESS TO USING AI	0.429	0.733	0.834			
financial literacy	0.499	0.434	0.760	0.461		
subjective norm	0.405	0.510	0.865	0.640	0.619	

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

	R-square	R-square adjusted
BEHAVIOR INTENTION	0.707	0.695
PERCEIVED USEFULLNESS TO USING AI	0.508	0.492

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

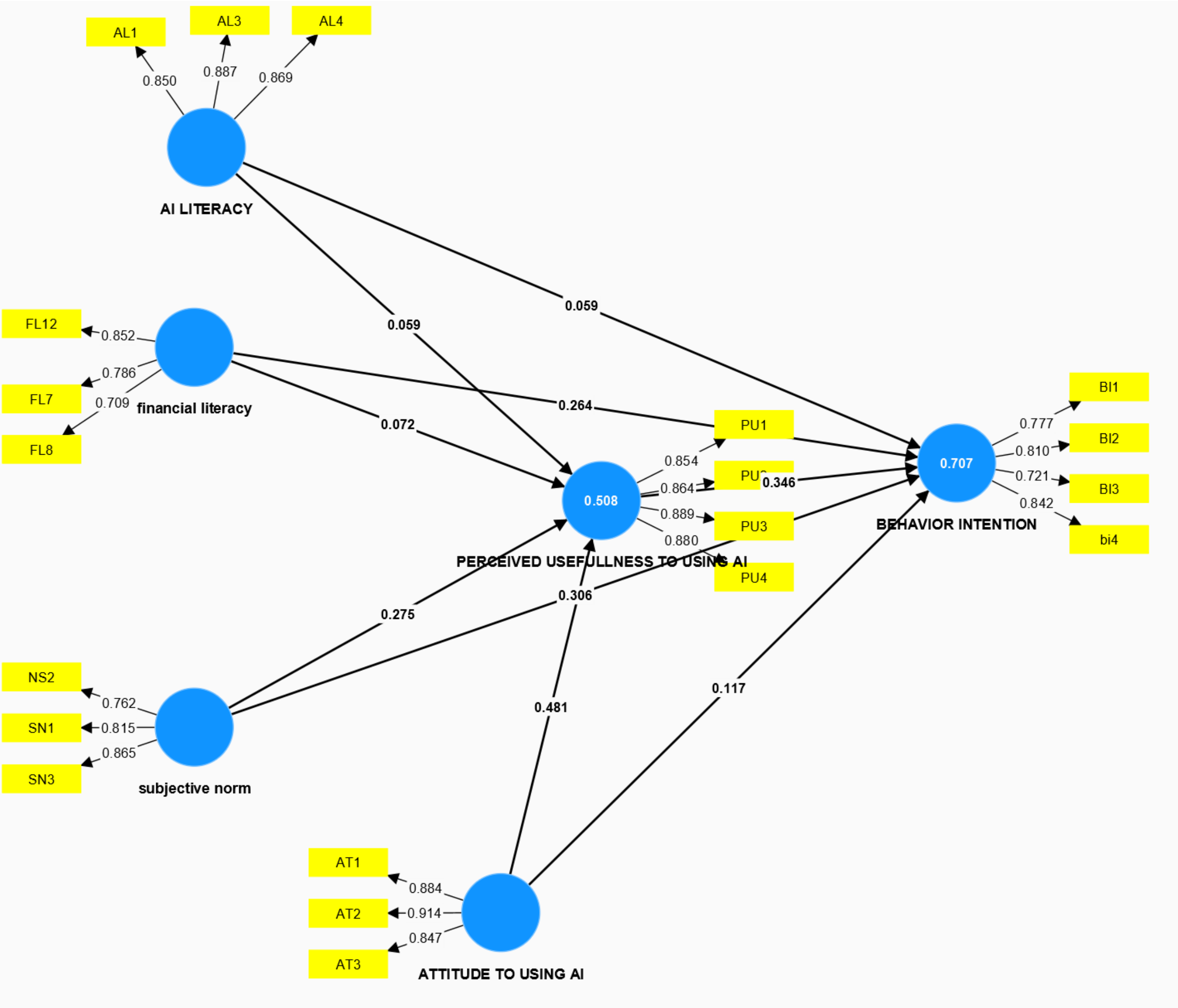


Figure 2. Outer Loading

Table 5. Bootstrapping

	Original sample (O)	T statistics (|O/STDEV|)	P values
AI LITERACY -> BEHAVIOR INTENTION	0.059	1.086	0.139
AI LITERACY -> PERCEIVED USEFULLNESS TO USING AI	0.059	0.877	0.190
ATTITUDE TO USING AI -> BEHAVIOR INTENTION	0.117	1.656	0.049
ATTITUDE TO USING AI -> PERCEIVED USEFULLNESS TO USING AI	0.481	6.033	0.000
PERCEIVED USEFULLNESS TO USING AI -> BEHAVIOR INTENTION	0.346	4.653	0.000
financial literacy -> BEHAVIOR INTENTION	0.264	4.926	0.000
financial literacy -> PERCEIVED USEFULLNESS TO USING AI	0.072	0.811	0.209
subjective norm -> BEHAVIOR INTENTION	0.306	4.244	0.000
subjective norm -> PERCEIVED USEFULLNESS TO USING AI	0.275	2.937	0.002

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.

Table 5. Specific Indirect

	Original sample (O)	T statistics (|O/STDEV|)	P values
financial literacy -> PERCEIVED USEFULLNESS TO USING AI -> BEHAVIOR INTENTION	0.025	0.763	0.223
subjective norm -> PERCEIVED USEFULLNESS TO USING AI -> BEHAVIOR INTENTION	0.095	2.400	0.008
AI LITERACY -> PERCEIVED USEFULLNESS TO USING AI -> BEHAVIOR INTENTION	0.021	0.843	0.200
ATTITUDE TO USING AI -> PERCEIVED USEFULLNESS TO USING AI -> BEHAVIOR INTENTION	0.167	3.750	0.000

DISCUSSION

The results of the hypothesis testing reveal several interesting relationships among the constructs. Firstly, AI Literacy does not significantly influence either Behavior Intention (p = 0.139) or Perceived Usefulness to Using AI (p = 0.190). This indicates that students' knowledge or awareness about artificial intelligence alone may not be sufficient to shape their behavioral intention or perception of usefulness. It suggests that while individuals may understand AI conceptually, this understanding does not automatically translate into intention to use or perceive it as beneficial in practice. Hence, awareness without application may have limited behavioral impact.

