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Factors Influencing the Adoption of AI Chatbots among TVET University Students

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Abstract

The growing use of artificial intelligence (AI) chatbots in higher education has transformed how students access information and support learning activities. However, empirical understanding of the factors influencing actual AI chatbot usage remains limited, particularly in the Malaysian TVET context. This study examines the adoption and usage patterns of AI chatbots among undergraduate students and identifies the factors with the strongest importance and performance in influencing actual usage. A quantitative survey was conducted among 310 undergraduate students from multiple faculties at Universiti Tun Hussein Onn Malaysia. Stratified probability sampling was applied to ensure faculty representation, while G*Power analysis indicated a minimum sample requirement of 146 respondents. Data were collected using a structured questionnaire comprising demographic items and construct measures based on a five-point Likert scale. A pilot test was conducted to refine the instrument before data collection. The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess the measurement and structural models, followed by Importance–Performance Map Analysis (IPMA), Necessary Condition Analysis (NCA), and combined IPMA (cIPMA) to identify key drivers and bottlenecks of actual usage. The findings show frequent AI chatbot use, with ChatGPT as the most preferred platform. Intention to use AI chatbots emerged as the strongest predictor of actual usage, while technological literacy, perceived usefulness, and self-directed learning with technology significantly influenced intention. Subjective norms and perceived ease of use were insignificant direct predictors of intention. The study highlights the need for structured AI literacy and guided learning activities to support effective chatbot adoption.

1. Introduction

In recent years, advancements in global science and technology have driven significant progress in artificial intelligence (AI), enabling its widespread application across multiple industries, including education (Huang *et al.*, 2021). AI is transforming the landscape of learning and teaching by enabling it to provide each learner with an individualized learning experience, as AI has the capacity to undertake tasks that would otherwise require human judgment, such as language comprehension, pattern recognition, and data analysis (Rizvi, 2023). In education, AI chatbots are commonly adopted as tools to enhance learning and student support (Korda *et al.*, 2024; Okonkwo & Ade-Ibijola, 2021). These chatbots mimic human communication by using machine learning techniques and natural language processing (Suleiman *et al.*, 2025), with examples including ChatGPT, DALL-E,

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Gemini, and Copilot (Fang *et al.*, 2025). By providing rapid and personalized responses, chatbots enable students to receive immediate assistance and tailored learning support, and they are increasingly being explored by educators to enhance engagement and understanding in digital learning environments (Ahmad *et al.*, 2025; Wang & Jiang, 2025). The use of AI in education is becoming increasingly acknowledged as a valuable strategy for enhancing research and learning opportunities, enabling students to study more efficiently, make informed decisions, and benefit from personalized teaching strategies (Gavira & Jiménez-Preciado, 2025; Karan & Chakma, 2025). Many higher education institutions have adopted an AI chatbot service to improve student services and educational effectiveness; however, despite their growing importance in the Fourth Industrial Revolution, Malaysian higher education institutions (HEIs) remain hesitant to fully implement AI chatbots for virtual student services, indicating that adoption is still at an early stage (Ahmad *et al.*, 2025; Rahim *et al.*, 2022; Perera & Uduwela, 2024). Although awareness of AI chatbots has increased, research on students' behavioral intention, beliefs, and motivations for using them in education remains limited, with most studies focusing on service-industry applications (Bilquise *et al.*, 2024). Furthermore, while AI chatbots offer automated feedback, real-time support, and individual learning experiences, the influence of subjective norms, such as peers, lecturers, and institutional support, and the role of technological literacy in shaping students' readiness to adopt AI chatbots for academic purposes, have not been sufficiently explored (Rahman *et al.*, 2025). With the integration of AI technology within the educational scene, concerns have arisen regarding bias, privacy, academic honesty, and overdependence on technology, creating potential threats within the educational context itself (Mohammad *et al.*, 2025). A survey carried out among Universiti Teknologi MARA (UITM) Melaka students, the result showed that 54.8% out of 228 students did not have much confidence regarding the application of AI technology within the protection of personal information (Mohsin *et al.*, 2024). These concerns contribute to students' anxiety regarding the sharing and use of personal data when engaging in AI technologies, particularly due to fears over privacy and security (Chan & Hu, 2023).

Another concern related to the application of AI chatbots in education is the quality and accuracy of the information presented by systems, as these systems may generate biased or erroneous outputs (Jasman *et al.*, 2024; Noordin & Nazarudin, 2024). It is important to have accurate information in decision-making when using AI to avoid misunderstandings in the learning process for the students (Noordin & Nazarudin, 2024). The widespread availability of AI-generated information has created challenges for academic institutions, particularly in relation to cheating and plagiarism facilitated by chatbots. Such practices raise concerns about the reliability of students' work and may negatively affect students' creativity and critical thinking capacities when chatbots are used to generate ideas instead of relying on their own abilities (Mokhtar *et al.*, 2024). Additionally, the unsupervised usage of AI chatbots may impede the growth of critical thinking, problem-solving, and human communication abilities. AI-driven chatbots have become effective tools for supporting student learning by providing timely feedback and assisting with information retrieval through the inclusion of AI in education. Higher education institutions, including Universiti Tun Hussein Onn Malaysia (UTHM), are increasingly interested in adopting flexible and personalized technologies to enhance learning outcomes in response to growing demands for individualized learning support. However, despite these technological advancements, many students are still facing challenges with academic engagement, motivation, and getting assistance outside the classroom. Although AI chatbots have potential for enhancing learning, their effectiveness in improving academic outcomes and their level of adoption among UTHM students remain uncertain. The limited empirical research in Malaysian technical universities reveals a gap in understanding chatbot acceptance and impact on academic performance, making it important for educators, system developers, and policymakers to address this issue to optimize chatbot integration in higher education learning environments. The study aims to examine the level of adoption and usage patterns of AI chatbots among TVET University students and to determine the factors that have the highest importance and performance on actual AI chatbot usage among TVET University students.

2. Literature Review

2.1 Actual AI Chatbot Usage

Artificial intelligence chatbots are computer programs that communicate with users using natural language, including applications such as chatterbots, virtual agents, dialogue systems, and conversational systems (Ndunagu *et al.*, 2022). Rapid evolution of AI chatbots has made them essential across various sectors, particularly in education, where they facilitate real-time communication and provide personalized support and information, thereby serving as transformative tools in the educational environment (Wang & Jiang, 2025). AI chatbots are increasingly transforming educational practices in higher education by providing personalized learning experiences, enhancing student engagement, and delivering immediate responses to inquirie (Rahman *et al.*, 2025). Scholarly studies have highlighted the growing role of chatbots in improving user engagement and

efficiency, with AI-driven chatbots demonstrating greater potential than rule-based systems in understanding context and producing accurate responses (Adamopoulou & Moussiades, 2020). In educational settings, AI chatbots are widely adopted to support learning, manage administrative tasks, and provide academic assistance, functioning as virtual learning assistants that offer immediate feedback, reminders, and personalized study strategies. They are also perceived by students as motivating tools that enhance self-regulated learning (Winkler & Soellner, 2018).

