JOURNAL OF COMMUNICATION, LANGUAGE AND CULTURE

Artificial Intelligence Literacy Among Language Academics at USIM: An Assessment of Affective, Behavioural, Cognitive and Ethical Dimensions

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ABSTRACT

Artificial Intelligence (AI)-based teaching approaches have gained increasing attention in Malaysia's higher education system, particularly in relation to the Higher Education Development Plan 2026–2035. Although previous studies have reported low to moderate levels of AI literacy among educators, limited empirical attention has been given to AI literacy within language education contexts, where pedagogical interaction, communicative competence, and ethical considerations are central topics. Drawing on a multidimensional AI literacy framework encompassing cognitive, affective, behavioural, and ethical dimensions, this study assessed AI literacy among language academics at the Faculty of Major Language Studies (FPBU) at Universiti Sains Islam Malaysia (USIM). A bilingual Malay–English version of the Artificial Intelligence Literacy Questionnaire (AILQ) was administered to 72 academic staff. Data were analysed using descriptive and inferential methods to determine overall AI literacy levels, relationships between demographic factors and AI literacy, and correlations among the AI literacy dimensions. The findings revealed a high level of self-reported AI literacy among the participants. Further analysis showed no significant relationship between gender, age, years of services and the participants' AI literacy. However, significant correlations were found between affective and behavioural learning and between affective and cognitive learning, while the correlation between affective and ethical learning was relatively low. Overall, the findings suggest that language academics at FPBU USIM report relatively high AI literacy across the measured dimensions. This study contributes to the theoretical understanding of AI literacy dimensions and offers practical implications for institutional policy, professional development, and AI integration strategies in language education.

Keywords: artificial intelligence literacy, AI-based teaching, language academics, language education, higher education

Received: 8 December 2025, **Accepted:** 4 April 2026, **Published:** 30 July 2026

Journal of Communication, Language and Culture
doi: https://doi.org/10.33093/jclc.2026.6.2.26

Published by MMU Press. URL: https://journals.mmupress.com/jclc

1.0 Introduction

In line with ongoing developments, the integration of AI into education has become increasingly important in recent years. AI plays an important role in strengthening the teaching and learning processes for both academics and students. The emergence of AI-based applications has brought notable changes to educational practices, producing both positive outcomes (Wicaksono and Sembiring 2023) and challenges (Sinaga et al. 2025). In the field of language education, the effectiveness of tools such as Grammarly, Chatsonic, and Tashkeel AI continues to be examined, particularly in relation to their impact on language skill development. Overall, these AI applications have the potential to support language learning (Ali & Rani, 2024), although some limitations have been observed.

Saili et al. (2024) and Ridzuan (2025) indicate that AI not only helps improve teaching efficiency but also offers opportunities to enhance students' learning experiences through more interactive and user-centred approaches. Students are no longer solely dependent on classroom learning; instead, AI allows them to engage in additional learning activities beyond the classroom to enhance their understanding. The accessibility of AI tools for language learning has also been identified as a key factor encouraging students to adopt AI in their studies (Adnan 2025).

Although the use of AI in higher education is becoming more common, the level of readiness and academics' AI literacy levels remain matters that require further research. AI literacy involves more than a basic awareness of AI and its functions; it also includes several important aspects, such as affective, behavioural, and cognitive learning and ethical understanding (Ng et al., 2024). In general, individuals with higher AI literacy have a stronger understanding of AI concepts and are better able to use and integrate AI tools in teaching. Ethical awareness of AI use is an essential component of comprehensive AI literacy.

Previous studies on students' AI literacy (Mansoor et al., 2024; Salleh et al., 2025) show that they tend to have moderate levels of AI literacy. Therefore, examining AI literacy among academics is crucial, as they play a central role in AI implementation in classrooms. Research focusing on lecturers and teachers has reported that their AI literacy levels range from low to moderate (Emiri et al., 2024; Odin & Selvam, 2025), highlighting the need for initiatives to strengthen AI-related skills among academics in higher education. Although previous studies have examined AI literacy among students and academics, limited attention has been paid to AI literacy in the context of language education. Existing research often treats academics as a homogeneous group, overlooking disciplinary differences in pedagogical goals and assessment practices.

This study focuses on a language-based faculty at USIM to assess the level of agreement with AI literacy among academics involved in language education. Academics in language faculties have an important responsibility in developing students' skills in writing, speaking, listening, and other areas of language. Thus, assessing AI literacy is relevant to ensure that AI can be effectively integrated into teaching practices and that students can benefit from its use. This is particularly important given the wide range of AI tools that support language learning, such as Grammarly, Duolingo, and Quillbot.

Language academics interact with AI differently than STEM or technical academics. Instead of focusing on how AI works as a system, language academics tend to use AI as a tool that affects how language is produced, interpreted, and evaluated (Liu et al., 2025). Examples include grammar-checking software, automated translation tools, speech recognition systems, and generative text models, which directly influence learners' language use. Therefore, AI literacy for language academics goes beyond knowing how to operate technology. It also involves understanding how to judge linguistic accuracy, ensure that communication fits its social context, uphold academic integrity, and respect cultural meanings in language (Rivero & Yin, 2025). These concerns tie the use of AI in language education closely to pedagogical decision-making, communication ethics, and assessment practices, making language academics a distinct group in terms of how they engage with AI.

