Information Management and Business Review (ISSN 2220-3796)
Vol. 17, No. 3(S), pp. 184-194, 2025

Integrating Technology Acceptance Model and Task-Technology Fit Theory: Investigating Students' Intention to Use AI Chatbots in Public Universities

*Cheong Yew Ooi, Ali Vafaei-Zadeh
Graduate School of Business, Universiti Sains Malaysia, Minden, Penang, Malaysia
Email: *cyooi@student.usm.my, vafaei@usm.my
Corresponding Author: Cheong Yew Ooi

Abstract: Technology has significantly enhanced access to education, enabling students to benefit from lower costs and higher productivity. This advancement has been further expedited by the incorporation of AI, especially through applications like AI chatbots. Despite these advancements, students in higher education- especially those enrolled in public universities in developing countries- often exhibit skepticism toward adopting AI chatbots for academic assistance. Thus, the main goal of this study is to find out how students in public universities in developing nations plan to use AI chatbots as teaching aids. The study will use a purposive sampling strategy to gather data from students at different public universities, with a focus on Malaysia. To construct a robust conceptual model that explains students' behavioral intentions toward AI chatbot usage, this research adopts an integrated framework combining the Technology Acceptance Model (TAM) and the Task–Technology Fit (TTF) theory. For data analysis, the study will use the PLS-SEM approach, a well-regarded regression technique suitable for examining complex relationships in structural models. The research's conclusions are anticipated to provide theoretical and practical insights. This study may theoretically add to the body of knowledge on AI chatbot adoption by illuminating the complex human behaviors linked to the adoption of new technologies. Practically, the findings may give governments, university administrators, and AI chatbot developers important information on how to work together to create AI chatbots that are more dependable, user-friendly, and attractive to students, especially in developing countries.

Keywords: *AI Chatbots, Task-Technology Fit, Technology Acceptance Model, Students' Intention, Public Universities*

1. Introduction and Background

With AI-based chatbots emerging as game-changers in higher education, the 21st century has brought about a surge of technological innovation (Saihi et al., 2024). Conversational agents, sometimes referred to as chatbots, are popular across a variety of industries. Intelligent conversational agents are reshaping teaching and learning by delivering real-time feedback, personalized support, and automation of routine administrative tasks (Yang & Chen, 2023). Prior studies similarly report gains in learning effectiveness when students can reflect instantly and obtain just-in-time help (Ng'ambi et al., 2016; Khan & Jawaid, 2020). Universities worldwide already operate such systems at scale: Georgia Tech's "Jill Watson" functions as a virtual teaching assistant (Mello et al., 2023); Deakin University's "Deakin Genie" keeps students organized and connected to services; and Staffordshire University's "Beacon" offers tailored guidance (Monserrat et al., 2022; Saihi et al., 2024). Taken together, these cases illustrate how chatbots can enrich the student experience while streamlining institutional workflows.

The broader push to embed emerging technologies in higher education has accelerated the uptake of AI tools (Ayanwale, 2024). Chatbots such as ChatGPT, Siri, and Alexa and academic platforms like Paperpal and Elicit are changing how students research, write, and collaborate (Ayanwale & Ndlovu, 2024), with reported improvements in accessibility, engagement, and teamwork (Bilquise et al., 2024). AI chatbots offer 24/7 assistance, removing conventional time and place constraints for students in need of help (Kamalov et al., 2023). Personalization further strengthens learning by adapting materials, feedback, and pathways to individual needs (Chang et al., 2023). Beyond pedagogy, these systems also assume administrative workloads by answering routine queries and maintaining course data, so staff can allocate more time to curriculum design and mentoring (Ahmad et al., 2022). AI chatbots are able to simulate real-world situations and promote active student participation through conversational design and natural language processing, hence promoting interactive learning (Belda-Medina & Calvo-Ferrer, 2022).

Despite the enormous potential for AI-based chatbots to revolutionize higher education, there are significant

obstacles to their acceptability and deployment (Hwang & Chang, 2023). Student perceptions hinge on trust in AI, perceived usefulness and ease of use, data-privacy assurances, and concerns about the potential dehumanization of education (Robayo-Pinzon et al., 2023). Skepticism remains a notable barrier: some learners question chatbot competence for high-stakes academic tasks (Araujo, 2018), and resistance can be reinforced by mechanical dialogue and limited socio-emotional sensitivity (Rapp et al., 2021). Where students doubt a system's ability, they are less inclined to use it fully (Adam et al., 2021). Even so, well-designed chatbots can foster interaction by making it easier to ask questions and sustain topic-focused discussion, thereby supporting more student-centered learning (Yildiz Durak & Onan, 2024).