2.2 Technology Acceptance Model (TAM)

According to Davis (1989), Technology Acceptance Model (TAM) is used to explain the users' decisions to accept or reject new technologies. TAM consists of two major perceptions that determine how much they accept information systems, which are perceived usefulness and perceived ease of use (Algerafi *et al.*, 2023). TAM is a well-established paradigm assessing technology use in educational settings and has been widely used in the field to forecast technology adoption among educators and students in a variety situation, such as Personal Learning Environments (PLE) and mobile learning (Roca *et al.*, 2024). TAM has been widely used to investigate how students feel about AI-based learning resources, especially chatbots. Perceived usefulness is a key factor in promoting student acceptance of AI chatbots. When students believe that these technologies improve academic achievement, increase learning efficiency, and offer academic help, they are more inclined to use them (Alshurideh *et al.*, 2024; Dahri *et al.*, 2024; Zogheib & Zogheib, 2024). Hence, TAM provides a straightforward and widely applicable framework for understanding why students adopt or reject AI chatbots in educational settings.

2.3 Theory of Planned Behaviour (TPB)

Ajzen (1991) proposed the Theory of Planned Behavior (TPB). According to TPB, the core components that influence behavioral intention are attitude, subjective norms, and perceived behavioral control (Ahadzadeh *et al.*, 2024). TPB is a prominent approach for predicting behaviors and analyzing them in various settings, providing a clear understanding of human decision methods (Chukwuere, 2024). TPB was employed by a study conducted by Ivanov *et al.* (2024) to examine how individuals perceive the risk potential, benefits, and disadvantages of using Generative AI Tools to influence individuals' attitudes toward subjective norms and perceived behavioral control. According to the findings, the perceived benefits and advantages positively impact these TPB components, ultimately determining individuals' intentions regarding the use of Generative Artificial Intelligence Technology. To Summarize: TPB is a prominent approach for analyzing human behaviors driven by several social, psychological phenomena surrounding personal attitudes, peer influence, perceived behavioral control, that impact college students' intention choices for using chatbots in Artificial Intelligence systems.

2.4 Factor Impact on Actual AI Chatbot Usage

2.4.1 Technology Literacy (TL)

Technological literacy refers to "the ability to effectively use technology to acquire, evaluate, integrate, create, and communicate information to enhance the learning process through problem solving and critical thinking" (Nes *et al.*, 2021). Technological literacy shows a significant positive correlation with students' willingness to utilize AI chatbots. Higher-tech skills increase the likelihood that students will adopt positive attitudes toward the use of AI in higher education. Individuals with advanced technological skills are more likely to interact with AI chatbots (Rahman *et al.*, 2025). Therefore, Hypothesis H1 is suggested.

H1: Tech literacy has a positive direct impact on intention to use AI chatbots.

2.4.2 Subjective Norms (SN)

Subjective norms refer to "people's opinions and attitudes toward their social circle, including friends, family members, and peers". These beliefs on how people behave and are essential to the development of behavioral intentions (Algerafi *et al.*, 2023). Previous research has indicated that subjective norms significantly influence people's intentions to use technology (Sungur-Gül & Ateş, 2021). A study from Moradi (2025) discussing the intention to use an AI chatbot was positively impacted by subjective criteria. It suggests that students' intentions to use ChatGPT are greatly influenced by peers' and lecturers' opinions of the tool's capacity to improve language skills. Therefore, Hypothesis H2 is suggested.

H2: Subjective norms have a positive direct impact on intention to use AI chatbots.

2.4.3 Perceived Ease of Use (PEU)

Perceived ease of use is one of the main elements of TAM, which recognizes that a system's learning and usage features have a big impact on technology acceptance and deployment (Rahman *et al.*, 2025). According to El-Sisi (2025), ease of use is the simplicity with which a tool or system can be operated, effectively reducing the effort required by the user. Ease of use pertains to characteristics of the chatbot system that offer a user-friendly environment and an intuitive interface. These characteristics facilitate seamless interactions and enable users to complete tasks efficiently, with minimal cognitive effort and time expenditure (Bilquise *et al.*, 2024). People's intention to utilize AI chatbots is positively impacted by their ease of usage (Almogren *et al.*, 2024; Alshurideh *et al.*, 2024). This result is consistent with the TAM, which suggests that people are more likely to plan to use something if it is user-friendly. A previous study found that students' opinions of the ease of use of chatbots affected their belief that these tools could effectively address their needs. If students perceive chatbots are user-friendly, they are more likely to consider them favorable and helpful to their educational experiences. Based on the above reasons, Hypotheses H3 and H4 are proposed.

H3: Perceived ease of use has a positive direct impact on perceived usefulness.
H4: Perceived ease of use has a positive direct impact on intention to use AI chatbots.

2.4.4 Perceived Usefulness (PU)

Perceived usefulness is another element of TAM, which implies that users' perceptions of a technology's actual use and effectiveness determine whether they adopt it (Rahman *et al.*, 2025). It refers to "the degree to which a person believes that using a particular system would enhance his/her job performance." (Al-Sharafi *et al.*, 2023). An individual's willingness to engage with technology greatly improves when they come to believe in the perceived utility of a specific technology and that it aligns with their personal beliefs (Algerafi *et al.*, 2023). Individuals' perceptions of the utility of chatbots are directly linked to their willingness to use these technologies (Kampa, 2023; Pillai *et al.*, 2024). Past studies indicate that perceived usefulness was the factor that most strongly influenced users' intention to adopt ChatGPT, which highlights the importance of this technology as a tool for students to achieve their learning goals (Alshammari & Babu, 2025). The result is particularly important to the learning field since recognizing the academic use of ChatGPT may positively affect learners' perceptions of its role as an extra educational resource. Students who perceive ChatGPT as a beneficial tool to reach their educational goals are evidently more willing to use the tool. Based on the justification, hypothesis H5 is proposed.

H5: Perceived usefulness has a positive direct impact on intention to use AI chatbots.

2.4.5 Self-Directed Learning with Technology (SDLT)

Self-directed learning (SDL) refers to an essential skill whereby learners independently recognize their learning needs, set their objectives, choose their methods, and assess their results (Esiyok *et al.*, 2024). Prior studies indicate that ChatGPT supports multiple SDL components, including goal, setting, resource identification, learning execution, performance monitoring, and strategy evaluation (Lin, 2023). Giray *et al.* (2025) further found that ChatGPT most strongly facilitates intentional learning, where learners view experiences as opportunities for continuous knowledge acquisition, thereby enhancing the development of SDL. As a result, ChatGPT can be said to be an excellent instrument for fostering independent learning and continuous educational progression. Students, when interacting with chatbots, might leverage their proficiency in technology, based on self-directed learning, largely resulting in both their heightened intention to use these tools and actual usage behavior (Esiyok *et al.*, 2024). Therefore, hypotheses H6 and H7 are proposed.

H6: Self-directed learning with technology has a positive direct impact on intention to use AI chatbots.
H7: Self-directed learning with technology has a positive direct impact on actual AI chatbot usage.

2.4.6 Intention to Use AI Chatbot (IUAC)

Behavioral intention to use AI chatbots is a pivotal concern in the research field of AI chatbots, which has a significant influence on the deployment of such technology (Lin, 2024). Previous research by Emon *et al.* (2023); Zogheib & Zogheib, (2024), which explores the real use of ChatGPT, reveals a very strong positive correlation with behavioral intention. Hence, students who declare their intention to use ChatGPT are the ones who will most probably carry out its use. The result is to emphasize the importance of the creation of positive behavioral intentions as a necessary condition for the real participation of the tool. In addition, a previous study by Awal & Haque (2024) has already pointed out that the declaration of an intent to adopt an AI chatbot is the factor that most influences the actual use of the AI chatbot. Consequently, hypothesis H8 is introduced.