The findings of this study are expected to provide an overall picture of the level of agreement on AI literacy among language academics at FPBU USIM, especially in preparing for the shift towards AI-driven educational practices and ensuring the ethical application of AI in teaching. In addition, the findings of this study are expected to provide meaningful insights for the advancement of Arabic language education, particularly in enhancing the integration of AI tools that support linguistic accuracy and language skills development. This study also contributes to ongoing efforts to strengthen AI-supported pedagogical practices in Arabic, ensuring that teaching and learning remain relevant and responsive to technological advancements. Ultimately, the results may contribute to the development of AI-based policies and training modules that are suitable for language education.

2.0 Literature Review

2.1 Conceptualising AI Literacy in Education

AI literacy has emerged as a crucial competency in the current technological era. Long and Magerko (2020) defined AI literacy as an individual's ability to understand basic AI concepts, use AI applications effectively, evaluate their social and ethical implications, and adapt to technological changes. From a broader policy perspective, frameworks developed by UNESCO emphasise digital competence as encompassing knowledge, skills, attitudes, values, and ethical awareness in technology use (Law et al., 2018). Within this framework, AI literacy can be understood as an advanced extension of digital literacy, particularly in relation to algorithmic awareness, data ethics and human-AI collaboration. Integrating these global competency frameworks strengthens the conceptual positioning of AI literacy as part of a comprehensive educational transformation.

This framework is further supported by Wong et al. (2020), who categorised AI literacy into several components, such as AI concepts, applications, and ethics. Similarly, the framework developed by Ng et al. (2021) highlights several key components that shape one's level of AI literacy, including conceptual knowledge of AI, practical skills in using AI, critical awareness of AI's potential and limitations, and ethical application of AI. These dimensions closely align with the affective, behavioural, and cognitive (ABC) framework in educational psychology, which highlights that attitudes, actions, and knowledge interact to shape human engagement with new phenomena. In this study, the ABC framework serves not only as a categorisation tool but also as a theoretical foundation for explaining how emotional readiness influences behavioural engagement and cognitive development in AI use.

Moreover, the affective and behavioural components of AI literacy can be theoretically grounded in technology adoption models such as the Technology Acceptance Model (TAM) introduced by Davis et al. (1989) and the Theory of Planned Behaviour (TPB) developed by Ajzen (1991). TAM states that perceived usefulness and perceived ease of use shape attitudes, which subsequently influence behavioural intention and actual usage. The TPB also emphasises attitudes, subjective norms, and perceived behavioural control as predictors of behaviour. These theoretical perspectives provide explanatory support for examining the relationships between affective learning, behavioural engagement, and cognitive awareness within AI literacy constructs. In this study, TAM and TPB were used as supporting theoretical perspectives to interpret AI-related attitudes and behaviours rather than as empirically tested structural models.

In the context of education, academics play an important role in facilitating teaching and learning processes. A high level of AI literacy enables teachers to utilise technology to enhance teaching quality, design interactive activities, and cultivate ethical awareness among students (Chundran, 2018; Rani et al., 2025). The emergence of AI-based applications that support language learning has increased over time. Rahman et al. (2025) assert that the development of AI has significantly expanded translation. According to their study, the combination of traditional translation methods and AI assistance can produce high-quality translations.

Adnan (2025) also examined students' high level of AI literacy in learning Arabic grammar. The findings indicate that they use AI to understand basic theories, place diacritics, identify meanings, and more. Therefore, language teaching that does not integrate AI in its implementation can be considered a loss in terms of effectiveness and relevance in contemporary education. However, while student AI literacy has received growing attention, structured investigations into academics' AI literacy, particularly within language-based faculties, remain scarce.

2.2 AI Literacy Levels Among Academics

AI literacy empowers academics to guide students responsibly, rather than react defensively to AI technologies. Chundran (2018) examined the readiness levels of academics from three polytechnics in Johor and found that respondents were still at a moderate level in terms of readiness, skills, and attitudes towards integrating AI into the teaching and learning process. The study recommends that relevant authorities take appropriate measures to enhance academic literacy levels. Emiri et al. (2024) conducted a study involving 231 Nigerian academics to assess their digital literacy, including AI literacy. The findings indicate that their literacy levels were moderate, but their actual usage remained limited. The study also suggests that specialised training courses should be provided to enable academics to fully leverage AI in teaching and learning settings.

Amaewhule (2025) distributed questionnaires to evaluate the AI literacy levels of academics, with 362 respondents participating in the study. The findings revealed that their AI literacy levels were low, although they did not express resistance to AI. The main challenge they faced was the lack of a clear framework from higher authorities to support the integration of AI. Another study involving 384 lecturers in universities in Riverdale also showed a low level of AI literacy among respondents (Amaewhule and Aderiye 2026).

From a theoretical standpoint, such findings may be interpreted through the Technology Acceptance Model (TAM), whereby positive attitudes do not necessarily translate into behavioural engagement without sufficient perceived control, institutional support and skills. This reinforces the importance of simultaneously examining the affective, behavioural, cognitive, and ethical dimensions rather than examining them in isolation. These studies indicate that many academics have yet to achieve a high level of AI literacy and require support and encouragement from relevant stakeholders to do so. Detailed research in the field of language education remains limited, indicating a research gap that this study aims to fill. Therefore, this study examined the level of self-reported AI literacy among language academics at FPBU, USIM.

