AI literacy among undergraduates: Determinants and productivity outcomes in a Malaysian comprehensive university

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ABSTRACT

AI literacy encompasses the knowledge, skills, and competencies required for individuals to effectively develop, manage, and understand the potential of AI across various domains, including education. However, previous research indicates a lack of studies focusing on AI literacy, particularly regarding its determinants and effects. This study therefore aims to examine AI literacy in relation to its influencing factors and effects within the educational sector, with a specific focus on undergraduate students at Malaysian local universities. A quantitative research methodology was employed, and responses were collected from undergraduate students in the Faculty of Information Science Studies across six Universiti Teknologi MARA (UiTM) branches. A total of 301 responses were obtained and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) and the Statistical Package for the Social Sciences (SPSS). The results provide empirical evidence of a significant and positive relationship between the influencing factors (cognitive absorption, digital divide, effort expectancy, and AI awareness) and AI literacy. However, contrary to previous studies, attitudes towards AI and performance expectation did not have a significant relationship with AI literacy. Furthermore, AI literacy was also found to be a predictor of students' productivity. The study provides significant empirical, practical, and theoretical contributions; researchers may use the theoretical model to further enhance knowledge of AI literacy. Institutions and policymakers may use the results to develop new subjects, syllabuses, and policies on AI literacy.

Keywords: Artificial intelligence; AI; AI literacy; AI education; Student productivity; AI impacts.

INTRODUCTION

Artificial intelligence (AI) has been applied in various sectors, including literature and medicine (Biagini, Cuomo, & Ranieri, 2024; Laupichler, Aster, & Raupach, 2023; Southworth et al., 2023), and is rapidly evolving to become an essential part of daily life (Al-Mughairi & Bhaskar, 2025). Artificial intelligence is defined as the capacity of computers to perform intellectual tasks, such as learning and problem-solving, which are typically associated with human thought processes (Alzahrani, 2023; Chen et al., 2022). Bancoro (2024) and Zhang & Lu (2021) state that AI is a knowledge endeavour that gathers and integrates diverse data, evaluates it, and explores different ways to share the results. This demonstrates how many people now use AI to assist with various jobs or professions (So et al., 2020; Chai et al., 2021).

The two primary elements of what was often considered literacy were the abilities to read and write (Ng et al., 2021b; McBride, 2015). According to Chiu et al. (2024) and Long & Magerko (2020), AI literacy is a set of abilities that enable individuals to use and evaluate AI systems, and to interact and collaborate with them. AI literacy equips students with the knowledge and skills needed to understand and use AI in a range of professional and personal contexts, extending beyond the boundaries of traditional education. Knowledge of AI will become as crucial as proficiency in reading, writing, and mathematics, indicating a significant shift in how education is delivered (Walter, 2024; Zhang et al., 2023). By promoting AI literacy as a key academic skill, universities should give students the opportunity to enhance their critical thinking skills and understanding of AI (Biagini, Cuomo, & Ranieri, 2024; Kandlhofer et al., 2016; Luckin et al., 2022; Ng et al., 2021b).

On the other hand, AI technology is now widely used due to its applications in daily tasks and the development of tools across various fields, demonstrating its capacity to increase productivity and quality in everyday activities (Bancoro, 2024). Applying AI literacy when using AI can enhance students' productivity. Students with a strong understanding of AI fundamentals may advance the field by creating programmes and conducting research, using their knowledge and skills to address a range of issues and overcome challenges in their future studies and careers (Mahadewi et al., 2025; Ng et al., 2021a). AI literacy enables university students to critically examine and evaluate the knowledge and information they encounter in their studies (Asio, 2024). AI-driven technologies facilitate evaluation by performing tasks automatically, such as data processing, presentation, and analysis, allowing students to focus on understanding statistical principles rather than spending time on manual calculations (Baluyos & Aclao, 2025; Cusirramos et al., 2023). AI enables personalised learning experiences by adapting statistical educational resources and tasks to the specific needs and abilities of each student, thereby enhancing learning outcomes (Baluyos & Aclao, 2025; García-Martínez et al., 2023). In addition, AI-powered systems provide instant feedback and automatic grading for statistics tasks, encouraging student participation and enabling the prompt identification of areas that require improvement (Baluyos & Aclao, 2025; Dhara et al., 2022).

However, this concept of AI has created obstacles and barriers to the advancement of AI literacy (Biagini, Cuomo, & Ranieri, 2024; Long & Magerko, 2020). Firstly, the lack of research on AI literacy presents challenges in adapting it to students' understanding. Relatively few studies on AI literacy have been published in educational journals (Ng et al., 2021b; Subaveerapandiyan, Paladhi, & Maruthaveeran, 2023). Ng et al. (2021b) note that there are few published works in this field, which leads to several clear issues regarding the development of AI literacy. Secondly, the authors of this study often acknowledge the absence of a clear definition of AI literacy. They primarily adopt Long and Magerko’s concept, but significant advances in AI have occurred since then (Almatrafi, Johri, & Lee, 2024; Gu & Ericson, 2025; Lee & Kwon, 2024; Long & Magerko, 2020). The lack of a specific definition, combined with substantial improvements in AI technology, creates various barriers to conducting a literature review on AI literacy (Gu & Ericson, 2025). Thirdly, the ethical use of AI technology is a major concern for AI literacy. Although most people are aware that AI products and tools exist, they rarely understand the underlying principles, technologies, or potential ethical considerations associated with AI (Burgsteiner, Kandlhofer, & Steinbauer, 2016; Ng et al., 2021a).

