

## FACTORS INFLUENCING ARTIFICIAL INTELLIGENCE (AI) ADOPTION AMONG MALAYSIAN STUDENTS: A PARTIAL LEAST SQUARE-STRUCTURAL EQUATION MODELING APPROACH

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### ABSTRACT

**Background and Purpose:** Artificial Intelligence (AI) is transforming higher education by enhancing learning experiences through personalised instruction, automated assessments, and intelligent tutoring systems. In Malaysia, AI adoption among students is gaining momentum, and it is influenced by digital literacy, perceived usefulness, and social influence. This study examines the key factors influencing AI adoption among Malaysian students.

**Methodology:** A survey research design was employed, utilising a structured questionnaire distributed to 286 students across four Malaysian universities. 224 valid responses were analysed using Partial Least Square (PLS-SEM) to test the hypothesised relationships among the variables.

**Findings:** Results indicate that social influence has the most substantial effect on AI adoption ( $\beta = 0.503$ ,  $p < 0.001$ ), followed by perceived usefulness ( $\beta = 0.236$ ,  $p < 0.001$ ) and digital literacy ( $\beta = 0.188$ ,  $p = 0.036$ ). These findings suggest that students are more likely to adopt AI when they observe

peers and educators using it effectively. Additionally, students who perceive AI as beneficial for academic performance are more willing to engage with AI technologies.

**Implication:** The study contributes to understanding AI adoption in higher education; institutions can better prepare students for an AI-driven academic and professional landscape by addressing the identified factors.

**Keywords:** AI adoption, digital literacy, Malaysian students, perceived usefulness, social influence.

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## 1.0 INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force in education, revolutionising traditional teaching and learning methods while significantly enhancing students' experiences (George, 2023). AI-powered tools are reshaping the educational landscape by offering personalised learning, automated assessments, intelligent tutoring systems, and data-driven decision-making for educators and institutions. In Malaysia, the adoption of AI among students is gaining momentum and is influenced by institutional, technological, and individual factors. Higher education institutions increasingly incorporate AI-driven solutions into their academic frameworks, leveraging technologies such as adaptive learning platforms, virtual assistants, and predictive analytics to optimise student learning outcomes.

The fundamental factor influencing AI adoption among students is perceived usefulness. When students perceive AI applications as important and beneficial in enhancing their learning efficiency and academic performance, they will be more persuaded to adopt such technologies (Cukurova et al., 2020). Furthermore, easy use plays a vital role, as students are more likely to engage with AI tools if they are user-friendly and require minimal effort to operate (Almusaed et al., 2023). The in-built AI application design, availability of user support, and accessibility of different devices contribute significantly to students' willingness to embrace AI in their academic activities.

Digital literacy is another important factor for students who want to adopt AI. AI adoption mainly depends on students' ability to effectively utilise and navigate digital tools (Capinding & Dumayas, 2024). Disparities in digital literacy exist among students because of

differences in educational backgrounds, access to digital resources and socio-economic status. Students exposed to digital learning concepts are more likely to adopt AI-driven technologies. However, academic institutions play a critical role in enhancing students' AI-related competencies by introducing AI-related courses into curricula, thus nurturing more AI-ready students.

Social influence also significantly shapes students' attitudes toward AI adoption (Sova et al., 2024). Students are more likely to embrace AI technologies if they observe their peers, educators, or role models using them effectively. Collaborative learning environments encouraging knowledge-sharing and AI experimentation foster positive attitudes toward AI adoption. Additionally, the role of educators is instrumental in influencing students' perceptions of AI. Teachers who incorporate AI-driven instructional methods and encourage students to explore AI-based problem-solving strategies can significantly enhance students' willingness to engage with AI technologies. It is against this backdrop; this study aims to investigate the influence of Artificial Intelligence (AI) Adoption among Malaysian Students.

## **2.0 LITERATURE REVIEW**

### **2.1 Artificial Intelligence (AI)**

Artificial Intelligence (AI) is the branch of computer science that focuses on creating systems capable of imitating human intelligence (Chatterjee, 2020). AI allows robots to carry out cognitive functions previously only possible for humans, such as learning, reasoning, problem-solving, perception, and language comprehension (Russell, 2022). AI makes choices, finds patterns, and gains experience using algorithms and massive databases over time. Artificial intelligence differs from traditional computer programs, which adhere to preset instructions without changing, in that it can learn and adapt (Kühl et al., 2022). AI uses various techniques, including machine learning, deep learning, and natural language processing.

Advances in power computing have driven the growth of AI, algorithm design improvements and large datasets availability (Chang et al., 2021). Modern AI uses enormous volumes of data to make judgments on its own in real-time, whereas early AI systems were rule-based and had a narrow scope. AI is currently included in many technologies, ranging from voice assistants and search engines to recommendation engines and self-driving cars. However, as AI becomes more powerful, concerns about ethics, privacy, and bias arise. Ensuring responsible AI development requires addressing issues such as data transparency, algorithmic fairness, and the societal impact of automation.