3.0 Methods

This study employed a quantitative approach using an online questionnaire to achieve three main objectives: (1) to assess language academics' perceptions and self-reported AI literacy-related competencies, (2) to examine the relationships between demographic factors and respondents' self-reported AI literacy levels, and (3) to investigate the relationships among the four dimensions of AI literacy, namely affective, behavioural, cognitive, and ethical literacy. The instrument used was the Artificial Intelligence Literacy Questionnaire (AILQ), developed and validated by Ng et al. (2024). Although the AILQ was originally developed for broader educational contexts, several items were contextually adapted to suit the academic staff. Minor wording modifications were made to ensure contextual appropriateness while preserving the original construct, structure, and meaning. The adaptation process focused on maintaining conceptual equivalence rather than altering the underlying dimensions of affective, behavioural, cognitive, and ethical AI literacy. To ensure content appropriateness for academics, the adapted questionnaire was reviewed by experts in educational technology and language education prior to distribution.

The AILQ consists of 32 items across four dimensions of AI literacy: affective, behavioural, cognitive, and ethical learning. The questionnaire was previously validated through expert evaluation, qualitative interview verification, a pilot study, and Confirmatory Factor Analysis (CFA). The CFA confirmed that the 32 items were appropriate for assessing the respondents' perception on AI literacy levels. Items were measured on a five-point Likert scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. The items were organised into four components: affective learning (Items 1–10), behavioural learning (Items 11–18), cognitive learning (Items 19–24), and ethical learning (Items 25–32).

Affective learning assessed academics' attitudes, perceptions, and self-confidence regarding artificial intelligence (AI). Behavioural learning evaluated the extent to which academics actively engaged in and participated in AI-related activities. Cognitive learning examines academics basic understanding of

AI concepts and functions. Ethical learning assessed academics' moral values and ethical awareness of the social implications of AI use.

The questionnaire was administered in a bilingual Malay–English format to facilitate respondents' comprehension and enhance item clarity. The bilingual version was prepared using forward and backward translation procedures to ensure linguistic equivalence. The original English items were first translated into Malay by bilingual academics familiar with educational technology terminology. The Malay version was subsequently back-translated into English by an independent bilingual reviewer to verify consistency of meaning. The translated instrument was then reviewed by experts in language education and educational technology to assess conceptual clarity, semantic equivalence, and contextual appropriateness prior to administration.

The translation and adaptation procedures were intended to establish linguistic and content equivalence rather than to re-establish the construct validity of the instrument. Although the original AILQ was previously validated by Ng et al. (2024), no exploratory or confirmatory factor analysis was conducted in the present study to verify whether the original factor structure was retained in the adapted bilingual version. Consequently, the findings should be interpreted within the context of an adapted instrument whose construct structure was not independently revalidated in this sample.

The questionnaire was distributed through official social media channels for approximately one month. This study involved 72 academics from the Faculty of Major Language Studies (FPBU), Universiti Sains Islam Malaysia (USIM), during the A251 2025 academic semester, representing approximately 78% of the accessible population of 92. Although purposive sampling was applied, as language-based academics were the most relevant group aligned with the study objectives, the high response rate indicates near population coverage within the faculty.

Based on the sample size determination table by Krejcie and Morgan (1970), with a 95% confidence level, 5.5% margin of error, and estimated population proportion of 50%, the required sample size was 72. Therefore, the number of respondents was considered adequate for generating meaningful findings on AI literacy among academics at FPBU, USIM. Future studies could be strengthened by involving a larger sample size to reduce the margin of error to 5%.

As the study was conducted within a single faculty at one institution, the findings are context-specific and should be interpreted with caution when applied to the broader population of language academics in other institutions. Nevertheless, this focused institutional context allows for an in-depth examination of AI literacy within a language-based faculty actively engaged in digital transformation.

Because the data were collected through a self-reported questionnaire administered at a single point in time, the potential for common method bias (CMB) was considered in this study. To minimise the likelihood of common method variance (CMV), both procedural and statistical remedies were implemented.

Several procedural strategies were applied, following the recommendations of MacKenzie and Podsakoff (2012). First, respondents were assured of confidentiality to reduce evaluation apprehension and social desirability bias. Second, the questionnaire instructions emphasised that there were no right or wrong answers, thereby encouraging honest responses. Third, clear and concise wording was used to reduce ambiguity and improve the clarity of the items. These steps were taken to minimise the respondents' tendency to provide overly consistent or socially desirable answers.

Harman's single-factor test was conducted using exploratory factor analysis (EFA). The results indicated that a single factor explained 46.27% of the total variance, which was below the 50% threshold value. This suggests that common method bias is unlikely to be a serious concern.

4.0 Results and Discussion

This section elaborates on the respondents' demographic profiles, self-reported AI literacy levels among language academics, the relationship between demographic factors and self-reported AI literacy levels, and the relationships among the four types of AI literacy.

4.1 Respondents' Demographic Profiles

Table 1 presents the respondents' demographic profiles. A total of 72 academics responded to the questionnaire, comprising 23 male academics (31.9%) and 49 female academics (68.1%). The higher proportion of female respondents reflects the broader trend of women's representation in the social sciences, particularly in education, where women constitute the majority of professionals (UNESCO 2024b).

The majority of respondents were aged between 41 and 50 years (47.2%), followed by those aged between 51 and 60 years (26.3%). This suggests that most respondents were experienced academics in the mid to late stages of their academic careers. This finding is consistent with the respondents' length of service, as half of them (50.0%) had served as academic staff for more than 20 years.

Table 1

Respondents' Demographic Profile

Variable	Value	%	Variable	Value	%
Gender			**Years of Service**		
Male	23	31.9	0–3	6	8.3
Female	49	68.1	4–7	2	2.7
Age			8–12	9	12.5
20–30	4	5.5	13–20	19	26.4
31–40	15	20.8	>20	36	50.0
41–50	34	47.2			
51–60	19	26.3			

4.2 Language Academics' Perceptions and Self-Reported AI Literacy-Related Competencies,

This section presents findings that were analysed descriptively using mean scores and standard deviations. Mean scores were interpreted using equal interval ranges for a five-point Likert scale, obtained by dividing the scale range ($5 - 1 = 4$) by the five response categories, yielding an interval width of 0.80 (Boone & Boone, 2012). The interpretation scale is shown in Table 2.