There has been limited research on the factors influencing students' AI literacy and productivity (Abdurrahim, 2025). Few studies have examined the consequences of AI usage, particularly in colleges and universities, despite evidence that AI can enhance learning outcomes and academic success for students (Baluyos & Aclao, 2025; Darvishi et al., 2024; Grajeda et al., 2024). Furthermore, a lack of AI ethics may lead to threats and misuse of AI. The importance of AI ethics is often overlooked, as it is considered unimportant or irrelevant to AI research (Bergdahl et al., 2023; Du et al., 2024; Ng et al., 2021b). Data confidentiality and student security are two key ethical issues related to AI. The use of AI technology in educational settings, which may involve collecting student information or student interaction with AI tools, can raise concerns about consent and security (Choi et al., 2025). Therefore, to address this gap, this study aims to investigate the determinants and impacts of AI literacy.

LITERATURE REVIEW

AI literacy

AI literacy comprises the abilities and knowledge that enable people to use AI tools and systems ethically and safely in an increasingly technologically advanced society (Mills, Ruiz, & Lee, 2024, February 21). Any attempt to educate people about AI has encountered the challenge of defining AI literacy. The authors' proposed definition of AI literacy includes three elements: using AI concepts for evaluation, applying AI principles to solve problems, and employing AI concepts to understand everyday life (Kong, Cheung, & Zhang, 2021).

AI literacy is a crucial intellectual component in AI education, reflecting people' understanding of and familiarity with AI concepts and applications (Chai et al., 2021; Du et al., 2024; Lin & van Brummelen, 2021; Ng et al., 2021b). Although they do not explicitly mention AI theory in their definition, Long and Magerko (2020) and Du et al. (2024) observed that literacy has traditionally been associated to access to knowledge, and suggested that understanding AI is a vital aspect of AI literacy. Experts maintain that all students, including those pursuing careers in computer science, should acquire AI literacy (Klein, 2023, May 10). Effective use of AI applications requires users to have AI literacy skills. Understanding the history of these technologies, critically examining their development and use, and maintaining a neutral perspective are all aspects of AI literacy. Making informed decisions about the use of AI also requires the ability to recognise its advantages and disadvantages (Crabtree, 2023, September 21).

Antecedents of AI literacy

Several factors influence AI literacy, as follows:

i. Cognitive absorption

The term "state of deep involvement with software" refers to cognitive absorption theory (CAT) (Agarwal & Karahanna, 2000; Balakrishnan & Dwivedi, 2021). Guo and Ro (2008) and Balakrishnan and Dwivedi (2021) define cognitive absorption as the degree to which a user becomes immersed in new technology. The cognitive absorption of university students is significant for AI literacy. When students engage with AI technology, their level of cognitive absorption can significantly affect how effectively they accept and understand AI-related information and skills (Obenza et al., 2024).

ii. Digital divide

The digital divide refers to the differences in opportunities for people, families, organisations, and regions at various socioeconomic levels to access and benefit from information and communication technologies (ICTs) and use the internet for various purposes (Samuel-Okon & Abejide, 2024). The divide encompasses the use of modern technology and its benefits, including computers and the internet (Adigwe et al., 2024; Samuel-Okon & Abejide, 2024). New technology enables people from diverse backgrounds to improve society by enhancing their personal and professional lives. Digital competence and effective use of a wide range of ICTs are essential for everyone. This skill set is crucial for success in today's technology-driven world. Adequate access to modern technology can affect people' ability to improve their status and reputation (Soomro et al., 2020).

iii. Attitudes towards AI

As stated by Eagly and Chaiken (1993) and Bergdahl et al. (2023), attitude is defined as a "psychological tendency, expressed through assessing something in particular with some degree of favour or disfavour." The use of new technologies or systems has shown that user attitude has a direct, positive, and significant impact on users' genuine objectives (Loh, 2023). The development, use, and adoption of new AI technologies are therefore affected by perceptions of AI, which in turn influence its environment (Bergdahl et al., 2023; Schepman & Rodway, 2020). Implementing AI in universities is crucial for increasing student performance, enhancing the quality of the learning environment, and improving institutional efficiency (Algerafi et al., 2023; Osman, Mohamad, & Kasbun, 2024). The successful integration and application of AI in colleges and universities depend on understanding the factors influencing motivation to use AI (Milicevic et al., 2024; Osman, Mohamad, & Kasbun, 2024). Students' intentions to use AI strongly correlate with their opinions about technology, and those with a positive opinion are much more likely to be interested in using AI (Osman, Mohamad, & Kasbun, 2024).

iv. Effort expectation

According to Mohsin et al. (2024), Horodyski (2023), and Venkatesh et al. (2003), Effort Expectation (EE) refers to the degree of ease associated with using a particular system or type of technology. When adopting new technologies, effort expectation is crucial, as users are more likely to accept and continue using the technology if they perceive it as easy to use (Au, 2023, December 13). This positive relationship highlights the importance of user experience and the ease of using AI technology (Mohsin et al., 2024; Raza et al., 2021). Dwivedi et al. (2019) and Jain, Garg, and Khera (2022) state that effort expectation in the context of AI is a technological factor. The impact of using AI technology is mediated by attitude, which is significantly influenced by effort expectation. AI that reduces the effort required to complete a task is more likely to be adopted (Chatterjee & Bhattacharjee, 2020; Jain, Garg, and Khera, 2022).

