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A PLS-SEM Analysis of Antecedents Influencing Polytechnic Students' Acceptance and Use of Artificial Intelligence (AI) Tools for Technical English

Kamilah Zainuddin[1]*, Khairul Azhar Mat Daud[2], Noor Asmaa Hussein[3]

[1, 3] General Studies Department, Politeknik Kota Bharu, Kelantan, Malaysia
[1, 2] Faculty of Creative Technology and Heritage, Universiti Malaysia Kelantan, Malaysia

[1] mila@pkb.edu.my
[2] azhar.md@umk.edu.my
[3] asmaa@pkb.edu.my

**Corresponding author*

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Abstract
Technical English (TE) proficiency is crucial for the future careers of polytechnic students. While Artificial Intelligence (AI) tools offer significant potential to enhance language learning, their effectiveness relies on student acceptance and use. There is limited understanding of what drives polytechnic students to adopt these tools specifically for TE. This study aims to identify the key factors influencing polytechnic students' acceptance and use of AI tools in this context and employ a quantitative approach based on the Technology Acceptance Model (TAM) and Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyse survey data collected from 100 Polytechnic Kota Bharu (PKB) students enrolled in TE courses. The research investigates core antecedents, primarily perceived usefulness (PU) and perceived ease of use (PEOU), and their impact on students' behavioural intention (BI) to use AI tools. The potential influence of external factors such as social influence and lecturer support are examined. The study found PEOU was identified as a critical antecedent, which significantly positively affected PU and BI. The study reaffirmed the significant predictive power of BI on AU, indicating that students' stated intentions reliably translate into their subsequent usage behaviour. This research will offer practical recommendations for educators seeking to integrate AI tools effectively into TE instruction. Theoretically, this study contributes to understanding technology adoption within the specific domain of technical and vocational language education, providing valuable insights for leveraging AI to improve essential communication skills for aspiring technical professionals.

Keywords: *Artificial Intelligence (AI) Tools; Technology Acceptance Model (TAM); PLS-SEM; Technical English; Polytechnic Students*

Introduction

In preparing polytechnic students for their future technical careers, strong communication skills are no longer just an advantage but essential (Ismail & Hassan, 2019; Ramamuruthy, Alias & DeWitt, 2021), particularly in Technical English (TE). The graduates must confidently read manuals (Krishnan et al., 2020; Nghia, Anh & Kien, 2023), write clear reports (Zainuddin et al.,2019; Scott et al., 2019), and communicate complex ideas effectively in English within their specific industries (Chan, 2021; Roshid & Kankaanranta, 2025). According to Renaldo (2024), the educational landscape has recently seen a dramatic shift with the rise of Artificial Intelligence (AI), bringing tools like sophisticated grammar checkers and chatbots into our students' learning routines. These technologies certainly hold promise, potentially offering personalised practice, instant feedback, and more engaging ways to learn complex technical language (Darwish, 2025). However, a study by Zhai, Wibowo, and Li (2024) found valid concerns, including the risk of over-reliance hindering skill development, issues of unequal access, and the ethical considerations surrounding AI use in academic work. Despite the exciting potential of AI in language learning, simply having these tools available does not guarantee that they will be used effectively (Farooqi, Amanat, & Awan, 2024; Abdullah & Basheer, 2024), especially within the unique context of polytechnic education, where students often have an efficient focus. When using AI tools for a skill-based subject like TE, there is a lack of clear understanding of whether our students are embracing these technologies or, more importantly, why they might choose to use them (Kommineni et al., 2025). There's a noticeable gap in research focusing on the factors influencing AI adoption among polytechnic students within this crucial area, making it difficult for us educators to guide students or leverage these tools optimally.

This situation leads to fundamental research objectives:

i. To examine the factors that affect the acceptance and use of Artificial Intelligence (AI) tools for Technical English (TE) among polytechnic students.

ii. To investigate the relationship between Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioural Intention (BI), and Actual Usage (AU) of Artificial Intelligence (AI) tools for Technical English (TE) among polytechnic students.