Table 2

Interpretation of the 5-point Likert Scale

Scale	Mean	Interpretation
1	1.00-1.8	Totally Disagree
2	1.81-2.60	Disagree
3	2.61-3.40	Neutral
4	3.41-4.20	Agree
5	4.21-5.00	Totally Agree

Based on Table 3, all items in the first component, representing affective learning (Items 1–10), recorded high mean scores ranging from 3.77 to 4.52, with an overall mean score of 4.12. This indicates that the respondents generally agreed with the statements. The findings suggest that academics reported positive attitudes and strong intrinsic motivation toward adopting AI, particularly in relation to items 3 and 4. They also perceived AI as relevant and beneficial to their professional work, as reflected in item 1.

Previous studies examining the intrinsic motivation of higher education academics to learn AI remain limited (Bai et al., 2021). However, Du et al., 2024 found that K–12 teachers' behavioural intentions to learn AI were significantly influenced by their perceptions of AI's social benefits and their self-efficacy in learning AI. Teachers also tend to believe that AI can add value to their professional roles (Hazzan-Bishara et al., 2025). In the present study, the respondents also reported strong confidence in their ability to learn AI-related skills. This suggests a high level of acceptance and openness among academics toward educational innovation and the integration of AI into teaching and learning (Nazaretsky et al., 2022). Such positive affective dispositions may provide a strong foundation for the future development of advanced AI competencies in language education, including Arabic-language education.

The relatively high overall mean score for affective learning ($M = 4.12$), together with the high score for the perceived relevance of AI in Item 1, suggests that the respondents generally viewed AI as relevant to their professional practice. Within the Technology Acceptance Model (TAM), Davis et al. (1989) proposed that perceived usefulness influences users' attitudes toward adopting new technology. In this context, respondents' recognition of AI's relevance of AI may be associated with their motivation to learn about it. This pattern also aligns with the principles of the ABC Framework, in which affective factors, such as perceived value and curiosity, support subsequent behavioural engagement and the development of technical competencies. However, these interpretations should be considered indicative rather than confirmatory, as the findings were based on self-reported data.

In the behavioural learning component, the questionnaire results showed high mean scores, particularly for items related to respondents' intentions and future commitment to continue using AI technologies. Respondents reported a willingness to engage actively in AI-related learning activities and training, such as staying updated on new developments and using supplementary learning resources. These findings align with Chai et al. (2024), who highlighted teachers' readiness to enhance their competence in AI-supported instruction and the need to strengthen the ethical and design-related aspects of AI to improve learning quality. However, despite respondents' strong intentions and commitment, collaboration-related items (Items 16 and 18), such as "I often try to explain the AI learning materials to my colleagues", and "I often spend spare time discussing AI with my colleagues", recorded slightly lower scores. This suggests that social engagement and collaborative learning activities can be improved further. A systematic literature review by Xue et al. (2025), covering studies from 2015 to 2024, reported an increasing trend in research on AI-based teaching methods. Nevertheless, the review also identified gaps, particularly the lack of studies examining AI adoption in peer collaborations. Therefore, approaches that emphasise teamwork, peer learning, and shared practical experiences should be encouraged to strengthen interaction and real-world applications in AI learning.

The strong relationship identified between the affective and behavioural dimensions ($p < .05$) can be interpreted from the TAM and TPB perspectives. This suggests that an educator's emotional orientation towards AI is similar to the 'Attitude' variable in TAM and TPB, which ultimately translates conceptual knowledge into a commitment to apply AI in teaching. Consequently, AI literacy is more than just a set of competencies; it is a process in which emotional readiness corresponds with behavioural engagement.

In language education, confidence and openness towards AI are particularly important, as instructors must decide when and how AI tools should support activities such as writing feedback, speaking practice, and vocabulary development. From the ABC framework perspective, this finding empirically reinforces the proposition that affective orientation is closely related to behavioural enactment. This finding indicates that affective and behavioural willingness may be related to pedagogically meaningful AI adoption in language classrooms, where human interaction remains central.

In terms of cognitive learning, the results show mean scores within the "agree" range, at approximately 3.8, although these scores were lower than those recorded for the other components. This indicates that the respondents had a good foundational understanding of AI concepts and applications, but their ability to apply and design AI solutions remained comparatively limited. For example, Item 20, "I know how to use AI applications", recorded a high mean score of 4.12, whereas Item 23, which assessed respondents' ability to design AI solutions, recorded the lowest mean score of 3.48. This finding aligns with that of Nuryadi et al. (2025), who reported that lecturers often struggle to apply AI in teaching because of the complexity of AI technologies.

This pattern suggests that most respondents are still at the level of basic cognitive understanding and have not yet fully developed higher-order cognitive skills, such as analysing, designing and evaluating AI technologies. Therefore, AI competency development should be supported through hands-on practical training provided by teaching and learning centres to strengthen academics' cognitive skills (UNESCO, 2024a).

The gap between high affective willingness and the lower score for creating AI-driven solutions (M = 3.48) can be further understood through the Theory of Planned Behaviour (TPB). Although respondents reported positive attitudes towards AI and high levels of ethical awareness, comparatively lower self-reported knowledge and skills related to AI design and creation may reflect lower perceived behavioural control (PBC). According to the TPB, motivation alone may be insufficient if individuals do not feel that they have the necessary skills, resources, or support to act. This suggests that while language academics may be emotionally ready to embrace AI, they require more practical support and training to move from being passive users to confident innovators in AI.