v. Performance expectation

Venkatesh et al. (2003) and Rizkalla et al. (2024) define performance expectation as the benefits and usefulness people experience from regularly using such technology. The degree to which people believe a technology will benefit them is termed performance expectation (Solórzano Solórzano et al., 2024; Thusi & Maduku, 2020). Performance expectation is also defined as a person's belief that using technology will make a task easier to complete (Cimperman, Brenčič, & Trkman, 2016; Solórzano Solórzano et al., 2024). The belief that AI will significantly increase efficacy, productivity, and goal attainment is referred to as AI performance expectation (Ma & Huo, 2023; Solórzano Solórzano et al., 2024). Students believe that AI-supported learning environments will increase productivity, enhance the educational experience, and change their perspective on learning (Lai, 2021; Mohsin et al., 2024).

vi. Awereness of AI
The term "awareness" refers to a person's sensitivity, alertness, and concern (mindful or heedful) regarding a particular topic or action (Du et al., 2024; Lin & van Brummelen, 2021; Sudarmadi et al., 2001). AI can be a useful tool for maintaining student interest and motivation. By examining each student's learning preferences, adaptive AI systems can customise information delivery to suit individual learning styles (OpenLearning, 2024). However, it is essential to assess these technologies carefully, as AI may not provide a perfect solution. Although AI is increasingly used in education, especially in active learning, it is crucial to consider its benefits carefully (Güneyli et al., 2024). Another important issue that must not be overlooked is ethics in the training and use of AI (Borenstein & Howard, 2021; Du et al., 2024; Lin et al., 2021; Qin, Li, & Yan, 2020). Research by Du et al. (2024), Lin et al. (2021), and Shih et al. (2021) showed that AI ethical awareness and AI literacy are strongly related. According to Long and Magerko (2020) and Du et al. (2024), those who are AI literate can evaluate AI critically. They can understand the potential risks of AI and its ethical implications. People with expertise in AI are more likely to recognise its potential risks, obstacles, and uncertainties. They are also more likely to be aware of the ethical issues associated with AI (Chai et al., 2021; Du et al., 2024; Lin et al., 2021; Ng et al., 2021b).

Productivity
AI productivity refers to the extent to which an individual, company, or country produces goods, and the quantity produced relative to the time, money, and effort required to create them (Hanushek & Ettema, 2017; Linna et al., 2010; Shukry et al., 2023). Student productivity measures a student's ability to manage time effectively, complete academic tasks, and perform well on assigned projects and tasks. Students must demonstrate preparation, attention, adaptability, and effective use of devices to achieve their academic goals (Mughal & Farooq, 2025). Although student productivity has been defined in various ways, it generally centres on a student's competence to complete academic tasks productively and properly, work effectively within a set schedule, and generate the necessary range of outcomes (Mughal & Farooq, 2025; Zimmerman, 2000). Both external (information, tools) and internal (encouragement, confidence) forms of support can influence student productivity. As AI technologies can help students plan their studies and efficiently manage their educational needs, they can serve as both supportive and assisting tools (Kitsantas & Zimmerman, 2009; Mughal & Farooq, 2025).

As AI becomes increasingly significant, it is essential for everyone, especially university students who will be future professionals and leaders in a rapidly changing global society, to understand its details (Asio, 2024; Crompton & Burke, 2023). In the future, AI technology will be used even more extensively. Students become more independent in a world that incorporates AI when they are introduced to advanced AI concepts early and develop comprehensive critical thinking skills. Rather than being mere users, students can guide and supervise AI to promote widely accepted standards of safety, productivity, and ethics (Activate Learning, 2025). AI literacy enables students to prepare more effectively for future careers that frequently utilise AI technology and equips them with the skills needed to navigate the rapidly evolving field of AI (Poth, 2024, May 13). Furthermore, integrating AI literacy into students' daily lives will enhance their work by providing the knowledge and skills to incorporate AI into their tasks, thereby increasing their productivity.

Research model

The research model for this study consists of eight first-order and second-order constructs, including the antecedents of AI literacy: cognitive absorption, digital divide, attitudes towards AI, effort expectation, performance expectation, and awareness of AI. AI literacy, as a second-order construct with four variables, includes Apply AI, Understand AI, Detect AI, and Ethics, with productivity as the dependent variable. Figure 1 presents the research model, and based on this, seven hypotheses were developed for the study.