However, AI-powered chatbots are still not widely used in higher education, especially in developing nations like Malaysia. Despite their growing potential, widespread integration is yet to be realized. Several studies have explored students' intention to adopt AI-chatbots from diverse theoretical and contextual perspectives. For instance, Yang & Chen (2023) examined the adoption intention of pre-service teachers by focusing on the perceived success and usefulness of AI chatbots. Students from different academic areas were compared in order to determine whether or not they intended to use chatbot technology (Stöhr et al., 2024). Saihi et al. (2024) explored AI-Chatbot adoption intentions among both students and educators, emphasizing the role of positive values in shaping user attitudes. The Innovation Diffusion Theory was used by Ayanwale & Ndlovu (2024) to examine the variables affecting college students' adoption of chatbots. Further, Sun et al. (2025) investigated students' intentions to use ChatGPT using the Stimulus-Organism-Response (S-O-R) paradigm. In a different approach, Bilquise et al. (2024) analyzed the functional, socio-emotional, and relational antecedents that influence students' willingness to adopt advising chatbots. Despite these important contributions, no research has yet examined students' intentions to use AI-supported chatbots by integrating the TAM and TTF theories. Therefore, the present study aims to address this gap by examining the following research questions.
Q1: To what extent does Task–Technology Fit influence Perceived Usefulness and Perceived Ease of Use?
Q2: To what extent do Perceived Usefulness and Perceived Ease of Use influence the Intention to Use an AI Chatbot?

Thus, this research may be very valuable from a managerial and theoretical standpoint. Theoretically, it may seek to advance the understanding of students' behavioral intention to adopt AI-supported chatbots by applying an integrated framework that may combine the TAM and TTF theories. By doing this, it may add to the expanding body of research on the adoption of AI chatbots and provide new information about the variables influencing students' use of this cutting-edge technology. From a management perspective, the results may offer useful recommendations for policymakers, AI chatbot developers, and institutions of higher learning. Specifically, the study may shed light on how to design and implement AI-powered chatbots that are more need-based, user-centric, and aligned with students' academic tasks. These insights may inform strategies for enhancing user experience, increasing adoption rates, and integrating chatbots more effectively into educational ecosystems. Therefore, the contributions of this study will be twofold: enriching theoretical knowledge and offering actionable implications for stakeholders aiming to optimize AI chatbot deployment in higher education.

