Asian Research Journal of Arts & Social Sciences

Volume 23, Issue 10, Page 112-124, 2025; Article no.ARJASS.144991
ISSN: 2456-4761

Determinants of Artificial Intelligence Adoption among Accounting Students: A Technology Acceptance Model Perspective

Aprilia Kurnia Saputri [a], Siti Mu'minatul Mahfudzoh [a*], Ragil Sukma Wicaksono [a], Kholilah Kholilah [a] and Dyah Febriantina Istiqomah [a]

[a] *UIN Maulana Malik Ibrahim, Malang, Indonesia.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: https://doi.org/10.9734/arjass/2025/v23i10806

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://pr.sdiarticle5.com/review-history/144991

Original Research Article

Received: 02/08/2025
Published: 08/10/2025

ABSTRACT

The rapid digital transformation and massive adoption of Artificial Intelligence (AI) in various sectors, including accounting, demands preparedness from future professionals. Understanding the factors that drive or hinder AI adoption among accounting students is crucial to ensuring the relevance of the educational curriculum and the competitiveness of graduates. Therefore, this study aims to analyze the influence of perceived usefulness, perceived ease, perceived risk, and social pressure on AI use with attitude as a mediating variable. This study employs the SEM PLS methodology and involves a cohort of 101 accounting students as participants. The findings

**Corresponding author: Email: 220502110023@student.uin-malang.ac.id;*

Cite as: *Aprilia Kurnia Saputri, Siti Mu'minatul Mahfudzoh, Ragil Sukma Wicaksono, Kholilah Kholilah, and Dyah Febriantina Istiqomah. 2025. "Determinants of Artificial Intelligence Adoption Among Accounting Students: A Technology Acceptance Model Perspective". Asian Research Journal of Arts & Social Sciences 23 (10):112–124. https://doi.org/10.9734/arjass/2025/v23i10806.*

substantiate that the aforementioned variables exert a positive impact on AI adoption, albeit without mediating the influence of perceived ease of use and perceived risk. The implications of this research can provide invaluable insights for accounting programs in designing curricula that are germane to preparing students for the digital era, socialization programs aimed at mitigating risk apprehensions, and promotional strategies that leverage social pressure to foster a cadre of accounting professionals who are more competent and adaptable in the digital age. However, this study has limitations in that it uses a single sample of students. Therefore, future research should develop models by adding cultural context variables or expanding the sample to include accounting professionals in order to achieve stronger generalizations.

Keywords: Artificial Intelligence; perceived usefulness; perceived ease; perceived risk; social pressure; attitude.

1. INTRODUCTION

The Society 5.0 era, first popularized by the Japanese government in the 5th Science and Technology Basic Plan in 2016, describes a human-centered society that fully integrates physical space with cyberspace (De Villiers, 2024). This concept focuses on technological advancement and how technology can solve various social problems, such as education, health, and the economy (Ramírez-Márquez et al., 2024). AI literacy is now seen as a crucial competency to prepare the younger generation for future social challenges (Rizvi et al., 2023).

In a social context, Society 5.0 emphasizes that technological developments, including artificial intelligence (AI), must be directed towards making life society better and preparing the younger generation to be able to adapt to the increasingly rapid digital transformation (Burhanuddin & Pharmacista, 2023). One concrete example of the implementation of Society 5.0 is using generative AI such as ChatGPT. Since its release by OpenAI in 2022, ChatGPT has become one of the AI applications capable of supporting learning, research, and professional work (Rahman & Watanobe, 2023).

In the field of accounting, ChatGPT has the potential to help students understand concepts, solve case studies, and analyze financial data, which is in line with the goals of Society 5.0, which prioritizes technological innovation to improve human capabilities (Filasari & Suranto, 2025). The presence of ChatGPT as an AI tool confirms that student adaptation to digital technology not an option anymore but an urgent necessity in the current era of digital transformation (Petre et al., 2025). However, its adoption also brings ethical, academic integrity, and trust concerns that require careful regulation in higher education (Technol et al., 2024).

AI greatly assists education, from administration and learning activities to assessment. AI can improve student assessment by automating the process, speeding up evaluation, and providing quick, individually tailored feedback. This is particularly significant (Kamalov et al., 2023). Almasri (2024) research states that one of the significant benefits of using AI is the improvement of exploratory learning through virtual laboratories and simulations. AI-supported tools can replicate complex logic tests, which may be illogical and dangerous to conduct in a conventional classroom environment. Studies also confirm that generative AI like ChatGPT has the potential to enhance student engagement and personalized learning, but caution is needed due to biases and risks of academic misconduct (Strzelecki, 2024).

This study aims to identify factors that influence accounting students' use of AI technology in Referring to the Technology Acceptance Model (TAM) introduced by Davis (1989), this framework serves as the primary foundation of the study. Fatmawati (2015) emphasizes that TAM offers a basis for understanding the internal factors that shape technology users' beliefs, attitudes, and intentions (Kholilah et al., 2022).