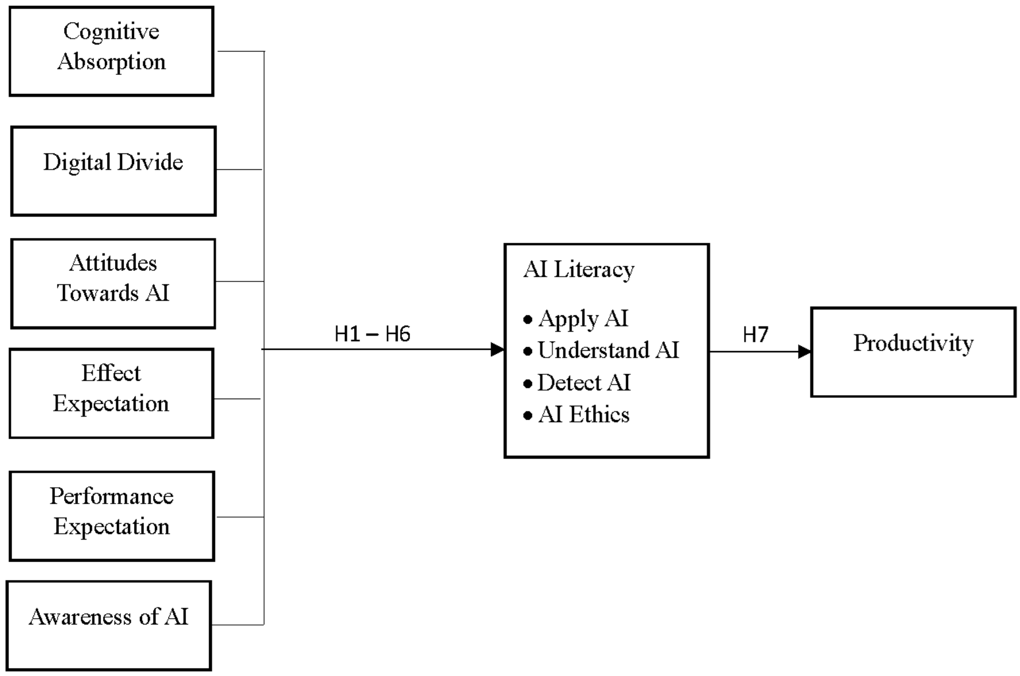

Figure 1: Research model of AI literacy and students' productivity

Antecedents and impact of AI literacy

Technology use and engagement are primarily driven by cognitive absorption (Celik, 2023; Agarwal & Karahana, 2000). This is particularly important for AI literacy, which is regarded as a modern approach to studying cognitive abilities (Obenza et al., 2024; Wang & Lu, 2023). The ISS model, which is used to explain this relationship, states that cognitive absorption determines whether an individual intends to develop AI literacy. In the context of AI literacy, students' cognitive absorption is especially significant. Students with greater control over technology are more likely to use it (Celik, 2023; Thomas, 2006). Therefore, it can be hypothesised that:

H1: Cognitive absorption has a significant positive relationship with AI literacy

The ISS model also states that the digital divide determines whether people wish to acquire AI literacy. The digital divide encompasses access to devices and the internet, the ability to use new technology, and the benefits derived from it (Adigwe et al., 2024; Samuel-Okon & Abejide, 2024). According to Radovanović et al. (2015), the digital divide significantly affects AI literacy and is crucial in its development (Celik, 2023). Therefore, it can be hypothesised that:

H2: The digital divide has a significant positive relationship with AI literacy

The ISS model, which is used for this relationship, states that one's attitude towards AI determines the desire to use or apply AI literacy. To effectively incorporate and implement AI in educational approaches, it is crucial to understand the factors that influence the motivation to use AI (Milicevic et al., 2024; Osman et al., 2024). A more thorough understanding of various perspectives on AI may lead to more efficient use and application of these technologies (Bergdahl et al., 2023; Kelly et al., 2023; Schepman & Rodway, 2020, 2023). Therefore, it can be hypothesised that:

H3: Attitudes towards AI have a significant positive relationship with AI literacy

Effort expectation is the determinant of the intention to use or apply AI literacy in the ISS model, which is used for this relationship. The Unified Theory of Acceptance and Use of Technology (UTAUT), which includes four key constructs – performance expectation, effort expectation, perceived trust, and facilitating conditions – is another theory used in this study. UTAUT can be used to examine and clarify the reasons behind people's adoption and use of new technology (Au, 2023; Sykes et al., 2009). When using the latest technologies, effort expectation is crucial, as it increases the likelihood that users will accept and continue using the technology if they believe it is easy to use (Au, 2023). Therefore, it can be hypothesised that:

H4: Effort expectation has a significant positive relationship with AI literacy

This connection is modelled using the ISS model, in which performance expectation determines the intention to use or apply AI literacy. UTAUT, the Unified Theory of Acceptance and Use of Technology, is another foundation for performance expectations. Studies have indicated a connection between AI and increased productivity, which relates to performance expectations (Cao et al., 2021; Duan et al., 2021; Jain et al., 2022; Ransbotham et al., 2018). The extent to which students use AI literacy or how it influences their academic success can be used to assess their performance. Early exposure to these concepts can help students learn and improve their knowledge of AI (Poth, 2024). Therefore, it can be hypothesised that:

H5: Performance expectation has a significant positive relationship with AI literacy

The relationship is based on the ISS model, which states that awareness of AI determines whether an individual intends to utilise AI literacy. Although AI is increasingly used in education, especially in active learning, it is crucial to carefully consider its benefits (Güneyli et al., 2024). Students require AI skills and understanding to appropriately utilise the latest technological advancements. Anticipation and fundamental knowledge should be taught early in the development of AI literacy. AI literacy is related to the growth of general awareness and understanding of AI (Kandlhofer et al., 2023). Understanding AI is essential for improving teaching and learning experiences for students. Therefore, it can be hypothesised that:

H6: Awareness of AI has a significant positive relationship with AI literacy

Productivity and AI literacy are theoretically related via the Information System Success Model (ISSM) (DeLone & McLean, 2003). As students intend to apply AI literacy to the tasks they receive to increase their productivity, productivity is the study's overall advantage, and AI literacy is their intention to use. Previous research has demonstrated that the hidden potential of AI to improve student academic achievement and learning may be further developed with consistent focus and effective implementation strategies (Shahzad et al., 2024; Salas-Pilco & Yang, 2022). By lowering barriers and fostering a more open environment, AI literacy increases productivity in school and significantly improves students' emotional well-being (Shahzad et al., 2024; Alam et al., 2021). Therefore, it can be hypothesised that:

H7: AI literacy has a significant positive relationship with productivity

METHODS

The main aim of this study is to examine AI literacy among students and its implications for productivity. Specifically, this study seeks to address the following research questions:
i. What is the relationship between antecedent characteristics associated with AI literacy among students?
ii. How does AI literacy affect student productivity?

