PLS-SEM Application in Determining AI-Powered Writing Tools Usage among University Students

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ABSTRACT

The growing use of Artificial Intelligence (AI) applications among students has dramatically changed several elements of education, including academic writing. This study analyses the factors that influence students' intentions to use AI-powered writing tools, such as ChatGPT and Perplexity, in their academic writing. The Value-Based Adoption Model (VAM) was applied as a theoretical framework to explore the perceptions of 281 university students regarding the perceived usefulness, enjoyment, technicality, and cost. Data collected through questionnaires were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM), and the findings concluded that perceived usefulness and enjoyment significantly influence students' intentions to use AI applications, while perceived technicality and cost have no significant influence on the use of AI applications in students' academic writing. In addition, the study confirms that PLS-SEM model provides better predictive accuracy than a simple linear regression approach. These findings suggest that universities should establish guidelines for appropriate AI use while capitalizing on its benefits for academic progress.

Keywords: Value-Based Adoption Model, AI Writing, PLS-SEM Application, Perceived Usefulness, Enjoyment, Technically, Cost

INTRODUCTION

The integration of Artificial Intelligence (AI) across various sectors including healthcare, finance, and education has become increasingly prominent in the context of Industry 5.0. In higher education, AI applications such as ChatGPT, ChatBots, and Perplexity are being adopted to support students' academic writing by improving productivity, enhancing writing quality, and minimizing errors (Utami et al., 2023). The effective use of AI tools requires a certain level of student preparedness, encompassing digital literacy, understanding of AI functions, and motivation to engage with these tools (Malik et al., 2023).

Value-Based Adoption Model (VAM) was introduced by Kim et al. (2007) to address the limitations of Technology Acceptance Model (TAM) (Davis, 1989) by incorporating the concepts of benefits and sacrifices to explain perceived value and adoption intention, particularly in the context of technology adoption. This study employs VAM to examine the factors influencing students' intention to adopt AI applications in academic writing. VAM evaluates user adoption based on perceived benefits, namely usefulness and enjoyment, and perceived sacrifices, which include technical complexity and cost (Liao et al., 2022). Perceived usefulness refers to the extent to which students believe that AI applications can improve the quality of their academic work, as it can positively influence their intention to use them (Liao et al., 2022). Similarly, perceived enjoyment captures the level of engagement and satisfaction students experience when using AI tools, further motivating adoption (Liao et al., 2022). Meanwhile, perceived technicality is defined as the complexity or difficulty in using AI tools, while perceived cost plays a critical role since students who perceive AI technologies as financially burdensome may be reluctant to adopt them, especially if the costs outweigh the anticipated benefits (Liao et al., 2022).

In the context of academic writing, perceived value influences students' adoption decisions. Students are more inclined to integrate such technologies when they prioritize their writing competence and perceive that AI tools contribute positively to their skill development. Moreover, prior research has suggested that AI integration in academic contexts can lead to improved academic performance, heightened engagement, and the cultivation of digital and critical thinking skills essential in the modern workforce (Ayanwale & Ndlovu, 2024). These perceptions are hypothesized to shape students' overall intention to use AI tools, with higher perceived value likely to increase adoption.

Although AI offers significant advantages in enhancing writing skills and supporting research activities, many students face barriers related to lack of familiarity, confidence, and formal training (Khalifa & Albadawy, 2024). Therefore, understanding the factors that affect student readiness and intention to adopt AI technologies is essential. This research specifically investigates the readiness and intention of students at Universiti Teknologi MARA (UiTM) Cawangan Kelantan, Kota Bharu Campus to use AI applications in academic writing. The study aims to provide insights into the effective integration of AI tools into academic environments and guide the development of more accessible and supportive AI-based educational technologies.

Related Work

The reviewed literature provides an examination of artificial intelligence (AI) adoption in academic writing, particularly among university students. AI has widespread applications, including in education, where it supports personalized learning, research, and writing assistance through tools such as Grammarly, ChatGPT, and Quill Bot (Zawacki-Richter et al., 2019).

Student's intention is the most important tool that determines the student's behaviour when using AI applications in academic writing. Many previous studies have used models to assess the intention to adopt and accept technologies (Shelvia et al., 2020). These models give researchers a strong theoretical foundation for developing a framework in measuring and evaluating independent variables. Technology Acceptance Model (TAM) (Davis, 1989) is one of the models that has been extensively used as a foundational theoretical framework to assess user behavioural intentions. The key determinants in TAM include perceived usefulness and perceived ease of use, which significantly influence user attitudes and intentions (Mahmud et al., 2024; Utami et al., 2023). However, TAM's limitations in addressing social and cultural dimensions have led to the inclusion of additional constructs such as attitudes and behavioural intentions, as supported by structural equation modelling studies (Al-Abdullatif, 2023; Liao et al., 2022). As such, the Value-based Adoption Model (VAM) is introduced, focusing on perceived value derived from the balance between perceived benefits (e.g., use-fulness and enjoyment) and perceived sacrifices (e.g., technicality and cost) to overcome TAM's limitations (Al-Maroof et al., 2021; Dai et al., 2020). Empirical findings indicate that perceived benefits positively influence adoption intention, while perceived sacrifices have a negative impact (Berto & Bursan, 2023; Shelvia et al., 2020). VAM has been extended to include social influence, self-efficacy, and personal innovativeness to better explain AI adoption among students (Mahmud et al., 2024).

