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POLYTECHNIC STUDENTS READINESS AND ACCEPTANCE OF AI-ASSISTED LEARNING: AN INTEGRATED TRI–TAM STUDY IN MALAYSIA

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ABSTRACT

Artificial Intelligent (AI) reshapes higher education through personalized, adaptive learning, yet its success depends on student readiness and acceptance. Grounded in the TRI and TAM frameworks, this quantitative study investigated the relationship between technology readiness and acceptance among Malaysian polytechnic students. Data were gathered from 167 participants at Politeknik Kota Bharu via a structured questionnaire mapping four TRI dimensions (optimism, innovativeness, discomfort, insecurity) against three TAM constructs (perceived usefulness, ease of use, behavioural intention). Descriptive statistics revealed moderate-to-high levels of technology readiness ($M = 3.68$) and AI acceptance ($M = 3.75$), indicating that students generally demonstrate positive attitudes towards AI-assisted learning. Pearson correlation analysis showed a strong and statistically significant positive relationship between readiness and acceptance ($r = .825$, $p < .001$), while regression analysis confirmed that technology readiness significantly predicts students' acceptance of AI-assisted learning. Gender differences in readiness were not statistically significant. These findings support the integrated TRI–TAM framework by demonstrating that students' psychological readiness enhances their perceptions of AI usefulness and ease of use, thereby strengthening behavioural intention to adopt AI-assisted learning. The study contributes to the growing body of AI adoption research in Malaysian higher education and provides practical implications for educators and policymakers in designing initiatives that strengthen students' digital readiness and encourage responsible AI integration into teaching and learning.

***Keywords**: AI Adoption; Technology Acceptance; Higher Education; Polytechnic Students.*

JEL Classification: I23; O33; O35; D83; C12

1.0 INTRODUCTION

Artificial Intelligence (AI) has become a cornerstone of higher education innovation, reshaping pedagogy through intelligent tutoring, adaptive platforms, automated feedback, and generative applications. By providing personalized instruction, boosting efficiency, and fostering independent study, these technologies significantly enhance the student learning experience (Zawacki-Richter et al., 2019; Mhlanga, 2023). This digital shift—highly accelerated by the COVID-19 pandemic—has pushed universities worldwide to institutionalize AI-assisted learning. As a result, cultivating AI-literate students has become a core institutional priority.

However, successful adoption requires more than just robust technological infrastructure; it hinges on student readiness. To successfully integrate AI into their study habits, students must possess the necessary psychological readiness, including technological competence, adaptability, and confidence. According to Parasuraman (2000), technology readiness reflects an individual's predisposition to embrace new tools, categorized by four dimensions: optimism, innovativeness, discomfort, and insecurity. Students who score higher in these readiness dimensions are inherently more willing to pilot emerging tools and recognize their educational value.

Technology acceptance is another critical determinant of successful AI adoption. According to the Technology Acceptance Model (TAM), individuals are more inclined to adopt a technology if they perceive it as useful and easy to use (Davis, 1989). These core perceptions shape behavioural intention, which serves as a robust predictor of actual usage. Extensive research confirms that perceived usefulness and perceived ease of use significantly dictate students' intentions to adopt digital learning tools, including AI-driven environments (Nguyen & Vo, 2023; Abulail et al., 2025). Consequently, a holistic understanding of both technology readiness and technology acceptance is vital to explaining AI adoption patterns among higher education students.

Within Technical and Vocational Education and Training (TVET), AI-assisted learning provides substantial opportunities to elevate practical competencies, problem-solving skills, and personalized learning. Malaysian polytechnics, in particular, have accelerated digital transformation initiatives to align graduates with Industry 4.0 demands and a rapidly shifting workforce. In this context, AI-powered platforms, intelligent assessment systems, and generative applications can scaffold technical knowledge acquisition while fostering self-directed learning. However, the success of these deployments' hinges on students' psychological readiness to use AI effectively and their willingness to accept it as an integral learning tool.

Prior literature offers promising insights into how higher education students perceive AI. For instance, Mat Yusoff et al. (2025) found that Malaysian university students widely view AI as a valuable asset for enriching their education, while Maryani and Puspitasari (2024) demonstrated that baseline technology readiness positively drives the acceptance of digital learning systems. Internationally, Owolabi et al. (2022) observed that despite facing infrastructural hurdles, Nigerian polytechnic students maintained a high awareness of AI technologies. Furthermore, adjacent studies underscore that digital literacy, institutional support, and self-efficacy remain pivotal in shaping student willingness to adopt AI-assisted frameworks (Roslan et al., 2023; Xuan et al., 2022).