This study employs a quantitative methodology. The development of the instruments was based on prior research in areas such as Artificial Intelligence, AI applications, and student productivity. The questionnaire is organised into nine sections, comprising 45 items (as shown in Appendix 1). Section A collects demographic information about the respondents. Sections B to I gather data on various study factors, including AI literacy (application, understanding, detection, and AI ethics), productivity, cognitive absorption, the digital divide, attitudes towards AI, effort expectation, performance expectation, and awareness of AI. The main aim of this study is to explore AI literacy in relation to its influencing factors and effects within the educational sector, with a specific focus on undergraduate students from Malaysian local universities. Table 1 below shows the variables of this study and its hypotheses.

The pre-test was conducted after the instruments were developed and reviewed by experts for approval. Following this review process, modifications were made to the instrument before initiating pilot testing. A total of 38 students participated in completing the questionnaire during the pilot test. The reliability of the instrument was then assessed using the Cronbach's Alpha coefficient. The result shows values ranging from 0.838 and its highest value of 0.927, exceeding the minimum threshold of 0.7 as suggested by Nunnaly (1975); this indicates the reliability of the instrument.

Apart from that, the sampling method used in this study was convenience sampling. Convenient sampling was chosen because the respondents are easy to reach and willing to participate in the study. The Information Science undergraduate students from six UiTM branches, which are UiTM Puncak Perdana, UiTM Kelantan, UiTM Kedah, UiTM Johor, UiTM Negeri Sembilan, and UiTM Sarawak, were selected for this study. This selection was made because students in this faculty are more likely to utilise AI technologies to complete their tasks and assignments, given that their coursework is closely related to AI and its applications.

The total number of accessible and observable variables determines the sample size. The sample size was estimated using the A-priori Size Calculator for Structural Equation Modelling (Soper, 2018). This calculator indicates that the minimum sample size required for this investigation is 151 respondents. In addition to the A-priori Size Calculator, the 10-times rule by Hair Jr et al. (2022) was also applied in this study. The 10-times rule states that the sample size must be at least 5 times and at most 10 times the total number of items

(Hair et al., 2022). According to the rule, the minimum sample size is 225 respondents and the maximum is 450 respondents. Figure 2 above illustrates the sample size for the research study.

Table 1: Variables of the study

Variables	Number of items	Sources	Hypothesis
Antecedents of AI Literacy			
Cognitive Absorption	4	(Agarwal & Karahanna, 2000; Celik, 2023; Thomas, 2006)	H1: Cognitive absorption has a significant positive relationship with AI literacy
Digital Divide	5	(Bassi & Pagallo, 2025; Donat et al., 2009; Hendawy, 2024)	H2: The Digital divide has a significant positive relationship with AI literacy
Attitudes Towards AI	4	(Grassini, 2023; Schepman & Rodway, 2023; Si, 2025)	H3: Attitudes toward AI have a significant positive relationship with AI literacy
Effort Expectation	4	(Beh & Ku, 2022; Ke et al., 2025; Sair & Danish, 2018; Venkatesh et al., 2003)	H4: Effort expectation has a significant positive relationship with AI literacy
Performance Expectation	4	(Ke et al., 2025; Sair & Danish, 2018; Venkatesh et al., 2003)	H5: Performance expectation has a significant positive relationship with AI literacy
Awareness of AI	4	(Al-Abdullatif, 2025; Wang et al., 2022)	H6: Awareness of AI has a significant positive relationship with AI literacy
AI Literacy			
Apply AI Understand AI Detect AI AI Ethics	16	(Carolus et al., 2023; Druga et al., 2019; Julie et al., 2020; Long & Magerko, 2020; Ng et al., 2021; Ng et al., 2022; Ng et al., 2023; Wang et al., 2022; Zhao et al., 2022)	H7: AI literacy has a significant positive relationship with productivity
Productivity	4	(Perry, 2023)	Not applicable

The questionnaire was then adapted into an online format using Google Forms and distributed to students for data collection. The instrument was approved by the Universiti Teknologi MARA Research Ethics Committee (REC), reference number REC/04/2025 (PG/MR/227). Data collection lasted one month after ethics approval was obtained. The collected data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) software, SmartPLS version 4.1.2, and the Statistical Package for the Social Sciences (SPSS) version 26. The model was validated using measurement and structural models to apply the PLS-SEM approach. This study successfully collected a valid sample of 301 respondents, which is considered sufficient for PLS-SEM, with assistance from a representative in each faculty across the six UiTM branches.