In contrast, Attitude Toward Using AI shows strong and significant effects on both Behavior Intention (p = 0.049) and Perceived Usefulness (p = 0.000). This finding supports the idea that positive emotional and cognitive evaluations of AI strongly influence users' motivation and their perceived value of adopting AI technologies. Individuals who enjoy, trust, and feel confident in AI are more likely to find it useful and intend to engage with it. This aligns with the Technology Acceptance Model (TAM), where attitude acts as a crucial mediator between cognitive factors (knowledge) and behavioral intention.

Furthermore, Perceived Usefulness to Using AI significantly predicts Behavior Intention (p = 0.000), confirming that users' belief in AI's usefulness is a major driver of their intention to adopt it. This relationship demonstrates that when users perceive AI as enhancing their efficiency, productivity, or learning outcomes, their likelihood of using AI increases substantially. The strength of this relationship underscores the importance of demonstrating practical benefits and real-world value to improve user adoption. Lastly, both Financial Literacy and Subjective Norm play meaningful roles in shaping behavioral outcomes. Financial literacy significantly affects Behavior Intention (p = 0.000) but not Perceived Usefulness (p = 0.209), implying that financially literate individuals are more likely to intend to use AI, possibly due to their ability to assess potential economic or investment benefits. Meanwhile, Subjective Norm significantly influences both Behavior Intention (p = 0.000) and Perceived Usefulness (p = 0.002), indicating that social influence and peer perception are strong motivational factors in adopting AI. Together, these findings highlight that personal attitudes, perceived usefulness, and social encouragement are the most powerful determinants of AI adoption behavior.