To assess the explanatory power of the Technology Acceptance Model (TAM) in the context of Artificial Intelligence (AI) tools for Technical English (TE) among polytechnic students, adoption using the Partial Least Square-Structural Equation Modelling (PLS-SEM) approach.

Literature Review

The integration of AI in English language instruction has gained significant attention in recent years, particularly in enhancing English for specific purposes (Huang et al., 2023; Loor et al., 2024; Kovalenko & Baranivska, 2024) such as Technical English (TE) for polytechnic students. Studies by Kong, Yang and Ho (2024), Kavitha and Joshith (2025), Sanchez-Prieto et al. (2020), and Otto et al. (2024) have explored the acceptance and pedagogical implications of AI tools, with a majority employing the Technology Acceptance Model (TAM) or the extended frameworks to evaluate factors influencing students' behavioural intention and actual use. Similarly, in a study by Pham and Wu (2023), they proposed a conceptual TAM-based framework examining learner attitudes toward AI chatbot use in English classrooms. Though empirical data were not collected, their work established theoretical relationships between PU, PEOU, attitude, and BI. Alike, Amanda and Hesty (2024) explored English for Foreign Language (EFL) learners' perceptions of

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ChatGPT using a qualitative approach. Their findings highlighted the tool's positive impact on vocabulary and grammar acquisition, although with noted limitations in pronunciation support.

Moreover, Wei, Zhao, and Ma (2025) offered a robust empirical foundation through a large-scale PLS-SEM analysis involving 351 Chinese EFL learners. Their study revealed that human likeness, social presence, and self-efficacy significantly influence motivation, predicting learning outcomes. Equally, Taufik and Fernandita (2025) investigated Indonesian EFL students' acceptance of ChatGPT for grammar learning, finding positive perceptions of PU and PEOU but noting concerns about over-reliance and academic integrity. Meanwhile, Yang (2024) conducted a mixed-methods study linking AI tool usage with increased motivation and achievement among EFL learners. Their research reinforced the potential of AI-mediated learning environments to foster autonomous and engaging learning experiences. Supporting that, Ansas et al. (2024) extended this discourse by evaluating vocational students' behavioural intention to use AI tools like Talk to GPT. Their findings emphasised improved fluency, pronunciation, and motivation, facilitated by the application's interactive feedback mechanisms.

Likewise, Harizah and Said (2024) addressed the intersection of cognitive styles and TAM, analysing how students' adaptive-innovative cognitive orientations influence their acceptance of ChatGPT and Kahoot. Although limited to a secondary school context, their quantitative study underscored the necessity of considering individual learner differences when implementing AI tools. Additionally, Wei (2023) conducted a controlled experimental study comparing AI-mediated instruction with traditional teaching. The AI group demonstrated significantly higher motivation, self-regulated learning, and English achievement, affirming the pedagogical merits of AI-enhanced language instruction.

Furthermore, Alharbi (2025) utilised an extended TAM framework incorporating perceived knowledge, engagement, and motivation to explain Saudi EFL learners' adoption of AI tools. Structural equation modelling confirmed the influence of these variables on PU and PEOU, ultimately predicting behavioural intention and usage. This large-scale study involving 472 university students offered generalizable insights while recognising the absence of faculty moderation effects. Supporting this, Salsabila and Widiastuty (2024) reinforced prior findings on AI's motivational benefits but highlighted limitations in accessibility due to freemium models of AI tools and the lack of integrated pronunciation features. Their qualitative insights supported the call for better curricular integration and technological enhancements.

Across those studies, several key themes emerge. Firstly, PU and PEOU consistently appear as primary determinants of AI acceptance. Validating TAM's applicability in various contexts is another thing to consider. Secondly, the BI is often driven by learners' motivation, confidence, and interaction with human-like AI features, as shown in Wei et al. (2025) and Alharbi (2025). Thirdly, structural models such as SEM or PLS-SEM are increasing, enabling more precise quantification of latent variables and their interrelationships. Despite these strengths, the reviewed literature reveals several limitations. Conceptual studies lack empirical validation, as in Pham and Wu (2023), while qualitative designs, though rich in insight, offer limited generalizability. Sample sizes and contexts vary, ranging from secondary to university levels, affecting cross-study comparability. Additionally, concerns about academic misconduct and the underdevelopment of specific AI features like pronunciation support were recurrent.