The strength of this model lies in its ability to explain failures in system utilization, which often occur due to users' low intention to adopt the technology (Fatmawati, 2015). In this research context, TAM is combined with additional relevant variables that are integrated into two core constructs, namely perceived usefulness and perceived ease of use.

The adoption of AI is greatly influenced by individuals' perceptions of usefulness (PU). Lee et al. (2024)**,** users have to build a positive attitude into AI because they believe using this technology can increase productivity and enable them to complete tasks faster. When students are convinced that AI will provide tangible benefits in their work, they tend to feel more confident using it. This creates a positive cycle in which belief in the usefulness of AI strengthens confidence, encouraging wider adoption of the technology.

Meanwhile, the perception of ease of use, which is also a significant factor in this study, shows the extent to which students feel that AI is easy to learn and use without requiring much effort, for example, through a user-friendly interface or interactive tutorials. Accounting students who feel that AI is easy to operate will have a positive impact on AI adoption got more sufficient and effective (Bui et al., 2025). Empirical evidence further shows that ease of use and perceived usefulness remain the strongest drivers of student adoption of AI platforms (Shahzad & Xu, 2024).

The next factor influencing AI adoption is Risk Perception (RP). Perceived risk by accounting students, such as concerns about their readiness for the world of work or data security issues, can be a significant barrier to AI acceptance. Research conducted by Syahril & Rikumahu (2019) states that risk perception reinforces the previous argument related to TAM to analyze indicators which cause failure in the use of technology. Therefore, it is important to identify how students assess the risks associated with AI adoption. Concerns around plagiarism, misuse, and ethical challenges are widely highlighted as risks that may limit student trust in generative AI (Technol et al., 2024).

Finally, social factors also act crucial role to form the individuals' opinions and behaviors toward new technologies. Social influence from the surrounding environment, such as lecturers, peers, or industry trends, can affect how accounting students view and behave toward adopting AI in their profession (Bui et al., 2025). As shown in the study by Changalima et al. (2024), social influence from the environment, such as peer opinions or information quality, has been proven to influence individuals to use generative AI such as ChatGPT. Habit and hedonic motivation have also been found to significantly impact students' behavioral intention to use ChatGPT (Strzelecki, 2024).

This study is an extension from Alshammari & Babu (2025) and Kholilah *et al*. (2022). The study by Alshammari & Babu (2025) analyzed the impact of perceived usefulness, ease of use, and behavioral intention on technology adoption, with satisfaction as a mediating variable. Meanwhile, Kholilah *et al*. (2022) examined the influence of perceived usefulness, personal interest, availability, and social pressure on cloud computing adoption.

Two main aspects distinguish this study from that conducted by Alshammari & Babu (2025). First, the specific object and focus of the study. This study targets accounting students and examines the direct use of ChatGPT, unlike Alshammari & Babu (2025). Second, we added the variables of perceived risk and social pressure as independent variables, which were not included in the previous study.

Meanwhile, the difference with the research by Kholilah et al. (2022) lies in the object of technology being studied. The research by Kholilah et al. (2022) focuses on adopting cloud computing, while this study specifically examines the use of AI, particularly ChatGPT, as a dependent variable.

The study before proves the food impact of AI in improving efficiency and productivity in the accounting sector (C. S. Lee & Tajudeen, 2020). However, there is a lack of understanding of how accounting students' perceptions of adopting this technology can affect their readiness for digital transformation. The novelty here focuses on the perceptions of accounting students in Indonesia, who are Generation Z. This generation has unique characteristics, including openness to technology and the need to adapt quickly to change.

This study implemented the TAM framework to observe the theoretical framework to identify of all those variables to adopt AI. This provides crucial insight into how accounting students view and respond to new technologies, and how their perceptions may shape accounting profession in Indonesia. Thus, this study provides new insights into the indicators that impact AI among accounting students and helps educational institutions adjust their curricula and learning strategies to prepare more competent accountants for the digital age.

2. LITERATURE REVIEWS AND RESEARCH HYPOTHESES DEVELOPMENT

2.1 Theory Acceptance Model (TAM)

The TAM theory explains how all variables are connected. This model shows that when users encounter new technology, several factors influence their decisions about how and when to use it (Tahar et al., 2020). According to TAM, user acceptance of technology depends on two main factors: perceived usefulness and perceived ease of use. These factors shape attitudes toward technology use, which can affect behavioral intentions to use, ultimately leading to actual system use.

2.2 Perceived Risk

Perceived risk is the process by which individuals assess a problem that can potentially cause adverse consequences, raising concerns about the level of risk involved. According to research by (Fanani & Wuryaningsih 2025), one of the elements influencing people's interest in using platforms for trading cryptocurrency assets is their sense of risk. Users' willingness to embrace digital financial technology may be lowered by perceived dangers, such as possible monetary losses, transaction security, and regulatory ambiguity. In other words, people are less likely to use blockchain-based services like Binance if they perceive a higher amount of risk.

Risk awareness has two important elements: uncertainty and the desired outcome (Fadila et al., 2022). In technology adoption, including AI, perceived risk refers to users' concerns about possible negative impacts, such as misinformation, data misuse, or loss of control (Featherman & Pavlou, 2003).