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H8: Intention to use AI chatbot has a positive direct impact on actual chatbot usage.

2.5 Conceptual Framework

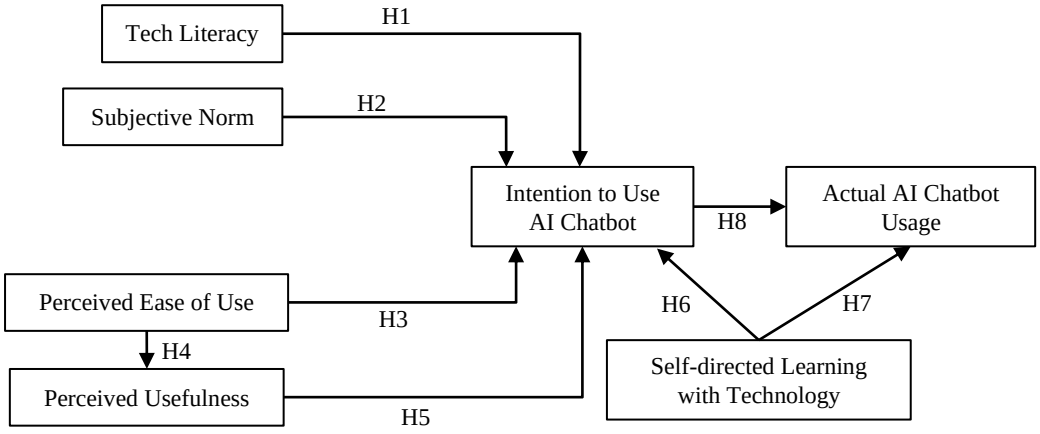

Fig. 1 *Research Framework*

3. Research Methodology

The research design is a plan that outlines the methods, procedures, and strategies utilized to collect and assess data to answer research questions or test hypotheses (Gamage, 2025). A quantitative method was used in this study to produce numerical data suitable for statistical analysis and to investigate the relationship between independent and dependent variables (Abuhamda *et al.*, 2021; Rahi, 2017). Quantitative research can be classified into experimental, correlational, descriptive, and causal-comparative designs. Structured questionnaires were distributed to a selected sample via surveys to describe the characteristics, attitudes, behaviors, or perspectives of a larger population (Ghanad, 2023). The quantitative data was obtained through structured instruments such as questionnaires to ensure the size of the samples was enough for a thorough understanding of the research questions (Dehalwar & Sharma, 2023). According to Ahmad *et al.* (2023), population is any group of people, things, or events that have similar characteristics and serve as the subject of study. The target population in this study consisted of 13,750 undergraduates from UTHM, representing various faculties on the campus in Parit Raja and Pagoh. The distribution of the population by faculty was shown in Table 2.

Table 1 *Population of TVET University Students*

Faculty	Population
Faculty of Civil Engineering and Built Environment (FKAAB)	1,677
Faculty of Electrical and Electronic Engineering (FKEE)	1,210
Faculty of Mechanical and Manufacturing Engineering (FKMP)	1,801
Faculty of Technology Management and Business (FPTP)	1,825
Faculty of Computer Science and Information Technology (FSKTM)	1,521
Faculty of Technical and Vocational Education (FPTV)	1,809
Faculty of Applied Sciences and Technology (FAST)	1,891
Faculty of Engineering Technology (FTK)	2,016

This study applied a probability sampling method, which was stratified sampling, to get representation. A probability sampling method gives all members of a population an equal probability of being selected, thus eliminating bias in the (Hossan *et al.*, 2023). The stratified sampling method was applied in the study by grouping the population into distinct subsets and then picking samples randomly (Ahmed, 2024). This study grouped the population according to faculty members, who were all given an equal chance of being selected as respondents. The sample size is determined by the population size and the required degree of precision (Mweshi & Sakyi, 2020). In this study, G*Power (version 3.1.9.4) was used for a pre-test power analysis to determine the minimum sample size required. The minimum required sample size was 146 students. To increase robustness and generalizability, this research collected data from 310 students of TVET University, which exceeds the minimum required sample size. A higher sample size will provide greater power within a statistical study to detect significant effects (Mohanasundaram & Harsha, 2024). The questionnaire separated into 8 sections. Section A consists of demographic information, as shown in the Appendix A. Sections B - H are questions for

independent variables and dependent variable, as shown in the Appendix B. This study applied nominal and ordinal levels of measurement, as presented in Appendix B. Nominal scales do not carry numerical value and cannot be used for mathematical operations, while ordinal scales indicate the order of variables rather than the magnitude of differences (Allanson & Notar, 2020). Hence, gender, race, faculty, type of AI chatbots commonly used, and the primary purpose of using AI chatbots in academic activities were measured using a nominal scale. Age, year of study, current CGPA, frequency of using AI chatbots, and independent and dependent variable constructs were measured using ordinal scales, as they involve ranked and Likert-type responses. Primary data is collected directly by the researcher (Mazhar, 2021). The primary data was collected through a questionnaire survey. According to Slater & Hasson (2024), questionnaire surveys have closed-ended questions with a predetermined list of possible answers. The questionnaire in this study included closed-ended questions with demographic profiling, multiple-choice options, and a 5-point Likert scale. Secondly, data refers to data that has already been collected and analyzed by others (Mazhar, 2021).

The pilot test is small-scale research used in perfecting research approaches, as well as the pretesting of research instruments to identify potential research issues in data gathering and implementation (Arifin *et al.*, 2022). The pilot test was conducted before the issuance of the questionnaire to ensure the questionnaire was clear, reliable, and relevant, to uncover potential technological problems, unclear instructions, or unclear wording. The clarity and consistency of the online questionnaire were refined based on the results of pilot testing. The compilation and analysis of results were done using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is a very useful and powerful approach for researchers aiming to analyze complex relationships existing within their data (Hair & Alamer, 2022).

4. Results and Discussion

4.1 Demographic Analysis

Table in Appendix D presents the profiles of the respondents. The distribution of gender was almost equal, with 50.3% male and 49.7% female, which reduced potential gender bias. Most respondents were Chinese (38.7%), followed by Malay (34.8%) and Indian (26.5%). Most students were aged 22–25 years (60.3%), and FPTP contributed the highest share of respondents (20.6%). Regarding academic performance, 41% of respondents had a CGPA between 3.51 and 4.00, while 19% were first-year students with a CGPA not yet applicable. Regarding AI chatbot usage, 41% used them often, and 31.3% used them always. ChatGPT (OpenAI) was the most popular (35.5%), followed by Microsoft Copilot (21.3%) and Google Gemini (17.1%). The main purposes for using AI chatbots were generating ideas for projects or research (29%), practicing language skills (21%), searching for academic information (20.3%), assisting in writing assignments (18.1%), and supporting coding tasks (11.6%).