The previous studies mentioned robustly support using TAM and extended models to analyse AI tool acceptance in English language learning. The SEM studies provide empirical clarity on the causal relationships among constructs like PU, PEOU, AU, and BI. These insights affirm the relevance and timeliness of a PLS-SEM analysis investigating Polytechnic students' acceptance and use of AI tools for TE, with strong theoretical and empirical backing.

Theoretical and Conceptual Frameworks and Hypotheses

This study is grounded in the Technology Acceptance Model (TAM) developed by Fred Davis (1989), which remains one of the most prominent theoretical frameworks for examining technology adoption. TAM posits that an individual's intention to adopt and use a particular technology is influenced by two fundamental cognitive beliefs Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). The TAM is applied to explore how polytechnic students accept and utilise AI tools such as grammar checkers, AI chatbots, paraphrasers, and summarisers for learning TE. The model assumes that when students perceive these AI tools as PEOU, they are more likely to find them PU. In turn, these beliefs are expected to shape their BI to use the tools in the future. Ultimately, this intention should lead to the tools' AU in their academic activities. Thus, TAM provides a structured and validated framework for evaluating technology acceptance in educational settings, particularly regarding students' engagement with AI-assisted learning platforms. The conceptual framework of this study is shown in Figure 1 below.

In adopting this model, the present study not only examines the direct relationships among PEOU, PU, BI, and AU but also supports the development of strategies to promote meaningful integration of AI tools in TE pedagogy for polytechnic students.

Based on the core constructs and interrelationships proposed by the Technology Acceptance Model (TAM), the following hypotheses are formulated for this study:

H1: Perceived Ease of Use (PEOU) of AI tools for Technical English (TE) positively influences the Perceived Usefulness (PU) of these tools.

H2: Perceived Ease of Use (PEOU) of AI tools for Technical English (TE) positively influences Behavioral Intention (BI) to use these tools.

H3: Perceived Usefulness (PU) of AI tools for Technical English (TE) positively influences Behavioral Intention (BI) to use these tools.

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H4: Behavioral Intention (BI) to use AI tools for Technical English (TE) positively influences the Actual Use (AU) of these tools.