While existing studies examine AI adoption, technology readiness, and technology acceptance independently, few have integrated the Technology Readiness Index (TRI) and the Technology Acceptance Model (TAM) to study AI-assisted learning among Malaysian polytechnic students. Most research focuses on general higher education or investigates student perceptions without examining how psychological readiness drives technology acceptance. Consequently, there is limited empirical evidence exploring how TRI dimensions (optimism, innovativeness, discomfort, and insecurity) interact with TAM constructs (perceived usefulness, ease of use, and behavioural intention) within Malaysian TVET institutions. Addressing this gap is vital, as polytechnic students navigate a unique, technology-intensive learning environment that merges theory with practical skills.

To address this, this study applies an integrated TRI–TAM framework to evaluate polytechnic students' readiness and acceptance of AI-assisted learning. Specifically, it assesses students' technology readiness, evaluates their AI acceptance, and examines the relationship between the two. By blending these theoretical perspectives, this study contributes to the literature on AI adoption in higher education. Furthermore, its empirical findings offer actionable insights for educators, institutional leaders, and policymakers to strengthen digital readiness and effectively integrate AI-assisted learning across Malaysian polytechnics.

2.0 LITERATURE REVIEW

2.1 Theoretical Framework

Artificial intelligence (AI) is rapidly transforming education, offering innovative tools that personalize learning, streamline teaching processes, and enhance student engagement (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). However, the successful integration of AI into learning environments depends not only on the technology's capabilities but also on students' readiness and willingness to adopt AI-assisted learning (Tzafilkou, Perifanou, & Economides, 2022). Research indicates that students' intentions to use AI tools are shaped by multiple factors, including perceived usefulness, technological readiness, and institutional support, highlighting the interaction between individual characteristics and contextual influences (Abulail, Badran, Shkoukani, & Omeish, 2025). In this context, students’ readiness refers to their preparedness, both in terms of skills and mindset, to engage effectively with AI-based learning tools (Parasuraman, 2000).

The Technology Acceptance Model (TAM), introduced by Davis (1989), explains technology adoption in terms of two core beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU refers to the belief that a technology enhances performance, while PEOU denotes the degree to which the technology is regarded as effortless to use. Together, these perceptions shape users' attitudes, which, in turn, influence their behavioural intention and actual use of the technology. To provide a more comprehensive understanding of technology adoption in educational settings, this study integrates TAM with the Technology Readiness Index (TRI). While TAM focuses on cognitive evaluations of a technology, TRI captures the psychological predispositions that shape an individual's readiness to engage with technological innovations. Integrating TRI and TAM thus allows the study to examine how students' psychological readiness and their cognitive perceptions of AI influence acceptance and adoption.

Empirical evidence supports the value of combining these two frameworks. Research shows that individuals with higher technology readiness, particularly in optimism and innovativeness, tend to perceive AI tools as more useful and easier to use, thereby strengthening their intention to adopt them (Chen et al., 2021; Lin et al., 2007). Recent studies on AI in education further highlight that readiness and acceptance interact closely, with optimism and perceived usefulness significantly enhancing engagement with AI-assisted learning (Li et al., 2024; Nguyen & Vo, 2023). Lin, Li, Zhang, and Yang (2023) also demonstrate that readiness influences PU and PEOU, while TAM constructs mediate the translation of readiness into actual adoption behaviour. Similarly, Lemke (2023) shows that an integrated TRI–TAM approach provides strong explanatory power in understanding students' dispositions toward AI-based text-generation tools. In addition, research on technological readiness and self-efficacy indicates positive correlations with online learning success, underscoring the role of confidence and preparedness in students' adoption of technology-enhanced learning environments (Dimo, Abalayan, Celestial, Achas, Majarucon, Tolentino, Setiawan, & Lobo, 2024).

Integrating TRI and TAM provides a comprehensive lens for examining AI-assisted learning adoption. TRI captures the psychological readiness to embrace technology, while TAM explains the cognitive evaluation process leading to acceptance. Together, they allow this study to assess how students' readiness (TRI dimensions) and acceptance (TAM constructs) interact to influence the adoption of AI-assisted learning tools. Additionally, research on technological readiness and self-efficacy has revealed positive correlations with online learning success, highlighting the role of confidence in improving readiness for tech-mediated education.

3.0 RESEARCH METHODOLOGY

This study employed a quantitative cross-sectional survey design to examine polytechnic students' readiness and acceptance o5f AI-assisted learning. A quantitative approach was considered appropriate because the study sought to measure the levels of technology readiness and technology acceptance and to examine the relationship between these constructs using statistical analyses. The study was conducted at Politeknik Kota Bharu, Malaysia, involving 167 diploma students from four academic departments who had prior experience using digital learning platforms and AI-assisted educational tools. Data were collected using an online questionnaire distributed via Google Forms through students' official class WhatsApp groups.