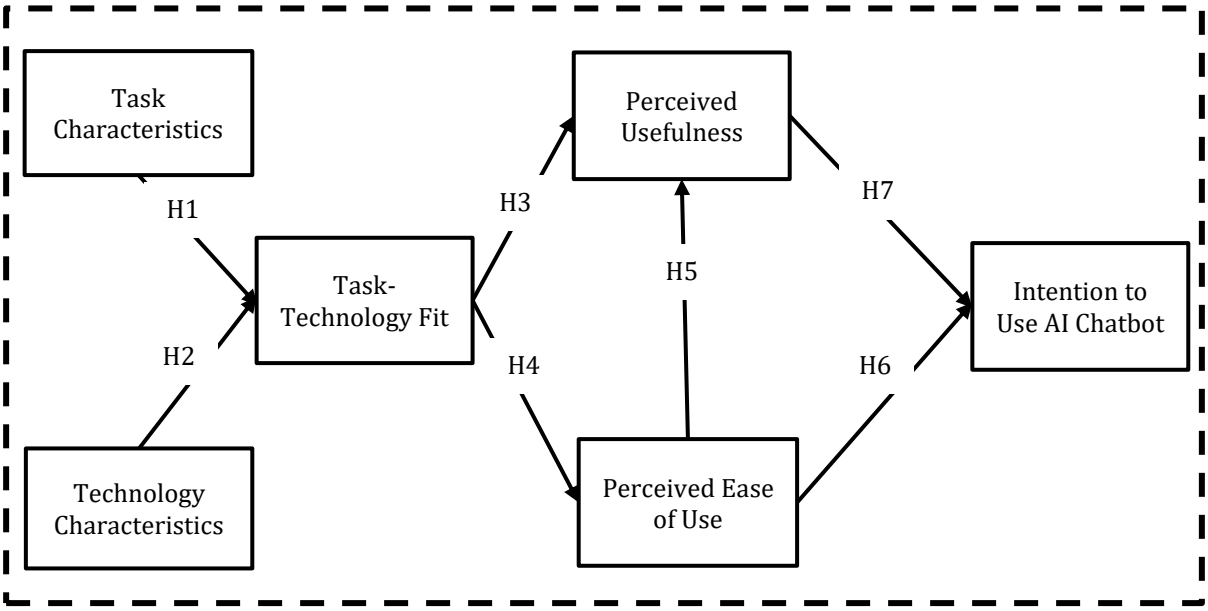
2. Literature Review

The Technology Acceptance Model (TAM) remains a mainstay for explaining and predicting consumer acceptance of information technology, which was originally developed by Davis in 1989. TAM posits that two beliefs, which are perceived usefulness (PU) and perceived ease of use (PEOU), shape users' intentions to adopt new systems, a relationship widely documented in the information systems literature (Bilquise et al., 2024). TAM has also been applied to AI chatbots, with studies reporting its value in modelling adoption intentions (Sánchez-Prieto et al., 2020; Gupta & Yadav, 2022). However, despite its strengths, TAM has been critiqued for its simplicity and limited scope. As Bagozzi (2007) argues, by focusing primarily on functional beliefs, TAM can understate the social, contextual, and affective complexities that accompany emerging technologies. To strengthen explanatory power, he recommends combining TAM with complementary theories. Following this logic, the present study integrates Task–Technology Fit (TTF) with TAM to develop a more comprehensive structural model (see Figure 1).

Introduced by Goodhue and Thompson (1995), TTF assesses the degree to which a technology's capabilities align with the demands of the tasks users must perform. When the fit is high, performance improves and

adoption becomes more likely (Wu & Chen, 2017). The model has proved useful for clarifying how information technology affects performance outcomes, for assessing the consequences of system use, and for articulating the interplay between task characteristics and technological functionality (Al-Mamary et al., 2024). Because task–technology fit is shaped jointly by task and technology attributes, it is expected to influence adoption behavior directly and indirectly. Prior work combining TAM and TTF supports this integrative approach, showing stronger explanations of new-technology adoption than either model alone (Wu & Chen, 2017).

Figure 1: Theoretical Framework



Task Characteristic (TC): The term task characteristics refers to the specific attributes and requirements of a task, such as its complexity, frequency, interdependence, and structure, that influence how the task should be performed (Lo Presti et al., 2021). These characteristics significantly impact TTF, which measures how well a technology supports task performance (Al-Emran, 2021; Al-Rahmi et al., 2023). According to TTF theory, task effectiveness and user satisfaction are enhanced when technological features are well-aligned with the task's demands (Koh et al., 2023). Research indicates that user performance and productivity improve when technology addresses elements like task complexity, interdependence, and information processing requirements (Dahri et al., 2024). In this context, if an AI chatbot aligns effectively with the needs of higher education students, such as offering assistance with writing or problem-solving, it is likely to be perceived as appropriate, thereby increasing the likelihood of its adoption and use. Al-Mamary et al. (2024) also found a strong association between the task characteristics of students and TTF. Therefore, this research can propose:
H1: Task characteristics impact Task-Technology Fit

Technology Characteristics (TEC): The qualities, functionalities, and capacities of a technology that define how well it can assist users in doing particular activities are referred to as its characteristics (Lo Presti et al., 2021). The usefulness of TECs in higher education is mostly dependent on factors like the AI chatbot's responsiveness, natural language processing skills, contextual awareness, personalization features, and user-friendly interface (Al-Rahmi et al., 2023). When these technological capabilities align with students' academic tasks—such as answering course-related queries, assisting with writing, offering feedback, or solving subject-specific problems- they create a strong TTF (Wang et al., 2021). This fit occurs because the AI chatbot is perceived as capable of meaningfully supporting students in their learning activities, thus fulfilling their task requirements efficiently (Koh et al., 2023). As a result, students are more likely to view the chatbot as a valuable educational tool, increasing both usage intention and actual performance outcomes. Almusawi & Durugbo (2024) found that the TEC of digital tools in education influences TTF by aligning with the specific needs of students. Therefore, this research can propose:
H2: Technology characteristics impact Task-Technology Fit

Task Technology Fit (TTF): TTF refers to the degree to which a technology's capabilities align with the specific requirements of a task, thereby enhancing both the effectiveness and frequency of its use in supporting task completion (Goodhue & Thompson, 1995). When an AI-powered chatbot demonstrates a high level of TTF, it efficiently supports students in carrying out academic tasks (Wang et al., 2021). These tasks may include answering complex questions, providing real-time feedback, assisting with academic writing, and offering step-by-step guidance in problem-solving processes (Al-Rahmi et al., 2023). The alignment between the chatbot's technological features and students' academic needs fosters a stronger perception of its usefulness and relevance in achieving learning goals more efficiently and effectively. As a result, students are more inclined to view the AI chatbot as a valuable academic tool—an outlook that resonates with the TAM core concept of perceived usefulness (Alturki & Aldraiweesh, 2022). Therefore, the closer the alignment between the technology and the academic tasks, the more beneficial the tool is perceived to be, increasing students' intention to adopt and consistently use the AI chatbot throughout their academic journey. This aligns with the findings of Alturki and Aldraiweesh (2022), who highlighted the relationship between TTF and perceived usefulness in the context of Google Meet adoption as an emerging educational technology.