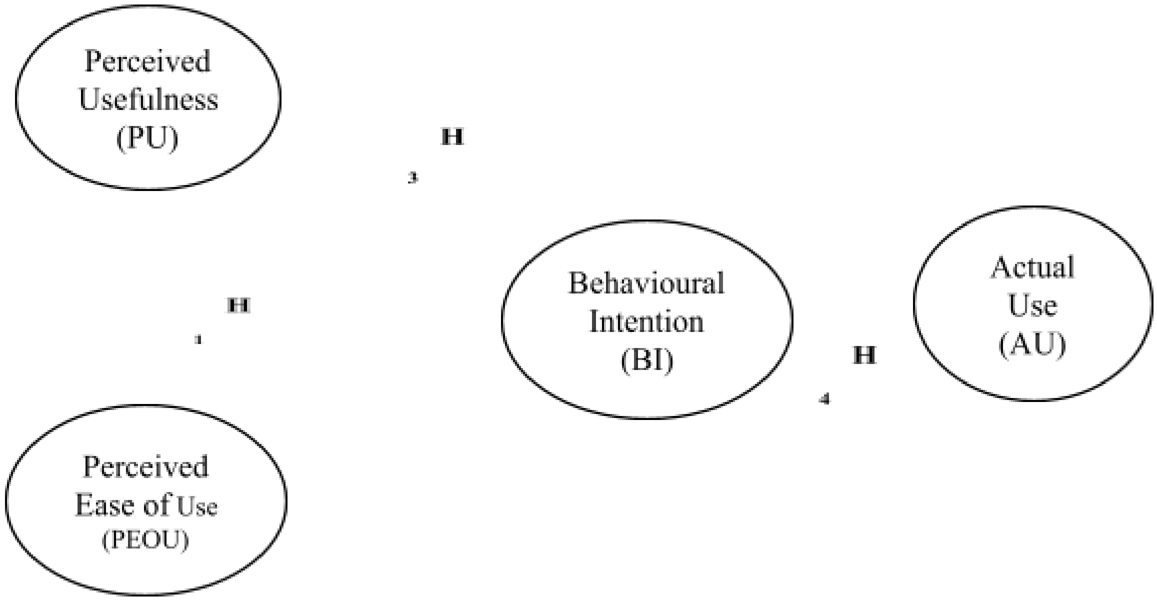

Figure 1: The Conceptual Framework of The Study based on TAM

Research Methodology

Context and subjects

The study was conducted at Politeknik Kota Bharu and targeted students in the TE subjects. This subject is a compulsory course designed for students in technical and engineering-related programmes. Politeknik Kota Bharu was selected as the research site due to the diverse student population across various engineering departments and its ongoing initiatives to incorporate digital and AI-assisted learning tools. The study used a non-probability sampling method, specifically purposive sampling, which was applied by selecting TE students with experience using AI tools. One hundred (100) students participated in the study, representing multiple academic programmes such as civil engineering, electrical engineering, and mechanical engineering. These students were chosen because they were actively engaged in learning activities requiring TE and were exposed to various AI tools during their coursework. The data was collected using an online Google Form questionnaire distributed to the students during the course session. Out of the targeted respondents, all 100 completed the questionnaire, resulting in a response rate of 100%. This high response rate reflects the students' interest and readiness to engage with emerging technologies, particularly in the context of AI-assisted language learning.

To ensure the adequacy of the sample size for this study, G-Power 3.1 was used to conduct an a priori power analysis for linear multiple regression, considering the minimum statistical power level of 0.80, an α =0.05, and a medium effect size ($f^2 = 0.15$) as suggested by Cohen (1988) (Gignac & Szodorai, 2016). Based on these parameters, the recommended minimum sample size for a model with four (4) predictors (PEOU to PU, PEOU, PU to BI, BI to AU) is approximately 85 respondents. Therefore, the sample size of 100 respondents in this study meets and slightly exceeds this requirement, ensuring sufficient power to detect meaningful effects within the tested model, which is supported by Hair et al. (2022), who suggested that for PLS-SEM, the minimum sample size should be determined by the 10-times rule, which recommends a minimum of ten times the maximum number of arrows pointing at any construct in the structural model. In this study, the most complex construct of BI has two (2) incoming paths (from PU and PEOU). Thus, the minimum required sample size would be $10 \times 2 = 20$. As such, the sample size of 100 far exceeds this threshold, meeting the accepted standards for PLS-SEM model estimation.

Survey instrument

The survey instrument for this study was adapted from the validated questionnaire developed by Saeed and Al-Emran (2018). The items were explicitly derived from Appendix A of the paper, which presents constructs aligned with TAM. The focus on the use of AI tools for TE learning among polytechnic students is applied to suit the context of this research, in which the original items were slightly modified to reflect the application of AI technologies, such as ChatGPT, Gemini, Quillbot, Grammarly, and Microsoft Co-Pilot, which represent language-related platforms. The questionnaire was divided into several key sections. The first part focused on gathering demographic information, including gender, department, programme of study, and familiarity with AI tools. This section provided context for understanding the profile of respondents. The second part measured the PU construct, examining students' beliefs about how AI tools help improve their performance, efficiency, and productivity in learning TE. There were seven (7) items under this construct. The third part assessed PEOU, which explored how easily students used AI tools for their academic tasks. This section included nine (9) items that captured students' perceptions of the simplicity, user-friendliness, and low effort required to operate the tools. The fourth part focused on BI, which gauged students' willingness and intention to continue using AI tools in the future. This construct was measured using three (3) items. Finally, the fifth part of the instrument measured AU, capturing how frequently students used AI tools in their TE learning. This section contains two (2) items. All responses in the instrument were collected using a five (5) point Likert scale ranging from strongly disagree to strongly agree. The instrument consisted of 20 construct-based items, ensuring comprehensive coverage of the students' acceptance and usage patterns of AI tools within the TAM framework.