A convenience sampling technique was used to efficiently recruit accessible participants who had direct experience with AI-assisted learning. This method is widely adopted in educational technology research, particularly for voluntary, survey-based studies (Etikan et al., 2016). While convenience sampling may limit the generalizability of the findings to all Malaysian polytechnic students, it is well-suited for exploratory and correlational research aimed at examining relationships between variables rather than estimating population parameters (Taherdoost, 2016). The final sample size of 167 respondents provided adequate statistical power for the study's analyses. For correlational research, Cohen (1992) suggests a minimum sample of 85 participants to detect a medium effect size (r = .03) at a significance level of .05 with a power of 0.8. Similarly, Hair et al. (2019) recommend between 100 to 150 respondents in behavioural science to ensure stable parameter estimations. Because the sample size of 167 exceeds both thresholds, it provides sufficient analytical power for the descriptive, correlation, regression, and independent-samples t-test analyses conducted.

Data were collected using a structured, self-administered questionnaire adapted from validated instruments. The readiness construct comprised 10 items based on Parasuraman's (2000) Technology Readiness Index (TRI) and Bandura's (1997) Self-Efficacy Theory, measuring optimism, innovativeness, discomfort, insecurity, confidence, and self-efficacy. The acceptance construct included 12 items adapted from Davis's (1989) Technology Acceptance Model (TAM) and Venkatesh et al.'s (2000) UTAUT to assess perceived usefulness, ease of use, and behavioural intention. Items were updated using recent higher education AI studies (Bećirović et al., 2025; Chen et al., 2025; Setälä et al., 2025) to ensure contextual relevance for Malaysian polytechnic students.

Face validity and content validity were established through expert evaluation by Ms. Kamilah binti Zainuddin, a PhD candidate specialising in Multimedia at the English Language Unit, Politeknik Kota Bharu. Based on the expert's recommendations, several items were revised to improve clarity, wording, and contextual relevance for AI-assisted learning. The final questionnaire employed a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The collected data were analysed using IBM SPSS Statistics Version 27. Descriptive statistics were used to determine students' levels of readiness and acceptance, while Pearson correlation analysis examined the relationship between the two constructs. The instrument demonstrated excellent internal consistency, with an overall Cronbach's Alpha coefficient of .971. According to Hair et al. (2019), Cronbach's Alpha values exceeding .90 indicate excellent reliability, suggesting that the instrument consistently measures the intended constructs with a high degree of internal consistency.

4.0 FINDINGS AND DISCUSSION

4.1 Mean and Standard Deviation of Readiness and Acceptance

Table 1 presents the overall levels of students' readiness and acceptance of AI-assisted learning. The findings indicate that respondents demonstrated moderate-to-high readiness ($M = 3.68$, $SD = 0.74$) and moderate-to-high acceptance (M = 3.75, SD = 0.72). These results suggest that most students possess positive psychological readiness towards AI technologies while also demonstrating favourable perceptions of their usefulness and applicability in learning. The findings provide preliminary evidence that AI-assisted learning is generally well received among Malaysian polytechnic students.

Table 1: Mean and Standard Deviation of Readiness and Acceptance

Variable	Mean (M)	Standard Deviation (SD)	Level
Readiness	3.68	0.74	Moderate–High
Acceptance	3.75	0.72	Moderate–High

4.2 Descriptive Statistics for Students' Readiness

The descriptive analysis in Table 2 shows that polytechnic students generally exhibit a positive level of readiness to use AI-assisted learning tools. Overall, the readiness construct recorded a mean score of 3.68, indicating that students are moderately confident and open toward integrating AI into their studies. Many students expressed strong willingness to explore and experiment with AI tools, as reflected in the highest-rated item, "I am open to experimenting with AI-assisted learning tools to improve my learning" (M = 3.85). Students also reported feeling capable of adapting to new AI technologies (M = 3.71) and overcoming challenges that may arise when using AI tools (M = 3.71), suggesting a positive mindset toward learning with technology. Additionally, they showed trust in AI's ability to support their academic success (M = 3.76). However, some students felt less confident in their technical skills, particularly in effectively using AI tools (M = 3.51), which was the lowest-rated item. The finding indicates that while students are enthusiastic and optimistic about AI-assisted learning, certain aspects, such as technical proficiency, may require additional support or training. Overall, the findings indicate that students demonstrate a strong level of readiness, marked by openness, optimism, and a willingness to engage with AI as part of their learning experience.