Language academics are often involved in assessment practices that rely on careful professional judgment, such as the evaluation of coherence, pragmatic use, and overall communicative effectiveness. When their ability to design or adapt AI tools is limited, ensuring that AI-generated feedback aligns closely with the intended communicative learning outcomes may become increasingly challenging. Therefore, professional development initiatives should emphasise not only how to use AI tools, but also how to adapt them in ways that support formative assessment in language learning (Wang et al., 2025).

The final component, ethical learning, recorded the highest score among all components, with an overall mean exceeding 4.5. This reflects a very high level of ethical awareness and perceived responsibility among academics. In particular, the exceptionally high scores in ethical learning may be associated with the university's emphasis on moral responsibility, accountability, and values-based education, which closely aligns with the ethical challenges posed by AI-mediated communication and language use.

Items such as "I think that AI systems should meet ethical and legal standards" and "I think that people should be accountable for using AI systems" received the highest scores, reporting a strong understanding of the importance of integrity and accountability in AI technology development and application. Nguyen et al. (2023) highlighted several ethical risks associated with AI in education, including personal data protection, student autonomy, fairness, and accountability issues. Similarly, Karran et al. (2025) emphasised the need for teachers to consider ethical dimensions and accountability when integrating AI into teaching. These findings underscore the need for academics to be aware of AI's moral and social implications. Such awareness signals a positive and responsible foundation for integrating AI into language education, ensuring that its adoption is grounded in ethical practices and human-centred values.

In language education, ethical concerns extend beyond data privacy to include issues such as authorship, plagiarism, cultural representation, and the preservation of linguistic authenticity. The strong ethical orientation observed in this study suggests that the language academics at FPBU USIM are well positioned to guide students in responsible AI use, particularly in tasks involving writing, translation, and organising language for communicative purposes. From the perspective of the Theory of Planned Behaviour (Ajzen, 1991), ethical considerations may influence behaviour through normative beliefs—that is, individuals' perceptions of what is socially appropriate or professionally expected—rather than through personal attitudes alone. Thus, institutional policies and professional training play crucial roles in shaping these normative beliefs. Therefore, ethical considerations should continue to serve as a core emphasis in institutional policies and training to promote ethical and socially responsible AI use.

Although the findings indicate a relatively high level of self-reported AI literacy based on Likert-scale responses, this "high" classification primarily reflects functional and applied AI literacy, rather than theoretical knowledge. The respondents reported relatively high levels of perceived understanding of

AI concepts, and ethically engaging with AI-supported tools. However, lower scores on items related to AI creation and design suggest limited proficiency in advanced AI development skills. This distinction highlights that language academics' AI literacy is stronger in terms of pedagogical application and ethical awareness than in technical innovation and system design.

Table 3

AI Literacy Level of Language Academics at FPBU, USIM

No.	Item	Mean	SD
	Affective Learning		
1	Artificial intelligence is relevant to my everyday life (e.g., personal, work).	4.33	.671
2	Learning AI is interesting.	4.52	.691
3	Learning AI makes my everyday life more meaningful.	4.08	.800
4	I am curious about discovering new AI technologies.	4.34	.772
5	I am confident I will perform well on AI-related tasks.	4.18	.718
6	I am confident I will do well on AI-related projects.	3.97	.804
7	I believe I can develop AI knowledge and skills.	4.19	.684
8	I believe I can earn good grades in AI-related assessments.	3.77	.773
9	I can understand AI-related resources/tools.	4.20	.603
10	I feel confident that I will do well in the AI-related tasks.	4.00	.650
	Component Mean (Affective Learning)	**4.12**	
	Behavioural Learning		
11	I will continue to use AI in the future.	4.36	.612
12	I will keep myself updated with the latest AI technologies.	4.22	.735
13	I plan to spend time exploring new features of AI applications in the future.	4.26	.711
14	I actively participate in AI-related learning activities.	4.11	.864
15	I am dedicated to AI-related learning materials.	4.05	.820
16	I often try to explain the AI learning materials to my colleagues.	3.83	.949
17	I try to work with my colleagues to complete AI learning tasks and projects.	4.01	.847
18	I often spend spare time discussing AI with my colleagues.	3.68	.990
	Component Mean (Behavioural Learning)	**4.01**	
	Cognitive Learning		
19	I know what AI is and recall the definitions of AI.	4.05	.669
20	I know how to use AI applications (e.g., Siri, chatbot).	4.12	.710

No.	Item	Mean	SD
21	I can compare the differences between AI concepts (e.g., deep learning, machine learning).	3.65	.921
22	I can apply AI applications to solve problems.	4.08	.726
23	I can create AI-driven solutions (e.g., chatbots, robotics) to solve problems.	3.48	1.087
24	I can evaluate AI applications and concepts for different situations.	3.69	.929
	Component Mean (Cognitive Learning)	**3.85**	
	Ethical Learning		
25	I understand how misuse of AI could result in substantial risk to humans.	4.45	.579
26	I think that AI systems need to be subjected to rigorous testing to ensure they work as expected.	4.51	.530
27	I think that users are responsible for considering AI design and decision processes.	4.51	.604
28	I think that AI systems should benefit everyone, regardless of physical abilities and gender.	4.47	.580
29	I think that users should be made aware of the purpose of the system, how it works and what limitations may be expected.	4.58	.524
30	I think that people should be accountable for using AI systems.	4.59	.521
31	I think that AI systems should meet ethical and legal standards.	4.68	.498
32	I think that AI can be used to help disadvantaged people.	4.43	.747
	Component Mean (Ethical Learning)	**4.52**	

Note. N = 72. Responses were recorded on a five-point scale ranging from 1 (*Strongly disagree*) to 5 (*Strongly agree*). *M* = mean; *SD* = standard deviation. Higher scores indicate stronger self-reported AI literacy.