2.3 Social Influence

Social influence considers the crucial opinions about the need to use the available system. Consumer attitudes regarding the usage of a service are greatly influenced by social pressure, which is quantified in terms of subjective norms. Suggestions or pressure from the environment (friends, family, and the community) can have a direct impact on attitudes and intends to use technology or services (Purwianti et al., 2025). Family and friendship influence individual decisions (Sharma et al., 2017). Venkatesh & Davis (2000) found that there is a two-way connection among the social influence, such as subjective norms, the level of willingness to use something, and how a person's self-image is affected, all of which contribute to a better understanding of a person's intention actually to use a technology or system. Therefore, researchers believe that social influence affects the use of artificial intelligence.

2.4 Artificial Intelligence (AI)

AI refers to developing computer systems are capable to making decisions (Russel & Norvig, 2003). AI applications, including process automation, predictive data analysis, and pattern recognition that previously required human intervention, demonstrate their potential to transform various industries.

3. METHODOLOGY

In this study, the researcher applied the positivist paradigm. (Creswell, 2014) Stated that the positivist paradigm has advantages in methods that can identify the causes of a problem. This paradigm guides researchers to take a quantitative research approach. According to Creswell (2014), quantitative methods are a way to test theories by linking one variable to another.

The data collection process uses a research instrument in the form of a questionnaire, followed by statistical testing of the collected data. The associative method determines the level of correlation between two or more variables. This study aims to explain whether the variables of X1 (Perceived Usefulness), X2 Perceived Ease, X3 (Perceived Risk), and Social Pressure (X4) influence the variable Y (Desire to Adopt Artificial Intelligence) mediated by the variable Z (Attitude Towards Use).

The population of this study consisted of active undergraduate accounting students at Maulana Malik Ibrahim State Islamic University (UIN) Malang and Universitas Brawijaya. The total population of both universities was 2,157 students, with 757 students from UIN Malang and 1,400 from Universitas Brawijaya. The sampling method used was convenience sampling, whereby selecting respondents based on their easy accessibility and availability to the researcher.

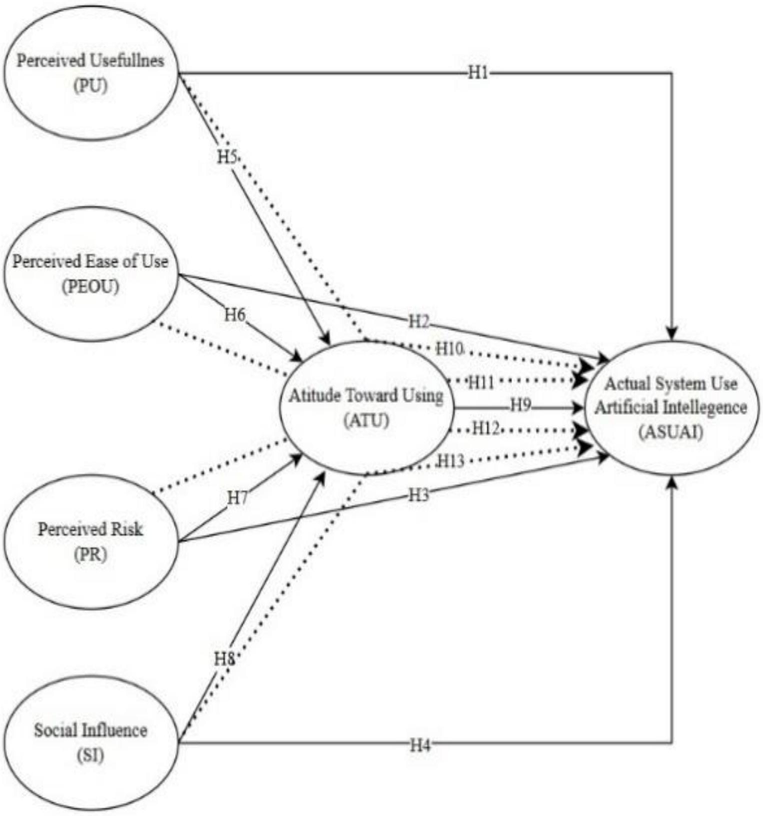

Fig. 1. Conceptual framework

The independent variables in this study are perceived usefulness (X1), perceived ease of use (X2), perceived risk (X3), and social pressure (X4). Meanwhile, the dependent variable (Y) uses artificial intelligence. In addition, the author also uses variable Z, which is the attitude towards the use of AI.

This study used questionnaires to collect data. The questionnaires were created using Google Forms with a 1-5 Likert scale, and the links were distributed via social media such as WhatsApp and Instagram using convenience sampling. The data used in this study are primary data obtained through questionnaires distributed to the sample. The data analysis technique applied is Structural Equation Modelling (SEM) with a Partial Least Squares (PLS) approach using SmartPLS 3.0 software.