4.2 Construct Reliability & Discriminant Validity

Indicator reliability determines the degree to which the latent constructs explain the variance for the indicators. Factor loadings greater than 0.70 are recommended, as they demonstrate that more than half the variance in the indicator is covered by the construction (Malik *et al.*, 2021; Shela *et al.*, 2023). According to the Table in Appendix F, all indicator loadings exceed 0.70, making them reliable for measuring their constructs. Internal consistency reliability assesses how consistently the indicators measure the same construct and is commonly evaluated using Cronbach's alpha (CA) and composite reliability (CR), which should be above 0.70 (Dolinting & Pang, 2022; Hair *et al.*, 2021). According to Table in Appendix F, it is visible that all the constructions have values for CR & CA above 0.70, meaning that there were adequate internal consistency and dependability. The Average Variance Extracted (AVE) with a threshold of 0.50 was used to test the convergent validity, which focuses on the correlation of indicators of a construct (Dolinting & Pang, 2022; Hair *et al.*, 2021; Subhaktiyasa, 2024). The value of the constructions was collectively above 0.50, indicating that there was convergent validity. Fornell-Larcker criterion and Heterotrait-Monotrait Ratio HTMT criterion have been employed to evaluate discriminant validity to ensure all constructs are unique and different. For Fornell-Larcker criterion, square roots of Average Variance Extracted should exceed values of their correlation, while values of HTMT ratios should not surpass 0.85 or 0.90 for constructs judged to have more discriminant validity (Hair *et al.*, 2021). As shown in Table 2, all constructions met these criteria, with AVE square roots exceeding the correlations while HTMT values less than 0.90, ensuring adequate validity of the discriminant.

Table 2: *Fornell-Larcker Criterion Heterotrait-Monotrait Ratio*

Fornell-Larcker Criterion							
Constructs	ACU	IUAC	PEU	PU	SDLT	SN	TL
ACU	0.805						
IUAC	0.753	0.809					
PEU	0.554	0.472	0.799				
PU	0.712	0.700	0.505	0.854			
SDLT	0.489	0.508	0.455	0.509	0.819		
SN	0.283	0.332	0.133	0.390	0.281	0.922	
TL	0.680	0.681	0.531	0.644	0.410	0.327	0.846
Heterotrait-Monotrait Ratio (HTMT)							
Constructs	ACU	IUAC	PEU	PU	SDLT	SN	TL
ACU	1						
IUAC	0.888	1					
PEU	0.704	0.614	1				
PU	0.817	0.822	0.633	1			
SDLT	0.572	0.61	0.585	0.590	1		
SN	0.312	0.375	0.182	0.429	0.324	1	
TL	0.779	0.798	0.666	0.734	0.475	0.359	1

4.3 Structural Model Assessment

For determining collinearity within the structural model, the Variance Inflation Factor (VIF) was used, and a value close to 3 or below indicates that there was no collinearity (Purwanto & Sudargini, 2021). As revealed by the results shown in Table 3, VIF values are below 3, and thus there are no collinearity issues. The coefficient of determination (R^2) measures how well the variance in the endogenous constructs can be explained by the exogenous construct (Zeng *et al.*, 2021). Most hypotheses, as presented in Table 3, have R^2 ranging between 0.582 and 0.601, meaning they have medium power of explanation, except for H4 that has 0.255, meaning that the power has weak explanation. Effect size (f^2) measures the effect of the independent variable on the dependent variable (Mansoori *et al.*, 2020; Subhaktiyasa, 2024). According to Table 3, IUAC → ACU (0.820) has a very large effect, PEU → PU (0.342) has a large effect, TL → IUAC (0.170) and PU → IUAC (0.162) have medium effects, SDLT → IUAC (0.041) and SDLT → ACU (0.037) have small effects, and SN → IUAC (0.001) and PEU → IUAC (0.001) have negligible effects.

The hypothesis of this study was assessed using the PLS Algorithm and the bootstrapping technique. The relationship between each variable is determined by p-values and path coefficients. The results were shown in Table 3. Hypothesis 1 was supported (β = 0.362, p-value = 0.002). It indicated that technologically competent students were more likely to use AI chatbots for academic purposes (Jang, 2024; Rahman, Hossain, *et al.*, 2025), as they were able to utilize AI tools in a way that was not only efficient but also led to better understanding (Pan *et al.*, 2025). Hypothesis 2 was rejected (β = 0.023, p-value = 0.250). It represented the students' decision to use the AI chatbot, which was not affected by the ideas, advice, and recommendations from the closest people, who think that they should use the chatbot (Rahim *et al.*, 2022; Pasindu Gayashan & Samarasinghe, 2024). Similarly, Hypothesis 3 was rejected (β = 0.020, p-value = 0.405). Even when the interface of AI chatbots was challenging, students continued to use AI chatbots, as they focused more on the usefulness of chatbots rather than ease of use (Falebita *et al.*, 2025; Ni & Cheung, 2023; Zogheib & Zogheib, 2024). Hypothesis 4 was supported (β = 0.505, p < 0.001). The finding indicated that if students perceive using AI chatbots to be easy, they can see value in using them for their educational pursuits (Ayanwale & Ndlovu, 2024; Chen *et al.*, 2025). Hypothesis 5 was supported (β = 0.369, p-value = 0.004). If students found AI chatbots helpful in their academic work, then they were more willing to use them (Achmadi *et al.*, 2025; Alshammari & Babu, 2025). Hypothesis 6 (β = 0.156, p-value = 0.032) and Hypothesis 7 (β = 0.144, p-value = 0.023) were supported. The students with greater self-directed learning are more capable of transitioning from intention to use. Also, in this regard, some studies reveal self-directed learning in students that facilitates their transition from intention to real-life usages (Esiyok *et al.*, 2024; Giray *et al.*, 2025). Hypothesis 8 was supported (β = 0.680, p < 0.001). The students who exhibit strong intentions to use AI chatbots were more prone to translating these intentions into actual use (Awal & Haque, 2024; Emon *et al.*, 2023).

Table 3:*Path Coefficient, Coefficient of determination (R^2), t value, and p-value*

Hypotheses	VIF	Path Coefficient (β)	Sample Means (M)	f^2	R^2	Adjusted R^2	T statistic	P values	Significance
H1 TL→IUAC	1.931	0.362	0.354	0.170	0.601	0.594	2.821	0.002	Significant
H2 SN→IUAC	1.230	0.023	0.020	0.001	0.601	0.594	0.675	0.250	Not Significant
H3 PEU→IUAC	1.613	0.020	0.034	0.001	0.601	0.594	2.631	0.405	Not Significant
H4 PEU → PU	1.000	0.505	0.502	0.342	0.255	0.253	5.248	0.000	Significant
H5 PU→IUAC	2.108	0.369	0.364	0.162	0.601	0.594	2.631	0.004	Significant
H6 SDLT→IUAC	1.478	0.156	0.158	0.041	0.601	0.594	1.996	0.032	Significant
H7 SDLT→ACU	1.347	0.144	0.144	0.037	0.582	0.579	0.675	0.023	Significant
H8 IUAC→ACU	1.347	0.680	0.679	0.820	0.582	0.579	10.246	0.000	Significant

4.4 Importance Performance Map Analysis (IPMA)

Importance Performance Map Analysis (IPMA) refers to an analytical technique that has improved the outcome generated by the estimated path coefficients (importance measure) with an extra dimension considering the average scores of the latent variable (performance) (Fakfare & Manosuthi, 2023). The IUAC indicators allocated in Q1 identify it as a primary driver with high performance (e.g., IUAC3 = 86.371, IUAC1 = 84.667). This indicates that students who would use AI chatbots are using them. The indicators for TL, PU, SDLT, and PEU were allocated in Q2. PEU indicators are positioned slightly apart from the other constructs. This suggests that while students still recognize AI chatbots as easy to use, PEU demonstrates strong performance; however, its relative influence on actual AI chatbot usage differs from that of TL, PU, and SDLT. The separation suggests that ease of use is well established and may no longer be a distinguishing factor in usage, as students are already familiar with and comfortable with AI chatbot technologies. The indicators for SN were positioned in Q3, indicating that SN had a minimal effect on students' intention to use AI chatbots and are perceived as weak. This suggests that students' adoption decisions are largely self-driven rather than influenced by peers or lecturers. Figure 2 illustrates the IPMA Chart.