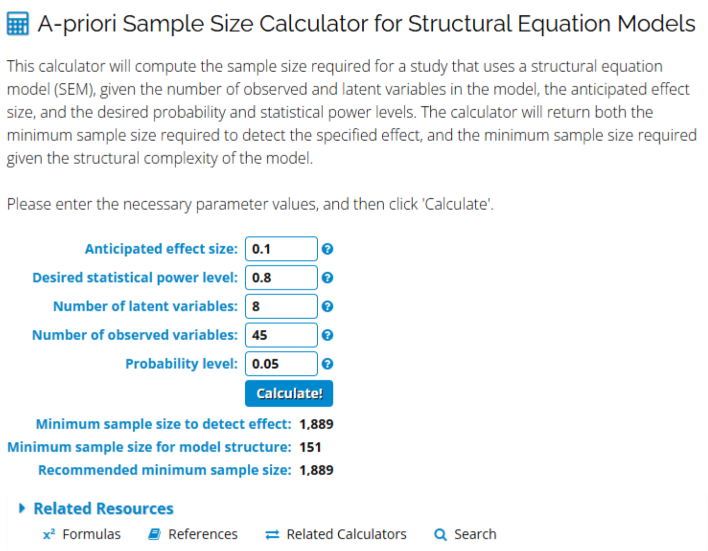

Figure 2: Priori sample size calculator for Structural Equation Models (SEM)

Assessment of the model

i. Convergent validity assessment

SmartPLS, the PLS-SEM software, was used to analyse the data in this study. The first step involved conducting a measurement model analysis, with particular focus on the assessment of convergent validity. For this research, tests were performed twice to ensure significant results, and one item (AWA4) was removed. The findings related to convergent validity are presented in Table 2, which shows that all indicators meet the required standards (factor loading > 0.5, AVE ≥ 0.5, CR ≥ 0.7) as established by Hair et al. (2014).

ii. Discriminant validity assessment

Following the convergent validity test, a discriminant validity assessment was conducted. The Heterotrait-Monotrait Ratio (HTMT) test was chosen to verify discriminant validity. As shown in Table 3, the results of the HTMT test indicate that no construct exceeds the threshold of 0.9. This suggests that discriminant validity has been successfully achieved and the measurement model analysis for the study has been validated.

iii. Coefficient of determination score (R^2)

R^2 measures the model's predictive accuracy and can also be interpreted as the cumulative effect of exogenous factors on endogenous variables. The adjusted R-squared value for AI literacy as the exogenous variable in this study is 0.603, indicating that AI literacy accounts for 60.3% of the result. Meanwhile, the adjusted R-squared value for productivity as an endogenous variable in this study is 0.509, indicating that productivity accounts for only 50.9% of the result. Adjusted R-squared was used instead of R-squared because it is important to address the issue with R^2: the R^2 value increases with the addition of more predictor variables in the framework. As more variables are incorporated into a model, the R^2 value will appear to increase without necessarily becoming consistent. It is therefore recommended to use the adjusted R^2 (Wherry, 1931). Ultimately, these values indicate that while AI literacy is a strong predictor of the outcomes studied, approximately half of the factors influencing productivity remain external to this specific framework. Table 4 shows the final result of R^2:

Table 2: Convergence validity assessment

Constructs	Indicator	Factor loading	CR	AVE
Antecedents of AI Literacy				
Cognitive Absorption			0.895	0.683
	CAB1	0.700		
	CAB2	0.873		
	CAB3	0.881		
	CAB4	0.838		
Digital divide				
	DID1	0.833		
	DID2	0.639		
	DID3	0.761	0.895	0.633
	DID4	0.842		
	DID5	0.879		
Attitudes towards AI				
	ATT1	0.867		
	ATT2	0.874	0.934	0.781
	ATT3	0.904		
	ATT4	0.890		
Effort expectation				
	EEX1	0.881		
	EEX2	0.916	0.940	0.797
	EEX3	0.874		
	EEX4	0.899		
Performance expectation				
	PEX1	0.916		
	PEX2	0.895	0.948	0.821
	PEX3	0.930		
	PEX4	0.883		
Awareness of AI				
	AWA1	0.904	0.937	0.833
	AWA2	0.936		
	AWA3	0.897		
AI Literacy				
Apply AI	APP1	0.662	0.907	0.709
	APP2	0.622		
	APP3	0.635		
	APP4	0.617		
Understand AI	UND1	0.707	0.910	0.716
	UND2	0.706		
	UND3	0.810		
	UND4	0.823		
Detect AI	DTC1	0.792	0.911	0.720
	DTC2	0.642		
	DTC3	0.663		
	DTC4	0.716		
AI ethics	ETC1	0.764	0.912	0.722
	ETC2	0.792		
	ETC3	0.788		
	ETC4	0.657		
Productivity	PRO1	0.872		
	PRO2	0.890		
	PRO3	0.889	0.939	0.794
	PRO4	0.913		

Table 3: Discriminant validity assessment

	AI Literacy	ATT	AWA	CAB	DID	EEX	PEX	PRO
AI Literacy								
ATT	0.676							
AWA	0.749	0.783						
CAB	0.748	0.894	0.793					
DID	0.743	0.702	0.711	0.657				
EEX	0.748	0.784	0.886	0.784	0.783			
PEX	0.689	0.883	0.820	0.886	0.704	0.801		
PRO	0.772	0.748	0.786	0.873	0.668	0.741	0.802	

Table 4: Result of the coefficient of determination score (R2)

Constructs	R Square	R Square Adjusted	Decision
AI Literacy	0.611	0.603	Moderate
Productivity	0.510	0.509	Moderate

RESULTS

Demographic profiles of the respondents

Table 5 presents the demographic profiles of the respondents in this study. In terms of gender, the majority are female, comprising 225 out of 301 participants, while 76 are male. Most respondents are under 25 years old, totalling 293, with 8 respondents in the 25 to 30 age range. The largest group is from Semester 4, with 113 participants, while the smallest group is from Semester 6, with only 10 respondents. Among the respondents, 190 are pursuing a degree and 111 are enrolled in a diploma programme.