4. RESULTS AND DISCUSSION

4.1 Results

The sample in this study consisted of active accounting students at Maulana Malik Ibrahim State Islamic University, Malang, and Universitas Brawijaya. The questionnaire was distributed from 28 July 2025 to 4 August 2025. One hundred and one questionnaires were collected, all completed according to the criteria, with complete data to analyze all questionnaires. Before testing the hypothesis or inner model, an outer model evaluation analysis was conducted by testing the validity and reliability of the variables by looking at the Outer Loadings, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) for each variable.

The results of the convergent validity test of the outer model, or the correlation between the construct and all variables showed a result of > 0.70. This indicates that the 21 statement items from the six variables in this study are valid.

Subsequently, the results of the discriminant validity test, which can be seen in Table 2, show that the Average Variance Extracted (AVE) value of all variables is > 0.50, which means that each variable has met the criteria for good discriminant validity.

Table 1. Convergent validity test results

Variable	Indicator	Outer Loadings	Description
Perceived Usefullness (X1)	X1.1	0.804	Valid
	X1.2	0.787	Valid
	X1.3	0.755	Valid
	X1.4	0.788	Valid
Perceived Ease of Use (X2)	X2.1	0.839	Valid
	X2.2	0.876	Valid
	X2.3	0.852	Valid
Perceived Risk (X3)	X3.1	0.910	Valid
	X3.2	0.776	Valid
	X3.3	0.907	Valid
Social Influence (X4)	X4.1	0.810	Valid
	X4.2	0.838	Valid
	X4.3	0.832	Valid
Attitude Toward Using (Z)	Z1.1	0.816	Valid
	Z1.2	0.889	Valid
	Z1.3	0.843	Valid
	Z1.4	0.868	Valid
Actual System Use Artificial Intelligence	Y1.1	0.720	Valid
	Y1.2	0.867	Valid
	Y1.3	0.826	Valid
	Y1.4	0.870	Valid

Table 2. Discriminant validity test results

Variable	Average Variance Extracted (AVE)	Description
PU (X1)	0.614	Valid
PEOU (X2)	0.733	Valid
PR (X3)	0.751	Valid
SI (X4)	0.684	Valid
ATU (X5)	0.730	Valid
AUAI (X5)	0.677	Valid

Based on Table 3, it can be seen that the composite reliability test results for all variables show a value of 0.70, meaning that each variable has met the criteria and can be said to be reliable.

Table 3. Composite reliability test results

Variable	Composite Reliability	Description
PU (X1)	0.864	Reliable
PEOU (X2)	0.892	Reliable
PR (X3)	0.900	Reliable
SI (X4)	0.866	Reliable
ATU (Z)	0.915	Reliable
AUAI (Y)	0.893	Reliable

As seen in Table 4, the results of Cronbach's alpha test show that all variables are > 0.70, so all variables can be considered reliable. From the results of the four outer model testing criteria, it can be said that they have been fulfilled.

Table 4. Cronbach's Alpha Test Results

Variable	Cronbach's Alpha	Description
PU (X1)	0.793	Reliable
PEOU (X2)	0.818	Reliable
PR (X3)	0.851	Reliable
SI (X4)	0.770	Reliable
ATU (Z)	0.877	Reliable
AUAI (Y)	0.839	Reliable

The inner model testing was conducted using the coefficient of determination (R^2), goodness of fit test, and hypothesis testing (direct effect and indirect effect).

The results of the Coefficient of Determination (R^2) test show the extent of the influence of the variables of perceived usefulness, perceived ease of use, perceived risk, and social influence on attitudes towards use, with a value of 0.686, which means that the ability of variables X1, X2, X3, and X4 to explain Z has a good value. Then, R Square was used to see the influence of perceived usefulness, perceived ease, perceived risk, and social influence on the actual use of Artificial Intelligence with a value of 0.564, which means that the ability of variables X1, X2, X3, and X4 in explaining Z has a moderate value.

Table 5. Coefficient determinant test results

Variable	R Square (R^2)	R Square Adjusted
ATU (Z)	0.686	0.670
AUAI (Y)	0.564	0.545

Model goodness of fit is assessed based on the Q2 value. The Q-Square calculation is as follows: Q Square = 1 - [(1 - R21) x (1 - R22)] = 0.86.

Based on the calculations, a Q2 value of 0.86 (86%) was obtained. This means that the research model created is able to explain 86% of the existing data diversity. Meanwhile, the remaining 14% is influenced by other factors not included in this study.

The research hypothesis can be tested by examining the t-statistic and p-value. A hypothesis is considered accepted if the p-value is < 0.05, and if the t-statistic is greater than 1.967 (based on the t-table with a significance level of 5%). then the effect is considered significant.

Based on the results of the direct effect test, the variables PU, PEOU, and SI were proven to have a significant effect on ATU, while the other variables did not have a significant effect on ASUAI or ATU. Only hypotheses H5, H8, and H9 were accepted, while the other six hypotheses were rejected. This indicates that perceived usefulness, social influence, and the relationship between ATU and ASUAI are the main factors that influence user acceptance.