Table 2: Descriptive Statistics for Students' Readiness

Items	M	SD
I am confident in my ability to use AI-assisted learning tools.	3.69	0.871
I have the necessary technical skills to use AI tools effectively for learning.	3.51	0.924
I can adapt quickly to new AI technologies used in education.	3.71	0.899
I am motivated to explore AI-assisted learning tools on my own.	3.66	0.904
I am prepared to integrate AI tools into my daily study routines.	3.63	0.894
I can overcome challenges when using AI-assisted learning tools.	3.71	0.822
I feel comfortable using AI tools even without detailed instructions.	3.56	0.979
I am open to experimenting with AI-assisted learning tools to improve my learning.	3.85	0.889

I am optimistic about the role AI can play in supporting my academic success.	3.68	0.920
I trust AI-assisted learning tools to provide reliable support in my studies.	3.76	0.850
CUMULATIVE MEAN	**3.68**	**0.74**

Interpreted through the Technology Readiness Index (TRI), these findings indicate that students possess a positive psychological readiness to engage with AI-assisted learning. High optimism scores show that students believe AI can enhance their academic performance, while strong innovativeness ratings reflect a genuine willingness to experiment with emerging applications. Although slightly lower confidence levels indicate a moderate degree of technical discomfort, low insecurity scores suggest that students generally trust AI technologies. Ultimately, while baseline readiness is positive, targeted training could further strengthen their technical confidence.

4.3 Descriptive Statistics for Students' Acceptance

The results in Table 3 show that polytechnic students are generally open and positive toward using AI-assisted learning tools, with a cumulative mean of 3.75, indicating strong acceptance. The findings indicate that polytechnic students' acceptance of AI-assisted learning can be explained using the Technology Acceptance Model (TAM). For instance, they agreed that AI improves their productivity (M = 3.93) and helps them understand topics more clearly (M = 3.88). The result indicates that students perceive AI as useful for learning, which is a strong driver of acceptance according to TAM. Many students feel that AI helps them learn better and work more efficiently.

Regarding Perceived Ease of Use (PEOU), high ratings for user-friendliness (M = 3.94) and ease of use (M = 3.98), along with confidence in using AI with minimal guidance (M = 3.77) or limited training (M = 3.66), indicate that students find the tools intuitive and approachable. Although students expressed confidence in using AI with minimal assistance (M = 3.77) and after limited training (M = 3.66), their future intention to use AI was rated somewhat lower (M = 3.60), while planning to use AI as a routine part of their studies yielded the lowest mean (M = 3.30), suggesting some hesitancy in long-term dependence on AI. Nonetheless, students remain open to increasing AI usage if supported by lecturers or institutions (M = 3.66). Overall, the results indicate that strong perceptions of usefulness and ease of use drive students' acceptance of AI, while their behavioural intention is still emerging, aligning with the core propositions of the Technology Acceptance Model (TAM).

Table 3: Descriptive Statistics for Students' Acceptance

Items	**M**	**SD**
I believe that using AI tools can improve my learning effectiveness.	3.81	0.869
AI-assisted learning tools help me better understand topics.	3.88	0.842

Using AI increases my productivity in completing assignments or studies.	3.93	0.837
AI adds value to my overall learning process.	3.83	0.819
I find AI tools easy to use in learning.	3.98	0.825
I can use AI without requiring much assistance.	3.77	0.898
AI tools are user-friendly and easy to learn.	3.94	0.819
I am confident using AI after only a little training or exposure.	3.66	0.796
I plan to continue using AI tools in my learning.	3.60	0.911
I will encourage my peers to use AI in their learning.	3.63	0.940
I plan to rely on AI as part of my study routine.	3.30	1.003
I will use AI more frequently if my lecturers or institution provides it.	3.66	0.948
CUMULATIVE MEAN	**3.75**	**0.72**

The technology acceptance findings align closely with the Technology Acceptance Model (TAM). High scores for perceived usefulness and perceived ease of use indicate that students view AI-assisted learning as valuable and user-friendly. However, behavioral intention yielded comparatively lower mean values, suggesting that while students appreciate AI's benefits, they remain cautious about integrating it regularly into their studies. This mismatch indicates that positive perceptions alone cannot guarantee sustained AI adoption; instead, continuous institutional support, lecturer encouragement, and guided practice are essential to translate positive attitudes into regular use.