Table 5: Demographic profiles of the respondents

Item	Sub-Items	Frequency	Percentage
Gender	Male	76	25.2
	Female	225	74.8
Age	Under 25	293	97.3
	25 - 30	8	2.7
	Semester 1	45	15.0
	Semester 2	51	16.9
Semester	Semester 3	39	13.0
	Semester 4	113	37.5
	Semester 5	43	14.3
	Semester 6	10	3.3
Level of study	Degree	190	63.1
	Diploma	111	36.9

Overview of the variables and sub-variables

Table 5 presents the demographic profiles of the respondents in this study. In terms of gender, the majority are female, comprising 225 out of 301 participants, while 76 are male. Most respondents are under 25 years old, totalling 293, with 8 respondents in the 25 to 30

age range. The largest group is from Semester 4, with 113 participants, while the smallest group is from Semester 6, with only 10 respondents. Among the respondents, 190 are pursuing a degree and 111 are enrolled in a diploma programme.

Table 6: Descriptive analysis of the variables

Variables	Mean	SD
Antecedents of AI literacy		
Cognitive absorption	3.81	0.847
Digital divide	3.54	0.897
Attitudes towards AI	3.69	0.844
Effort expectation	3.81	0.793
Performance expectation	3.77	0.804
Awareness of AI	3.94	0.808
AI Literacy		
Apply AI	3.79	0.871
Understand AI	3.77	0.841
Detect AI	3.81	0.840
AI ethics	3.83	0.805
Productivity	3.92	0.792

Factors that influence AI literacy among students

Table 7 presents the results of the structural model analysis examining the factors that influence AI literacy and clarifies the relationships between the antecedents or factors affecting AI literacy.

Table 7: Structural model analysis

	Hypothesis and variables	t-value	p-value	Result
H1	Cognitive absorption -> AI literacy	3.821	0.01	Supported
H2	Digital divide -> AI literacy	4.11	0.01	Supported
H3	Attitudes toward AI -> AI literacy	0.387	0.349	Not supported
H4	Expectation -> AI literacy	1.649	0.01	Supported
H5	Performance expectation -> AI literacy	0.059	0.476	Not supported
H6	Awareness of AI -> AI literacy	3.347	0.01	Supported

Hypothesis 1 shows that cognitive absorption has a significant and positive relationship with AI literacy (H1: Supported, $p < 0.05$, $t = 3.821$**). Hypothesis 2 demonstrates that the digital divide has a significant and positive relationship with AI literacy (H2: Supported, $p < 0.05$, $t = 4.110$**). Hypothesis 3 indicates that attitudes towards AI do not have a significant and positive relationship with AI literacy (H3: Not Supported, $p > 0.05$, $t = 0.387$). For Hypothesis 4, the results highlight a significant and positive relationship between effort expectation and AI literacy (H4: Supported, $p < 0.05$, $t = 1.649$*). Hypothesis 5 shows that performance expectation does not have a significant and positive relationship with AI literacy (H5: Not Supported, $p > 0.05$, $t = 0.059$). Finally, Hypothesis 6 confirms a significant and positive relationship between awareness of AI and AI literacy (H6: Supported, $p < 0.05$, $t = 3.347$**).

AI literacy affecting student productivity

Table 8 presents the results of the structural model analysis examining the relationship between AI literacy and productivity, and subsequently clarifies the relationship between the variables. Hypothesis 7 indicates that AI literacy has a significant and positive relationship with productivity (H7: Supported, $p < 0.05$, $t = 22.129^{**}$).

Table 8: Structural model analysis between AI literacy and productivity

Hypothesis and variables		t-value	p-value	Result
H7	AI Literacy -> Productivity	22.129	0.01	Supported

DISCUSSION

The structural model analysis validated five of the seven hypotheses, while the remaining two were not supported. AI literacy was significantly influenced by cognitive absorption, the digital divide, effort expectation, and awareness of AI. The findings also revealed a positive and significant relationship between AI literacy and productivity. The significant relationship between cognitive absorption and AI literacy is supported by earlier findings from Agarwal and Karahanna (2000), who found that intensive use of technology promotes the development of new skills and the retention of existing information. According to Obenza et al. (2024), cognitive absorption is one of the main factors affecting AI literacy. Greater expertise with AI increases the likelihood that students can assess AI technology results (Celik, 2023; Hou, Shiau, and Shang, 2019). Therefore, it may serve as a substitute for advancing AI literacy (Celik, 2023).

The impact of the digital divide was significant, consistent with research showing that access to technology is necessary to acquire digital capabilities (van Dijk, 2020). There is a significant and positive relationship between AI literacy and the digital divide, indicating that students affected by this issue are probably less knowledgeable about AI. Authors from previous studies suggest that the growth of AI literacy may be impeded by restricted use of technology and digital skills, which are elements of the digital divide (Celik, 2023).

However, there was no significant relationship between AI literacy and attitudes towards AI or performance expectations. Reyes et al. (2024) found that while most students had favourable opinions of AI, these opinions had little effect on their levels of AI literacy. This suggests that the students only used AI and did not consider AI literacy as a platform or knowledge base for learning about the correct and safe use of AI. In addition, performance expectation and AI literacy did not significantly correlate. This may indicate a gap between students' awareness of AI's potential advantages and their ability or confidence to use it in real-world and course-related situations. In other words, even if students think AI might help them perform better, this belief may not result in skill development without structured applications (Al-Emran, Mezhuyev, and Kamaludin, 2018).