Several key factors influencing student's intention to use AI are discussed. Perceived usefulness is a dominant predictor, with evidence suggesting that students are more inclined to use AI tools if they believe these tools improve writing efficiency and academic outcomes (Bolanos et al., 2024; Salido, 2023). Perceived enjoyment, representing hedonic value, also significantly contributes to intention, as emotionally engaging and satisfying AI applications are more likely to be adopted (Liao et al., 2022; Sohn & Kwon, 2020). Conversely, perceived technicality, defined as the complexity and ease of use of AI tools, can deter usage if systems are seen as overly complicated (Deepika et al., 2022). However, some findings suggest technical proficiency may positively impact adoption, particularly among experienced users (Mahmud et al., 2024). Lastly, perceived cost, both monetary and non-monetary, is found to negatively influence students' attitudes and intentions, reinforcing the importance of minimizing costs to encourage sustained use (Andersson & Heinonen, 2002; Fan & Jiang, 2024).

The VAM framework conceptualizes adoption intention as a function of perceived value, which is the trade-off between perceived benefits (e.g., usefulness, enjoyment) and perceived sacrifices (e.g., technical complexity, cost) associated with a technology (Rruplli et al., 2024). This model is particularly suitable for studying AI writing tools in educational contexts because it captures both functional and emotional values alongside potential barriers to use. Research has consistently identified usefulness and enjoyment as primary perceived benefits that drive students' adoption of AI writing tools (Amani & Bisriyah, 2025; Rruplli et al., 2024). In addition, Li et al.'s (2024) study on generative AI-powered writing assistance highlighted that students value the content generation capabilities of AI, especially for creative writing tasks, which can reduce writing time and improve grammar, thereby enhancing overall writing experience and self-efficacy.

Technicality and perceived cost are critical factors that can hinder the adoption of AI. Technicality refers to the complexity or difficulty students experience when learning and using AI writing tools. According to Rruppli et al. (2024), if the tools are perceived as too technical or require significant effort to master, students may be reluctant to adopt them. Meanwhile, perceived cost includes not only monetary aspects but also time investment and potential privacy concerns. As stated by Amani and Bisriyah (2025), these sacrifices must be outweighed by the benefits for students to perceive a positive value and thus the intention to use AI writing tools. Empirical evidence from focus groups and surveys indicates that students who recognize clear academic benefits and enjoy using AI tools are more likely to adopt them, provided that technical barriers and costs are manageable (Amani & Bisriyah, 2025; Rruppli et al., 2024). Conversely, students who perceive high sacrifices relative to benefits tend to resist adoption.

Based on the literature above, this study applies the selected variables of Value-based Adoption Model (VAM) to fulfil the proposed study objective. Figure 1 illustrates the independent variables of VAM which include perceived usefulness, perceived enjoyment, perceived technicality, and perceived cost that are hypothesized to influence the dependent variable of students' intention to use Artificial Intelligence (AI) applications in academic writing.

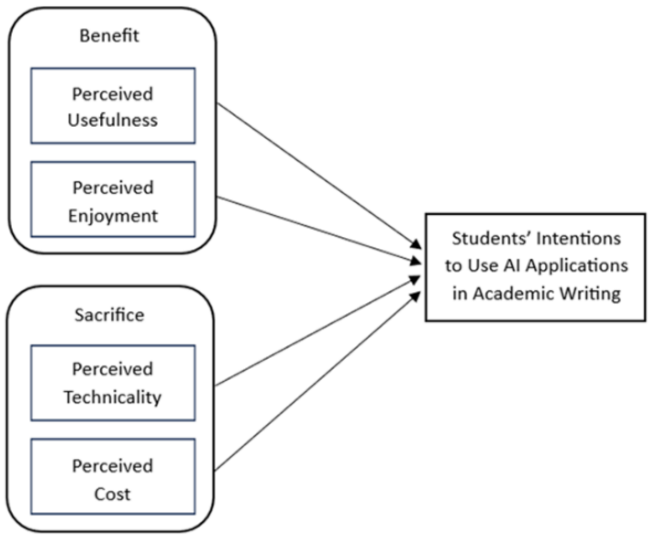

Figure 1: Value-based Adoption Model (VAM)

In summary, applying the Value-Based Adoption Model to students' use of AI writing tools underscores the importance of perceived value as a balance between benefits and sacrifices. Usefulness and enjoyment emerge as key benefits that enhance perceived value, while technicality and cost represent significant sacrifices that can diminish it. Understanding this balance offers valuable insights for educators and developers aiming to improve AI writing tool adoption in academic settings by maximizing benefits and minimizing barriers.