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Data Analysis

Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed for the data analysis in this study. PLS-SEM is a powerful statistical method widely used for analysing complex relationships between latent variables, primarily when the research focuses on prediction and theory testing (Hair, Risher, Sarstedt & Ringle, 2019). This method was chosen due to the flexibility in handling small sample sizes, non-normal data, and the ability to model reflective and formative constructs (Ramayah, 2024; Memon et al., 2021), making it ideal for examining the relationships within the Technology Acceptance Model (TAM). The data were analysed using SmartPLS version 4.1.1.2 software, which allowed for the assessment of both the measurement model for reliability and validity and the structural model to test the relationships between constructs. In addition to PLS-SEM, descriptive statistics were calculated to summarise the responses across the different constructs, offering a clear understanding of how students perceive and use AI tools in their TE learning. The analysis also included tests for convergent validity using average variance extracted (AVE) and discriminant validity using the Fornell-Larcker criterion and Heterotrait-Monotrait ratio to ensure the robustness of the model (Ramayah, 2024; Heir et al., 2022). The combination of PLS-SEM for hypothesis testing and descriptive statistics for summarising participant responses provided a comprehensive approach to understanding the factors influencing the acceptance and use of AI tools for learning TE.

Result and Findings

Descriptive statistics

The sample predominantly comprises male students, representing 80% of the total (Table 1.0). In terms of the academic department, half of the respondents (52%) belong to the Electrical Engineering department, while the Mechanical Engineering and Civil Engineering departments account for 31% and 21%, respectively. The distribution across study programmes is diverse, with the highest concentrations found in the diploma in electrical engineering (30%), diploma in electrical & electronic engineering (22%), diploma in civil engineering (20%), and diploma in mechanical engineering (19%). Regarding AI tool usage for TE learning, ChatGPT, Gemini, and Microsoft Co-Pilot (35%) were the most frequently reported combinations, followed by ChatGPT alone (19%). ChatGPT appears in nearly all the reported combinations of tools used by the students.

Table 1: Demographic information

Items	Values	Frequency	Percentage
Gender	Male	81	80%
	Female	19	20%
Department	Civil engineering department	20	21%
	Electrical engineering department	50	52%

	Mechanical engineering department	30	31%
Study Programme	Diploma in civil engineering	19	20%
	Diploma in quantity surveying	2	2%
	Diploma in electronic engineering (communication)	3	3%
	Diploma in electrical & electronic engineering	21	22%
	Diploma in electrical engineering	28	30%
	Diploma in mechanical engineering	18	19%
	Diploma in mechanical engineering (automotive)	1	1%
	Diploma in mechanical engineering (agricultural)	8	8%
AI tools used in TE learning	ChatGPT, Gemini, Microsoft Co-Pilot	35	35%
	ChatGPT	19	19%
	ChatGPT, Microsoft Co-Pilot, Grammarly	14	14%
	ChatGPT, Gemini, Grammarly	9	9%
	ChatGPT, Gemini	6	6%
	ChatGPT, Gemini, Quillbot	5	5%
	ChatGPT, Grammarly, Quillbot	5	5%
	ChatGPT, Grammarly	2	2%
	ChatGPT, Gemini, Microsoft Co-Pilot, Grammarly	2	2%
	ChatGPT, Gemini, Microsoft Co-Pilot, Grammarly, Quillbot	1	1%
	ChatGPT, Microsoft Co-Pilot, Quillbot	1	1%
	Gemini, Microsoft Co-Pilot, Grammarly	1	1%