4.4 Correlation Between Readiness and Acceptance of AI-Assisted Learning

Pearson correlation analysis as shown in Table 4 revealed a strong positive relationship between technology readiness and acceptance of AI-assisted learning ($r = .825$, $p < .001$). This result indicates that students who demonstrate greater optimism, confidence, and preparedness toward AI technologies are also more likely to perceive AI as useful, easy to use, and worthy of continued adoption. The strong association supports the proposition that technology readiness forms an important foundation for technology acceptance among Malaysian polytechnic students.

Table 4: Correlation between Readiness and Acceptance

Variables	Readiness	Acceptance
Readiness	1	0.825**
Acceptance	0.825**	1

Note: **p < .001

This study examined Malaysian polytechnic students' readiness and acceptance of AI-assisted

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learning using an integrated Technology Readiness Index (TRI) and Technology Acceptance Model (TAM) framework. The findings revealed that students demonstrated moderate-to-high levels of both technology readiness and technology acceptance, indicating generally positive perceptions of AI-assisted learning. These findings are consistent with previous studies that reported increasing acceptance of AI technologies among higher education students (Ameen et al., 2025; Qaribu Yahaya Nasidi et al., 2025). More importantly, the study demonstrates that technology readiness provides a psychological foundation for technology acceptance. Students with higher levels of optimism and innovativeness were more likely to perceive AI-assisted learning as useful and easy to use, thereby strengthening their behavioural intention to adopt AI. This finding supports Parasuraman's (2000) Technology Readiness Index and reinforces the Technology Acceptance Model (Davis, 1989), suggesting that students' psychological readiness shapes their perceptions of AI before influencing their intention to use it. Therefore, readiness and acceptance should be viewed as complementary rather than independent constructs.

The findings indicate that while optimism and innovativeness drive AI adoption, discomfort highlights a need for technical confidence rather than a distrust of the technology. This suggests that students recognize AI's educational value but require practical experience to use it effectively, meaning institutions should prioritize continuous competency training. Theoretically, this study contributes to the literature by demonstrating the complementary roles of TRI and TAM within Malaysian polytechnics. While TRI captures students' psychological readiness, TAM explains how this readiness shapes perceptions of usefulness and ease of use to determine behavioral intention. Integrating these frameworks provides a far more comprehensive explanation of adoption than using either model in isolation. Practically, these insights emphasize the need for AI literacy programs, hands-on training, and ongoing institutional backing to boost student confidence, encourage responsible use, and ensure sustainable AI integration.

5.0 CONCLUSION AND RECOMMENDATIONS

This study investigated Malaysian polytechnic students' readiness and acceptance of AI-assisted learning by integrating the Technology Readiness Index (TRI) and Technology Acceptance Model (TAM). The findings revealed moderate-to-high levels of readiness and acceptance, with psychological readiness emerging as a powerful predictor of AI acceptance. Students exhibiting higher optimism, confidence, and adaptability were significantly more likely to view AI tools as useful and user-friendly, reinforcing their intention to adopt them.

Theoretically, this research proves that blending TRI and TAM offers a more holistic understanding of AI adoption than using either framework in isolation, providing valuable empirical insights within the Malaysian TVET landscape. Practically, the results suggest that higher education institutions should cultivate student AI readiness through targeted literacy programs, hands-on training, and ongoing academic support. Furthermore, educators must champion the ethical use of AI, encouraging students to treat these applications as tools to enrich—rather than replace—critical thinking and independent study.

Despite its insights, this study possesses certain limitations. The reliance on convenience sampling from a single institution restricts the generalizability of the findings, while the cross-sectional design captures student perceptions at only a single point in time. To broaden these insights, future research should incorporate probability sampling across multiple institutions, employ longitudinal designs, and evaluate additional variables such as AI literacy, trust, perceived risk, and facilitating conditions. Ultimately, this study underscores that building internal technological readiness is the true foundation for the sustainable integration of AI in higher education.

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DECLARATIONS

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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ETHICAL APPROVAL

Formal ethical approval was not obtained for this study. However, the study adhered to recognized ethical guidelines, including voluntary participation, informed consent, confidentiality, anonymity, and the responsible handling of participant data.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

ARTIFICIAL INTELLIGENCE (AI) DECLARATION

The authors declare that artificial intelligence tools (ChatGPT and Grammarly) were used to assist in language editing and improving the readability of the manuscript. The authors take full responsibility for the content, accuracy, and integrity of the manuscript

AUTHOR CONTRIBUTIONS

N.A.H.: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft preparation; N.N.F.N.D.: Conceptualization, Methodology, Investigation, Writing – review & editing, Visualization; K.Z.: Writing – review & editing, Supervision. All authors have read and agreed to the published version of the manuscript.

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