## **2.2 Perceived Usefulness and Artificial Intelligence (AI) Adoption**

Perceived usefulness plays a vital role in adopting Artificial Intelligence (AI), as it directly influences users' willingness to integrate AI-driven technologies into their personal and professional lives (Gerlich, 2023a; Nasidi et al., 2022). Perceived usefulness is the degree to which an individual believes using a particular system will enhance their performance or productivity (Wilson et al., 2021). When AI systems demonstrate clear benefits, such as increased efficiency, improved decision-making, or automation of repetitive tasks, users are more likely to adopt and trust these technologies. AI adoption is often driven by its ability to provide concrete advantages in different fields, AI-driven data analytics tools enhance decision-making processes, encouraging businesses to integrate AI into their operations (Abadi & Hasanuddin, 2024). However, other aspects influence AI acceptability besides performance advantages, such as dependability, simplicity of integration, and user-friendliness (Massoudi et al., 2024).

AI-generated outputs strongly impact perceived usefulness; students may be reluctant to rely on AI if they think it is inaccurate or unfair (Frenkenberg & Hochman, 2025). AI continues to evolve, and understanding the relationship between perceived usefulness and adoption remains essential for businesses, policymakers, and technology designers. Strategies such as user education improved human-AI collaboration, and ethical AI development can enhance perceived usefulness and accelerate AI adoption. Ultimately, the extent to which AI is embraced depends on how effectively it aligns with users' expectations, needs, and trust in its capabilities. Researchers like Rahman et al. (2023), Damerji and Salimi (2021), Lee and Chen (2022) established the relationship between perceived usefulness and AI adoption. Based on the above literature, the research proposed the following hypothesis:

H<sub>1</sub>: Perceived Usefulness (PU) significantly influences Artificial Intelligence (AI) Adoption

## **2.3 Digital Literacy and Artificial Intelligence (AI) Adoption**

Digital literacy is vital in adopting Artificial Intelligence (AI), as it determines users' ability to understand, interact with, and effectively utilise AI-driven technologies (Zhang & Zhang, 2024). Digital literacy is locating, assessing, and effectively using digital information and technology (Nikou et al., 2022). It covers a variety of abilities, such as fundamental computer skills, data interpretation, critical thinking, and ethical concerns concerning digital instruments. People who are more digitally literate are more likely to adopt and fully use AI technology as they become increasingly integrated into different industries. A person's confidence and

proficiency with digital technologies significantly impact their adoption of AI. Strong digital literacy users can better comprehend AI features, decipher AI-generated outputs, and use AI solutions in personal and professional contexts (Khan et al., 2022; Nikou et al., 2022).

The digital divide remains a significant barrier to AI adoption, particularly in developing regions with limited access to digital resources and education. Individuals with low digital literacy may struggle to understand AI applications, leading to scepticism, fear of job displacement, or resistance to adoption (Kar et al., 2021). Additionally, simplifying AI interfaces and making AI tools more user-friendly can lower the digital literacy barrier, enabling broader adoption across diverse demographics. Eventually, digital literacy will be a key enabler of AI adoption, as it will equip individuals with the knowledge and confidence needed to interact with AI-driven technologies. By bridging digital literacy gaps, societies can ensure more inclusive and responsible AI adoption, maximising the benefits of AI in various domains. The research established the relationship between Digital Literacy and Artificial Intelligence (AI) Adoption (Anurogo et al., 2023; Ciampa et al., 2023; Ma & Lei, 2024; Makeleni et al., 2023). Based on the above literature, the research proposed the following hypothesis:

H<sub>2</sub>: Digital Literacy (DL) significantly influences Artificial Intelligence (AI) Adoption

## **2.4 Social Influence and Artificial Intelligence (AI) Adoption**

Social influence plays a significant role in adopting Artificial Intelligence (AI) by shaping individuals' attitudes, perceptions, and behaviours toward AI technologies (Gerlich, 2023a). Social influence is the term used to describe how peer judgments, cultural values, professional advice, and societal standards affect a person's decision to adopt and use new technology (Joa & Magsamen-Conrad, 2022). In AI adoption, social influence manifests through various channels, including word-of-mouth recommendations, organisational pressure, media narratives, and government policies.

One of the key ways social influence affects AI adoption is through peer and professional networks. When individuals observe colleagues, friends, or industry leaders successfully using AI-powered tools, they are more likely to perceive AI as valuable and trustworthy (Chung et al., 2021). Thus, Mainstream media, social media influencers, and technology experts play a significant role in framing AI as either a beneficial innovation or a disruptive force. Positive narratives emphasising AI's potential to improve efficiency, decision-making, and convenience can encourage adoption (Papagiannidis et al., 2023).

Cultural and societal norms also influence AI adoption patterns across different regions. In societies with high uncertainty avoidance, individuals may be more hesitant to adopt AI due to concerns about control and transparency.