Measurement Model Assessment

The factor loading should be measured to assess the reliability of each item. The assessment of the measurement model indicates strong psychometric properties for all constructs, namely PU, PEOU, BI, and AU. Acceptable indicator reliability was established, as all item loadings exceeded the recommended threshold of 0.70, ranging from 0.709 (PEOU8) to 0.913 (AU1). Furthermore, the internal consistency reliability for each construct was confirmed, with Cronbach's Alpha (α) values surpassing 0.70 (PU=0.916, PEOU=0.925, BI=0.828, AU=0.795) and Composite Reliability values also exceeding the 0.70 benchmark (PU=0.933, PEOU=0.938, BI=0.897, AU=0.907). Convergent validity was supported as the Average Variance Extracted (AVE) for all constructs was above the minimum requirement of 0.50 (PU=0.666, PEOU=0.627, BI=0.744, AU=0.830). These results (Table 2) collectively demonstrate that the measurement model possesses adequate reliability and validity.

Table 2: Measurement Model result

Constructs	Items	Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Perceived Usefulness	PU1	0.823	0.916	0.933	0.666
	PU2	0.831			

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(PU)	PU3	0.771			
	PU4	0.800			
	PU5	0.827			
	PU6	0.794			
	PU7	0.862			
Perceived Ease of Use (PEOU)	PEOU1	0.815	0.925	0.938	0.627
	PEOU2	0.730			
	PEOU3	0.855			
	PEOU4	0.772			
	PEOU5	0.750			
	PEOU6	0.818			
	PEOU7	0.828			
	PEOU8	0.709			
	PEOU9	0.838			
Behavioural Intention to use (BI)	BI1	0.895	0.828	0.897	0.744
	BI2	0.824			
	BI3	0.868			
Actual Use (AU)	AU1	0.913	0.795	0.907	0.830
	AU2	0.909			

Discriminant validity was assessed using the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait ratio of correlations (HTMT). The HTMT results (Table 5), which are considered the most reliable criterion for assessing discriminant validity in PLS-SEM, indicated that all values were below the conservative threshold of 0.85 (ranging from 0.695 to 0.848), which strongly supports the constructs' distinctiveness (AU, BI, PEOU, PU). Examination of the cross-loadings (Table 4) further supported discriminant validity, as all indicators loaded more highly on their respective constructs than on any other construct. While the Fornell-Larcker criterion (Table 3) suggested potential concerns, particularly regarding the distinction between PEOU, PU, and BI due to high inter-construct correlations relative to the square roots of the AVEs, the robust evidence from the HTMT analysis confirms that discriminant validity is adequately established for this measurement model.

Table 3: Fornell Larcker Criterion Result

	AU	BI	PEOU	PU
AU	0.911			
BI	0.813	0.863		
PEOU	0.808	0.894	0.792	
PU	0.786	0.848	0.925	0.816

Table 4: Cross-Loading Result

	AU	BI	PEOU	PU
AU1	0.913	0.747	0.734	0.694
AU2	0.909	0.734	0.737	0.739
BI1	0.769	0.895	0.773	0.757
BI2	0.669	0.824	0.797	0.715
BI3	0.661	0.868	0.743	0.721
PU1	0.664	0.675	0.721	0.823
PU2	0.595	0.696	0.757	0.831
PU3	0.607	0.664	0.708	0.771
PU4	0.608	0.679	0.761	0.800
PU5	0.723	0.708	0.768	0.827
PU6	0.586	0.650	0.727	0.794
PU7	0.702	0.763	0.832	0.862
PEOU1	0.675	0.723	0.815	0.760
PEOU2	0.524	0.630	0.730	0.651
PEOU3	0.666	0.790	0.855	0.814
PEOU4	0.613	0.730	0.772	0.700
PEOU5	0.643	0.604	0.750	0.728
PEOU6	0.670	0.718	0.818	0.789
PEOU7	0.717	0.807	0.828	0.767
PEOU8	0.546	0.662	0.709	0.624
PEOU9	0.682	0.682	0.838	0.737

Table 5: Heterotrait Monotrait (HTMT) Result

	AU	BI	PEOU	PU
AU				
BI	0.797			
PEOU	0.707	0.825		
PU	0.695	0.782	0.848	

Structural Model Assessment

The model's explanatory power is evaluated by measuring the discrepancy amount in the dependent variables of the model. The structural model was assessed to test the hypothesised relationships between PEOU, PU, BI, and AU. The results of the hypothesis testing are presented in Table 6 and visualised in Figure 2. The analysis reveals that PEOU had a significant positive influence on PU (H_1: β = 0.925, p = 0.000) and a significant positive influence on BI (H_2: β = 0.145, p = 0.000). Furthermore, BI demonstrated a strong positive effect on AU (H_4: β = 0.813, p = 0.000). However, the hypothesised path from PU to BI (H3: β = 0.145, p = 0.372) was found to be non-significant ($p > 0.05$). Therefore, hypotheses H_1, H_2, and H_4 were supported, while H_3 was not supported in this study. Additionally, the model explained a substantial amount of variance in the endogenous constructs, specifically 85.5% of the variance in PU ($r^2 = 0.855$), 80.2% of the variance in BI ($r^2 = 0.802$), and 66.1% of the variance in AU ($r^2 = 0.661$).

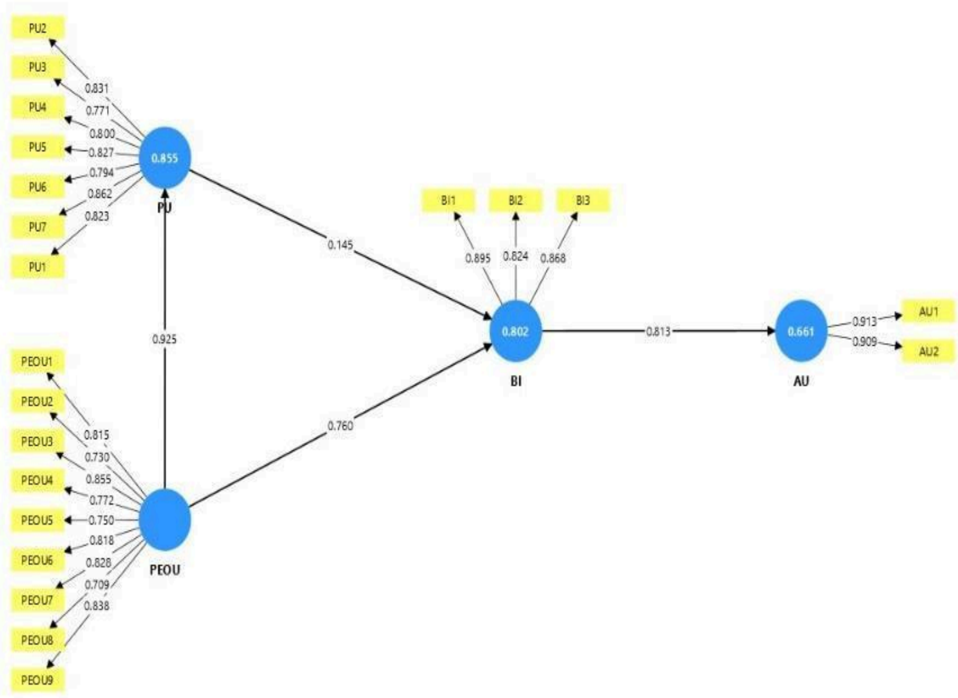

Figure 2: Path Analysis Result

Table 6: Hypotheses Testing Result

Hypothesis	Path	Path Coefficients	*P*- value	Remarks
H_1	PEOU → PU	0.925	0.000	Supported
H_2	PEOU →BI	0.760	0.000	Supported
H_3	PU→BI	0.145	0.372	Not Supported
H_4	BI→AU	0.813	0.000	Supported

Conclusion and Future Work

This study investigated the determinants influencing the acceptance and use of AI tools for TE among polytechnic students, employing the TAM as the guiding theoretical framework and following a rigorous assessment that confirmed the strong reliability and validity of the measurement model constructs, the hypothesised relationships (PEOU, PU, BI, and AU). The empirical results provide significant insights into the adoption process within this educational context. PEOU was identified as a critical antecedent, which significantly positively affected PU and BI, consistent with the previous study by Wiprayoga et al. (2023), Basuki et al. (2022), Chen and Aklikokou (2020) also, Wilson et al. (2021). This finding strongly emphasises the necessity of user-friendliness and intuitive design for fostering positive perceptions and adoption intentions among polytechnic students. Furthermore, the study reaffirmed the significant predictive power of BI on AU, indicating that students' stated intentions reliably translate into their subsequent usage behaviour.

However, a particularly noteworthy finding was the non-significant relationship between PU and BI. Similar findings were exposed by Wang and Wang (2024), Lee et al. (2003), and Yousaf et al. (2024). Their studies stated that when the use of AI or technology is compulsory, perceived usefulness might become less relevant in forming intention compared to factors like ease of use or social pressure. This deviation from the classic TAM framework suggests that within the specific context of this study, perceptions of the technology's utility, while positively influenced by PEOU, did not directly motivate an intention to use it. This outcome may stem from various factors, such as the dominant influence of PEOU potentially overshadowing utility considerations in intention formation, or perhaps the benefits associated with usefulness are not fully recognised or leveraged to stimulate intention, possibly influenced by mandatory usage policies or specific instructional approaches. Consequently, while establishing the ease of use of technology is fundamental for acceptance among polytechnic students, PU alone may not drive BI in this setting. The model, however, demonstrated considerable explanatory power, accounting for substantial variance in PU (r^2=0.855), BI (r^2=0.876), and AU (r^2=0.661).

From a practical standpoint, these results suggest that polytechnic educators and administrators should prioritise selecting and implementing technologies characterised by high usability. Moreover, support initiatives should extend beyond operational training to strategically emphasise how the technology's usefulness translates into tangible benefits within specific learning activities, potentially bridging the gap between perceived utility and usage intention; for technology developers serving the TVET sector, simplicity, and intuitive design remain paramount. Nevertheless, the study acknowledges limitations, including the cross-sectional nature, which precludes definitive causal claims over time, and the reliance on self-reported data. The findings' generalisability might also be constrained by the specific sample population drawn from a single polytechnic. Additionally, the model focused primarily on core TAM constructs, omitting other potentially influential variables.

Future Work

The findings and limitations of the current study pave the way for several promising directions for future research. Foremost among these is the need for further investigation into the non-significant relationship between perceived usefulness and behavioural intention observed in this context. Qualitative methodologies, such as in-depth interviews or focus group discussions with students, could yield rich insights into the underlying reasons for this disconnection. Concurrently, quantitative approaches could explore potential moderating variables, including the voluntariness of system use, the alignment between technology features and specific academic tasks (task-technology fit), individual differences in learning preferences, or specific course design elements that might condition the PU-BI relationship.

Future research endeavours should also develop more comprehensive models by integrating additional relevant constructs from established theories like the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Theory of Planned Behaviour (TPB). Exploring the potential roles of social influence, facilitating conditions, perceived behavioral control, or individual characteristics such as technology-related self-efficacy could offer a more holistic understanding of the factors driving technology acceptance and utilisation among polytechnic students.

Author contributions

Kamilah Zainuddin: Conceptualization, Methodology, Data Collection, Writing – Original Draft.
Khairul Azhar Mat Daud: Supervision, Validation, Formal Analysis, Writing – Review & Editing.
Noor Asmaa Hussein: Data Curation, Visualization, Writing – Review & Editing.

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Data availability statement

The author confirms that the data supporting the findings of this study is available within the article and/or its supplementary materials.

Conflicts of interest

The authors affirm that they have no competing interests or conflicts of interest to disclose.

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