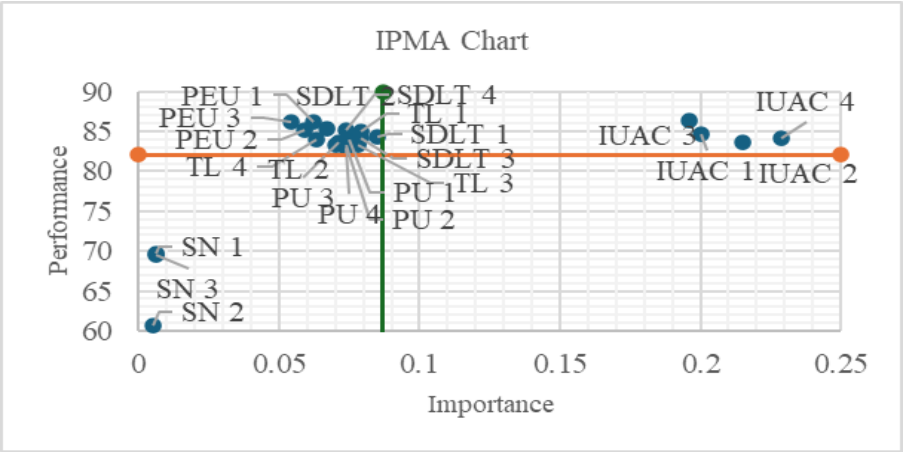

Fig. 2: *Importance Performance Map Analysis*

4.5 Necessary Condition Analysis (NCA)

Necessary Condition Analysis (NCA) identifies bottlenecks by examining the levels of factors necessary to reach a specified goal (Choi *et al.*, 2026). Effect sizes (d) were interpreted as small ($0 < d < 0.1$), medium ($0.1 \leq d < 0.3$), large ($0.3 \leq d < 0.5$), and very large ($d \geq 0.5$) (Troiville *et al.*, 2025). As shown in Table 4, PEU (d = 0.392) had a

large effect, IUAC (d = 0.203) and PU (d = 0.132) had medium effects, TL (d = 0.115) had a small effect, and SDLT (d = 0.067) and SN (d = 0.010) had negligible effects, indicating their relative necessity for ACU.

Table 4 *Necessary Condition Analysis Map*

Constructs	Actual AI Chatbots Usage	
	Effect size d	p-value
Tech Literacy (TL)	0.115	0
Subjective Norms (SN)	0.010	0.09
Perceived Ease of Use (PEU)	0.392	0
Perceived Usefulness (PU)	0.132	0
Self-directed Learning with Technology (SDLT)	0.067	0.007
Intention to use AI Chatbots (IUAC)	0.203	0

4.6 Combined Importance Performance Map Analysis (cIPMA)

The combined Importance Performance Map Analysis (cIPMA) further develops the traditional Importance Performance Map and includes the results obtained from NCA to emphasize important constructs and critical bottlenecks for achieving the desired outcome (Garg *et al.*, 2025). IUAC was allocated in Q1. This suggests that students with the intention of using AI chatbots were actively engaging with them in practice (Awal & Haque, 2024; Emon *et al.*, 2023). TL, PU, SDLT, and PEU were allocated in Q2, indicating that students performed well in these areas; however, they were not the primary drivers of actual AI chatbot usage. These factors supported usage, but improvements here were unlikely to significantly increase adoption, as students were already competent and comfortable with technology. SN was positioned in Q3 with low importance and low performance. This prioritizes functional aspects such as efficiency, speed, and task completion over social expectations. AI chatbots were largely goal-oriented and user-centric, where decisions were based on individual interaction with the technology rather than social influence. Consequently, social norms became less relevant in determining the adoption of AI chatbots (Rahman *et al.*, 2025).

Table 5 *Combined Importance Performance Map Analysis*

Constructs	Effect Size	Necessary Condition 85%	Importance	Performance	Permutation p-value
TL	0.115	6.452	0.246	83.877	0
SN	0.01	0	0.016	67.301	0.09
PEU	0.392	2.903	0.140	85.839	0
PU	0.132	3.548	0.251	83.476	0
SDLT	0.067	1.935	0.250	84.725	0.007
IUAC	0.203	5.484	0.680	84.659	0

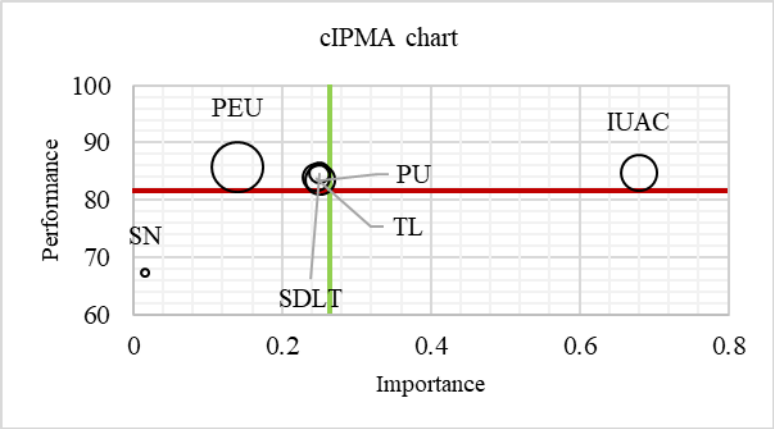

Fig. 3 *Combined Importance Performance Map Analysis*

The findings indicate a high level of adoption and frequent usage of AI chatbots among TVET University students, with 41.0% of respondents reporting frequent use and 31.3% indicating that they always use AI chatbots. This suggests that AI chatbots have become an integral part of students' academic routines rather than tools used only occasionally. Similar trends have been reported in previous studies, which have found that university students are increasingly relying on AI chatbots to support their learning activities and academic performance (Lutfi *et al.*, 2025).

Among the various platforms, ChatGPT (OpenAI) emerged as the most used AI chatbot, accounting for 35.5%, followed by Microsoft Copilot at 21.3% and Google Gemini at 17.1%. The preference for ChatGPT among UTHM students aligns with its global popularity and rapid adoption. Its high-quality and versatile responses, combined with the ability to retain contextual information from previous interactions and its early market presence, contribute to its perceived usefulness and ease of use (Stöhr *et al.*, 2024). Students use AI chatbots in academic activities primarily to generate ideas for projects or research (29.0%), practice language or communication skills (21.0%), search for academic information or explanations (20.3%), assist in writing assignments or reports (18.1%), and support coding or technical tasks (11.6%). These uses reflect the role of chatbots in facilitating information retrieval, idea generation, language practice, academic writing support, and technical problem-solving in higher education (Morell-Mengual *et al.*, 2025; Stoyanova *et al.*, 2025; Wiboolyasarin *et al.*, 2025). According to the results in Table 6 and Figure 3, the analysis revealed that intention to use AI chatbots (IUAC) was positioned in Q1 with the highest importance score (0.68). This means that it was the critical driver of actual AI chatbot usage, confirming the study objective of identifying the factor with the highest impact. These results aligned with previous studies highlight that behavioral intention is a strong predictor of technology adoption in an educational context (Awal & Haque, 2024; Emon *et al.*, 2023). Additionally, perceived ease of use (PEU) is positioned in Q2 with the highest performance score (85.839). This indicates that students found the use of AI chatbot easy; however, this perception does not encourage them to use the AI chatbots (Falebita *et al.*, 2025).

Table 6 *Implication of this study.*

Type	Best Implication
Theoretical Implication	The study reinforces behavioral intention as the central mechanism explaining actual AI chatbot usage. The strong relationship between intention to use AI chatbots and actual usage (β = 0.680) supports the proposition that students' intention is the most important predictor of actual technology-use behaviour in the TVET higher-education context.
Practical Implication	Universities should prioritize strengthening students' intention to use AI chatbots through structured AI literacy and guided learning activities. Since intention to use is the strongest predictor of actual usage, institutions should focus on improving students' confidence, technological literacy, understanding of AI usefulness, and meaningful integration of AI chatbots into academic learning.

Table 7 *Summary of Research Findings*

Research Objective	Dimension	Questionnaire Grating	Frequency	Relative Frequency (%)	Objective Statues
RO 1	Frequency of using AI Chatbots	Rarely	29	9.4	Achieved
		Sometimes	57	18.4	
		Often	127	41.0	
		Always	97	31.3	
	Type of AI Chatbots Most Used	ChatGPT (OpenAI)	110	35.5	
		Google Gemini	53	17.1	
		Microsoft Copilot	66	21.3	
		DeepSeek	51	16.1	
		Perplexity	31	10.0	
	Primary purpose of using AI chatbots in academic activities	To search for academic information or explanations	63	20.3	
		To assist in writing assignments or reports	56	18.1	
		To generate ideas for projects or research	90	29.0	
		To practice language or communication skills	65	21.0	
		To assist with coding or technical tasks	36	11.6	

Research Objective	Constructs	Effect Size	Necessary Condition	Importance	Performance	Permutation p-value	Objective Statues
RO 2	TL	0.115	6.452	0.246	83.877	0	Achieved
	SN	0.010	0	0.016	67.301	0.090	
	PEU	0.392	2.903	0.140	85.839	0	

PU	0.132	3.548	0.251	83.476	0
SDLT	0.067	1.935	0.250	84.725	0.007
IUAC	0.203	5.484	0.680	84.659	0

This study was conducted among undergraduate students at TVET University; therefore, the findings may not be applicable to students in other higher education institutions, including postgraduate students. Additionally, this study utilized self-administered questionnaires, as the results depend on the respondents' opinions. This could lead to response bias as respondents may overestimate or underestimate their usage of AI chatbots. This study employed quantitative methods. Since the research methodology only permits respondents to answer sections of the questionnaire that address specific viewpoints, the findings may be limited to the scope of the questionnaire content. Future studies are encouraged to sample a wide range of students at different academic levels and universities and adopt a longitudinal study design to examine changes in students' intentions and actual AI chatbot use over time. The use of qualitative or mixed-method approaches is recommended to gain deeper insights. In addition, universities are encouraged to promote training in AI and digital skills, offering instructional courses and providing on-site campus technical support to enhance students' confidence and ability to use AI chatbots within learning environments (Rahman *et al.*, 2025). Educators can also integrate AI chatbots into teaching to provide personalized support, customized content, or tailored learning experiences to enable students to perceive AI chatbots as beneficial in their academic activities (Labadze *et al.*, 2023). Additionally, developers of AI chatbots can increase the accuracy of data by providing evidence-based responses (McLean & Hristidis, 2025).

5. Conclusion

This study examine the adoption levels and usage patterns of AI chatbots among TVET University students and to determine the factors that have the highest importance and performance among these students. Data was collected via a questionnaire survey among 310 students, and PLS-SEM, IPMA, NCA, and cIPMA were utilized to analyze the data. The findings showed a high level of adoption of AI chatbots among students at UTHM, specifically to generate ideas, learn languages, and carry out academic research. Additionally, factors affecting the use of AI chatbots include technological literacy, perceived usefulness, self-directed learning with technology, and intention to use AI chatbots. The cIPMA results showed that perceived ease of use had the highest performance, and intention to use had the highest importance on actual usage. As part of this research, finding solutions for improving academic capacity and self-directed learning for personalized education and academic experiences through the optimal utilization of AI chatbots will help promote SGD4, focusing on "Quality Education.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: **study conception and design:** Teng Yi Xin, Nor Aziati **data collection:** Teng Yi Xin, Nor Aziati; **analysis and interpretation of results:** Teng Yi Xin, Nor Aziati, Che Muji **draft manuscript preparation:** Teng Yi Xin, Che Muji, All authors reviewed the results and approved the final version of the manuscript.

Appendix A: Demographic Information

Variable	Dimensions	Questionnaire Grating	Level of Measurement
Demographic	Gender	a. Male b. Female	Nominal
	Race	a. Malay b. Chinese c. Indian d. Other	Nominal
	Age	a. 18 - 21 years b. 22 – 25 years c. 26 – 29 years d. 30 and above	Ordinal
	Year of Study	a. 1st Years b. 2nd Years c. 3rd Years d. 4th Years	Ordinal
	Faculty	a. FKAAB b. FKEE c. FKMP d. FPTP e. FSKTM f. FPTV g. FTK h. FAST	Nominal
	Current CGPA	a. Not applicable (First-year student) b. Below 1.50 c. 1.51 – 2.00 d. 2.01 – 2.50 e. 2.51 – 3.00 f. 3.01 – 3.50 g. 3.51 – 4.00	Ordinal
	Frequency of using AI chatbots	a. Never b. Rarely c. Sometimes d. Often e. Always	Ordinal
	Type of AI chatbots most used	a. ChatGPT (OpenAI) b. Google Gemini c. Microsoft Copilot d. DeepSeek e. Perplexity	Nominal
	Primary purpose of using AI chatbots in academic activities	a. To search for academic information or explanations b. To assist in writing assignments or reports c. To generate ideas for projects or research d. To practice language or communication skills e. To assist with coding or technical task	Nominal