METHODOLOGY

Research Design

This study employed a quantitative cross-sectional research design to investigate the relationship between perceived usefulness, perceived enjoyment, perceived technicality, and perceived cost with students' intentions to use AI tools in academic writing. Data were collected using a self-administered online questionnaire distributed via Google Form. The instrument utilised a 7-point Likert scale, ranging from "strongly disagree" to "strongly agree".

Population, Sample and Sampling Technique

The target population comprised of 1043 full-time undergraduate students at Universiti Teknologi MARA (UiTM) Cawangan Kelantan, Kota Bharu Campus, during October 2024 to February 2025 academic session. It only consisted of full-time undergraduate students but excluded those currently undergoing industrial training or internships and part-time or distance learning students. As such, a sample size of 310 respondents was determined by using the Qualtrics (2023) sample size calculator, based on a 95% confidence level, 5% margin of error, and an additional 10% buffer for non-response. A stratified random sampling technique was applied to ensure proportional representation across academic programs. The population was divided into six strata based on course codes, and the sample size for each stratum was determined using proportionate allocation. Table 1 below shows the summary of sample size for each stratum.

Table 1: Sample Size of Each Stratum

Course Code	Number of Students	Strata Sample Size
BA240/270	201	(201/1043) x 310 = 60
BA242/272	276	(276/1043) x 310 = 82
BA249/279	150	(150/1043) x 310 = 45
BA250/280	135	(135/1043) x 310 = 40
CDCS/CS241	249	(249/1043) x 310 = 74
CDCS/CS291	32	(32/1043) x 310 = 9
Total	**1043**	**310**

Data Collection

Data were collected using a self-administered online questionnaire developed via Google Form. This method enables the respondents to complete the survey independently, without the presence or assistance of an interviewer, and at their own convenience. The questionnaire consisted of six sections. Section A has five questions on demographic profile, Section B has seven questions on student's intention to use AI, Section C has seven questions on perceived usefulness, Section D has seven questions on perceived enjoyment, Section E has seven questions on perceived technicality, and Section F also has seven questions on perceived cost. The questionnaire was distributed through online messaging platforms, including WhatsApp and Telegram, to ensure broad accessibility and encourage participation.

Data Analysis

Reliability analysis is conducted using Cronbach's alpha to ensure the internal consistency of the measurement scales in which the Cronbach's alpha values range from 0 to 1, with higher values reflecting stronger internal consistency (Tavakol & Dennick, 2011). A coefficient value above 0.70 is considered acceptable (Lai et al., 2022). Meanwhile, descriptive statistics are used to summarize and present the characteristics of the sample and the main study variables. Descriptive analysis also helps to ensure that the data meet the assumptions required for further statistical testing, while frequencies and percentages are used to describe both categorical and numerical data, offering a clear overview of the dataset (Dong, 2023).

The study adopted the procedure recommended by Podsakoff et al. (2003) to assess potential bias from common method variance (CMV). CMV occurs when the measurement method inflates the relationship between the constructs rather than reflecting true associations (Chang et al., 2010). A marker variable, unrelated to the study's constructs, was included within the perceived technicality section of the questionnaire (Lindell & Whitney, 2001). The R^2 values for the endogenous construct of student's intention to use AI in

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academic writing were compared before and after including the marker variable using SmartPLS, and a difference of more than 10% in R^2 would indicate substantial CMV (Tehseen et al., 2017). This analysis confirmed that CMV is not a significant concern in the present study.

Measurement Model

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to assess the proposed research model. Data analysis was conducted using SmartPLS version 4.1.0.9, following the standard two-step procedure involving the evaluation of measurement model and structural model (Hair et al., 2019). The reliability of each indicator was assessed by examining the outer loadings; if the indicator loading is above 0.708, the construct explains more than 50% of the variance in the item, which indicates it is acceptable (Hair et al., 2017). Items with loadings below 0.708 are only removed if it improves the overall reliability or validity. Items with very low loadings (below 0.40) are removed to maintain content and construct validity (Hair et al., 2017; Henseler et al., 2015).