The results of the no direct effect test show that the PU and SI variables through ATU have a significant effect on ASUAI, so hypotheses H10 and H13 are accepted. Meanwhile, the PEOU and PR variables through ATU do not have a significant effect on ASUAI, so hypotheses H11 and H12 are rejected. These findings indicate that perceived usefulness and social influence play an important indirect role in adoption.

4.2 Discussion

Based on the results of the hypothesis test, H1 was rejected. This study found that even though individuals view AI technology as applicable, this perception does not directly encourage the actual use of AI in daily activities. This means that perceived usefulness does not directly influence AI usage. These results confirm that perceived usefulness is not a significant factor in technology adoption (Falebita & Kok, 2025). Research conducted by Wu et al. (2024) found that perceived usefulness does not significantly affect actual behavior in the context of digital technology implementation.

The results of hypothesis testing show that H2 is rejected. This study found that the ease of use of AI does not automatically encourage individuals to adopt and use the technology in real activities.

Table 6. Direct effect test results

Parth	T Statistics	P Values	Decision
PU -> ASUAI	0.848	0.398	H1 rejected
PEOU -> ASUAI	0.558	0.578	H2 rejected
PR -> ASUAI	0.124	0.902	H3 rejected
SI -> ASUAI	1.375	0.172	H4 rejected
PU -> ATU	4.271	0.000	H5 accepted
PEOU -> ATU	1.039	0.301	H6 rejected
PR -> ATU	0.939	0.350	H7 rejected
SI -> ATU	3.057	0.003	H8 accepted
ATU -> ASUAI	6.488	0.000	H9 accepted

Table 7. Test Results no direct effect

Parth	T Statistics	P Values	Desicion
PU -> ATU -> ASUAI	3.298	0.001	H10 accepted
PEOU -> ATU -> ASUAI	1.041	0.300	H11 rejected
PR -> ATU -> ASUAI	0.908	0.366	H12 rejected
SI -> ATU -> ASUAI	3.124	0.002	H13 accepted

Ardiyanti & Susilowati's (2024) study also found the same results, especially among respondents unfamiliar with interacting directly with AI systems in their daily work. Even though users consider the technology easy to learn and operate, this does not necessarily encourage actual use if it is irrelevant to their needs or work environment. In addition, external factors such as limited access, lack of training, and minimal institutional support can be significant obstacles even though AI is perceived as easy to use (Mutambara, 2022). H2 Therefore, it can be concluded that the perception of ease does not directly affect the use of AI.

The data processing results show that H3 is rejected. This finding indicates that individuals' concerns about the risks of using AI, such as data leaks, are not a significant obstacle to using this technology. H3 kalimat ke 3 Therefore, it can be said that risk perception does not directly affect the use of AI. These results align with Russo's (2024) research, which examined the use of AI in software engineering and found that AI adoption is more determined by the compatibility of the technology with existing workflows than by the perceived level of risk.

The results of the hypothesis test show that H4 is rejected. These findings indicate that even though someone may receive encouragement or persuasion from their social environment, such as friends, to use AI, this does not directly encourage them to use the technology in practice. This shows that social pressure does not directly influence the use of AI. Research by Zou et al. (2024) shows similar findings in higher education, where students do not automatically use AI simply because of the influence of friends or lecturers, but rather because of the convenience and ease of completing academic assignments.

The data processing results show that H5 is accepted. This finding indicates that the higher an individual's perception of the benefits of AI, the more positive their attitude toward its use. The perception of the value and contribution of AI in improving efficiency, effectiveness, or work results plays an important role in shaping attitudes that support the application of this technology. This means that perceived usefulness influences AI adoption through attitude, rather than directly. Research by Geddam et al. (2024) and Liesa et al. (2023) reinforces this finding by concluding that perceived usefulness is one of the dominant factors in shaping attitudes toward technology acceptance, whether in education, business, or public services.

The hypothesis test results show that H6 is rejected. These findings indicate that even though individuals feel that AI is easy to use, this is not enough to form a positive attitude towards its use. In AI-based education, ease of use does not significantly affect students' attitudes because they consider the learning outcomes obtained more (Hao-En & Duen-Huang, 2023)**.** Meanwhile, Suleman (2019) states that user attitudes are more influenced by practical value and efficiency factors, not merely perceptions of technical ease. Therefore, it can be said that the perception of ease does not influence AI adoption directly or through attitude.

The data processing results show that H7 is rejected. This finding indicates that individuals' concerns about the risks inherent in AI use, such as privacy violations, data leaks, or the potential replacement of human roles by machines, do not significantly affect their attitudes toward using this technology. This indicates that risk perception does not influence AI adoption either directly or through attitudes. This finding is reinforced by Jayeon's (2021) research, which states that although risks such as concerns about data security and loss of control over technological decisions often arise in public discourse, these perceptions do not directly influence attitudes toward AI, especially among users who have positive experiences or high exposure to the technology. Users tend to be neutral or even favorable toward AI if they see clear and tangible benefits.

The results of data processing show that H8 is accepted. These findings indicate that social pressures such as peer influence, family, or other social environments shape individuals' attitudes toward using AI technology. When someone feels that their environment supports or uses specific technology, they tend to develop a more positive attitude toward it. Sutrisno (2023) also reinforces that social influence is an important factor in the Technology Acceptance Model (TAM), where social pressure from the surrounding environment can influence users' attitudes and behavior toward adopting digital technology. Therefore, it can be said that social pressure influences the adoption of AI through attitudes, not directly.

Based on the results of path analysis in data processing using SmartPLS, it is known that H9 is accepted. This finding shows that user attitudes towards Artificial Intelligence play an important role in influencing the actual behavior of using this technology. A positive attitude can reflect an individual's trust, acceptance, and readiness to integrate AI into their daily lives, whether in academic, work, or social contexts. This study is also reinforced by the findings of Cao et al. (2021), who state that in the context of digital transformation, user attitudes are one of the key elements in adopting innovative technology-based systems such as AI.

The results of data processing show that H10 is accepted. The perceived usefulness (PU) variable has a positive and significant effect on the use of Artificial Intelligence (ASUAI) through attitudes toward use (ATU). These findings indicate that attitudes toward use significantly mediate the effect of perceived usefulness on actual system use. In other words, the perception that AI systems help complete tasks will increase positive attitudes among users, which will then encourage the actual adoption of AI. These results align with research conducted by Damerji & Salimi (2021)**,** which found that perceived usefulness significantly mediates the relationship between technological readiness and AI technology adoption among accounting students. The study states that students who believe AI can improve their performance and effectiveness are more likely to have a positive attitude and use the technology in practice.

The results of the analysis on Specific Indirect Effects using SmartPLS show that H11 is rejected. This indicates that perceived ease of use does not affect AI through attitudes toward usage. In other words, even though users find AI technology easy to use, this does not necessarily increase the actual use of AI if the formation of positive attitudes does not accompany it. This finding is in line with the research by AlBanani & Hapsari (2022), which found that perceived ease of use does not always significantly affect attitudes toward use in e-commerce, especially if ease of use is considered uniform across platforms. They explain that in situations where the level of ease is relatively the same across systems, users do not consider this factor a major driver of attitude formation.

The path analysis results in data processing using SmartPLS show that the risk perception (PR) variable does not impact significantly on the actual system usage (ASUAI) through the mediating variable of attitude toward usage (ATU), thus rejecting H12. Similar findings were also obtained by Makhitha & Ngobeni (2024) in the context of online shopping in South Africa, where various dimensions of perceived risk (financial, convenience, security, social, and product) can influence attitudes, but not all lead to significant changes in intention to use when mediated by attitude. This study confirms that risk factors in technology use can often be minimized through user trust in the platform, familiarity with the system, and the perception of more dominant benefits than the perceived risks.

The results of the bootstrapping analysis in SmartPLS show that the social influence variable has a positive effect on the use of Artificial Intelligence (AI) through attitude toward use, thus accepting H13. This indicates that the greater the social influence individuals feel, the higher their tendency to form positive attitudes toward AI use, which increases the level of technology use. This is relevant to Liu et al. (2024), which shows that social impact significantly influences behavioral intention in the use of Large Language Models (LLMs) in education. Social influence includes encouragement from peers, family, and the surrounding environment, which can influence an individual's attitude toward adopting new technology. A supportive social environment will strengthen an individual's belief in the benefits of technology, thereby further shaping a positive attitude toward its use.

5. CONCLUSION

From those variables, in addition, perceived usefulness (PU) and perceived risk (PR) also do not directly influence AI usage. Attitudes toward usage (ATU) are proven to be able to mediate the influence of perceived usefulness (PU) and social pressure (SI) on usage (AUAI), but do not mediate the impact of PEOU and PR. These findings indicate that strengthening positive attitudes toward Artificial Intelligence is important in encouraging its use, primarily through increasing perceived usefulness and social support.

This study implies that forming positive attitudes toward AI use is a key factor in increasing technology acceptance, so stakeholders should focus on increasing perceived usefulness and social support. This research has limitation because the size of sample’s small so the results do not represent the border population fully. Therefore, further research is recommended to use a larger sample size and add other relevant variables, such as user trust, previous technology experience, or cultural factors, so that this can provide a more comprehensive picture of the acceptance of Artificial Intelligence technology.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

ACKNOWLEDGEMENT

The author would like to express his gratitude to Allah SWT for His blessings and grace, which enabled this research to be completed successfully and on time. The author would also like to express his deepest gratitude to the Faculty of Economics, UIN Maulana Malik Ibrahim Malang, for organising the 2025 Competitive Student Research Program, which provided the author with the opportunity and support to carry out this research. We would also like to thank all respondents who were willing to participate and all parties who contributed to the smooth running of this research until its completion. We hope that this research can provide benefits and positive contributions to the development of science and the academic community of the Faculty of Economics, UIN Maulana Malik Ibrahim Malang.