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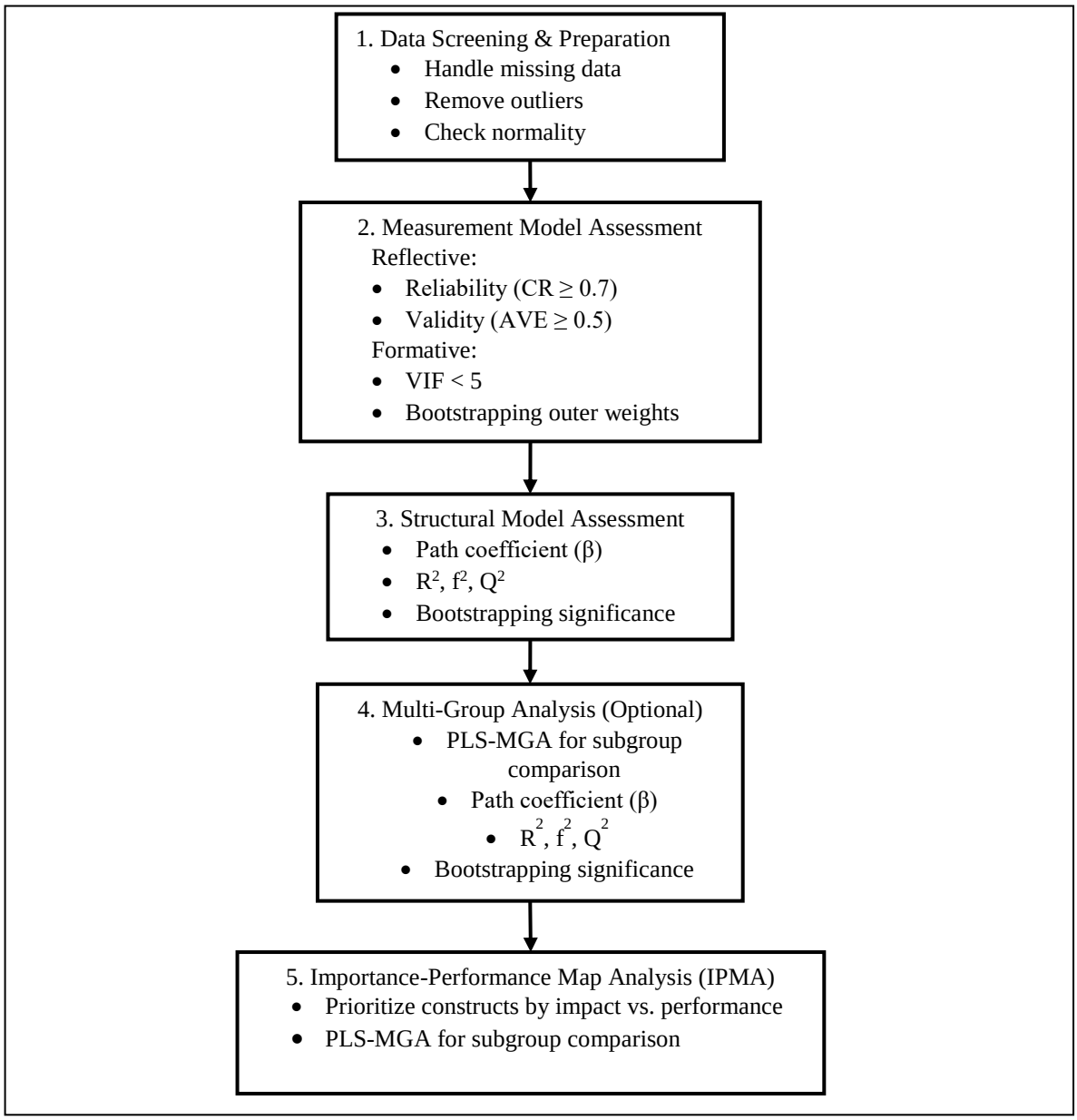
Appendix B: Measurement Scale

Constructs	Position in the Model	Indicator	Adapted from
Tech Literacy (TL)	Exogenous	TL 1: I understand how AI chatbots assist in learning. TL 2: I frequently use AI chatbots for my studies. TL 3: I feel comfortable using AI chatbot applications for academic purposes. TL 4: I can quickly learn how to use new AI chatbots without assistance.	Rahman, Hossain, *et al.* (2025)
Subjective Norm (SN)	Exogenous	SN 1: My classmates encouraged me to use AI chatbots for my studies. SN 2: My lecturers recommend using AI chatbots for learning. SN 3: Most students in my university use AI chatbots for academic purposes.	Rahman *et al.* (2025)
Perceived Ease of Use (PEU)	Exogenous	PEU 1: The interface of the AI chatbot is easy to understand. PEU 2: I find it easy to access and use the AI chatbots for my academic needs. PEU 3: The instructions provided by the AI chatbots are clear and easy.	Esiyok *et al.* (2024)
Perceived Usefulness (PU)	Exogenous	PU 1: Using AI chatbots improves my learning performance. PU 2: AI chatbots help me complete my learning tasks more efficiently. PU 3: AI chatbots save me time when searching for learning resources. PU 4: AI chatbots save me time by providing quick answers to my academic questions.	Rahman *et al.* (2025)
Self-directed Learning with Technology (SDLT)	Exogenous	SDLT 1: I find more information on the AI chatbots to help me better understand my lessons. SDLT 2: I utilize AI chatbots to access information for my learning purposes. SDLT 3: I use the computer to get ideas from different websites and people to learn more about a topic. SDLT 4: I use the AI chatbots to become better at a skill that I am interested in e.g., learn a language.	Esiyok *et al.* (2024)
Intention to use AI chatbots (IUAC)	Exogenous	IUAC 1: I plan to utilize AI chatbots in my learning activities. IUAC 2: I am likely to use AI chatbots to support my studies. IUAC 3: I plan to use AI chatbots regularly for academic purposes. IUAC 4: I will recommend AI chatbots to my classmates as a resource for learning assistance.	Rahman *et al.* (2025)
Actual AI chatbot usage (ACU)	Endogenous	ACU 1: I have started using AI chatbots for my learning activities. ACU 2: I frequently use AI chatbots to assist with my studies. ACU 3: I prefer AI chatbots over traditional learning support methods. ACU 4: I feel comfortable using AI chatbots for academic tasks. ACU 5: I believe AI chatbots improve my overall experience.	Rahman *et al.* (2025)

Appendix C: Process of PLS-SEM



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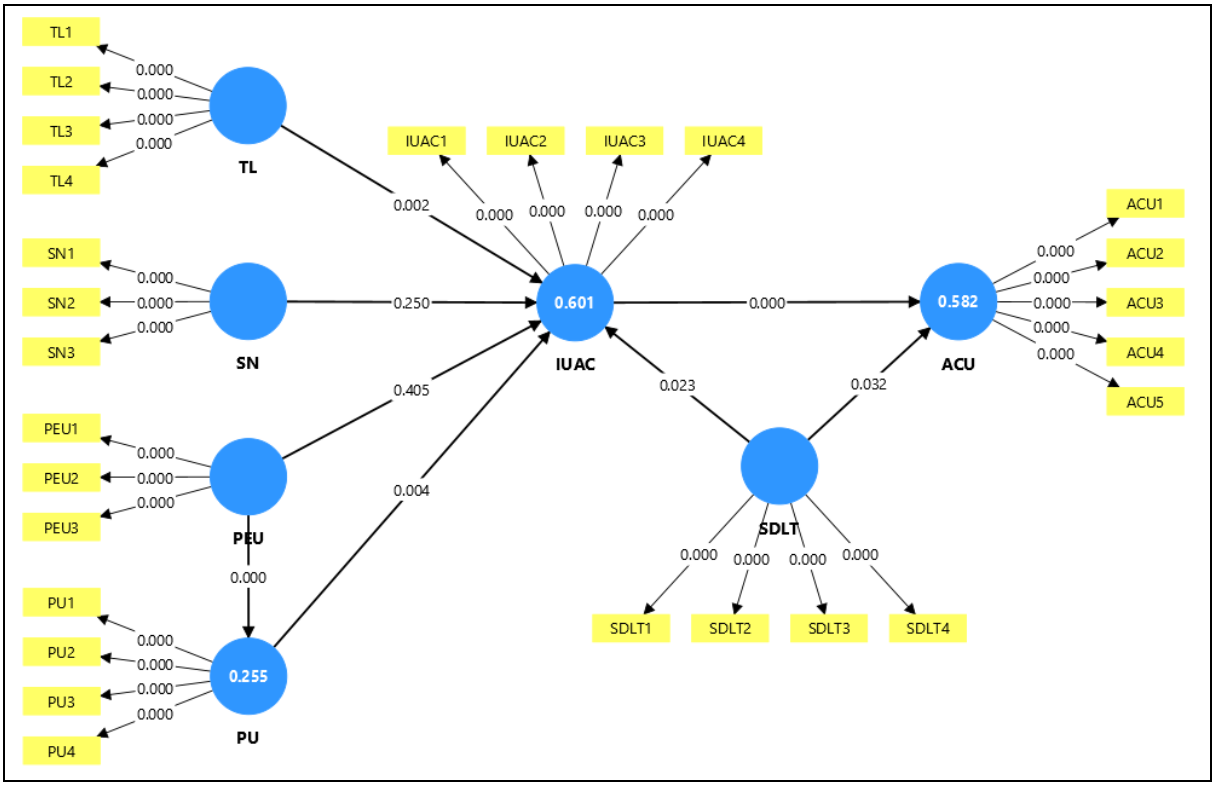
Appendix D: Summary of Respondents' Profile

Gender	**Frequency**	**Relative Frequency (%)**
Male	154	50.3
Female	156	49.7
Race	**Frequency**	**Relative Frequency (%)**
Malay	108	34.8
Chinese	120	38.7
Indian	82	26.5
Age	**Frequency**	**Relative Frequency (%)**
18 – 21 years	123	39.7
22 – 25 years	187	60.3
Year of Study	**Frequency**	**Relative Frequency (%)**
1st Years	57	19.3
2nd Years	66	22.4
3rd Years	80	27.1
4th Years	92	31.2
Faculty	**Frequency**	**Relative Frequency (%)**
FKAAB	33	10.6
FKEE	36	11.6
FKMP	43	13.9
FPTP	64	20.6
FSKTM	33	10.6
FPTV	40	12.9
FTK	33	10.6
FAST	28	9
Current CGPA	**Frequency**	**Relative Frequency (%)**
Not Applicable (First-year Student)	59	19
2.01 – 2.50	1	0.3
2.51 – 3.00	35	11.3
3.01 – 3.50	88	28.4
3.51 – 4.00	127	41
Frequency of using AI Chatbots	**Frequency**	**Relative Frequency (%)**
Rarely	29	9.4
Sometimes	57	18.4
Often	127	41
Always	97	31.3
Type of AI Chatbots Commonly Used	**Frequency**	**Relative Frequency (%)**
ChatGPT (Open AI)	110	35.5
Google Gemini	53	17.1
Microsoft Copilot	66	21.3
DeepSeek	51	16.1
Perplexity	31	10
Primary purpose of using AI chatbots in academic activities	**Frequency**	**Relative Frequency (%)**
To search for academic information or explanations	63	20.3
To assist in writing assignments or reports	56	18.1
To generate ideas for projects or research	90	29
To practice language or communication skills	65	21
To assist with coding or technical tasks	36	11.6

Appendix E: Outer Loadings, Cronbach's Alpha, Composite Reliability, rho_a, and AVE

Constructs	Items	Loadings	VIF	Cronbach's alpha	CR	rho_A	AVE
Tech Literacy	TL 1	0.869	2.241	0.868	0.910	0.875	0.716
	TL 2	0.846	2.119				
	TL 3	0.869	2.288				
	TL 4	0.799	1.820				
Subjective Norm	SN 1	0.949	4.250	0.912	0.944	0.939	0.850
	SN 2	0.869	2.387				
	SN 3	0.945	4.075				
Perceived Ease of Use	PEU 1	0.834	1.496	0.716	0.841	0.721	0.638
	PEU 2	0.794	1.381				
	PEU 3	0.766	1.364				
Perceived Usefulness	PU 1	0.850	2.101	0.876	0.915	0.877	0.729
	PU 2	0.851	2.124				
	PU 3	0.844	2.101				
	PU 4	0.872	2.391				
Self-directed Learning with Technology	SDLT 1	0.859	2.037	0.836	0.89	0.843	0.670
	SDLT 2	0.763	1.603				
	SDLT 3	0.826	1.843				
	SDLT 4	0.823	1.872				
Intention to Use AI Chatbot	IUAC 1	0.808	1.795	0.824	0.884	0.827	0.655
	IUAC 2	0.786	1.582				
	IUAC 3	0.808	1.804				
	IUAC 4	0.834	1.817				
Actual AI Chatbots Usage	ACU 1	0.822	1.996	0.864	0.902	0.865	0.647
	ACU 2	0.788	1.785				
	ACU 3	0.783	1.763				
	ACU 4	0.795	1.847				
	ACU 5	0.833	2.108				

Appendix F Path Coefficient



Appendix G Bottleneck Table – CE-FDH

	LV scores - ACU	LV scores - IUAC	LV scores - PEU	LV scores - PU	LV scores - SDLT	LV scores - SN	LV scores - TL
0.000%	9.769	0.000	0.000	0.000	0.000	0.000	0.000
5.000%	14.280	0.323	0.000	0.000	0.000	0.000	0.000
10.000%	18.792	0.323	0.000	0.000	0.000	0.000	0.000
15.000%	23.304	0.323	0.000	0.000	0.000	0.000	0.000
20.000%	27.815	0.323	0.000	0.000	0.000	0.000	0.000
25.000%	32.327	0.968	0.000	0.323	0.000	0.000	0.323
30.000%	36.838	0.968	1.935	0.323	0.000	0.000	0.323
35.000%	41.350	0.968	1.935	0.323	0.000	0.000	0.323
40.000%	45.861	0.968	1.935	0.323	0.000	0.000	0.323
45.000%	50.373	0.968	2.258	0.323	0.000	0.000	0.323
50.000%	54.884	0.968	2.258	0.323	0.000	0.000	0.323
55.000%	59.396	0.968	2.581	0.323	0.000	0.000	0.323
60.000%	63.908	0.968	2.581	0.323	0.000	0.000	0.323
65.000%	68.419	0.968	2.581	0.323	0.000	0.000	0.323
70.000%	72.931	0.968	2.581	0.323	0.000	0.000	0.323
75.000%	77.442	0.968	2.581	0.323	0.000	0.000	0.323
80.000%	81.954	4.516	2.581	3.548	0.000	0.000	1.613
85.000%	86.465	5.484	2.903	3.548	1.935	0.000	6.452
90.000%	90.977	8.387	2.903	6.129	5.806	0.000	6.452
95.000%	95.488	8.387	2.903	6.129	5.806	12.903	6.452
100.000%	100.000	8.387	2.903	6.129	5.806	12.903	6.452

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