Overall, the level of AI literacy among language academics at FPBU USIM was high across all four learning components: affective, behavioural, cognitive, and ethical learning. The findings indicate that the respondents possessed strong intrinsic motivation, openness, and self-confidence regarding the integration of AI into language teaching and learning. In terms of behavioural learning, they demonstrated willigness and commitment to continue using AI technologies, although AI-related knowledge-sharing practices among colleagues need to be strengthened.

However, respondents reported relatively high levels of perceived understanding of fundamental AI concepts, whereas items relating to the application and creation of AI-based solutions received comparatively lower ratings, suggesting that further practical training and institutional support may be beneficial (Alkeraida, 2024). In addition, respondents reported high levels of ethical awareness regarding AI use, which may provide a favourable basis for promoting responsible AI practices in educational settings (Airaj, 2024). Overall, the findings indicate relatively high levels of self-reported AI literacy among language academics, while also highlighting opportunities to strengthen more advanced AI-related knowledge and skills through continued professional development.

4.3 Relationship Between Demographic Factors and Self-Reported AI Literacy-Related Competencies

This section examines the relationship between demographic factors, namely gender, age, years of service, and the self-reported AI literacy levels of academics. The study employed a one-way analysis of variance (ANOVA) to test whether there were statistically significant differences in mean scores among three or more independent groups for each demographic variable. Prior to conducting this analysis, the data reliability, validity, and distribution were assessed (Emerson, 2022).

Cronbach's alpha test was conducted to ensure data reliability. The results, as shown in Table 4, indicate that Cronbach's alpha was 0.960. This value perceived an exceptionally high level of internal consistency for the scale used in this study (George & Mallery, 2003) based on the study sample. Furthermore, a detailed analysis of the subscales revealed consistently strong reliability coefficients. The values for affective learning (.927) and behavioural learning (.940) reached the "excellent" threshold, while cognitive learning (.895) and ethical learning (.879) demonstrated "good" to "excellent" internal consistency. These results indicate that the instrument is a highly stable and dependable tool for measuring constructs within the study sample.

Table 4

Cronbach's Alpha Values

Dimension	Item	Cronbach's Alpha
Affective Learning	10	.927
Behavioural Learning	8	.940
Cognitive Learning	6	.895
Ethical Learning	8	.879
Overall	**32**	**.960**

Levene's test was conducted to assess the homogeneity of variances, an important assumption for ANOVA. As shown in Table 5, the demographic variables of age (p = .694), years of service (p = .416), produced p-values greater than .05, suggesting that the assumption of equal variances across groups was met. However, the gender variable produced a significant result (p = .008), indicating unequal variance. Therefore, Welch's ANOVA, which does not assume homogeneity of variance, was used.

Table 5

Levene's Test

Variable	P values (Levene's Test)	Interpretation
Gender	.008	Non-homogeneous Variance
Age	.694	Homogeneous Variance
Years of Service	.416	Homogeneous Variance

The next stage of the study involved conducting the Kolmogorov–Smirnov and Shapiro–Wilk normality tests to determine whether the distribution of AI literacy scores met the assumption of normality. Normality was assessed using composite scores representing each AI literacy dimension: affective, behavioural, cognitive, and ethical learning. This approach is recommended in scale-based research because inferential analyses, such as ANOVA and Pearson correlation, are conducted using aggregated construct scores rather than individual-item responses. All components recorded p-values below .05, indicating that the data were not normally distributed. Therefore, the normality assumption was not satisfied.

In conclusion, the reliability analysis showed that the Cronbach's alpha value for all AI literacy items was 0.96, indicating excellent reliability (George and Mallery, 2003). Subsequently, Levene's test results revealed that two demographic factors, namely age and years of service, recorded p-values greater than .05, indicating that the assumption of homogeneity of variances across groups was met. However, the test results for gender showed an opposite trend. The Kolmogorov–Smirnov and Shapiro–Wilk normality tests indicated p-values below .05, confirming that the normality assumption was not satisfied.

Although the normality tests indicated that the data were not normally distributed, parametric tests were retained for the analysis. This decision was based on evidence that one-way ANOVA is robust to violations of normality, particularly when the sample sizes are moderate and the group variances are homogeneous (Glass et al., 1972; Schmider et al., 2010). As Levene's test confirmed homogeneity of variance for most demographic variables, parametric tests were retained because the sample size exceeded 30, which satisfies the robustness assumption under the Central Limit Theorem. Parametric procedures are considered sufficiently robust to moderate violations of normality, particularly when skewness and kurtosis values fall within acceptable ranges. Skewness ranged between −2.21 and 0.03, while kurtosis ranged between −1.26 and 8.26. Although one kurtosis value exceeded the commonly suggested ±2 threshold, Kline (2009) stated that distributions with skewness < 3 and kurtosis < 10 are typically acceptable for many statistical procedures. Therefore, ANOVA was deemed appropriate for this analysis.

Table 6 presents the comparison of self-reported AI literacy scores by gender. Welch's ANOVA found no statistically significant difference between male and female academics, $F(1, 32.13) = 1.26, p = .270$. This finding is consistent with Wang et al. (2023), who reported no significant gender differences in teachers' AI literacy, and Guillén-Gámez et al. (2021), who found no significant gender differences in the digital competence of higher education teachers. However, the absence of statistical significance should not be interpreted as evidence that the groups were identical or that gender has no role in AI literacy.