COMPETING INTERESTS

Authors have declared that they have no known competing financial interests or non-financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

AlBanani, M. T., & Hapsari, R. D. V. (2022). Pengaruh perceived usefulness, perceived ease of use terhadap purchase intention dan attitude toward using sebagai mediasi. *Jurnal Manajemen Pemasaran dan Perilaku Konsumen, 1*(4), 466–475. https://doi.org/10.21776/jmppk.2022.01.4.06

Almasri, F. (2024). Exploring the impact of artificial intelligence in teaching and learning of science: A systematic review of empirical research. *Research in Science Education, 54*, 977–997. https://doi.org/10.1007/s11165-024-10176-3

Alshammari, S. H., & Babu, E. (2025). The mediating role of satisfaction in the relationship between perceived usefulness, perceived ease of use and students' behavioural intention to use ChatGPT. *Scientific Reports, 15*(1), 1–13. https://doi.org/10.1038/s41598-025-91634-4

Ardiyanti, A., & Susilowati, E. (2024). Perceived usefulness and technology readiness mediate perceived ease of use and digital competence on technology adoption of artificial intelligence. *Proceedings of 7th International Conference of Economic, Business and Government Challenges 2024, 7*(1), 124–133.

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., Siemens, G., & Technol, J. E. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education, 21*, Article 21. https://doi.org/10.1186/s41239-023-00436-z

Bui, H. Q., Phan, Q. T. B., & Nguyen, H. T. (2025). AI adoption: A new perspective from accounting students in Vietnam. *Journal of Asian Business and Economic Studies, 32*(1), 40–51. https://doi.org/10.1108/JABES-06-2024-0300

Burhanuddin, S. F., & Pharmacista, G. (2023). Transformation of companies and trade in the era of Society 5.0. *International Journal of Science and Society, 5*(5), 1067–1077. https://doi.org/10.54783/ijsoc.v5i5.973

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation, 106*, 102312. https://doi.org/10.1016/j.technovation.2021.102312

Changalima, I. A., Amani, D., & Ismail, I. J. (2024). Social influence and information quality on generative AI use among business students. *The International Journal of Management Education, 22*(3), 101063. https://doi.org/10.1016/j.ijme.2024.101063

Creswell, J. W. (2014). *Research design: Qualitative, quantitative and mixed methods approaches* (4th ed.). Sage Publications.

Damerji, H., & Salimi, A. (2021). Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. *Accounting Education, 30*(2), 107–130. https://doi.org/10.1080/09639284.2021.1872035

De Villiers, C. (2024). The impact of Society 5.0 on curriculum development in higher education. *Journal of Ethics in Higher Education, 4*(4), 1–25. https://doi.org/10.26034/fr.jehe.2024.5953

Fadila, N., Goso, G., Hamid, R. S., & Ukkas, I. (2022). Pengaruh literasi keuangan, financial technology, persepsi risiko, dan locus of control terhadap keputusan investasi pengusaha muda. *Owner, 6*(2), 1633–1643. https://doi.org/10.33395/owner.v6i2.789

Fanani, A., & Wuryaningsih. (2025). Analisis penggunaan Binance dengan Technology Acceptance Model (TAM). *Jurnal Riset Akuntansi Jambi, 8*(1), 1–14.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

Filasari, I. N. E., & Suranto, S. (2025). Transformative effect of ChatGPT on accounting education: A new era AI chatbot. *Jurnal Paedagogy, 12*(1), 185. https://doi.org/10.33394/jp.v12i1.13709

Geddam, S. M., Nethravathi, N., & Ameer Hussian, A. (2024). Understanding AI adoption: The mediating role of attitude in user acceptance. *Journal of Informatics Education and Research, 4*(2), 1664–1672. https://doi.org/10.52783/jier.v4i2.975

Hao-En, C., & Duen-Huang, H. (2023). Usage intention model of digital assessment system. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2022.113469

Jayeon, L. (2021). Perceptions of benefits and risks of AI, attitudes toward AI, and support for AI policies. *The Journal of the Korea Contents Association, 21*, 193–204. https://doi.org/10.5392/JKCA.2021.21.04.193

Kamalov, F., Calonge, D. S., & Gurrib, I. (2023). New era of artificial intelligence in education: Towards a sustainable multifaceted revolution. *Sustainability, 15*, 12451. https://doi.org/10.3390/su151612451

Kholilah, K., Kawulur, H. R., & Subekti, I. (2022). Perceived usefulness, perceived ease of use, facilitating condition, social influence, and personal innovativeness of accounting students cloud computing adoption. *Organum: Jurnal Saintifik Manajemen dan Akuntansi, 5*(2), 141–151. https://doi.org/10.35138/organum.v5i2.257

Lee, C. S., & Tajudeen, F. P. (2020). Usage and impact of artificial intelligence on accounting: Evidence from Malaysian organisations. *Asian Journal of Business and Accounting, 13*(1), 213–239. https://doi.org/10.22452/ajba.vol13no1.8

Lee, S., Jones-Jang, S. M., Chung, M., Kim, N., & Choi, J. (2024). Who is using ChatGPT and why?: Extending the Unified Theory of Acceptance and Use of Technology (UTAUT) model. *Information Research, 29*(1), 54–72. https://doi.org/10.47989/ir291647