Social influence significantly affects students' attitudes toward AI adoption. Peer groups, educators, media narratives, and institutional policies contribute to shaping students' perceptions of AI technologies (Gerlich, 2023b). Observing peers and educators effectively using AI tools can encourage students to explore and adopt AI-driven solutions (Sova et al., 2024). Additionally, social media platforms and industry leaders are crucial in framing AI as either a beneficial innovation or a disruptive force (Papagiannidis et al., 2023). Cultural factors also influence AI adoption, as societies with high uncertainty avoidance may resist AI integration due to concerns about transparency and control (Hasija & Esper, 2022). Empirical studies by Gupta et al. (2024) and Upadhyay et al. (2022a) confirm the strong influence of social factors on AI adoption, highlighting the need for collaborative learning environments that promote knowledge-sharing and AI experimentation. The relationship between social influence and artificial intelligence adoption was established in the literature (Gupta et al., 2024; Hasija & Esper, 2022; Upadhyay et al., 2022a). Based on the above literature, the research proposed the following hypothesis:

H<sub>3</sub>: Social Influence (SI) significantly influences Artificial Intelligence (AI) Adoption.

### **3.0 RESEARCH DESIGN**

The research methodology involved the identification of four variables, categorised as perceived usefulness, digital literacy, and social influence as factors influencing artificial intelligence AI adoption among Malaysian students. Based on previous studies, hypotheses were formulated to establish the variables' relationships. The research framework is depicted in Figure 1, illustrating the relationships between the independent and dependent variables.

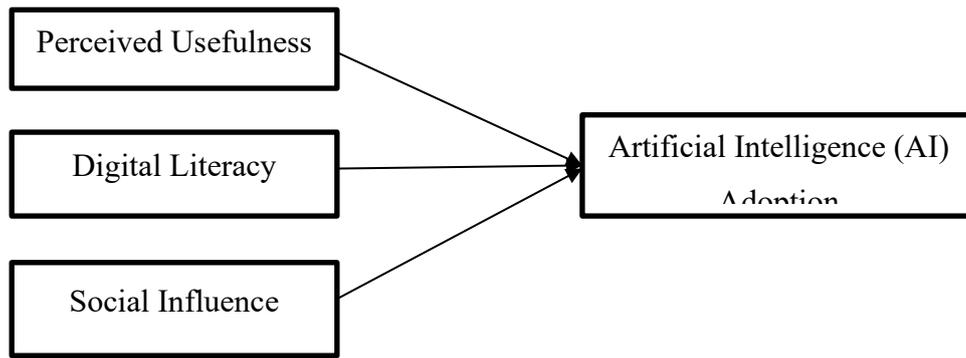


Figure 1: Research framework

A survey research design was adopted for this study to collect and analyse data from a targeted population. This design is particularly suitable for understanding attitudes, perceptions, and behaviours, as it allows researchers to gather standardised responses from a large sample. A structured questionnaire served as the primary instrument for data collection. The questionnaire was carefully designed, incorporating items adapted from previous studies (Bogoslov et al., 2024; Kelly et al., 2023; Rahman et al., 2023; Sadriwala & Sadriwala, 2022; Sharma et al., 2022; Zhang & Zhang, 2024). Each item was measured using a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). Smart PLS (Partial Least Squares Structural Equation Modeling) was employed to analyse the collected data. This software is well-suited for predictive modelling and allows for examining complex relationships between variables. The path model was utilised to test the research hypotheses by estimating regression coefficients, which indicate the strength and direction of relationships between the independent and dependent variables.

The respondents for this study were international students from four Malaysian universities: University Malaysia Terengganu (UMT), University Technology Malaysia (UTM) in Johor, University Putra Malaysia (UPM) in Selangor, and University Utara Malaysia (UUM) in Kedah. These students were selected based on the assumption that they possess comprehensive knowledge about artificial intelligence (AI) relevant to the study's objectives. Simple Random Sampling (SRS) was employed to determine the appropriate sample size, ensuring that each student had an equal chance of being selected. The sample size was initially determined using the SurveyMonkey sample size calculator, which provided a reliable estimate based on the study's population and confidence level requirements. To moderate the risks of non-response bias and sample size errors, the sample size was increased by 10%, as Hair et al. (2021) recommended. Therefore, an additional 26 respondents (10% of 260) were included,

bringing the total selected sample to 286 students. During data collection, 224 questionnaires were completed and returned, yielding a response rate of 78.2%. This response rate is considered excellent for survey research, indicating a high level of engagement from the participants. Since incomplete or missing responses could affect data reliability, only the 224 fully completed questionnaires were included in the final analysis.

## **4.0 ANALYSIS AND DISCUSSION**

### **4.1 Reliability and Validity**

Table 1 presents reliability and validity statistics for four constructs: Artificial Intelligence, Digital Literacy, Perceived Usefulness, and Social Influence. The measures reported include Cronbach's Alpha (CA), rho\_A, Composite Reliability (CR), and Average Variance Extracted (AVE), all of which are critical for assessing the internal consistency and convergent validity of the constructs. Cronbach's Alpha, a widely used measure of reliability, indicates how items within a construct consistently measure the underlying concept. A threshold of 0.7 is commonly accepted, with higher values indicating more substantial reliability. The results show that Artificial Intelligence has a Cronbach's Alpha of 0.746, demonstrating acceptable reliability, while Digital Literacy (0.915), Perceived Usefulness (0.939), and Social Influence (0.922) exhibit excellent reliability, as their values exceed 0.9. Composite Reliability, which provides a more comprehensive measure of reliability by considering factor loadings, confirms these findings. All constructs have CR values above the recommended 0.7 thresholds, indicating strong internal consistency, with Digital Literacy (0.94), Perceived Usefulness (0.95), and Social Influence (0.939) displaying exceptionally high reliability.