In instances where a strong TTF is present, the functionalities of an AI chatbot are effectively aligned with the academic tasks that students are expected to perform, such as seeking detailed explanations, composing essays, or resolving subject-specific problems (Wang et al., 2021). This alignment facilitates seamless, intuitive, and efficient interactions between the students and the technology (Koh et al., 2023). Students are more likely to believe that the system is simple to use since the chatbot's capabilities are immediately incorporated into their academic workflows and reduce the cognitive and procedural effort needed to perform tasks (Lo Presti et al., 2021). The TAM states that one important aspect affecting the possibility of technology adoption is perceived ease of use (Lin, 2024). Therefore, when the AI chatbot integrates naturally within the educational environment and caters to students' academic needs with minimal complexity, it fosters greater confidence and comfort in its usage, ultimately reinforcing the perception that the tool is user-friendly and readily accessible (Al-Rahmi et al., 2023). Al-Emran (2021) found a significant relationship between TTF and perceived ease of use in the context of smartwatch adoption intention. Similarly, Alturki & Aldraiweesh (2022) also identified a relationship between TTF and perceived ease of use. Therefore, this research can propose:
H3: Task-Technology Fit impacts perceived usefulness
H4: Task-Technology Fit impacts perceived ease of use

Perceived Ease of Use (PEOU): The degree to which a person feels that using a certain technology involves little effort is known as PEOU (Lin, 2024). The PEOU of an AI-powered chatbot is crucial in determining how students view its value in the context of higher education (Pillai et al., 2024). Students are more likely to recognize the chatbot's usefulness in supporting academic assignments when they perceive it as user-friendly, intuitive, and able to provide pertinent and understandable answers with little effort (Al-Abdullatif, 2023). According to the TAM, user-friendly technologies efficiently eliminate cognitive and operational barriers, allowing users to focus on their academic goals instead of juggling complexity (Maheshwari, 2024). Consequently, students' perceptions of the AI chatbot's overall utility will be strengthened if they view it as both accessible and a helpful tool for finishing tasks, overcoming academic obstacles, and comprehending complex ideas. According to Myin & Watchravesringkan (2024), the PEOU of an AI chatbot effectively contributes to generating perceived usefulness among customers engaged in apparel shopping.

Students' intentions to use AI chatbots in higher education are also significantly influenced by PEOU (Rahman et al., 2025). Students are less likely to become frustrated or experience cognitive overload when they find the chatbot straightforward to use, which is typified by an intuitive user interface, clear instructions, and quick response times (Maheshwari, 2024). This ease of interaction fosters greater confidence and comfort, thereby reducing resistance to the technology and promoting increased engagement (Saihi et al. 2025). According to TAM, users' attitudes towards technology are positively impacted when a system is viewed as user-friendly, which in turn increases their intention to adopt and continue using it (Maheshwari, 2024). Consequently, the more user-friendly and accessible the AI chatbot appears, the more likely students are to integrate it into their academic routines as a reliable and efficient support tool. Ayanwale & Ndlovu (2024) uncovered in their study that PEOU influences Intention to Use AI Chatbot among the students in higher education. Moreover, Urbani et al. (2024) also observed a strong association between PEOU and the use intention of the AI chatbot. Therefore, this research can propose:

H5: Perceived ease of use impacts perceived usefulness
H6: Perceived ease of use impacts intention to use an AI chatbot

Perceived Usefulness (PU): The degree to which a person thinks that using a certain technology will improve their performance or make it easier to accomplish objectives is known as PU (Lin, 2024). PU is a key factor in determining students' intentions to use AI chatbots in higher education (Al-Abdullatif, 2023; Pillai et al., 2024). When students perceive that the chatbot effectively contributes to their academic success by improving assignment quality, providing timely academic support, or simplifying complex learning activities, they are more likely to adopt and consistently utilize the tool (Rahman et al., 2025). According to the TAM, when users perceive a technology as beneficial to their task performance, they are more likely to acquire a strong intention to adopt it (Lin, 2024). Consequently, the greater the perceived usefulness of the AI chatbot in meeting students' academic needs, the stronger their motivation becomes to incorporate it into their educational practices. In their study, Urbani et al. (2024) found a substantial correlation between the intention to adopt AI chatbots and PU. Moreover, Rahman et al. (2025) concluded that students' use intentions of AI chatbots in higher education are strongly influenced by their perceptions of the chatbots' usefulness. