Training, Language and Culture
Volume 9 Issue 4, 2025, pp. 112-129
rudn.tlcjournal.org
doi: 10.22363/2521-442X-2025-9-4-112-129

Original Research

AI knowledge readiness among university students: A cross-sectional quantitative study

by Luke Teoh Rong Guang[1], Manjet Kaur Mehar Singh[2] and Jayanthi Muniandy[2]

[1]Toyo University, Tokyo, Japan
[2]Universiti Sains Malaysia, Penang, Malaysia

Artificial intelligence is now part of many ordinary routines, often in ways that people barely notice, and it has started to find its way into university work as well. For students, this means that some familiarity with AI is becoming less of an advantage and more of an expectation. Much of this comes down to knowing enough about AI to use it sensibly in their studies, or at least not feeling lost when it appears in academic tasks. In this study, that basic level of knowledge – enough to work with AI without relying on it blindly – is taken as the starting point for the study of AI readiness. The investigation centres on students in the English for Professionals programme, which is an applied-linguistics degree. The study looks at how prepared these students feel to handle AI in the course of their academic work. Using a cross-sectional design, 291 students from different academic years completed a structured questionnaire measuring four dimensions of AI readiness: cognition, ability, vision, and ethics. The results show that AI readiness generally increases with academic progression, with second- and third-year students reporting higher levels of ability, cognition, and vision. The ethics dimension, however, remains low across all groups. Gender differences were minimal. The findings indicate a need for earlier inclusion of AI-related material and a more sustained focus on AI ethics in the applied linguistics curriculum. More broadly, the programme requires considerable revision to incorporate computational linguistics and AI-related topics, ensuring that applied linguistics students leave with the level of preparation now expected in professional contexts where AI routinely plays a role.

KEYWORDS: *applied linguistics, artificial intelligence, AI, university students*

CRediT AUTHOR STATEMENT: Manjet Kaur: Conceptualisation, Writing – Reviewing and Editing, Methodology. Luke Teoh Rong Guang: Writing – Original Draft, Investigation. Jayanthi Muniandy: Software, Data Curation, Validation.

CONFLICT OF INTEREST: The authors declared no conflict of interest.

DATA AVAILABILITY STATEMENT: The data supporting this study's findings are available from the corresponding author, Manjet Kaur Mehar Singh, at manjeet@usm.my, upon reasonable request.

FUNDING: No funding was reported for this research.

ACKNOWLEDGEMENTS: The researchers would like to acknowledge students at School of Languages, Literacies and Translation, Universiti Sains Malaysia for their support.

ARTICLE HISTORY: Submitted April 21, 2025 | Revised November 16, 2025 | Accepted November 27, 2025

FOR CITATION: Teoh, L. R. G., Singh, M. K. M., & Muniandy, J. (2025). AI knowledge readiness among university students: A cross-sectional quantitative study. *Training, Language and Culture*, *9*(4), 112-129. https://doi.org/10.22363/2521-442X-2025-9-4-112-129

1. INTRODUCTION

Artificial intelligence (AI) is one of the most transformative technologies of the 21st century (Russell & Norvig, 2020). AI is profoundly strategised as intelligent systems that are capable of replacing human capacity in thinking, learning and acquiring knowledge. In the context of higher education, the stakeholders cannot compete with the pace of educational changes forced by AI to improve their curricula. This has led to ill-prepared graduates for an AI-driven workforce (Katsantonis & Katsantonis,

2024) as AI is extremely fast-paced in redefining the future of work and employability. Such a scenario indicates a mismatch between graduate preparedness and industry expectations, particularly as employers require workers who are equipped to function in increasingly AI-oriented workplaces (Kurtz et al., 2024; Mustapha et al., 2023; Yusuf et al., 2024).

To mitigate the mismatch between the academia and industry, AI should be integrated as part of the curricula in higher education. This involves positioning AI readiness as a central agenda in preparing students to meet the demands of an AI-oriented professional landscape. AI readiness encompasses an institution's ability to integrate AI into its teaching and learning frameworks, ensuring that students develop the necessary skills for the future (Karaca et al., 2021). This readiness can be evaluated through four core dimensions, which are ability, cognition, vision, and ethics. Ability refers to the practical competencies required to operate AI technologies effectively, while cognition involves intellectual understanding, including the capacity to analyse and interpret AI systems and data (Karaca et al., 2021). Vision relates to the foresight needed to anticipate AI's evolving role across industries, and ethics concerns the moral and societal implications of responsible AI usage (Karaca et al., 2021).

Building on this conceptualisation of AI readiness, the current study shifts the focus to students enrolled in the English for Professionals degree programme, an applied linguistics based-degree programme at a public university in Malaysia. This research seeks to understand how prepared these students are to engage with linguistic AI, which refers to AI systems that process, understand, and generate human language in ways that mirror cognitive decision-making processes (McShane & Nirenburg, 2021). These systems go beyond simple pattern recognition, offering deep language comprehension and the ability to make informed decisions based on linguistic inputs. Such capabilities are central to the future of professional communication, especially in fields where language plays a critical role (Dai et al., 2024).

The study is not solely concerned with individual readiness levels. The students' preparedness for linguistic AI also reflects, to some extent, the degree to which the applied linguistics programme has incorporated AI within its curriculum. A high level of student readiness would suggest that the teaching practices are evolving to incorporate AI technologies, positioning the institution as a leader in integrating AI across academic disciplines. While previous research has primarily focused on AI readiness in STEM (Science, Technology, Engineering, and Mathematics) fields (Sidhu et al., 2024; Xu & Ouyang, 2022; Xuan et al., 2023), this study responds to a gap in research by examining AI readiness in the social sciences and humanities and observing how applied linguistics programmes are adapting to AI. The gap is significant as in the social sciences and humanities, AI is in the category of incidental use and not part of the formal education. The current applied linguistics curricular does not offer integrated or stand-alone AI related courses.

The study's focus on this group pf university students is particularly relevant. These students engage in professional communication and apply English in various real-world contexts, which makes them ideal candidates for evaluating AI readiness within the broader spectrum of social sciences. In addition, the study looks at how academic progression and gender relate to students' levels of AI readiness. The results suggest that individual differences play a part in how students begin to make use of AI in building their professional skill sets.

The research has two main aims. The first is to compare AI readiness across students in different years of their programme — first, second, and final year — to see whether there are noticeable differences in confidence or preparedness as they advance through their studies. The second aim is to examine whether there are any gender-related patterns in AI readiness and, if so, what they might tell us about how students approach AI technologies. The study adds to the emerging discussion of AI readiness in non-STEM fields and offers several directions for adjusting the applied linguistics curriculum to better support students in this area.

2. THEORETICAL BACKGROUND

AI has begun to leave a noticeable mark on different sectors, including education, where its presence is steadily growing in importance. Globally, educational institutions are tasked with preparing students for an AI-driven future, yet readiness levels vary widely across disciplines and regions (Hankins et al., 2023; Wu & Zhang, 2023). In many cases, institutions are challenged by outdated curricula that do not adequately incorporate AI-related skills (Kurtz et al., 2024). The gap between the rapid advancement of AI and the slow pace of academic adaptation has been noted, with many students feeling unprepared for the technological demands of modern workplaces (Mustapha et al., 2023).

In acknowledgement, many educational systems, particularly in economically driven countries, have extensively integrated AI into their curricula, especially within STEM fields, moving beyond surface-level adoption (Hornberger et al., 2023; Xu & Ouyang, 2021). For example, the United States and China are leading AI education, with MIT integrating AI into curricula that balance technical skills and AI ethics, while the Chinese University of Hong Kong promotes AI literacy through practical, collaborative initiatives like AI4Future (Casal-Otero et al., 2023). In contrast, students from non-technical disciplines often have limited exposure to AI, especially those from underserved communities and low-resource countries, whereas this challenge is less common in middle-income and high-income nations (Devisakti et al., 2023; Hankins et al., 2023; Huang et al., 2023; Reuben et al., 2024).

2.1. AI readiness among different cohorts

Academic progression has been shown to influence students' AI readiness. Freshmen, with limited exposure to advanced technological concepts, typically exhibit lower readiness compared to senior students who have had more opportunities to engage with AI in their coursework. For instance, Wang et al. (2023) found that senior students often perceive technology as more useful than their junior counterparts, which may translate into higher AI readiness as they approach the later stages of their education .

Furthermore, Slimi (2023) reports that as students move closer to graduation, their attitudes toward AI often become more pragmatic, as they start to consider the real-world applications of AI in their future careers. This is particularly evident in studies that compare readiness across academic levels, where senior students generally exhibit higher levels of technological literacy and adaptability due to their greater engagement with digital tools and professional demands (Karagul et al., 2021).

Moreover, comparative studies have shown that differences in AI readiness are not uniform across academic disciplines or institutions. Delcker et al. (2024) revealed that in more AI-integrated academic environments, even first-year students had comparable AI readiness scores to seniors in less technologically integrated institutions. The curriculum plays a critical role here, with some programmes embedding AI-related content across all years of study, while others introduce it only in advanced stages. This discrepancy points to the importance of curriculum design in fostering AI readiness throughout a student's education (Southworth et al., 2023).

2.2. Gender dynamics in AI readiness

The interplay between gender and technology engagement has also been extensively documented in AI education, with studies frequently reporting that male students display greater confidence and engagement with AI technologies compared to their female peers (Dai et al., 2020; Ofosu-Ampong, 2023). This trend is consistent with findings across the broader field of digital literacy, where males often exhibit higher technological self-efficacy and a stronger inclination toward technology-driven careers (Chan, 2022; Qazi et al., 2021). These differences are not just a matter of personal inclination. They are bound up with wider societal patterns that have traditionally framed technology and AI as areas associated with men (Chan, 2022). This androcentric approach to AI development has resulted in gender biases within the design and application of AI technologies (O'Connor & Liu, 2023; Shihadeh et al., 2022). The biases manifest in how AI systems, such as recruiting algorithms and voice recognition tools, often disadvantage women due to the male-centric data and assumptions fed into these technologies. Besides, the underrepresentation of women in AI-related professions is further perpetuated by societal expectations and educational patterns that discourage female participation in technical fields from an early age (Gomez-Herrera & Koeszegi, 2022).

Nevertheless, it is crucial to recognise that intra-gender disparities in AI readiness among university students may not be universal and can be significantly mitigated by inclusive educational practices. For instance, Evans and Sinha (2024) found that when male and female students are provided with equitable access to AI-related resources and curricula, the perceived gap in AI readiness diminishes substantially. This finding brings into focus the importance of structural interventions, such as equal access to AI learning opportunities, in reducing or even eliminating gender-based or class-based differences.

The literature points to the ways in which education is evolving with the integration of AI. The gap in the literature points to disparities in readiness across disciplines, regions, and demographic groups. This remains an issue that requires further investigation. Developed nations are taking actions in integrating AI into curricula of STEM fields. However, AI integration in non-technical disciplines is not on the higher education priority agenda.

The literature notes that AI readiness tends to rise as students progress through their programmes, with senior students generally showing a firmer sense of preparedness than those in their first year. It also points to a recurring pattern in which male students report greater confidence and engagement with AI than their female peers. Earlier studies further suggest that these gaps can be softened through more inclusive educational practices that give all students fair access to AI-related tools and learning opportunities.

3. MATERIAL AND METHODS

3.1. Research design and instrumentation

The research design utilised in this study is a cross-sectional quantitative comparative study, focused on examining differences in AI readiness across distinct groups, specifically by year of study and gender. Data was collected using a structured questionnaire specifically designed to assess AI readiness and attitudes towards AI in both academic and professional contexts. The questionnaire comprised demographic questions, Likert-scale items, and open-ended questions.

The questionnaire was adapted from the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS). The modifications involved replacing terms such as *medical students* with *students in the English for Professionals degree programme.* The original instrument captures general attitudes of medical students towards technology (Karaca et al., 2021; Xuan et al., 2023). The use of the scale in the current study involved only minor modification involving the labelling of target group being tested. In this study, the four key AI readiness dimensions – cognition, ability, vision, and ethics – were defined based on Karaca et al.'s (2021) framework to ensure these aspects are effectively captured in the context of language-related professional applications.

3.2. Pilot testing

To ensure the reliability and validity of the adapted instrument, a pilot test was conducted with 30 participants who had similar demographic characteristics to the target population. This preliminary phase allowed the researchers to gather feedback on the clarity, relevance, and understanding of the questionnaire items. Minor adjustments were made to the wording of certain items based on participants' feedback, ensuring the instrument matched the linguistic and cognitive abilities of the target group. These refinements helped reduce potential misunderstandings and improved the face and content validity of the questionnaire. The Cronbach Alpha yielded a strong value of 0.918. The value indicates internal consistency with high level of reliability.

3.3. Participants

The study applied stratified random sampling that involved 291 English for Professionals degree programme undergraduates from a public university in Malaysia. Stratified random sampling was used to ensure proportional representation across academic years, resulting in a sample of 88 first-year, 98 second-year, and 105 final-year students. A total of 242 female participants and 49 male participants took part in the study. The initial sample size of 310 was reduced to 291 after 19 responses were excluded due to incomplete data.

3.4. Data analysis

Statistical Package for Social Sciences (SPSS) version 28 was applied for data analysis. Data analysis involved descriptive statistics of data summary to provide an overview of AI readiness across different years of study and gender groups. This followed statistical analysis to identify the differences in AI readiness. Significant variations across different years of study involved one-way analysis of variance (ANOVA). Apart from that, the differences within gender groups and year of study in influencing AI readiness were determined via two-way ANOVA. In addition, effect sizes were calculated to identify the differences. These provide practical importance of the observed variations.

3.5. Ethical considerations

Ethical integrity was ensured by ensuring voluntary participation. Participants were briefed on the nature of the study, objectives and procedures before the commencement of the study. Participants were provided informed consent form to indicate their voluntary participation in the study. Participants were assured that they could withdraw from the study at any point without any restrictions. Furthermore, the confidentiality and anonymity of the participants were assured by ensuring anonymising of data and securely stored data.

4. STUDY RESULTS

4.1. Data preparation

The quantitative data were analysed using SPSS, incorporating tests for normality, homogeneity of variance, reliability and validity. The skewness and kurtosis values fell within the acceptable range of -1 to +1, showing that the data were normally distributed. In addition, the data were screened for outliers via boxplots, which identified 19 extreme values that were removed to improve data quality. The p-value for Levene's test is greater than 0.05 and therefore, the assumption of homogeneity of variance is met. The Cronbach's alpha coefficient was used to assess the internal consistency of each questionnaire item. The Cronbach's alpha value for the 29 questionnaire items was 0.918. Hinton et al. (2004) state that an alpha value above 0.7 indicates high reliability of the questionnaire items.

4.1.1. AI readiness across different years of study

A one-way ANOVA test was conducted to answer the first research question.

Table 1 suggests that AI readiness among the undergraduates varies by year of study, with Year 2 (mean = 2.99) and Year 3 (mean = 2.94) students having higher readiness on average compared to Year 1 (mean =2.81). An ANOVA test was conducted to examine the differences in AI readiness scores across Year 1, Year 2, and Year 3 students.

Table 2 indicates a significant difference in overall AI readiness scores between the years of study with an F-value of 7.266, $p < .001$. This reveals that the year of study significantly affects AI readiness among the undergraduates. A post hoc test was conducted to identify where the differences lie.

To control for Type 1 error, Tukey's HSD post hoc was used. The post hoc comparisons in Table 3 show that the mean score for AI readiness among Year 1 students was significantly lower than that for Year 2 students (mean difference = -.18092, $p<.001$) and Year 3 students (mean difference = -.13681, $p = .014$).

However, there was no significant difference between Year 2 and Year 3 students (mean difference = .04411, $p>.05$).

Volume 9 Issue 4, 2025, pp. 112-129 doi: 10.22363/2521-442X-2025-9-4-112-129

Table 1
The mean score of students' overall AI readiness across different years of study

YEAR OF STUDY	TOTAL NUMBER OF STUDENTS (*N*)	MEAN	STANDARD DEVIATION
Year 1	88	2.8077	.32018
Year 2	98	2.9887	.37070
Year 3	105	2.9446	.31190
Total	291	2.9180	.34240

Table 2
ANOVA test

OVERALL READINESS	SUM OF SQUARES	DF	MEAN SQUARE	F	SIG.
Between groups	1.633	2	.817	7.266	<.001
Within groups	32.366	288	.112		
Total	33.999	290			

Note: df = Degree of Freedom, F = F-Value, Sig. = Significance

Table 3
Tukey's HSD post hoc test

YEARS OF STUDY (*I*)	YEARS OF STUDY (*J*)	MEAN DIFFERENCE (*I-J*)	STD. ERROR	SIG.
Year 1	Year 2	-.18092*	.04923	<.001
	Year 3	-.13681*	.04845	.014
Year 2	Year 1	.18092*	.04923	<.001
	Year 3	.04411	.04709	.617
Year 3	Year 1	.13681*	.04845	.014
	Year 2	-.04411	.04709	.617

Note: Std. Error = Standard Error; a.* The mean difference is significant at the 0.05 level; b. Dependent variable: Overall readiness

For further analysis, an ANOVA test for each dimension of AI readiness (cognition, ability, vision and ethics) was carried out to determine if there are significant differences across years of study. Table 4 shows there are significant differences in cognition ($F = 3.197$; $p = .042$), ability ($F = 10.532$; $p < .001$), and vision ($F = 3.604$; $p = .028$) scores across years of study. However, there are no significant differences in ethics scores between the groups.

The results from Table 5 suggest that Year 2 students tend to have higher scores in cognition (MD = .17651; $p=.032$), ability (MD = .25865; $p<.001$), and vision (MD = .17799; $p = .024$) compared to Year 1 students. Additionally, Year 3 students have significantly higher ability scores (mean difference = .21535; $p < .001$) compared to Year 1 students. No significant differences were found between Year 2 and Year 3 for any of the dimensions.

Table 4
ANOVA test for each dimension of AI readiness

DIMENSION	OVERALL	SUM OF SQUARES	DF	MEAN SQUARE	F	SIG.
Cognition	Between groups	1.446	2	.723	3.197	.042
	Within groups	65.116	288	.226		
	Total	66.562	290			
Ability	Between groups	3.521	2	1.761	10.532	<.001
	Within groups	48.148	288	.167		
	Total	51.669	290			
Vision	Between groups	1.521	2	.761	3.604	.028
	Within groups	60.784	288	.211		
	Total	62.305	290			
Ethics	Between groups	.835	2	.417	1.896	.152
	Within groups	63.386	288	.220		
	Total	64.221	290			

Table 5
Tukey's HSD Post Hoc Test for each dimension of AI readiness

DIMENSION	YEARS OF STUDY (*I*)	YEARS OF STUDY (*J*)	MEAN DIFFERENCE (*I-J*)	STD. ERROR	SIG.
Cognition	Year 1	Year 2	-.17651*	.06983	.032
		Year 3	-.08876	.06872	.401
	Year 2	Year 1	.17651*	.06983	.032
		Year 3	.08776	.06679	.389
	Year 3	Year 1	.08876	.06872	.401
		Year 2	-.08776	.06679	.389
Ability	Year 1	Year 2	-.25865*	.06005	<.001
		Year 3	-.21535*	.05909	<.001

Volume 9 Issue 4, 2025, pp. 112-129
doi: 10.22363/2521-442X-2025-9-4-112-129

	Year 2	Year 1	.25865*	.06005	<.001
		Year 3	.04329	.05743	.732
	Year 3	Year 1	.21535*	.05909	<.001
		Year 2	-.04329	.05743	.732
Vision	Year 1	Year 2	-.17799*	.06747	.024
		Year 3	-.12170	.06640	.161
	Year 2	Year 1	.17799*	.06747	.024
		Year 3	.05629	.06453	.658
	Year 3	Year 1	.12170	.06640	.161
		Year 2	-.05629	.06453	.658

Note: * The mean difference is significant at the 0.05 level.

Table 6
ANOVA effect sizes[a] for overall AI readiness

		POINT ESTIMATE	95% CONFIDENCE INTERVAL	
			LOWER	UPPER
Overall readiness	Eta-squared	.048	.009	.100
	Epsilon-squared	.041	.002	.094
	Omega-squared fixed-effect	.041	.002	.093
	Omega-squared random-effect	.021	.001	.049

Note: a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

ANOVA effect sizes for overall AI readiness among the EFP undergraduates were determined for a more comprehensive result. Table 6 reveals that approximately 4.8% of the variance in overall AI readiness scores can be explained by the year of the study. The confidence interval shows that this estimation could range from as low as 0.9% to as high as 10%. All the measures of the ANOVA effect sizes indicate there is a small but significant effect of the year of the study on AI readiness scores.

Table 7 shows that the year of study has a small effect on cognition (0.7% to 2.2%) and vision (0.9% to 2.4%). However, the confidence intervals, some of which include negative values, indicate that the results are uncertain and may have no effect at all. For ability, the year of study has a moderate effect (3.2% to 6.8%) on ability scores. The confidence intervals are positive, indicating a more certain effect. Regarding ethics, all effect size measures (1.3% to 0.3%) indicate a very small proportion of explained variance. The confidence intervals, especially Epsilon-squared and Omega-squared, encompass zero and negative values, suggesting that the year of study has no significant impact on ethics scores.

4.1.2. Intragender differences in AI readiness

A two-way ANOVA test was performed to answer the second research question.

Table 7
ANOVA effect sizes for each dimension of AI readiness[a,b]

		POINT ESTIMATE	95% CONFIDENCE INTERVAL	
			LOWER	UPPER
Cognition	Eta-squared	.022	.000	.061
	Epsilon-squared	.015	-.007	.054
	Omega-squared fixed-effect	.015	-.007	.054
	Omega-squared random-effect	.007	-.003	.028
Ability	Eta-squared	.068	.020	.126
	Epsilon-squared	.062	.013	.120
	Omega-squared fixed-effect	.061	.013	.120
	Omega-squared random-effect	.032	.007	.064
Vision	Eta-squared	.024	.000	.065
	Epsilon-squared	.018	-.007	.059
	Omega-squared fixed-effect	.018	-.007	.059
	Omega-squared random-effect	.009	-.003	.030
Ethics	Eta-squared	.013	.000	.046
	Epsilon-squared	.006	-.007	.039
	Omega-squared fixed-effect	.006	-.007	.039
	Omega-squared random-effect	.003	-.003	.020

Note: a. Eta-squared and Epsilon-squared estimated based on the fixed-effect model; b. Negative but less biased estimates are retained, not rounded to zero.

Table 8 shows that the highest AI readiness scores are observed in the 18–22 age group, particularly in Year 2 for both male (mean score = 3.22) and female (mean score = 2.93) students. The findings also reveal that the mean scores generally decrease with age among male students, except for a slight increase in the 23–27 age group. In contrast, the scores are relatively consistent across age groups with slight variations among female students.

The p-values obtained from Levene's test (0.406, 0.492, 0.492, and 0.387) are all greater than the conventional threshold of 0.05. This result indicates that there is no significant difference in the variances of overall readiness scores across the groups defined by gender, age, and year of study. Therefore, the assumption of homogeneity of variances is satisfied, justifying the use of further parametric analyses such as ANOVA that assume equal variances.

The main effect of gender was not statistically significant ($F = 1.788$, $p = 0.182$) (Table 10). This indicates that there is no significant difference in AI readiness scores between male and female students. The findings also indicate that the interaction involving gender (Gender *

Volume 9 Issue 4, 2025, pp. 112-129
doi: 10.22363/2521-442X-2025-9-4-112-129

Table 8
Descriptive statistics

GENDER	AGE	YEARS OF STUDY	MEAN	STANDARD DEVIATION	N
Male	18-22	Year 1	2.8957	.28797	10
		Year 2	3.2230	.36600	16
		Year 3	3.1235	.47493	7
		Total	3.1027	.38618	33
	23-27	Year 1	2.7857	— / —	1
		Year 2	3.0392	.39150	6
		Year 3	3.0279	.31770	8
		Total	3.0163	.33061	15
	28-32	Year 2	2.8839	— / —	1
		Total	2.8839	— / —	1
	Total	Year 1	2.8857	.27520	11
		Year 2	3.1603	.36946	23
		Year 3	3.0725	.38674	15
		Total	3.0718	.36559	49
Female	18-22	Year 1	2.7959	.32826	76
		Year 2	2.9389	.36879	69
		Year 3	2.9215	.30051	69
		Total	2.8825	.33822	214
	23-27	Year 1	2.8542	— / —	1
		Year 2	2.9033	.19273	6
		Year 3	2.9291	.28244	21
		Total	2.9209	.25740	28
	Total	Year 1	2.7966	.32616	77
		Year 2	2.9360	.35719	75
		Year 3	2.9232	.29484	90
		Total	2.8869	.32966	242

Total	18-22	Year 1	2.8075	.32387	86
		Year 2	2.9924	.38276	85
		Year 3	2.9401	.32153	76
		Total	2.9119	.35226	247
	23-27	Year 1	2.8199	.04840	2
		Year 2	2.9712	.30264	12
		Year 3	2.9563	.29023	29
		Total	2.9541	.28486	43
	28-32	Year 2	2.8839	– / –	1
		Total	2.8839	– / –	1
	Total	Year 1	2.8077	.32018	88
		Year 2	2.9887	.37070	98
		Year 3	2.9446	.31190	105
		Total	2.9180	.34240	291

Table 9
Levene's test of equality of error variance[a,b]

		LEVENE STATISTICS	df1	df2	SIG.
Overall readiness	Based on Mean	1.043	9	278	.406
	Based on Median	.939	9	278	.492
	Based on Median and with adjusted df	.939	9	259.498	.492
	Based on trimmed Mean	1.067	9	278	.387

Note: df1 = Between-Groups Degrees of Freedom, df2 = Within-Groups Degrees of Freedom; a. Dependent variable: Overall readiness; b. Design: Intercept + Gender + Age + Year_study + Gender * Age + Gender * Year_study + Age * Year_study + Gender * Age * Year_study

Age, Gender * Year of Study, and Gender * Age * Year of Study) were not significant. This is proven by p-values being > 0.05. The non-significant ANOVA results indicate that both male and female participants display same level of AI readiness.

The descriptive statistics in Table 11 indicate slight differences in mean AI readiness scores between male (mean score = 2.997) and female (mean score = 2.890) participants. Male participants indicate slightly higher mean score. The higher mean score, nevertheless, does not indicate statistical significance due to the 95% confidence intervals. Table 11 findings align with the findings in Table 10 that indicate that there is no significant effect of gender on overall readiness scores. In general, the findings state similar levels of AI readiness among both male and female students.

Volume 9 Issue 4, 2025, pp. 112-129
doi: 10.22363/2521-442X-2025-9-4-112-129

Table 10
Tests of between-subjects effects

	TYPE III SUM OF SQUARES	DF	MEAN SQUARE	F	SIG.	PARTIAL ETA-SQUARED
Corrected Model	3.165[a]	12	.264	2.378	.006	.093
Intercept	179.983	1	179.983	1622.734	<.001	.854
Gender	.198	1	.198	1.788	.182	.006
Age	.106	2	.053	.478	.620	.003
Year_study	.238	2	.119	1.071	.344	.008
Gender * Age	.062	1	.062	.557	.456	.002
Gender * Year_study	.065	2	.032	.291	.748	.002
Age * Year_study	.027	2	.014	.123	.884	.001
Gender * Age * Year_study	.004	2	.002	.016	.984	.000
Error	30.834	278	.111			
Total	2511.856	291				
Corrected Total	33.999	290				

Note: R Squared = .093 (Adjusted R Squared = .054)

Table 11
Descriptive statistics for gender

GENDER	MEAN	STD. ERROR	95% CONFIDENCE INTERVAL	
			LOWER BOUND	UPPER BOUND
Male	2.997	.077	2.846	3.148
Female	2.890	.062	2.768	3.013

Note: Dependent Variable = Overall readiness

5. DISCUSSION

5.1. Progressive increment in AI-based pedagogical approaches from primary level

The findings indicate that progression through the academic programme plays a clear role in shaping students' levels of AI readiness. Year 3 students show the highest levels of readiness, followed by those in Year 2, with first-year students reporting the lowest levels. In other words, AI readiness appears to rise in tandem with the number of years spent in the university. One plausible explanation for this gradual increase is the incidental development of AI literacy that accompanies routine academic work. AI has become a part of everyday academic practices, particularly through the steady stream of assessments that require students to search for literature, develop ideas, and devise strategies for completing their assignments. These tasks rely heavily on academic literacy skills supported by digital competence, and AI platforms now play an important role in helping students generate ideas. As students advance through the programme, their competencies and skills naturally expand, reinforcing the connection between length of study and AI readiness. The results suggest that the duration of study has a noticeable effect on students' familiarity and confidence with AI. In light of this, universities should place stronger emphasis on incorporating AI-based content into their programmes, including courses that are not explicitly linked to AI and particularly those offered in the first year. At the same time, the Education Ministry may need to begin embedding AI-oriented pedagogical approaches at the primary school level to ensure a steadier increase in AI readiness by the time students reach the workforce (Mustapha et al., 2023).

At present, the Malaysian school curriculum does not give sustained attention to AI-based pedagogical approaches or to advanced forms of digital literacy. This gap contributes to the relatively low levels of AI readiness among students entering higher education, many of whom arrive with little or no structured exposure to the field. Although the new subject Technology and Digital is expected to introduce basic AI concepts to primary school pupils by 2027, progress has been slow, and the initiative has yet to make an impact on the cohort represented in this study. The findings therefore point to the need to accelerate the introduction of basic AI instruction at the primary level, given the rapidly shifting nature of AI technologies and the attendant need for ongoing relearning, retooling, and reskilling. Secondary schools, in turn, continue to face considerable challenges even in delivering foundational IT education, limited by uneven infrastructure, insufficient network access, and teachers' lack of specialised training (Ghavifekr et al., 2016).

As a result, introducing more advanced AI-related topics in secondary schools – such as machine learning (ML), neural networks, or natural language processing (NLP) – remains unrealistic under current circumstances (Nisheva-Pavlova, 2021). This issue is particularly acute for students from rural areas or from lower socioeconomic backgrounds, who often experience restricted access to digital resources and opportunities (Devisakti et al., 2023). These conditions likely explain the lower levels of AI readiness observed among Year 1 students in this study, who are only beginning to encounter AI-related content upon entering university.

By contrast, students in their second and third years have had more sustained contact with AI-related topics, particularly linguistic AI, both through their coursework and through extracurricular engagement. This extended exposure appears to support the development of greater familiarity and confidence with the technology (Wang et al., 2023). The progression observed across the three cohorts points to the importance of continuous engagement with linguistic AI throughout the educational pathway to allow students to build their knowledge and skill sets gradually in this increasingly important area.

5.2. AI capability vs. ethical responsibility

Next, the findings also reveal distinct differences in AI-related skills – cognition, ability, vision and ethics – across the years of study, with ability showing the highest level of preparedness, followed by cognition and vision, while ethics remained unaffected by the year of study. This trend indicates that as students advance through their academic journey, their ability to select and apply appropriate linguistic AI applications improves significantly. This progression reflects their increasing preparedness to effectively use AI tools in both academic and professional contexts (Slimi, 2023).

Cognition, which measures their cognitive preparedness in areas such as AI terminology, linguistic knowledge, and data science, also shows moderate improvement, indicating that students gradually become more familiar with the foundational concepts and logic of linguistic AI as they advance through their studies. Vision, which assesses the capacity to foresee potential risks and opportunities related to linguistic AI while articulating its limitations and advantages, also improves, though at a slower rate. This suggests that the students develop a broader awareness of linguistic AI's applications and implications over time, enhancing their ability to articulate and understand the broader context of its usage (Wang et al., 2023).

However, the stagnation in ethics, which measures adherence to legal and ethical standards in AI usage, remains concerning. As the students' technical preparedness in linguistic AI improves, their understanding of the ethical implications of AI should evolve concurrently (Usher & Barak, 2024). The lack of preparedness in this area points to a critical gap in the curriculum, where the students are becoming more adept at applying linguistic AI technologies without a corresponding increase in their awareness of responsible and ethical AI use. This is especially important in the context of Malaysia, a nation rapidly advancing in AI readiness but still in the early stages of establishing comprehensive legal frameworks for AI regulation (Hankins et al., 2023; Edhan & Yen, 2023; Morden, 2023). Without proper attention to ethical preparedness, students may not be fully equipped to manage the ethical challenges presented by AI in a real-world context.

Therefore, academic programmes such as English for Professionals, Social Sciences, and Humanities need to balance technical preparedness with ethical training (Alaqlobi et al., 2024). The current lack of focus on AI ethics in the curriculum could result in a generation of linguistic AI professionals who are proficient in AI applications but unprepared for the ethical and societal responsibilities that come with them (Borenstein & Howard, 2020). To address this gap, ethics needs to be brought into AI teaching in a clear and deliberate way, giving students a chance to think through the social, legal, and moral questions that accompany these systems (Usher & Barak, 2024). With that

Volume 9 Issue 4, 2025, pp. 112-129
doi: 10.22363/2521-442X-2025-9-4-112-129

grounding in place, they are far better positioned to deal with AI responsibly once they move into professional work.

5.3. Gender parity in AI readiness

Finally, the findings suggest that gender does not have a significant effect on AI readiness, with both male and female students exhibiting similar levels of preparedness. This finding clearly indicates that both male and female students are inclined towards preparing themselves for AI use as they are involved in doing their academic assessments required by their academic programmes. In the context of the domains, both groups require the AI knowledge readiness of the four domains. Cognition is required by both female and male students to ensure the academic activities are critically viewed and conducted. In term of ability and vision, both group of students also find the ability to manoeuvre their activities are important for academic performance. The use of AI effectively contributes towards the greater implementation of their academic activities. As for ethics in the use of AI, both groups demonstrate the need for integrity and honesty on how information is procured from AI platforms and the use of the knowledge ethically.

6. STUDY'S IMPLICATIONS AND RECOMMENDATIONS

The recommendations in this study rest on the premise that the curriculum of applied-linguistics-based academic programmes should be revisited to develop clearer strategies for incorporating AI-related content and pedagogical approaches. Such revisions are necessary to prepare graduates for the expectations of an increasingly AI-oriented workplace. The recommendations focus on strengthening the relevant skill domains and narrowing the gaps observed between students at different stages of their studies.

6.1. Integration of AI-related content

Firstly, university education across all academic programmes, whether science-based or non-science-based, should consider the systematic inclusion of AI-related content. Such inclusion would provide students with early training that strengthens their AI readiness for the workplace. One approach is to introduce an introductory course in the first year that covers fundamental topics such as NLP, basic machine learning, computational linguistics, and practical applications of AI in language-related fields (Zawacki-Richter et al., 2019). For instance, a first-year module on text classification could be incorporated, allowing applied linguistics students to explore how AI algorithms categorise texts by topic or sentiment (Bird et al., 2009). Interactive learning methods, including project-based assignments, may also be used – for example, tasks in which students develop simple chatbots using basic NLP techniques to understand language parsing and generation (Young et al., 2013). Such initiatives would strengthen the cognition and ability domains of AI readiness.

In addition, weaving more AI concepts into existing applied linguistics courses throughout the programme can reinforce learning and illustrate the interdisciplinary nature of AI applications. This would involve introducing AI-related content into courses such as History of English, Sociolinguistics, or Language in Legal Context, where it can enrich teaching and learning while supporting broader aims of improving human communication (Jurafsky & Martin, 2025). Integrating AI-based content into non-science programmes also has the potential to enhance the appeal of these degrees by aligning them more closely with the demands of a 21st-century workplace that increasingly values digital and AI literacy.

6.2. Higher education AI units

Universities should invest in establishing dedicated AI units or laboratories to ensure that students in non-science programmes receive adequate training in applying AI technologies within their language and linguistics curriculum. Equipped with state-of-the-art hardware and software (including high-performance computers and specialised tools for NLP, speech synthesis, and machine translation), such a laboratory would function as a teaching resource, a research space, and an innovation centre (Zawacki-Richter et al., 2019). Facilities of this kind would play an important role in strengthening both the cognitive and practical domains of AI knowledge readiness.

For instance, university students could use the laboratory to work on projects such as developing an AI-driven language tutoring system that adjusts to learners' proficiency levels or creating speech recognition models for underrepresented Malaysian languages and dialects (Besacier et al., 2013; Lin et al., 2023). They might also conduct sentiment-analysis projects using social media texts to examine public opinion on various topics, or design predictive text input tools for mobile devices in multiple languages (Chen et al., 2023; Giachanou & Crestani, 2016). The laboratory could further serve as a venue for hackathons in which students collaborate to build AI applications that address real-world linguistic challenges, such as automated translation systems for legal documents or accessibility tools for individuals with speech impairments (Albanesi, 2022; Elsahar et al., 2019). The outcomes of laboratory-based projects would reinforce both the practical and vision components of AI knowledge readiness.

The laboratory can also support workshops on using AI tools such as TensorFlow or PyTorch for language modelling and provide training in data annotation and corpus development (Gries & Berez, 2017; Otter et al., 2020). Through this kind of hands-on work, students grow more confident with the technical side of things, and they also help produce linguistic resources that matter outside the course (Devisakti et al., 2023).

6.3. AI-related ethical issues in curriculum

The addition of AI-related material, whether in the form of courses, programme content, or assessment tasks, has to be accompanied by some attention to ethics if students are to use these tools with any real sense of responsibility. As AI makes its way more firmly into university teaching, it becomes important not only to show students what the technology can do but also to help them think through its implications. Linguistics courses provide a natural setting for this kind of work. A subject like Sociolinguistics, for instance, can open up discussions about the ways AI systems may reproduce existing biases or, in some cases, help reduce them, and how these patterns matter for questions of discrimination and social justice (Birhane, 2021). Students may also be trained to develop ethical-use guidelines or modules that reflect responsible approaches to AI deployment (Jobin et al., 2019). When students are given room to think through the ethical stakes of AI, they leave their programmes better prepared to handle the technology responsibly. This kind of work naturally feeds into the strengthening of the ethics component of AI knowledge readiness.

6.4. Interdisciplinary programmes

To produce graduates who are globally competent, interdisciplinary knowledge and competence are essential components of their development. When students in non-science programmes get to acquire knowledge and skills through AI-related courses, they can develop in a more holistic manner, both in terms of what they know and what they can do (Spelt et al., 2009). This can be supported through joint courses and electives co-taught by faculty from departments such as Computer Science, Data Science, and Philosophy. For example, an elective on AI and Society could examine the philosophical facets of AI in human communication, taught collaboratively by linguistics and philosophy staff (Mittelstadt et al., 2016). Collaborative coursework may involve students from applied-linguistics programmes working together with computer science students to design a multilingual chatbot to support language learning. Such an exercise would bring together linguistic knowledge and programming skills (Wang & Xue, 2024). In partnership with the Psychology department, students might also investigate aspects of human–computer interaction to improve how AI systems respond to emotional cues in language (Liu, 2024).

Interdepartmental workshops and seminars can address themes such as AI in Education, where students explore how AI can personalise learning, or Ethics in AI Development, where they may consider legal and societal implications (Chen et al., 2020; Crawford & Calo, 2016). Cross-disciplinary research opportunities might include projects on using AI to document or preserve endangered languages, requiring collaboration between linguists, AI specialists, and anthropologists (Bird, 2020). Such collaborative experiences help prepare students for professional environments in which complex problems call for multiple forms of expertise and collective problem-solving, and they equip students to adapt to the demands of rapidly changing work settings.

6.5. Limitations and future research

One of the limitations of the study concerns the uneven gender distribution among participants. This imbalance is both visible and difficult to avoid, as female enrolment consistently exceeds male enrolment at the university and in the applied linguistics programme in particular. Such an uneven sample limits the extent to which the findings on gender-based AI readiness can be generalised. Future research should therefore consider programmes in which the numbers of male and female students are more evenly matched. Addressing this limitation would make it possible to produce more comprehensive data on gender-related patterns of AI readiness.

Expanding the research to include multiple institutions and disciplines with different gender ratios would also offer a more representative sample. For instance, incorporating students from STEM programmes (where male enrolment is generally higher) alongside those from language-based programmes could provide a more comparative view of gender-based AI readiness across academic contexts. This approach would not only help resolve issues arising from gender imbalance but would also allow researchers to identify interdisciplinary differences in how students from various fields engage with AI technologies.

A second limitation concerns the study's reliance on self-reported data. Future work could address this by incorporating objective measures of AI proficiency. In addition to self-report surveys, it would be useful to include tasks in which students actually work with NLP and ML tools such as NLTK, TensorFlow, or PyTorch. Exercises of this sort give a sense of what students can do in practice, since the work produces observable output. Using both kinds of evidence together would give a fuller picture of the technical abilities that students are developing, and it would also give them some experience with the kinds of tools they are likely to encounter once they move into working environments where AI is used on a daily basis.

7. CONCLUSION

This study shows why it is worth keeping track of students' levels of AI readiness at the university level. Doing so gives institutions a more grounded sense of where their students stand and what needs attention if graduates

Volume 9 Issue 4, 2025, pp. 112-129 doi: 10.22363/2521-442X-2025-9-4-112-129

are to leave with a workable understanding of AI. The study also provides a fuller picture of the four areas used to describe AI readiness – cognition, ability, vision, and ethics. Of these, the most immediate concern is the ethical dimension, which continues to lag behind the others. This is a difficult issue for universities, especially now that AI-generated material is so easy to obtain and can, in some cases, pull students away from the sort of analytical work they are expected to do on their own.

In later studies concerned with the use and implementation of AI in educational settings (both theoretical and practical), it would be useful to examine more carefully how students' grasp of AI concepts interacts with their sense of what is ethically acceptable. That kind of focus might show how students can be steered toward using AI in a way that keeps the work their own, with AI serving as a helpful tool rather than a replacement for their own judgement.

References

Alaqlobi, O., Alduais, A., Qasem, F., & Alsubaie, A. (2024) Artificial intelligence in applied (linguistics): A content analysis and future prospects. *Cogent Arts and Humanities, 11*(1), Article 2382422. https://dx.doi.org/10.1080/23311983.2024.2382422

Albanesi, E. (2022) Legislative drafting in multilingual legal orders and computer-assisted translation tools. *European Journal of Law Reform 24*(2), 178–194. https://doi.org/10.5553/EJLR/138723702022024002002

Besacier, L., Barnard, E., Karpov, A., & Schultz, T. (2013) Automatic speech recognition for under-resourced languages: A survey. *Speech Communication, 56,* 85–100. https://doi.org/10.1016/j.specom.2013.07.008

Bird, S. (2020, December 8-13). Decolonising speech and language technology. In D. Scott, N. Bel, & C. Zong (Eds.), *Proceedings of the 28th International Conference on Computational Linguistics* (pp. 3504–3519). International Committee on Computational Linguistics. https://doi.org/10.18653/v1/2020.coling-main.313

Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with Python.* O'Reilly Media.

Birhane, A. (2021). Algorithmic injustice: A relational ethics approach. *Patterns, 2*(2), Article 100205. https://doi.org/10.1016/j.patter.2021.100205

Borenstein, J., & Howard, A. (2020). Emerging challenges in AI and the need for AI ethics education. *AI and Ethics, 1*(1), 61–65. https://doi.org/10.1007/s43681-020-00002-7

Casal-Otero, L., Catala, A., Fernández-Morante, C., & Rodríguez-García, A. M. (2023). AI literacy in K-12: A systematic literature review. *International Journal of STEM Education, 10*(1), Article 29. https://dx.doi.org/10.1186/s40594-023-00418-7

Chan, R. C. H. (2022). A social cognitive perspective on gender disparities in self-efficacy, interest, and aspirations in Science, Technology, Engineering, and Mathematics (STEM): The influence of cultural and gender norms. *International Journal of STEM Education, 9*(1), Article 37. https://doi.org/10.1186/s40594-022-00352-0

Chen, B., Wang, G., Guo, H., & Li, Y. (2023, October 16-18). Understanding multi-turn toxic behaviors in open-domain chatbots. In *Proceedings of the 26th International Symposium on Research in Attacks, Intrusions and Defenses* (pp. 282–296). Association for Computing Machinery.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8,* 75264–75278. https://doi.org/10.1109/access.2020.2988510

Crawford, K., & Calo, R. (2016). There is a blind spot in AI research. *Nature, 538*(7625), 311–313. https://doi.org/10.1038/538311a

Dai, D. W., Suzuki, S., & Chen, G. (2024). Generative AI for professional communication training in intercultural contexts: Where are we now and where are we heading? *Applied Linguistics Review, 16*(2), 763–774. https://doi.org/10.1515/applirev-2024-0184

Dai, Y., Chai, C.-S., Lin, P.-Y., Wang, X., & Hwang, G.-J. (2020). Promoting students' well-being by developing their readiness for the artificial intelligence age. *Sustainability, 12*(16), Article 6597. https://dx.doi.org/10.3390/su12166597

Delcker, J., Heil, J., Ifenthaler, D., & Yilmaz, M. (2024). First-year students' AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education. *International Journal of Educational Technology in Higher Education, 21,* Article 18. https://doi.org/10.1186/s41239-024-00452-7

Devisakti, A., Muftahu, M., & Xiaoling, H. (2023). Digital divide among B40 students in Malaysian higher education institutions. *Education and Information Technologies, 29*(2), 1857–1883. https://dx.doi.org/10.1007/s10639-023-11847-w

Edhan, N. H., & Yen, H. W. (2023, November 1). Legal landscape of generative AI governance in Malaysia. *@azmilaw Newsletter.* https://azmilaw.com/insights/legal-landscape-of-generative-ai-governance-in-malaysia

Elsahar, Y., Hu, S., Bouazza-Marouf, K., Kerr, D., & Mansor, A. (2019). Augmentative and alternative communication (AAC) advances: A review of configurations for individuals with a speech disability. *Sensors, 19*(8), Article 1911. https://doi.org/10.3390/s19081911

Evans, R., & Sinha, N. (2024, March 25-27). Bridging the gap: Diversity initiatives in AI education. In R. Petrick & C. Geib (Eds.), *AAAI 2024 Spring Symposium Series* (pp. 474–477). AAAI Press. https://doi.org/10.1609/aaaiss.v3i1.31260

Ghavifekr, S., Kunjappan, T., Ramasamy, L., & Anthony, A. (2016). Teaching and learning with ICT tools: Issues and challenges from teachers' perceptions. *Malaysian Online Journal of Educational Technology, 4*(2), 38–57.

Giachanou, A., & Crestani, F. (2016). Like it or not: A survey of Twitter sentiment analysis methods. *ACM Computing Surveys, 49*(2), Article 28. https://dx.doi.org/10.1145/2938640

Gomez-Herrera, E., & Koeszegi, S. T. (2022, August 30). A gender perspective on artificial intelligence and jobs: The vicious cycle of digital inequality. *Bruegel*. https://bruegel.org/working-paper/gender-perspective-artificial-intelligence-and-jobs-vicious-cycle-digital-inequality

Gries, S. T., & Berez, A. L. (2017). Linguistic annotation in/for corpus linguistics. In N. Ide & J. Pustejovsky (Eds.), *Handbook of linguistic annotation* (pp. 379–409). Springer. https://dx.doi.org/10.1007/978-94-024-0881-2_15

Hankins, E., Nettel, P. F., Martinescu, L., Grau, G., & Rahim, S. (2023). Government AI Readiness Index 2023. *Oxford Insights*. https://oxfordinsights.com/wp-content/uploads/2023/12/2023-Government-AI-Readiness-Index-1.pdf

Hinton, P. R., McMurray, I., & Brownlow, C. (2004). *SPSS explained* (1st ed.). Routledge. https://dx.doi.org/10.4324/9780203642597

Hornberger, M., Bewersdorff, A., & Nerdel, C. (2023). What do university students know about artificial intelligence? Development and validation of an AI literacy test. *Computers and Education: Artificial Intelligence, 5*(1), Article 100165. https://dx.doi.org/10.1016/j.caeai.2023.100165

Huang, X., Zou, D., Cheng, G., Xie, H., & Wang, F. L. (2023). Trends, research issues and applications of artificial intelligence in language education. *Educational Technology & Society, 26*(1), 112–131. https://dx.doi.org/10.30191/ETS.202301_26(1).0009

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*(9), 389–399. https://dx.doi.org/10.1038/s42256-019-0088-2

Jurafsky, D., & Martin, J. H. (2025). *Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition, with language models* (3rd ed.). Stanford. https://web.stanford.edu/~jurafsky/slp3

Karaca, O., Çalışkan, S. A., & Demir, K. (2021). Medical artificial intelligence readiness scale for medical students (MAIRS-MS): Development, validity and reliability study. *BMC Medical Education, 21*(1), Article 112. https://doi.org/10.1186/s12909-021-02546-6

Karagul, B. I., Seker, M., & Aykut, C. (2021). Investigating students' digital literacy levels during online education due to COVID-19 pandemic. *Sustainability, 13*(21), Article 11878. https://doi.org/10.3390/su132111878

Katsantonis, A., & Katsantonis, I. G. (2024). University students' attitudes toward artificial intelligence: An exploratory study of the cognitive, emotional, and behavioural dimensions of AI attitudes. *Education Sciences, 14*(9), Article 988. https://dx.doi.org/10.3390/educsci14090988

Kurtz, G., Amzalag, M., Shaked, N., & Barak, M. (2024). Strategies for integrating generative AI into higher education: Navigating challenges and leveraging opportunities. *Education Sciences, 14*(5), Article 503. https://doi.org/10.3390/educsci14050503

Lin, C.-C., Huang, A. Y. Q., & Lu, O. H. T. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: A systematic review. *Smart Learning Environments, 10*(1), Article 41. https://dx.doi.org/10.1186/s40561-023-00260-y

Liu, J. (2024). ChatGPT: Perspectives from human–computer interaction and psychology. *Frontiers in Artificial Intelligence, 7,* Article 1418869. https://doi.org/10.3389/frai.2024.1418869

McShane, M., & Nirenburg, S. (2021). *Linguistics for the age of AI*. MIT Press.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society, 3*(2). https://dx.doi.org/10.1177/2053951716679679

Morden, Z. (2023, June 7). Putrajaya working towards framework to regulate AI. *Malay Mail*. https://malaymail.com/news/malaysia/2023/06/07/putrajaya-working-towards-framework-to-regulate-ai/73129

Mustapha, R., Ruslan, R. A. A., & Kashefian-Naeeini, S. (2023). A qualitative study on Malaysian university students' digital literacy. *International Journal of Multicultural and Multireligious Understanding, 10*(11), 352–359. https://dx.doi.org/10.18415/ijmmu.v10i11.5482

Nisheva-Pavlova, M. M. (2021, September 27-28). AI courses for secondary and high school: Comparative analysis and conclusions. In A. Eskenazi, G. Totkov, I. Koychev, & K. Ivanova (Eds.), *Proceedings of the 14th International Conference Education and Research in the Information Society* (pp. 9–16). Central Europe (CEUR) Workshop Proceedings. https://ceur-ws.org/Vol-3061/ERIS_2021-art01(sh).pdf

O'Connor, S., & Liu, H. (2023). Gender bias perpetuation and mitigation in AI technologies: Challenges and opportunities. *AI & Society, 39,* 2045–2057. https://doi.org/10.1007/s00146-023-01675-4

Ofosu-Ampong, K. (2023). Gender differences in perception of artificial intelligence-based tools. *Journal of Digital Art & Humanities, 4*(2), 52–56. https://dx.doi.org/10.33847/2712-8149.4.2_6

Otter, D. W., Medina, J. R., & Kalita, J. K. (2020). A survey of the usages of deep learning for natural language processing. *IEEE Transactions on Neural Networks and Learning Systems, 32*(2), 604–624. https://dx.doi.org/10.1109/TNNLS.2020.2979670

Qazi, A., Hasan, N., Abayomi-Alli, O., Sulaiman, A., Marić, M., & Naseem, U. (2021). Gender differences in information and communication technology use & skills: A systematic review and meta-analysis. *Education and Information Technologies, 27*(3), 4225–4258. https://doi.org/10.1007/s10639-021-10775-x

Reuben, B., Samuel, O., & Lawal, A. U. (2024). A review of artificial intelligence (AI) readiness in higher education institutions: A case study of northern states of Nigeria. *Global Journal of Engineering and Technology (GJET), 3*(6), 35–45. https://gsarpublishers.com/wp-content/uploads/2024/07/GJET452024-Gelary-script.pdf

Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Prentice Hall.

Volume 9 Issue 4, 2025, pp. 112-129 doi: 10.22363/2521-442X-2025-9-4-112-129

Shihadeh, J., Ackerman, M., & Troske, A. (2022, September 8-11). Brilliance bias in GPT-3. In *Proceedings of the 2022 IEEE Global Humanitarian Technology Conference (GHTC)* (pp. 62–69). Institute of Electrical and Electronics Engineers (IEEE). https://dx.doi.org/10.1109/GHTC55712.2022.9910995

Sidhu, P., Abdullah, F. S., & Jalil, M. S. (2024). Awareness and readiness of Malaysian Generation Z students towards the Fourth Industrial Revolution (IR4.0). *Semarak International Journal of STEM Education, 1*(1), 20–27.

Slimi, Z. (2023). The impact of artificial intelligence on higher education: An empirical study. *European Journal of Educational Sciences, 10*(1), 17–33. https://dx.doi.org/10.19044/ejes.v10no1a17

Southworth, J., Migliaccio, K., Glover, J., Glover, J. N., Reed, D., McCarty, C., ... & Thomas, A. (2023). Developing a model for AI across the curriculum: Transforming the higher education landscape via innovation in AI literacy. *Computers and Education: Artificial Intelligence, 4,* Article 100127.

Spelt, E. J. H., Biemans, H. J. A., & Tobi, H. (2009). Teaching and learning in interdisciplinary higher education: A systematic review. *Educational Psychology Review, 21*(4), 365–378. https://dx.doi.org/10.1007/s10648-009-9113-z

Usher, M., & Barak, M. (2024). Unpacking the role of AI ethics online education for science and engineering students. *International Journal of STEM Education, 11*(1), Article 35. https://doi.org/10.1186/s40594-024-00493-4

Wang, F., King, R. B., Chai, C. S., & Zhang, J. (2023). University students' intentions to learn artificial intelligence: The roles of supportive environments and expectancy–value beliefs. *International Journal of Educational Technology in Higher Education, 20*(1), Article 51.

Wang, Y., & Xue, L. (2024). Using AI-driven chatbots to foster Chinese EFL students' academic engagement: An intervention study. *Computers in Human Behavior, 159,* Article 108353.

Wu, T., & Zhang, S. H. (2023, August 25-26). Applications and implication of generative AI in non-STEM disciplines in higher education. In F. Zhao & D. Miao (Eds.), *Proceedings of the 1st International Conference on AI-generated Content* (pp. 341–349). Springer. https://doi.org/10.1007/978-981-99-7587-7_29

Xu, W., & Ouyang, F. (2021). A systematic review of AI role in the educational system based on a proposed conceptual framework. *Education and Information Technologies, 27*(3), 4195–4223. https://dx.doi.org/10.1007/s10639-021-10774-y

Xu, W., & Ouyang, F. (2022). The application of AI technologies in STEM education: A systematic review from 2011 to 2021. *International Journal of STEM Education, 9*(1), Article 59. https://dx.doi.org/10.1186/s40594-022-00377-5

Xuan, P. Y., Fahumida, M. I. F., Hussain, M. I. A., Al Nazir Hussain, M. I., Jayathilake, N.T., Khobragade, S., ... & Htay, M. N. N. (2023). Readiness towards artificial intelligence among undergraduate medical students in Malaysia. *Education in Medicine Journal, 15*(2), 49–60. https://doi.org/10.21315/eimj2023.15.2.4

Young, S., Gašić, M., Thomson, B., & Williams, J. D. (2013). POMDP-based statistical spoken dialog systems: A review. *Proceedings of the IEEE, 101*(5), 1160–1179. https://doi.org/10.1109/JPROC.2012.2225812

Yusuf, A., Pervin, N., & Román-González, M. (2024). Generative AI and the future of higher education: A threat to academic integrity or reformation? Evidence from multicultural perspectives. *International Journal of Educational Technology in Higher Education, 21,* Article 21. https://doi.org/10.1186/s41239-024-00453-6

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education, 16,* Article 39. https://doi.org/10.1186/s41239-019-0171-0

ABOUT THE AUTHORS

Luke Teoh Rong Guang
MA in International Culture and Communication Studies
Graduate School of Letters
Toyo University, Tokyo, Japan
Postal address: 5-28-20 Hakusan, Bunkyo-ku, Tokyo 112-8606, Japan
Email: luke.teohrguang@gmail.com
ORCID ID: https://orcid.org/0009-0007-7002-316X

Manjet Kaur Mehar Singh
PhD in Linguistics, Senior Lecturer
Department of the Bachelor of Arts English for Professionals, School of Languages, Literacies and Translation
Universiti Sains Malaysia, Penang, Malaysia
Postal Address: Minden, 11800, Penang, Malaysia
Email: manjeet@usm.my
ORCID: https://orcid.org/0000-0002-7805-4215

Jayanthi Muniandy
PhD in Education, Lecturer
Department of English for Professionals, School of Languages, Literacies and Translation
Universiti Sains Malaysia, Penang, Malaysia
Postal Address: Minden, 11800, Penang, Malaysia
Email: jayanthi@usm.my
ORCID ID: https://orcid.org/0000-0001-7391-3984