Internal consistency is evaluated by using Cronbach's alpha, composite reliability (ρ_c) and Dijkstra–Henseler's (ρ_A) (Henseler et al., 2015). Cronbach's alpha provides a conservative estimate, while composite reliability may be overly liberal. ρ_A serves as a balanced estimate of reliability. Reliability scores between 0.70 and 0.90 are considered acceptable (Hair et al., 2019), while scores above 0.95 suggest redundancy or response bias. The formulas used are as follows:

$$\alpha = \frac{N.\bar{c}}{\bar{v} + (N-1)\bar{c}} \tag{1}$$

where N is number of items, $\bar{v}$ is average variance and $\bar{c}$ is average inter-item covariance among the items (Hair et al., 2019).

$$\rho_c = \frac{(\sum_{i=1}^{p} \lambda_i)^2}{(\sum_{i=1}^{p} \lambda_i)^2 + \sum_{i}^{p} v(\sigma_i)} \tag{2}$$

where λ_i is completely standardized loading for the i^{th} indicator, $V(\sigma_i)$ is variance of the error term for the i^{th} indicator and p is number of indicators (Hair et al., 2019).

Average Variance Extracted (AVE) is used to evaluate convergent validity. A construct explains at least 50% of the variance in its indicators if AVE value is of 0.50 or above, which is calculated using the following formula (Hair et al., 2017):

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n} \tag{3}$$

where λ_i^2 is standardized loading of each indicator on the construct and n is number of indicators for that construct.

Heterotrait-Monotrait Ratio (HTMT) is used to assess discriminant validity in which values below 0.85 (or 0.90 for conceptually similar constructs) suggest that the con-structs are distinct (Henseler et al., 2015). The HTMT ratio is calculated as follows:

$$HTMT = \frac{\bar{r}_{ig.jh}}{\sqrt{\bar{r}_{ig.ih}.\bar{r}_{jg.jh}}} \tag{4}$$

where $\bar{r}_{ig,jh}$ is the arithmetic mean of the heterotrait-heteromethod correlations, $\bar{r}_{ig,ih}$ is the arithmetic mean of the indicator correlation within ξi and $\bar{r}_{jg,jh}$ is the arithmetic mean of the indicator correlation within ξi (Henseler et al., 2015).

According to Hair et al. (2017), bootstrap confidence intervals are used to further validate discriminant validity, in which the 95% confidence interval of HTMT must not include 1.0 or exceed the selected threshold (0.85 or 0.90). This study used 10,000 bootstrap samples to ensure robust estimates, applying the percentile method for confidence interval estimation (Hair et al., 2017; Henseler et al., 2015).

Structural Model

The structural model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) as recommended by Edeh et al. (2023). This step involves analysing the relationships among latent constructs and testing the model's predictive power. Initially, collinearity among predictor constructs must be examined to ensure unbiased results before interpreting path coefficients. Latent variable scores are used to compute Variance Inflation Factor (VIF) values. VIF values below 5 indicate no significant multicollinearity (Edeh et al., 2023), allowing for valid interpretation of the regression paths.

The coefficient of determination (R^2) measures the model's explanatory power for each endogenous variable. R^2 values range from 0 to 1, with higher values indicating stronger predictive accuracy (Hair & Alamer, 2022). According to Edeh et al. (2023), R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively. In addition, Q^2 statistic is used to evaluate the model's predictive relevance obtained through blindfolding procedures (Yahaya et al., 2019). Based on Yahaya et al. (2019), Q^2 value greater than 0 suggests the model has predictive relevance for a given endogenous construct while Q^2 values above 0.25 and 0.50 indicate medium and large predictive relevance, respectively.

Path coefficients are examined to assess the strength and significance of the hypothesized relationships between the constructs. Bootstrapping with 5,000 resamples is conducted to obtain standard errors and confidence intervals (Hair et al., 2022). A path coefficient is considered statistically significant at the 5% level if its 95% confidence interval does not include zero (Yahaya et al., 2019). Moreover, PLSpredict technique is applied to further evaluate model prediction. This approach involves generating k-fold cross-validated prediction errors, with k = 10 as recommended. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to assess the model's predictive accuracy (Shmueli et al., 2019). These metrics compare the model's predictions to observe the values which are calculated as follows:

$$MAE = \frac{\sum_{i=1}^{n} | y_i - x_i |}{n} \tag{5}$$

where y_i is prediction, x_i is true value and n is total number of data points (Shmueli et al., 2019).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{6}$$

where $\hat{y}_i$ is predicted values, y_i is observed value and n is total number of data points (Shmueli et al., 2019).

If none of the indicators produce greater RMSE or MAE than those of a naïve linear model (LM) benchmark, a model is considered to have high predictive power (Shmueli et al., 2019). The model has medium predictive power if only a few indicators exceed the benchmark, and if most indicators exceed the benchmark, the model has low predictive power (Shmueli et al., 2019).

Findings

Preliminary Analysis

Reliability analysis was conducted to assess the internal consistency of the measurement constructs. Table 2 indicates that the items used to measure each construct of this study are stable and consistent since Cronbach's Alpha values range from 0.845 to 0.974.

Table 2: Reliability Analysis

Construct	No. of Items	Cronbach's Alpha	
		Pilot	Actual
Students' Intention to Use AI	7	0.928	0.927
Perceived Usefulness	7	0.974	0.951
Perceived Enjoyment	7	0.971	0.958
Perceived Technicality	7	0.948	0.935
Perceived Cost	7	0.845	0.861

A total of 220 valid responses were collected from 310 questionnaires distributed, resulting in a response rate of 71%. This exceeds the commonly accepted threshold of 50%, supporting the adequacy of the sample size for further analysis. Data were then coded and cleaned using Statistical Package for the Social Sciences (SPSS) before proceeding with advanced statistical analysis.

Descriptive Analysis

Table 3 shows the demographic information of 220 undergraduate students at UiTM Kota Bharu. Most respondents were female (73.2%) and aged between 21 and 25 years (91.4%). The largest group of participants came from CS241/CDCS241 program (35.5%), followed by BA242/BA272 (25.9%), while CS291/CDCS291 had the fewest respondents (2.7%). Most students were from Semester 2 (39.5%). In terms of AI usage, 47.7% used AI two to three times per week, and 33.2% used it four to five times per week. A smaller portion (18.2%) reported using AI six or more times weekly, while only 0.9% indicated they never used AI.

Table 3: Respondents' Demographics Profile

Characteristic	Group	Cases	Percentage (%)
Gender	1) Male	59	26.8
	2) Female	161	73.2
Age	1) Below 20	15	6.8
	2) 21 – 25	201	91.4
	3) Above 25	4	1.8
Programme	1) BA240/BA270	28	12.7
	2) BA242/BA272	57	25.9
	3) BA249/BA279	25	11.4
	4) BA250/BA280	26	11.8
	5) CS241/CDCS241	78	35.5
	6) CS291/CDCS291	6	2.7
Semester	1) 2	87	39.5
	2) 3	43	19.5
	3) 4	13	5.9
	4) 5	46	20.9
	5) 6	31	14.1
Frequency of using AI	1) 2 or 3 times a week	105	47.7
	2) 4 or 5 times a week	73	33.2

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	3) 6 times and above a week	40	18.2
	4) Never	2	0.9

The study employed a marker variable technique using perceived cost as the marker to address the potential issue of common method bias due to the self-reported nature of the data. The comparison of R^2 values with (0.771) and without (0.772) the marker variable showed a negligible difference of less than 1%. This suggests that common method bias is not a significant concern in this study.

Measurement Model Assessment

It is essential to evaluate the measurement model to ensure that the constructs are both reliable and valid before analysing the structural model in PLS-SEM. This assessment includes tests for reliability indicator, internal consistency, convergent validity, and discriminant validity.

Reliability indicator is confirmed through factor loadings which should exceed the recommended threshold of 0.70. Internal consistency is measured using Composite Reliability (CR) and Cronbach's Alpha, both of which should exceed 0.70, indicating good consistency across items. Convergent validity is assessed through Average Variance Extracted (AVE) with values above 0.50 to confirm adequate item correlation within constructs. Discriminant validity is evaluated using two methods of the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT). Both tests should meet the respective criteria square roots of AVE which are greater than inter-construct correlations, while HTMT values have to be below 0.90 to demonstrate that the constructs are distinct from one another.

Table 4 shows that most questionnaire items have factor loadings above the recommended threshold of 0.70. Although two items PC5 (0.669) and PC7 (0.529) fall slightly below this value, they are still within acceptable limits, as factor loadings of 0.50 or higher are considered acceptable in some cases (Byrne, 2000). Therefore, all items meet the minimum reliability standards. In addition, all constructs show strong internal consistency, with Cronbach's Alpha and Composite Reliability values exceeding 0.70. Average Variance Extracted (AVE) for each construct is also above 0.50, confirming that the model has good convergent validity.

Table 4: Reliability and Validity Assessments

Item	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Students' Intention (SI)		0.930	0.944	0.707
SI1	0.845			
SI2	0.876			
SI3	0.858			
SI4	0.705			
SI5	0.884			
SI6	0.848			
SI7	0.856			
Perceived Usefulness (PU)		0.952	0.961	0.778
PU1	0.895			
PU2	0.910			
PU3	0.906			
PU4	0.820			
PU5	0.934			
PU6	0.874			
PU7	0.828			
Perceived Enjoyment (PE)		0.958	0.965	0.800
PE1	0.899			
PE2	0.887			
PE3	0.904			
PE4	0.900			

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PE5 PE6 PE7	0.895 0.892 0.883			
Perceived Technicality (PT) PT1 PT2 PT3 PT4 PT5 PT6 PT7	 0.823 0.880 0.868 0.894 0.881 0.882 0.688	0.935	0.947	0.719
Perceived Cost (PC) PC1 PC2 PC3 PC4 PC5 PC6 PC7	 0.772 0.768 0.787 0.704 0.669 0.704 0.529	0.855	0.875	0.503

Table 5 shows that the square root of the AVE values is greater than the values in its row and column. The square root of AVE for PC √0.503 = 0.710, which is higher than the other correlation values of 0.255, 0.553, 0.217, and 0.288. Thus, this suggests the model achieves good discriminant validity.

Table 5: Discriminant Validity Test (Fornell-Larcker)

Dimension	**AVE**	**PC**	**PE**	**PT**	**PU**	**SI**
PC	0.503	**0.710**				
PE	0.800	0.255	**0.894**			
PT	0.719	0.553	0.034	**0.848**		
PU	0.778	0.217	0.891	0.0211	**0.882**	
SI	0.707	0.288	0.837	0.097	0.860	**0.841**

Note: The bold slash text is the square root value of AVE, and the rest are the correlation coefficients between the various dimensions

The Heterotrait-Monotrait Ratio analysis in Table 6 shows that not all values are less than 0.9 (PU<->PE = 0.931 and SI<->PU = 0.906), indicating a lack of discriminant validity between the constructs. Therefore, bootstrapping is conducted to test the HTMT significance. If the confidence interval does not include 1, discriminant validity may still be established even if the HTMT value exceeds 0.9 (Roemer et al., 2021).

Table 6: Heterotrait-Monotrait Ratio of Correlations

Dimension	**PC**	**PE**	**PT**	**PU**	**SI**
PC					
PE	0.201				
PT	0.683	0.058			
PU	0.164	0.931	0.055		
SI	0.238	0.880	0.097	0.906	

Table 7 below displays the output of confidence intervals for HTMT values after performing the bootstrapping using 25% confidence intervals. The column of 2.5% represents the lower bound, whereas 97.5% represents the upper bound. Since the confidence interval does not include 1, the discriminant validity can still be acceptable despite a high HTMT value.

Table 7: Confidence Intervals for HTMT Values (Bootstrapping)

Relationship	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
PE ↔ PC	0.201	0.223	0.144	0.334
PT ↔ PC	0.683	0.677	0.531	0.801
PT ↔ PE	0.058	0.100	0.054	0.191
PU ↔ PC	0.164	0.191	0.121	0.304
PU ↔ PE	0.931	0.931	0.896	0.960
PU ↔ PT	0.055	0.097	0.056	0.181
SI ↔ PC	0.238	0.255	0.162	0.389
SI ↔ PE	0.880	0.881	0.815	0.933
SI ↔ PT	0.097	0.125	0.062	0.249
SI ↔ PU	0.906	0.906	0.863	0.944

Overall, the measurement model meets the required standards for reliability and validity, allowing the study to proceed with structural model analysis.

Structural Model Assessment

After validating the measurement model, structural model assessment was performed to ensure that the hypothesized relationships in the model are statistically significant and meaningful. The first step of evaluating structural equation modeling is to check the multicollinearity. To check the collinearity, the Variance Inflation Factor (VIF) values for all predictor constructs must be below 5. Table 8 shows the VIF values for the PC-SI (1.568) and PT-SI (1.468) are less than 5, indicating no collinearity among the dimensions. However, the VIF values for PE-SI (4.959) and PU-SI (4.850) are close to the common threshold of 5. In this case, moderate collinearity exists, but it is still acceptable to proceed with structural model assessment.

Table 8: Collinearity Analysis

Dimensions	VIF
PC → SI	1.568
PE → SI	4.959
PT → SI	1.468
PU → SI	4.850

The second step in structural model assessment involves evaluating the significance and relevance of the path coefficients using the bootstrapping technique. Table 9 presents the results, including path coefficients, t-values, and p-values for the relationships between the independent variables; Perceived Cost (PC), Perceived Enjoyment (PE), Perceived Technicality (PT), and Perceived Usefulness (PU) with the dependent variable of Students' Intention (SI) to use AI tools.

The analysis showed that both PU and PE have significant positive effects on SI, with p-values less than 0.01 and t-values exceeding the critical threshold of 2.576, indicating significance at the 1% level. PU demonstrates the strongest influence on SI. In contrast, PC and PT are not statistically significant, as their p-values exceed 0.05 and their t-values fall below 1.96. These findings suggest that students' intention to use AI tools in academic writing is primarily influenced by how useful and enjoyable they perceive the tools to be, while cost and technical complexity do not significantly impact their decision. The PLS-SEM path analysis model is shown in Figure 2.

Table 9: Path analysis verification

Path Analysis	Path Coefficient	T value	P value	Interpretation
PC → SI	0.064	1.591	0.112	Not significant

PE → SI	0.322	3.250 *	0.001	Significant
PT → SI	0.039	0.803	0.422	Not significant
PU → SI	0.559	5.980 *	0.000	Significant

* Significant at p<0.01

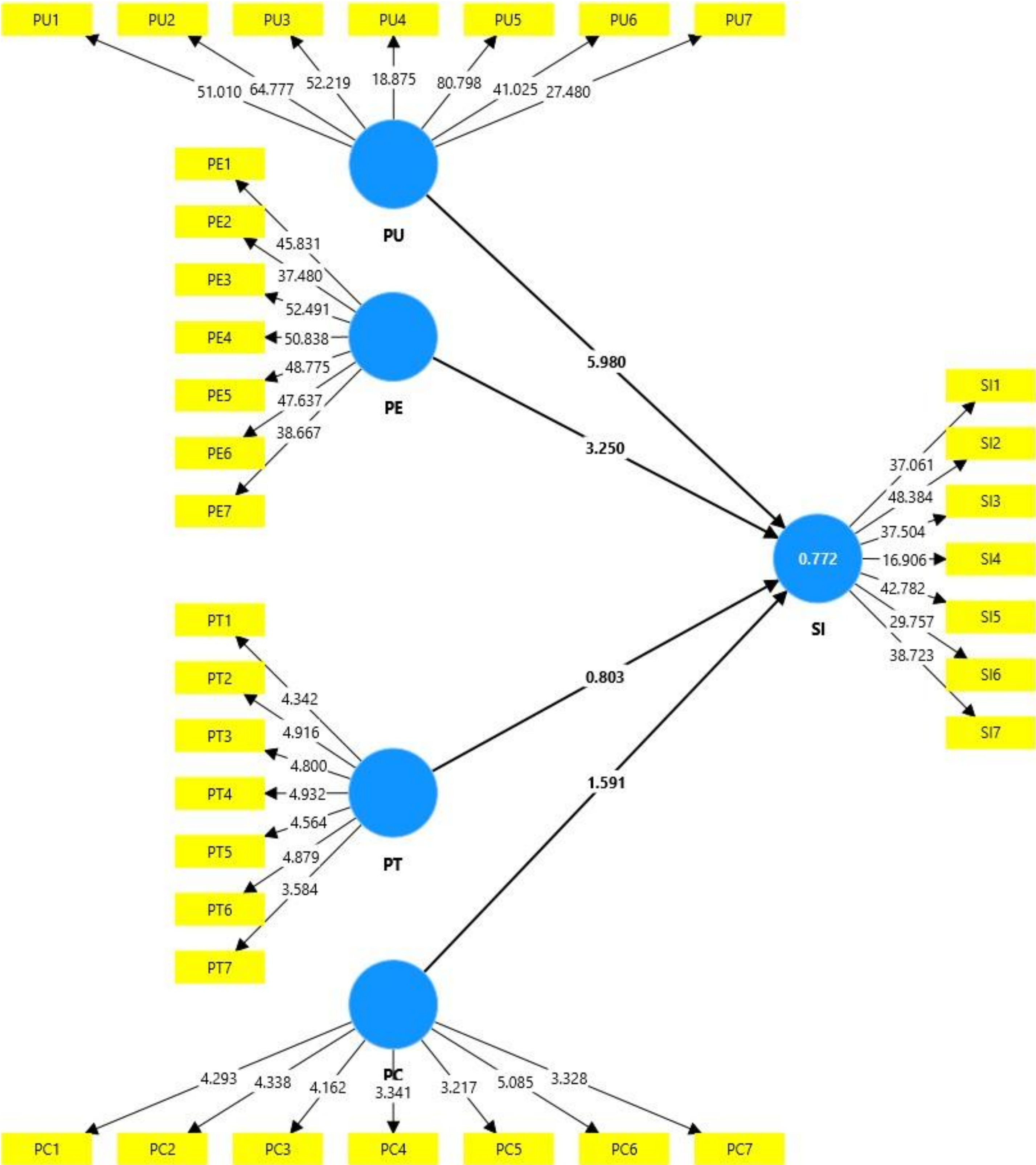

Figure 2: Model of PLS-SEM Path Analysis Diagram

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Table 10 below depicts that the explanatory power of students' intention is 77.2%, indicating that the model in this study explains the latent variables very well, and it has a high degree of explanatory power. The value of Q^2 obtained is 0.758 which is greater than zero, indicating that the model has predictive relevance for the endogenous construct. Thus, the structural model can provide a prediction of the endogenous latent variable indicators.

Table 10: Coefficient of Determination and Predictive Relevance

	R^2	Q^2
SI	0.772	0.758

The last step in evaluating structural equation modeling is assessing the model's out-of-sample predictive power using the PLSpredict procedure. If the PLS-SEM error is lower than the linear regression error, the PLS-SEM model demonstrates better predictive performance. Table 11 illustrates the values of prediction error metrics (RMSE and MAE) for both PLS-SEM model and linear regression benchmark.