The results of the specific indirect effects analysis reveal that only two mediation paths show significant indirect relationships toward Behavior Intention through Perceived Usefulness to Using AI. The strongest indirect effect is observed in the path Attitude Toward Using AI → Perceived Usefulness → Behavior Intention (β = 0.167, p = 0.000), indicating that students with positive attitudes toward AI are more likely to perceive AI as useful, which in turn enhances their behavioral intention to use it. Similarly, the path Subjective Norm → Perceived Usefulness → Behavior Intention (β = 0.095, p = 0.008) is also significant, suggesting that social influence contributes indirectly to behavioral intention through the perception of usefulness. In contrast, the indirect effects of Financial Literacy (β = 0.025, p = 0.223) and AI Literacy (β = 0.021, p = 0.200) are not significant, implying that knowledge alone—whether financial or technological—does not automatically increase intention unless individuals first perceive AI as beneficial. Overall, these findings highlight that the perceived usefulness of AI serves as a crucial mediating variable that transforms positive attitudes and social support into concrete behavioral intentions to adopt AI in financial decision-making.

CONCLUSION

Based on the R-square values presented in the model, the variable Perceived Usefulness to Using AI has an R^2 of 0.508, while Behavior Intention achieves an R^2 of 0.707. These values indicate that the model has a strong explanatory power in predicting behavior intention toward using AI tools. Specifically, 70.7% of the variance in behavior intention can be explained by the predictor variables—attitude toward using AI, financial literacy, subjective norm, perceived usefulness, and AI literacy—while 50.8% of the variance in perceived usefulness is explained by attitude, financial literacy, subjective norm, and AI literacy. This suggests that the model fits the data well and that students' behavioral intentions and perceptions of AI usefulness are strongly shaped by psychological and contextual factors.

When ranking the path coefficients that directly influence Behavior Intention, the strongest predictor is Perceived Usefulness to Using AI ($\beta = 0.346$, $p = 0.000$), followed by Financial Literacy ($\beta = 0.264$, $p = 0.000$), Subjective Norm ($\beta = 0.306$, $p = 0.000$), Attitude Toward Using AI ($\beta = 0.117$, $p = 0.049$), and lastly AI Literacy ($\beta = 0.059$, $p = 0.139$), which is not statistically significant. This ordering shows that students' intention to use AI is more strongly driven by their perceived benefits and the influence of peers or social expectations rather than their technical understanding of AI. In other words, students who perceive AI as practically valuable and who are influenced by positive social norms are more inclined to use AI in investment decision-making. Perceived Usefulness, the largest contributing factor ($\beta = 0.346$), followed by Subjective Norm ($\beta = 0.306$), Financial Literacy ($\beta = 0.264$), attitude of using AI ($\beta = 0.117$), and AI Literacy ($\beta = 0.059$) and R^2 of Behavior Intention is 70.7% These results emphasize that students' perception of AI usefulness is shaped primarily by their emotional and cognitive attitudes, how enjoyable and beneficial they believe AI and by social encouragement. Once again, knowledge alone about AI (AI literacy) does not directly translate into perceiving it as useful. Students' enthusiasm, openness, and social exposure to AI-related applications are far more decisive in enhancing perceived usefulness.

Taken together, these findings imply that fostering a positive attitude and usefulness perception toward AI technologies is the key to boosting adoption intentions. Programs that demonstrate tangible benefits of generative AI, such as automating data analysis, forecasting stock performance, and generating investment insights are likely to strengthen students' behavioral intention to use AI for financial decision-making. Educational interventions should, therefore, emphasize hands-on experiences, case-based learning, and exposure to real-world AI applications rather than just theoretical explanations of AI mechanisms.

From a practical standpoint, to improve students' behavioral intention toward stock investment using generative AI tools, universities and educators should combine three strategies: (1) enhance experiential learning by allowing students to use generative AI for investment simulations and portfolio analysis, (2) build positive attitudes and confidence by showing AI's accuracy and reliability in decision support, and (3) cultivate peer and mentor influence through collaborative projects and competitions that highlight AI's role in intelligent investing. By linking AI literacy with practical relevance, enjoyment, and social encouragement, students can transition from passive understanding to confident, active users of generative AI in financial investment contexts.

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