Liesa, M., Cecilia, O., Cosculluela, L., & Sierra, V. (2023). Links between ease of use, perceived usefulness and attitudes towards technology in older people in university: A structural equation modelling approach. *Education and Information Technologies, 28*, 2419–2436. https://doi.org/10.1007/s10639-022-11292-1

Liu, F., Chang, X., Zhu, Q., Huang, Y., Li, Y., & Wang, H. (2024). Assessing clinical medicine students' acceptance of large language model: Based on technology acceptance model. *BMC Medical Education, 24*(1), 1–12. https://doi.org/10.1186/s12909-024-06232-1

Makhitha, K. M., & Ngobeni, K. M. (2024). The effect of perceived risk in online shopping intention: Does attitude mediate the relationship? *Expert Journal of Marketing, 12*(1), 1–22.

Mutambara, D. (2022). Rural STEM preservice teachers' acceptance of virtual learning. *International Journal of Learning, Teaching* *and Educational Research, 21*(2), 155–175. https://doi.org/10.26803/ijlter.21.2.9

Petre, I. L., Hristache, D. A., Dobrescu, M. M., Constantin, A., Dumitra, E. C., & Radu, C. G. (2025). Digital communication in higher education settings: A pilot study on students' behavioural trends. *Sustainability, 17*(7), 1–12. https://doi.org/10.3390/su17073038

Purwianti, L., Jason, & Yulianto, E. (2025). The influence of price value, E-WOM, subjective norm, perceived behavior control on online purchase intentions through attitude. *Management and Economic Journal, 8*(3), 265–284.

Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for education and research: Opportunities, threats, and strategies. *Applied Sciences, 13*(9). https://doi.org/10.3390/app13095783

Ramírez-Márquez, C., Posadas-Paredes, T., Raya-Tapia, A. Y., & Ponce-Ortega, J. M. (2024). Natural resource optimization and sustainability in Society 5.0: A comprehensive review. *Resources, 13*(2). https://doi.org/10.3390/resources13020019

Rizvi, S., Waite, J., & Sentance, S. (2023). Artificial intelligence teaching and learning in K-12 from 2019 to 2022: A systematic literature review. *Computers and Education: Artificial Intelligence, 4*, 100145. https://doi.org/10.1016/j.caeai.2023.100145

Russell, S. J., & Norvig, P. (2003). *Artificial intelligence: A modern approach* (2nd ed.). Prentice Hall.

Russo, D. (2024). Navigating the complexity of generative AI adoption in software engineering. *ACM Transactions on Software Engineering and Methodology, 33*(5), 1–50. https://doi.org/10.1145/365215

Shahzad, M. F., & Xu, S. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *(Journal name and volume missing — please provide for complete citation).*

Sharma, S. K., Gaur, A., Saddikuti, V., & Rastogi, A. (2017). Structural equation model (SEM)-neural network (NN) model for predicting quality determinants of e-learning management systems. *Behaviour & Information Technology, 36*(10), 1053–1066. https://doi.org/10.1080/0144929X.2017.1340973

Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education, 49*(2), 223–245. https://doi.org/10.1007/s10755-023-09686-1

Suleman, D. (2019). Consumer decisions toward fashion product shopping in Indonesia: The effects of attitude, perception of ease of use, usefulness, and trust. *Management Dynamics in the Knowledge Economy, 7*(2), 133–146. https://doi.org/10.25019/MDKE/7.2.01

Sutrisno, T. F. C. W. (2023). Digital payment transformation: The role of the technology acceptance model to repurchase intention. *Review of Management and Entrepreneurship, 7*(1), 1–24. https://doi.org/10.37715/rme.v7i1.3679

Syahril, W. N., & Rikumahu, B. (2019). Penggunaan Technology Acceptance Model (TAM) dalam analisis minat perilaku penggunaan e-money pada mahasiswa Universitas Telkom. *[Journal name missing]*, *1*(2), 201–214.

Tahar, A., Riyadh, H. A., Sofyani, H., & Purnomo, W. E. (2020). Perceived ease of use, perceived usefulness, perceived security and intention to use e-filing: The role of technology readiness. *Journal of Asian Finance, Economics and Business, 7*(9), 537–547. https://doi.org/10.13106/JAFEB.2020.VOL7.NO9.537

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.

Wu, H., Wang, Y., & Wang, Y. (2024). "To use or not to use?" A mixed-methods study on the determinants of EFL college learners' behavioral intention to use AI in the distributed learning context. *International Review of Research in Open and Distributed Learning, 25*(3), 158–178. https://doi.org/10.19173/irrodl.v25i3.7708

Zou, X., Rau, P. P., & Zhao, Y. (2024). Investigating the impact of different stressors on trust in intelligent decision support systems. In *Lecture Notes in*

Computer Science (Vol. 14540, pp. 309–326). Springer. https://doi.org/10.1007/978-3-031-60901-5_22

Peer-review history:
The peer review history for this paper can be accessed here:
https://pr.sdiarticle5.com/review-history/144991