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Exploring the Determinants of AI Tool Adoption in Technical English Learning: A PLS-SEM Approach among Polytechnic Students

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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 Modeling (PLS-SEM) to analyze 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' behavioral 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.

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1. INTRODUCTION

In today's technical and vocational education landscape, English communication skillsparticularly in Technical English (TE) are indispensable for employability and workplace readiness (Ismail & Hassan, 2019; Ramamuruthy, Alias & DeWitt, 2021). Polytechnic graduates are expected to read technical manuals (Krishnan et al., 2020; Nghia, Anh & Kien, 2023), write reports (Zainuddin et al., 2019; Scott et al., 2019), and communicate effectively in international technical environments (Chan, 2021; Roshid & Kankaanranta, 2025). Artificial Intelligence (AI) tools such as grammar checkers, chatbots, and summarizers (Renaldo, 2024; Darwish, 2025) offer opportunities to support these skills. However, challenges remain: risk of over-reliance, digital inequities, and ethical concerns (Zhai, Wibowo & Li, 2024; Farooqi, Amanat & Awan, 2024). Merely providing AI tools does not guarantee their adoption or effective use in TE learning (Abdullah & Basheer, 2024).

Despite extensive research on AI adoption in general education, there is limited empirical evidence on polytechnic students' acceptance of AI tools specifically for TE. This gap prevents educators from optimizing technology integration in technical language instruction. This study addresses this gap by investigating the determinants of AI tool adoption among polytechnic students using the Technology Acceptance Model (TAM). While AI tools hold potential to enhance TE learning, there is insufficient understanding of the factors that drive or hinder their adoption among polytechnic students. Without this knowledge, integration efforts risk failure.

This situation leads to fundamental research objectives and research questions as follow:

i. To examine the factors influencing the acceptance and use of AI tools for TE among polytechnic students.
ii. To investigate the relationships among Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioral Intention (BI), and Actual Usage (AU).
iii. To evaluate the explanatory power of TAM in the context of AI tools for TE using PLS-SEM.

Research Questions:

i. What factors influence polytechnic students' acceptance and use of AI tools for TE?
ii. How do PEOU, PU, BI, and AU relate in the adoption of AI tools?
iii. To what extent does TAM explain AI adoption in TE learning?

The hypotheses are presented in the theoretical framework section.

2. LITERATURE REVIEW

The integration of AI in language education has gained momentum, with many studies demonstrating its potential in enhancing English for Specific Purposes (ESP), including TE (Huang et al., 2023; Loor et al., 2024; Kovalenko & Baranivska, 2024). To systematically review prior work, this section is structured around the key constructs of the Technology Acceptance Model (TAM): Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention (BI), and Actual Usage (AU). Perceived Usefulness (PU): PU refers to the degree to which a student believes that AI tools enhance their learning effectiveness and performance. Prior studies (Pham & Wu, 2023; Amanda & Hesty, 2024; Wei, Zhao & Ma, 2025) have highlighted PU as a critical determinant of learners' motivation and outcomes. Alharbi (2025) found that perceived knowledge, engagement, and motivation influence PU, which in turn shapes behavioral intention.

Additionally, the Perceived Ease of Use (PEOU) reflects the extent to which students find AI tools simple and effortless to use. Research consistently shows the strong predictive power on both PU and BI (Taufik & Fernandita, 2025; Harizah & Said, 2024). Ease of access and intuitive design are essential in encouraging adoption, particularly among technical students who may prioritize efficiency. Similarly to the Behavioral Intention (BI) which capture the willingness to use AI tools in future learning activities. Studies such as

Wei (2023) and Yang (2024) have confirmed that BI is positively associated with motivation and achievement in AI-assisted language learning environments. BI is often influenced by social presence, confidence, and attitudes toward technology.

In the other hand, the Actual Usage (AU) represents the real, observable use of AI tools. Research demonstrates a strong linkage between BI and AU (Ansas et al., 2024; Otto et al., 2024), reaffirming TAM's predictive validity. However, over-reliance on AI may hinder skill development and raise academic integrity concerns (Zhai, Wibowo & Li, 2024).

Across these studies, PU and PEOU consistently emerge as the strongest antecedents of BI and AU, validating the applicability of TAM. However, limitations persist: some studies remain conceptual (Pham & Wu, 2023), while others offer limited generalizability due to small or context-specific samples (Salsabila & Widiastuty, 2024). Furthermore, academic misconduct risks and underdeveloped AI features highlight challenges for sustainable integration. Therefore, a PLS-SEM analysis focusing on polytechnic students' adoption of AI tools for TE is both timely and necessary, providing empirical clarity on these interrelationships.

2.1 Theoretical, 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 utilize AI tools such as grammar checkers, AI chatbots, paraphrasers, and summarizers 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:

i. H1: Perceived Ease of Use (PEOU) of AI tools for Technical English (TE) positively influences the Perceived Usefulness (PU) of these tools.
ii. H2: Perceived Ease of Use (PEOU) of AI tools for Technical English (TE) positively influences Behavioral Intention (BI) to use these tools.
iii. H3: Perceived Usefulness (PU) of AI tools for Technical English (TE) positively influences Behavioral Intention (BI) to use these tools.
iv. H4: Behavioral Intention (BI) to use AI tools for Technical English (TE) positively influences the Actual Use (AU) of these tools.

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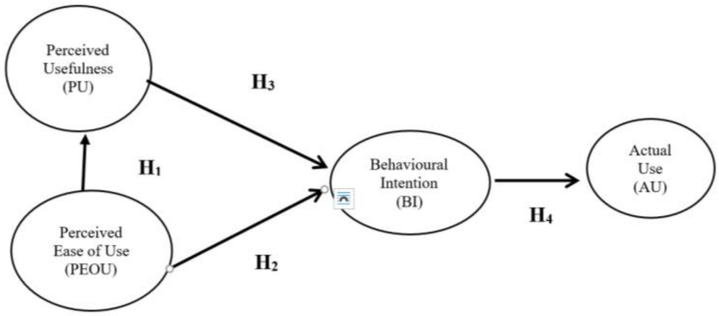

Figure 1: The conceptual framework of the study based on TAM

3. METHODOLOGY

3.1 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 programs. 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 programs 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.

3.2 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, program 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.

3.3 Data Analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed for the data analysis in this study. PLS-SEM is a powerful statistical method widely used for analyzing 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 analyzed 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 summarize 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 summarizing participant responses provided a comprehensive approach to understanding the factors influencing the acceptance and use of AI tools for learning TE.

4. RESULT AND FINDINGS

4.1 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 programs 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%

4.2 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 (PU)	PU1	0.823	0.916	0.933	0.666
	PU2	0.831			
	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	

4.3 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 hypothesized relationships between PEOU, PU, BI, and AU. The results of the hypothesis testing are presented in Table 6 and visualized in Figure 2. The analysis reveals that PEOU had a significant positive influence on PU (H_1: $\beta = 0.925$, $p = 0.000$) and a significant positive influence on BI (H_2: $\beta = 0.145$, $p = 0.000$). Furthermore, BI demonstrated a strong positive effect on AU (H_4: $\beta = 0.813$, $p = 0.000$). However, the hypothesized path from PU to BI (H3: $\beta = 0.145$, $p = 0.372$) 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).

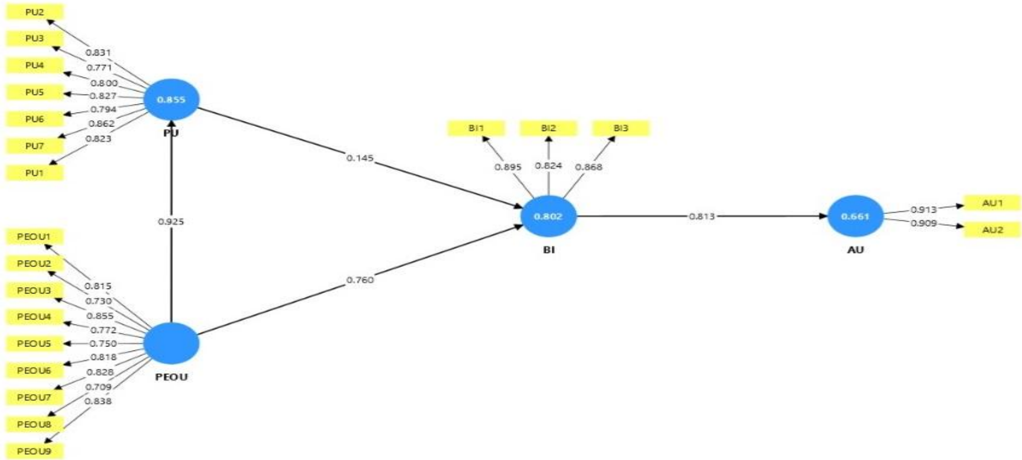

Figure 2: Path Analysis Result

Table 6: Hypotheses Testing Result

Hypothesis	Path	Path Coefficients	*P*- value	Remarks
H_I	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

5. CONCLUSION AND FUTURE WORKS

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 hypothesized 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 emphasizes 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 recognized 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 prioritize selecting and implementing technologies characterized by high usability. Moreover, support initiatives should extend beyond operational training to strategically emphasize 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' generalizability 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.

5.1 Future Works

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 endeavors 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 utilization among polytechnic students.

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7. CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

8. AUTHORS' CONTRIBUTIONS

Kamilah Zainuddin led the research design, conceptual framework development, data collection, and manuscript writing. **Assoc. Prof. Ts. Dr. Khairul Azhar Mat Daud** contributed to the theoretical foundation, data analysis, and critical revisions of the manuscript. **Noor Asmaa Hussein** supported the literature review, assisted in data collection, and participated in proofreading and editing the final draft. All authors reviewed and approved the final version of the manuscript.

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