Table 11: Prediction Error of PLS-SEM Model and Linear Regression Benchmark

	Q^2 Predict	PLS-SEM RMSE	PLS-SEM MAE	LM RMSE	LM MAE
SI1	0.562	0.899	0.667	0.954	0.725
SI2	0.583	0.869	0.632	1.018	0.743
SI3	0.610	0.812	0.611	0.870	0.639
SI4	0.281	1.418	1.102	1.621	1.204
SI5	0.515	1.046	0.797	1.153	0.866
SI6	0.488	1.040	0.747	1.169	0.848
SI7	0.668	0.825	0.608	0.891	0.635

The PLSpredict results indicate that the PLS-SEM model has strong out-of-sample predictive power. Most indicators related to Students' Intention (SI1, SI2, SI3, SI5, SI6, SI7) showed high predictive relevance, with Q^2 values exceeding 0.35. One item, SI4, has a Q^2 value of 0.281, indicating only moderate predictive relevance.

When compared with a linear regression benchmark, the PLS-SEM model consistently produced lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values across most indicators. This demonstrates better predictive accuracy. For example, SI1 has lower RMSE (0.899) and MAE (0.667) in the PLS-SEM model compared to linear regression (RMSE = 0.954, MAE = 0.725). Similar trends are observed for SI2 through SI7. However, SI4 showed relatively higher error values, suggesting it is more difficult to predict accurately.

Overall, the findings confirm that the PLS-SEM model outperforms linear regression in predictive accuracy, with strong Q^2 values and lower error metrics. Nonetheless, the weaker performance of SI4 highlights the need for further refinement in the model.

CONCLUSION

This study explores the intention of using artificial intelligence (AI) in academic writing among UiTM Kota Bharu students by focusing on factors derived from the Value-Based Adoption Model (VAM). The analyses of reliability and validity tests which include investigating the values of factor loading, Cronbach's alpha, composite reliability and AVE of each item indicate that the measurement model has acceptable indicator reliability, internal consistency and convergent validity. Furthermore, the result of discriminant validity test using the Fornell-Larcker criterion concludes that the model achieves good discriminant validity. In addition, bootstrapping performed to test the HTMT significance also indicated that discriminant validity is still acceptable despite a high HTMT value. The study also found that there is moderate collinearity between the research facets, but it is still appropriate to evaluate the structural model. The R^2 and Q^2 values prove that the model has a high degree of explanatory power and predictive relevance for the endogenous construct. Overall, the model in this study is not sufficiently well-fitted.

It can be seen from the path relationship of the model that perceived usefulness and perceived enjoyment significantly influence students' intention to use AI applications in academic writing ($p < 0.01$ and $t > 2.576$). This highlights the importance of tools that not only improves productivity and writing quality but also creates engaging and satisfying user experiences. On the other hand, perceived technicality and perceived cost do not significantly influence students' intentions to use AI applications in academic writing ($p > 0.05$ and $t < 1.96$). This shows that while complexity and expenditure are issues, they do not outweigh the perceived benefits for the majority of students. These findings are similar to a study conducted by Shelvia et al. (2020) that applied multiple linear regression analysis and found perceived benefits (perceived usefulness and perceived enjoyment) have a positive effect on customers' continuance intention to use mobile payments, while perceived sacrifice (perceived cost and perceived risk) has a negative effect on customers' ongoing intention to use mobile payments. The Value-Based Adoption Model (VAM) has effectively explained user acceptance, with enjoyment as the strongest predictor of purchase intention, followed by subjective norms (Sohn & Kwon, 2020). Mahmud et al. (2024) also asserted that perceived usefulness, enjoyment, social influence, self-efficacy, and personal innovativeness significantly influence students' attitudes toward using ChatGPT as a learning tool. Research by Rruplli et al. (2024) also supported that perceived usefulness remains the most significant factor, particularly in the context of technology adoption and online interactions, since AI analysis assigns greater importance to cost and less to enjoyment than human evaluations. These findings suggest that students may prioritize affordability and practicality more than previously understood. Therefore, the VAM should be adjusted to reflect varying weights among factors, enabling educators and developers to better address student concerns and enhance AI adoption.

Moreover, the results of the prediction error metrics demonstrate that the PLS-SEM model consistently has lower RMSE and MAE values compared to the linear regression model for all indicators. Thus, it confirms that the PLS-SEM model provides better predictive accuracy than a simple linear regression approach. These results are also in line with previous research, where Hair and Alamer (2022) found that the PLS model outperforms the naïve LM benchmark in predicting outcome variables, with lower RMSE in all indicators.

In conclusion, these findings suggest that educational institutions must focus on improving knowledge of the practical benefits of AI in academic writing while also addressing students' concerns about complexity and expense. By providing training programs and promoting ethical principles, institutions can boost students' confidence and skills in using AI appropriately. As AI advances, future study should look into its larger implications for students' learning experiences, especially its effects on creativity, critical thinking, and academic integrity. The research provides the basis for understanding the factors that influence the use of AI in education and focuses on the potential of these technologies to help students achieve academic achievement.

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