AI literacy was found to be significantly, though only slightly, influenced by effort expectancy. This aligns with Venkatesh et al. (2012) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which identify perceived ease of use as a key factor in technology adoption. Students are more likely to use AI applications if they find them easy to use and evaluate. This suggests that effort expectancy will affect AI literacy when AI applications are straightforward and appropriate for students' tasks.

The hypothesis indicates that awareness of AI has a significant and positive relationship with AI literacy. Specifically, higher AI literacy is linked to greater access to and understanding of AI, particularly through critical engagement with AI tools and real-world applications (Tzirides et al., 2024). This implies that awareness of correct and ethical AI use can support students in developing AI literacy.

Furthermore, AI literacy significantly enhances productivity, consistent with previous research by Long and Magerko (2020) and Ng et al. (2021), which showed that AI skills enable individuals to make data-driven decisions, streamline processes, and generally increase productivity. Higher levels of AI literacy are typically associated with improved academic performance, likely due to more effective use of AI technologies for research, learning, and problem-solving (Shi, Liu, & Hu, 2025). Therefore, AI literacy can improve students' productivity, leading to better academic outcomes.

CONCLUSIONS

The findings indicate that, as hands-on experience has been shown to improve understanding of technology, universities should prioritise providing students with practical knowledge of AI through workshops, course integration, and experimental opportunities (Long & Magerko, 2020). The significance of this digital divide highlights the need for laws ensuring fair access to AI resources, tools, and connectivity, especially for underprivileged students (van Dijk, 2020). This study has several limitations. It was confined to one faculty at Universiti Teknologi MARA, which limits the generalisability of the results. As many students now rely on AI for their tasks, future research should include other faculties. Additionally, factors such as social norms and prior technology experience were not examined, and the constructs tested may not sufficiently address current aspects of AI literacy, such as generative AI skills and ethical reasoning. Future studies should consider including more constructs to improve respondents' understanding of AI literacy. Nonetheless, this study makes significant contributions by validating a framework of AI literacy in relation to its determinants and impact.

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CONFLICT OF INTEREST

The authors have no relevant competing interests to declare in relation to the content of this article.

AUTHOR CONTRIBUTIONS

Conceptualisation: [all authors], Methodology: [Mohamad Rosman, M.R., Saiful Bahry, F.D], Formal analysis and investigation: [Yusnilzahri, N.A.S], Writing - original draft preparation: [Yusnilzahri, N.A.S]; Writing - review and editing: [Yusnilzahri, N.A.S, Mohamad Rosman, M.R.]

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Appendix 1: Variables and items of the research instrument

Variables	Item Code	Items
Antecedents of AI Literacy		
Cognitive Absorption (CAB)	CAB1	I notice that time passes quickly when I use AI technology.
	CAB2	I am fully engaged in the tasks I perform while using AI technology.
	CAB3	I enjoy using AI technology.
	CAB4	I have fun interacting with AI technology.
Digital Divide (DID)	DID1	I have sufficient access to AI applications.
	DID2	I am not afraid of AI technology.
	DID3	I have good access to internet facilities.
	DID4	I am competent in using technology.
	DID5	I have adequate technical skills to use AI applications.
Attitude Towards AI (ATT)	ATT1	Using AI is a good idea.
	ATT2	AI is essential for enhancing my knowledge.
	ATT3	My attitude towards AI is very positive.
	ATT4	I have positive feelings towards AI.
Effort Expectation (EEX)	EEX1	Learning AI technology is easy for me.
	EEX2	AI technology is understandable.
	EEX3	It will be easy for me to become skilled in using AI technology.
	EEX4	Overall, using AI technology is easy.
Performance Expectation (PEX)	PEX1	Using AI technology improves my efficiency in daily tasks.
	PEX2	Using AI technology enables me to complete my tasks conveniently.
	PEX3	Using AI technology enhances my effectiveness in daily tasks.
	PEX4	Using AI technology improves my productivity in tasks.
Awareness of AI (AWA)	AWA1	I have heard about AI.
	AWA2	I know how AI technology can help me.
	AWA3	I think AI will be a useful tool for my tasks.
	AWA4	I know that AI technology is important for my tasks.
AI literacy		
Apply AI (APA)	APA1	I can operate AI applications to complete the daily tasks of my studies.
	APA2	I use AI applications to complete my tasks easily.
	APA3	I use AI applications effectively to achieve my goals.
	APA4	I find AI applications useful for my daily tasks.
Understand AI (UND)	UND1	I know the definition of artificial intelligence.
	UND2	I can assess the limitations of using AI.
	UND3	I can assess the opportunities of using AI.
	UND4	I can evaluate the advantages of artificial intelligence technology for myself.
Detect AI (DTC)	DTC1	I am able to determine whether I am working with an artificial intelligence-based application.
	DTC2	I can differentiate between devices that use AI and those that do not.

	DTC3	I can distinguish whether I am interacting with an AI or a real human.
	DTC4	I can identify AI technology in the applications and products I use.
AI Ethics (ETC)	ETC1	I can consider the implications off deploying AI for society.
	ETC2	I can incorporate ethical considerations when deciding whether to use data provided by AI.
	ETC3	I can analyse AI-based applications for their ethical implications.
	ETC4	I am alert to privacy and information security issues when using AI applications or products.
Productivity (PRO)	PRO1	AI applications help me increase my productivity.
	PRO2	AI applications help me generate new ideas.
	PRO3	AI applications allow me to accomplish more work than usual.
	PRO4	AI applications help me try out innovative ideas.