The table also assesses convergent validity through the Average Variance Extracted (AVE), which measures the extent to which a construct explains variance in its observed indicators. An AVE value of 0.5 or higher suggests that the construct adequately explains its indicators. The results indicate that all constructs meet this criterion, with Artificial Intelligence having an AVE of 0.573, while Digital Literacy (0.798), Perceived Usefulness (0.732), and Social Influence (0.722) exceed 0.7, further reinforcing the validity of these measures. Additionally, rho\_A, an alternative reliability coefficient that often provides a more accurate estimate than Cronbach's Alpha, confirms the robustness of the constructs. The values range from 0.814 for Artificial Intelligence to 0.94 for Perceived Usefulness, exceeding the recommended minimum of 0.7. These results collectively indicate that the constructs exhibit strong reliability and convergent validity, making them suitable for further analysis. The high-

reliability scores suggest that the measurement model is well-structured, while the AVE values confirm that the constructs effectively capture the intended theoretical concepts.

Table 1: Reliability and validity

Constructs	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Artificial Intelligence	0.746	0.814	0.839	0.573
Digital Literacy	0.915	0.918	0.94	0.798
Perceived Usefulness	0.939	0.94	0.95	0.732
Social Influence	0.922	0.93	0.939	0.722

#### 4.2 Discriminant Validity

Table 2 presents the Fornell-Larcker criterion for assessing discriminant validity among the constructs: Artificial Intelligence, Digital Literacy, Perceived Usefulness, and Social Influence. Discriminant validity ensures that a construct is empirically distinct from other constructs in a model, confirming that each variable measures a unique concept rather than overlapping with others (Fornell & Larcker, 1981). According to this criterion, discriminant validity is established when the square root of the Average Variance Extracted (AVE) for each construct (shown as diagonal values in Table 2) is greater than its correlation with other constructs (off-diagonal values).

The findings indicate that the square root of AVE for each construct is higher than its correlations with other constructs, confirming discriminant validity. Artificial Intelligence has a diagonal value of **0.757**, which is greater than its correlations with Digital Literacy (**0.769**), Perceived Usefulness (**0.703**), and Social Influence (**0.806**). Similarly, Digital Literacy has a square root of AVE of **0.893**, which exceeds its correlations with Perceived Usefulness (**0.722**) and Social Influence (**0.828**). Perceived Usefulness also meets the criterion, with a square root of AVE of **0.856**, greater than its correlation with Social Influence (**0.667**). Finally, social influence has a value of 0.85, higher than its correlation with all other constructs.

These results confirm that each construct maintains sufficient discriminant validity, indicating that the constructs are empirically distinct. This is crucial for structural equation modelling, as it ensures that observed relationships are not influenced by conceptual redundancy or measurement errors (Sarstedt et al., 2021). Establishing discriminant validity enhances the theoretical rigour of the study and supports the reliability of further structural model analysis.

Table 2: Fornell-Lacker criterion: Discriminants validity

Constructs	Artificial	Digital Literacy	Perceived	Social Influence
	Intelligence		Usefulness	
Artificial Intelligence	<b>0.757</b>			
Digital Literacy	0.769	<b>0.893</b>		
Perceived Usefulness	0.703	0.722	<b>0.856</b>	
Social Influence	0.806	0.828	0.667	<b>0.85</b>

Table 3 presents the cross-loading values for assessing discriminant validity through item-level analysis. Cross-loadings are used to determine whether each item loads more strongly on its associated construct than on other constructs in the model (Sarstedt et al., 2021). According to the discriminant validity criterion, an item should exhibit its highest loading on the construct it is intended to measure. In contrast, its loadings on other constructs should be significantly lower.

The results confirm that all items load more strongly on their respective constructs than on others, indicating satisfactory discriminant validity. For example, AI2 and AI3, which are intended to measure Artificial Intelligence, have their highest loadings on this construct (0.864 and 0.884, respectively). In contrast, their correlations with other constructs, such as Digital Literacy (0.724, 0.732), Perceived Usefulness (0.635, 0.652), and Social Influence (0.709, 0.746), are lower. Similarly, for Digital Literacy, DL2 (0.93) and DL3 (0.924) have their highest loadings on their assigned construct, while their correlations with other constructs remain lower.

For Perceived Usefulness, all items load highest on their designated construct, with PU3 (0.879) and PU6 (0.88) showing the strongest correlations within the construct while maintaining lower correlations with Artificial Intelligence, Digital Literacy, and Social Influence. Likewise, Social Influence items demonstrate high internal consistency, with SI4 (0.892) and SI5 (0.885) having the highest correlations within their construct, confirming that each item distinctly measures its intended factor rather than overlapping with other constructs. The result indicates that all constructs exhibit strong discriminant validity, ensuring that each latent variable is uniquely defined by its indicators. This supports the robustness of the measurement model and reduces the risk of construct redundancy (Henseler et al., 2015). By confirming discriminant validity through cross-loadings, the study ensures that the constructs are conceptually distinct, providing a solid foundation for further structural model analysis.

Table 3: Cross loading: Discriminants validity

Item Code	Artificial Intelligence	Digital Literacy	Perceived Usefulness	Social Influence
AI1	0.642	0.406	0.396	0.486
AI2	0.864	0.724	0.635	0.709
AI3	0.884	0.732	0.652	0.746
AI4	0.594	0.352	0.376	0.43
DL1	0.633	0.88	0.617	0.716
DL2	0.691	0.93	0.644	0.769
DL3	0.729	0.924	0.642	0.739
DL4	0.687	0.836	0.674	0.734
PU1	0.627	0.605	0.858	0.543
PU2	0.639	0.585	0.867	0.563
PU3	0.585	0.638	0.879	0.588
PU4	0.551	0.574	0.807	0.537
PU5	0.594	0.608	0.884	0.566
PU6	0.635	0.689	0.88	0.626
PU7	0.574	0.623	0.812	0.572
SI1	0.694	0.739	0.613	0.835
SI2	0.528	0.56	0.528	0.742
SI3	0.685	0.669	0.56	0.85
SI4	0.708	0.758	0.557	0.892
SI5	0.686	0.724	0.54	0.885
SI6	0.777	0.748	0.602	0.884

### 4.3 Hypothesis Testing

Table 4 presents the path coefficients for the hypothesised relationships in the model, providing a perception of the strength and significance of the relations between constructs. The path analysis results include Beta ( $\beta$ ) values, standard deviations, T-statistics, and P-values, which are critical in evaluating the validity of the proposed hypotheses. The Beta value represents the strength and direction of the relationship, with higher values indicating more substantial effects. The T-statistic and P-value assess statistical significance, where a T-statistic above 1.96 and a P-value below 0.05 suggest a significant relationship (Hair et al., 2021).

The results confirm that all three hypotheses are supported. Hypothesis 1 (H1) examines the relationship between Digital Literacy and Artificial Intelligence, yielding a Beta value of **0.188** with a T-statistic of **2.106** and a P-value of **0.036**. This indicates a significant but moderate positive effect, suggesting that individuals with higher digital literacy are likelier to engage with and understand artificial intelligence technologies. Hypothesis 2 (H2) tests the

effect of Perceived Usefulness on Artificial Intelligence, with a Beta value of **0.236**, a T-statistic of **4.025**, and a P-value of **0.000**, demonstrating a strong and highly significant positive relationship. This implies that the more individuals perceive artificial intelligence as useful, the greater their adoption and engagement.

Hypothesis 3 (H3) explores the influence of Social Influence on Artificial Intelligence, yielding the highest Beta value of **0.503**, with a T-statistic of **5.139** and a P-value of **0.000**. This suggests a robust and significant effect, indicating that social influence is crucial in shaping individuals' attitudes and engagement with artificial intelligence. The results highlight that social influence has the strongest impact among the three factors examined, followed by perceived usefulness and digital literacy.

Table 4: Path coefficients

Hypotheses	Path Analysis	Beta Value	Standard deviation	T statistics	P values	Decision
H1	Digital Literacy -> Artificial Intelligence	0.188	0.092	2.106	0.036	Supported
H2	Perceived Usefulness -> Artificial Intelligence	0.236	0.059	4.025	0.000	Supported
H3	Social Influence -> Artificial Intelligence	0.503	0.095	5.139	0.000	Supported

#### 4.4 Structural Model

The analytical technique is translated into visuals using SmartPLS 3.0.0. The diagram is depicted in Figure 2, and the direction of the hypotheses put forward in the framework determines the direction of the arrows connecting the study's components. To confirm that the research construct has a causal effect, single-headed arrows are employed.

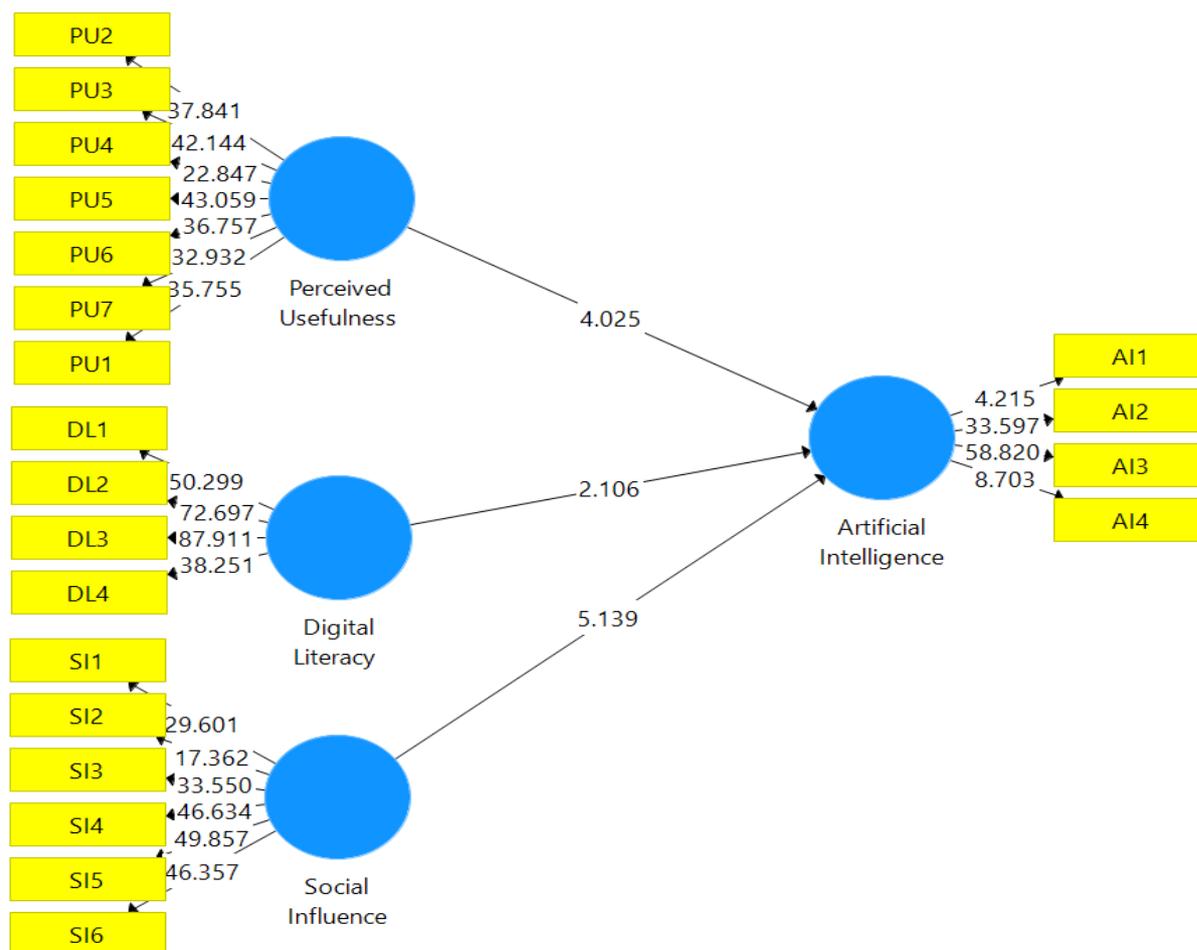


Figure 2: Graphical results

The findings of this study contribute to the growing body of research on AI adoption in higher education by signifying the significant influence of social influence, perceived usefulness, and digital literacy on students' willingness to engage with AI technologies. These results align with previous studies. For instance, this study found that social influence substantially impacts AI adoption among Malaysian students ( $\beta = 0.503, p < 0.001$ ). This finding is consistent with previous research emphasizing the role of peer networks, educators, and societal norms in shaping students' technology adoption behaviors (Gerlich, 2023b; Upadhyay et al., 2022b). Studies such as those by Gupta et al. (2024) and Hasija and Esper (2022) also highlight that students are more likely to embrace AI when they see others, especially authority figures like lecturers and mentors, using AI effectively.

The study confirmed that perceived usefulness significantly influences AI adoption ( $\beta = 0.236, p < 0.001$ ), supporting the proposed hypothesis. This aligns with prior research indicating that users adopt AI technologies when they perceive them as beneficial for improving efficiency, productivity, or learning outcomes (Rahman & Watanobe, 2023; Wilson

et al., 2021). Similar findings have been reported in studies by Damerji and Salimi (2021) and Sadriwala and Sadriwala (2022), where perceived usefulness emerged as a key determinant of AI adoption in professional and academic settings. However, some studies indicate that perceived usefulness alone may not be sufficient to drive AI adoption. For example, Frenkenberg and Hochman (2025) highlight that users may resist AI due to concerns about bias, reliability, or ethical considerations, even if they recognize its benefits. This suggests that trust in AI technology plays a moderating role in how perceived usefulness translates into adoption, an area that future research could explore further.

Moreover, the study also found that digital literacy positively influences AI adoption ( $\beta = 0.188$ ,  $p = 0.036$ ), though its impact was weaker than social influence and perceived usefulness. This finding aligns with research by Chen and Zainudin (2024), who argue that students with higher digital literacy are better positioned to understand, evaluate, and effectively utilize AI tools. Other studies, such as those by Almaiah et al. (2022) and Nikou et al. (2022), further emphasize that digital literacy reduces technological anxiety and enhances users' confidence in interacting with AI applications. Studies conducted in less digitally developed regions highlight digital literacy as a significant barrier to AI adoption. For instance, Dwivedi et al. (2021) found that digital literacy plays a much stronger role in AI adoption in developing countries with limited digital infrastructure, sometimes outweighing perceived usefulness.

## **5.0 CONCLUSION**

A combination of perceived usefulness, digital literacy, and social influence influences the adoption of Artificial Intelligence (AI) among Malaysian students. The study findings indicate that social influence exerts the most substantial effect on AI adoption, followed by perceived usefulness and digital literacy. This suggests that students are more likely to embrace AI when they observe their peers, educators, and role models using AI-powered tools effectively. Additionally, students who perceive AI as helpful in enhancing their academic performance demonstrate a greater willingness to integrate AI into their learning routines. However, digital literacy remains crucial, as students with higher competency in digital technologies are better equipped to utilize AI tools effectively.

The findings of this study have significant implications across several domains. From the perspective of a policymaker, Government and educational policymakers should prioritize AI adoption by developing strategic policies that promote digital literacy and equitable access to AI technologies. Investments in AI infrastructure, training programs, and research initiatives

will ensure that students are equipped with the necessary skills to navigate AI-driven academic and professional landscapes. Policymakers must also address AI ethics, data privacy, and algorithmic bias concerns to ensure responsible AI deployment in education. For educational intuitions, higher education institutions must take proactive measures to facilitate AI adoption among students. This includes integrating AI-related courses into curricula, providing digital literacy training, and fostering an AI-friendly learning environment. Universities should also encourage educators to incorporate AI-driven teaching methodologies, as this will enhance students' familiarity and confidence in using AI tools. Additionally, collaborative learning environments should be established to allow students to share knowledge and experiences related to AI applications.

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## **REFERENCES**

- Abadi, I., & Hasanuddin, H. (2024). The role of leadership in effective and efficient human resource management decision making. *Journal of Economics Review*, 4(2), 170-183.
- Almaiah, M. A., Alfaisal, R., Salloum, S. A., Hajje, F., Thabit, S., El-Qirem, F. A., Lutfi, A., Alrawad, M., Al Mulhem, A., & Alkhdour, T. (2022). Examining the impact of artificial intelligence and social and computer anxiety in e-learning settings: Students' perceptions at the university level. *Electronics*, 11(22), 1-22.
- Almusaed, A., Almssad, A., Yitmen, I., & Homod, R. Z. (2023). Enhancing student engagement: Harnessing "AIED"'s power in hybrid education—A review analysis. *Education Sciences*, 13(7), 1-24.
- Anurogo, D., La Ramba, H., Putri, N. D., & Putri, U. M. P. (2023). Digital literacy 5.0 to enhance multicultural education. *Multicultural Islamic Education Review*, 1(2), 109-179.
- Bogoslov, I. A., Corman, S., & Lungu, A. E. (2024). Perspectives on artificial intelligence adoption for European Union elderly in the context of digital skills development. *Sustainability*, 16(11), 1-34.
- Capinding, A. T., & Dumayas, F. T. (2024). Transformative pedagogy in the digital age: Unraveling the impact of artificial intelligence on higher education students. *Problems of Education in the 21st Century*, 82(5), 630-657.

- Chang, Z., Liu, S., Xiong, X., Cai, Z., & Tu, G. (2021). A survey of recent advances in edge-computing-powered artificial intelligence of things. *IEEE Internet of Things Journal*, 8(18), 13849-13875.
- Chatterjee, R. (2020). Fundamental concepts of artificial intelligence and its applications. *Journal of Mathematical Problems, Equations and Statistics*, 1(2), 13-24.
- Chen, Z., & Zainudin, Z. (2024). Systematic review on developing digital literacy approach in higher education institution. *Uniglobal Journal of Social Sciences and Humanities*, 3(2), 234-241.
- Chung, Y., Li, Y., & Jia, J. (2021). Exploring embeddedness, centrality, and social influence on backer behavior: The role of backer networks in crowdfunding. *Journal of the academy of marketing science*, 49(1), 925-946.
- Ciampa, K., Wolfe, Z. M., & Bronstein, B. (2023). ChatGPT in education: Transforming digital literacy practices. *Journal of Adolescent & Adult Literacy*, 67(3), 186-195.
- Cukurova, M., Luckin, R., & Kent, C. (2020). Impact of an artificial intelligence research frame on the perceived credibility of educational research evidence. *International Journal of Artificial Intelligence in Education*, 30(2), 205-235.
- 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.
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., & Eirug, A. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57(1), 101994.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.
- Frenkenberg, A., & Hochman, G. (2025). It's scary to use it, it's scary to refuse it: The psychological dimensions of AI Adoption—Anxiety, motives, and dependency. *Systems*, 13(2), 1-25.
- George, A. S. (2023). Preparing students for an AI-driven world: Rethinking curriculum and pedagogy in the age of artificial intelligence. *Partners Universal Innovative Research Publication*, 1(2), 112-136.
- Gerlich, M. (2023a). Perceptions and acceptance of artificial intelligence: A multi-dimensional study. *Social Sciences*, 12(9), 1-24.

- Gerlich, M. (2023b). The power of virtual influencers: Impact on consumer behaviour and attitudes in the age of AI. *Administrative Sciences*, 13(8), 1-21.
- Gupta, R., Nair, K., Mishra, M., Ibrahim, B., & Bhardwaj, S. (2024). Adoption and impacts of generative artificial intelligence: Theoretical underpinnings and research agenda. *International Journal of Information Management Data Insights*, 4(1), 100232.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.
- Hasija, A., & Esper, T. L. (2022). In Artificial Intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. *Journal of Business Logistics*, 43(3), 388-412.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115-135.
- Joa, C. Y., & Magsamen-Conrad, K. (2022). Social influence and UTAUT in predicting digital immigrants' technology use. *Behaviour & Information Technology*, 41(8), 1620-1638.
- Kar, S., Kar, A. K., & Gupta, M. P. (2021). Modeling drivers and barriers of artificial intelligence adoption: Insights from a strategic management perspective. *Intelligent Systems in Accounting, Finance and Management*, 28(4), 217-238.
- Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, 77(1), 101925.
- Khan, N., Sarwar, A., Chen, T. B., & Khan, S. (2022). Connecting digital literacy in higher education to the 21st century workforce. *Knowledge Management & E-Learning*, 14(1), 46-61.
- Kühl, N., Schemmer, M., Goutier, M., & Satzger, G. (2022). Artificial intelligence and machine learning. *Electronic Markets*, 32(4), 2235-2244.
- Lee, J.-C., & Chen, X. (2022). Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: The intelligent and anthropomorphic perspectives. *International Journal of Bank Marketing*, 40(4), 631-658.
- Ma, S., & Lei, L. (2024). The factors influencing teacher education students' willingness to adopt artificial intelligence technology for information-based teaching. *Asia Pacific Journal of Education*, 44(1), 94-111.

- Makeleni, S., Mutongoza, B. H., & Linake, M. A. (2023). Language education and artificial intelligence: An exploration of challenges confronting academics in global south universities. *Journal of Culture and Values in Education*, 6(2), 158-171.
- Massoudi, A., Zaidan, M. N., & Agha, A. Q. (2024). The adoption of technology acceptance model in e-commerce with artificial intelligence as a mediator. *GECONTEC: Revista Internacional de Gestión del Conocimiento y la Tecnología*, 12(2), 20-36.
- Nasidi, Q., Ahmad, M., Abdulkadir, J., & Garba, M. (2022). Analysing the mediating effect of social media on online shopping using partial least square. *Online Journal of Communication and Media Technologies*, 12(2), e202213.
- Nikou, S., De Reuver, M., & Mahboob Kanafi, M. (2022). Workplace literacy skills—how information and digital literacy affect adoption of digital technology. *Journal of Documentation*, 78(7), 371-391.
- Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI governance: Identifying best practices and potential barriers and outcomes. *Information Systems Frontiers*, 25(1), 123-141.
- Rahman, M., Ming, T. H., Baigh, T. A., & Sarker, M. (2023). Adoption of artificial intelligence in banking services: An empirical analysis. *International Journal of Emerging Markets*, 18(10), 4270-4300.
- Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for education and research: Opportunities, threats, and strategies. *Applied Sciences*, 13(9), 5783.
- Russell, S. (2022). Artificial Intelligence and the problem of control. In H. Werthner, E. Prem, A. Lee, & E.A., Ghezzi, C. (Eds.), *Perspectives on digital humanism* (pp. 19-24). Springer.
- Sadriwala, M. F., & Sadriwala, K. F. (2022). Perceived usefulness and ease of use of artificial intelligence on marketing innovation. *International Journal of Innovation in the Digital Economy*, 13(1), 1-10.
- Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research* (pp. 587-632). Springer.
- Sharma, S., Islam, N., Singh, G., & Dhir, A. (2022). Why do retail customers adopt artificial intelligence (AI) based autonomous decision-making systems? *IEEE Transactions on Engineering Management*, 71(1), 1846-1861.

- Sova, R., Tudor, C., Tartavulea, C. V., & Dieaconescu, R. I. (2024). Artificial intelligence tool adoption in higher education: A structural equation modeling approach to understanding impact factors among economics students. *Electronics*, *13*(18), 3632.
- Upadhyay, N., Upadhyay, S., Abed, S. S., & Dwivedi, Y. K. (2022a). Consumer adoption of mobile payment services during COVID-19: Extending meta-UTAUT with perceived severity and self-efficacy. *International Journal of Bank Marketing*, *40*(5), 960-991.
- Upadhyay, N., Upadhyay, S., & Dwivedi, Y. K. (2022b). Theorizing artificial intelligence acceptance and digital entrepreneurship model. *International Journal of Entrepreneurial Behavior & Research*, *28*(5), 1138-1166.
- Wilson, N., Keni, K., & Tan, P. H. P. (2021). The role of perceived usefulness and perceived ease-of-use toward satisfaction and trust which influence computer consumers' loyalty in China. *Gadjah Mada International Journal of Business*, *23*(3), 262-294.
- Zhang, J., & Zhang, Z. (2024). AI in teacher education: Unlocking new dimensions in teaching support, inclusive learning, and digital literacy. *Journal of Computer Assisted Learning*, *40*(4), 1871-1885.