Table 6

Welch's ANOVA Comparing Self-Reported AI Literacy by Gender

Test	F	df1	df2	p
Welch's ANOVA	1.26	1	32.13	.270

Table 7 presents the results of the One-Way ANOVA conducted to assess differences in AI literacy levels among academics based on two demographic variables (age and years of service). The results indicated no statistically significant differences across any category: age ($F(3, 68) = 1.028, p = .386$), years of service ($F(4, 67) = 0.283, p = .888$. Correspondingly, the effect sizes (η^2) ranged from .017 to .069, indicating that these demographic factors explained only a small proportion of the variance in AI literacy. These findings suggest that AI literacy levels remain relatively consistent among academics, regardless of their demographic backgrounds.

Regarding age, these findings align with those of Xu et al. (2024) and Ghimire et al. (2024), who similarly found no significant relationship between age and AI or digital literacy. However, other studies have reported contrasting findings, indicating that age may play a significant role in specific contexts. For example, Korkmaz and Akçay (2024) concluded that academics aged 30 years and below reported significantly higher levels of AI literacy than those aged 56 years and above. Similarly, Zhang and Villanueva (2023) and Berber et al. (2023) reported that individuals aged 21–30 years demonstrated higher literacy levels. Overall, the literature presents mixed evidence regarding age, although there is a general tendency for younger academics to exhibit higher AI literacy than older groups.

Regarding years of service, the study similarly found no significant relationship with AI literacy, although academics with 8–12 years of service recorded the highest mean compared to other groups. In contrast, Dringó-Horváth et al. (2025) reported that academics with longer service durations showed a weaker relationship between digital competence and AI literacy ($B = -0.144, p = 0.043$). Thus, the demographic factor of years of service warrants more detailed investigation in future research to establish stronger and more consistent hypotheses.

Table 7

One-Way ANOVA Analysis for Respondent Demographics (Age, Position, Years of Service, Field of Teaching)

Variable	Sum of Squares	df	Mean Square	F	Sig.	η^2
Age	778.220	3	259.407	1.028	.386	.043
Year of Service	297.868	4	74.467	.283	.888	.017

4.4 Relationships Among the Four Components of AI Literacy

Pearson's correlation analysis was conducted to examine the relationships among the four main learning components used to assess the AI literacy level of language academics at FPBU USIM. These four components are affective, behavioural, cognitive, and ethical learning.

The correlation results presented in Table 8 revealed a significant positive relationship between affective learning and behavioural learning ($r = .789$, $p < .01$) and cognitive learning ($r = .746$, $p < .01$). Meanwhile, the relationship between affective learning and ethical learning was also significant but weaker ($r = .297$, $p < .05$). The conceptualization of AI literacy in this result is grounded in the tripartite ABC model of attitudes, which comprises affective, behavioural, and cognitive dimensions (Fishbein & Ajzen, 1975). This framework explain why attitudes can be conceptualized through affective, behavioural, and cognitive dimensions.

Additionally, behavioural learning showed a strong positive correlation with cognitive learning ($r = .786$, $p <.01$) and a moderately strong correlation with ethical learning ($r = .452$, $p <.01$). Cognitive learning also showed a significant positive relationship with ethical learning ($r = .428$, $p <.01$). The ABCE framework (Ng et al., 2024), which examines the interrelationships among affective, behavioural, cognitive, and ethical components, further supports these findings by indicating the relationships among all components of AI literacy among the FPBU USIM academics in this study.

Overall, the results indicate that the four AI literacy dimensions were positively and significantly correlated with one another. These findings suggest that academics who reported higher levels in one AI literacy dimension (affective, behavioural, cognitive, or ethical) also tended to report higher levels in the other dimensions. This pattern supports the multidimensional nature of AI literacy as conceptualised in the AILQ framework.

Table 8

Pearson Correlation Analysis

AI Literacy Dimension	Affective Learning	Behavioural Learning	Cognitive Learning	Ethical Learning
Affective Learning	1			
Behavioural Learning	.789**	1		
Cognitive Learning	.746**	.786**	1	
Ethical Learning	.297*	.452**	.428**	1

AI Literacy Dimension	Affective Learning	Behavioural Learning	Cognitive Learning	Ethical Learning

Note. N = 72. Values represent Pearson correlation coefficients (two-tailed). $^*p < .05$; $^{**}p < .01$.

Although preliminary normality assessments indicated that the component scores deviated from the assumption of normal distribution, Pearson's product-moment correlation was retained as the primary analysis because it remains robust under moderate departures from normality, particularly with a sample size exceeding 50 participants. Furthermore, to verify the stability of the findings, Spearman's rank-order correlations were conducted as a non-parametric robustness check. The Spearman correlation results showed similar correlation patterns and significance levels across all AI literacy dimensions, confirming the consistency of the relationships identified through Pearson's correlation analysis.

The Spearman correlation analysis revealed statistically significant positive relationships among all four AI literacy dimensions ($p < .01$). The strongest association was observed between Affective Learning and Behavioural Learning ($\rho = .765$, $p < .01$), followed by the relationship between Behavioural Learning and Cognitive Learning ($\rho = .752$, $p < .01$), and between Affective Learning and Cognitive Learning ($\rho = .731$, $p < .01$). These findings indicate strong positive associations among the affective, behavioural, and cognitive dimensions of AI literacy.

The Ethical Learning dimension demonstrated positive but comparatively weaker relationships with the other dimensions. Ethical Learning was moderately correlated with Behavioural Learning ($\rho = .469$, $p < .01$) and Cognitive Learning ($\rho = .420$, $p < .01$), while its relationship with Affective Learning was weaker but remained statistically significant ($\rho = .317$, $p < .01$). These findings suggest that although ethical awareness is positively associated with affective, behavioural, and cognitive aspects of AI literacy, it represents a relatively distinct dimension within the overall AI literacy construct.

Importantly, the Spearman correlation coefficients analysis as shown in table 9 closely mirrored the corresponding Pearson correlation coefficients reported in Table 8, with only minor differences in magnitude and no changes in the direction or statistical significance of the relationships. This consistency indicates that the observed associations among the AI literacy dimensions are robust and are not substantially affected by the departure from normality. Therefore, the Spearman correlation analysis provides additional evidence supporting the validity and stability of the relationships identified among the four AI literacy dimensions.

Table 9

Spearman Correlation Matrix among AI Literacy Dimension

AI Literacy Dimension	Affective Learning	Behavioural Learning	Cognitive Learning	Ethical Learning
Affective Learning	1	.765**	.731**	.317**
Behavioural Learning		1	.752**	.469**
Cognitive Learning			1	.420**
Ethical Learning				1

Note. N = 72. Values represent Pearson correlation coefficients (two-tailed). $^*p < .05$; $^{**}p < .01$.

5.0 Limitation

Several limitations of this study should be acknowledged when interpreting the findings. First, the study was conducted within a single faculty, namely the Faculty of Major Language Studies (FPBU), Universiti Sains Islam Malaysia (USIM). Consequently, the findings reflect the context of one academic setting and may not be generalisable to lecturers from other faculties, disciplines, or higher education institutions with different organisational and technological environments.

Second, the study employed purposive sampling to recruit participants who met the predetermined inclusion criteria. Although this approach was appropriate for the study objectives, it may introduce selection bias and limit the representativeness of the sample. Future studies should consider probability sampling techniques involving multiple institutions to enhance the external validity of the findings.

Third, the data were collected through self-administered questionnaires, which are inherently subject to self-report bias. Participants may have overestimated or underestimated their AI literacy due to recall errors, personal perceptions, or social desirability, particularly given the increasing expectation for academics to demonstrate competence in AI-related technologies.

Fourth, the cross-sectional design captures participants' AI literacy at a single point in time and therefore does not permit causal inferences or examination of changes in AI literacy over time. Longitudinal research is recommended to investigate how lecturers' AI literacy develops following institutional initiatives, professional development programmes, or increasing exposure to AI technologies.

Fifth, because all variables were measured using the same survey instrument completed by the same respondents during a single data collection period, the findings may be susceptible to common-method bias. Although the instrument demonstrated excellent internal consistency and satisfactory construct validity, future research should consider employing procedural and statistical approaches to minimise and assess common-method variance, such as collecting data from multiple sources, separating measurement occasions, or conducting statistical tests for common-method bias.

Lastly, the Artificial Intelligence Literacy Questionnaire (AILQ) used in this study was adapted to suit the Malaysian higher education context. While the adapted instrument demonstrated excellent reliability and acceptable validity, further validation across diverse institutional settings, academic disciplines, and cultural contexts is necessary to strengthen its generalisability and measurement equivalence.

6.0 Conclusion

Theoretically, this study contributes to the growing literature on AI literacy by providing context-specific evidence from language education. By examining the affective, behavioural, cognitive, and ethical dimensions of AI literacy, the findings support the conceptualisation of AI literacy as a multidimensional construct shaped by disciplinary and pedagogical contexts. The results further suggest that AI literacy in language education extends beyond technical knowledge to include attitudes, behavioural engagement, and ethical considerations relevant to educational practice.

This study found that language academics at FPBU USIM reported relatively high levels of self-reported AI literacy across the measured dimensions. Higher ratings were observed for items relating to AI use and ethical awareness, whereas comparatively lower ratings were found for items associated with designing and creating AI-based solutions. These findings suggest potential areas for future professional development, particularly in strengthening more advanced AI-related knowledge and skills. The study provides practical implications for universities and educational policymakers in designing evidence-informed professional development initiatives that support the effective, ethical, and contextually appropriate use of AI in language education.

The findings also offer insights for national AI education policy. As Malaysia advances AI integration in higher education under the Malaysian Higher Education Development Plan 2026–2035, structured professional development frameworks that address technical knowledge, pedagogical considerations, and ethical governance may support AI literacy development among academics. Policymakers may also consider incorporating AI literacy competencies into national academic development frameworks to encourage consistent and responsible AI adoption across disciplines, including language education.

Conflict of Interest

The authors have declared that no competing interests exist.

Author Contribution Statement

WMSWA: Project Administration, Writing – Review & Editing; ASB: Literature Review, Data Synthesis and Interpretation; NZ: Manuscript Drafting and Data Analysis; MIAG: Data Collection, Final Manuscript Review.

Funding

We would like to express our sincere appreciation to the Faculty of Major Language Studies (FPBU), Universiti Sains Islam Malaysia (USIM), for funding this research under the research code (PPPI/PTJ/FPBU/USIM/15925).

Ethics Statement

This study involved primary data collection through a self-administered questionnaire distributed to academic staff. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. This research did not require IRB approval because it involved an anonymous survey with no collection of personal or sensitive data. All responses were treated confidentially and used solely for research purposes.

Data Access Statement:

Research data supporting this publication are available upon request to the corresponding author.

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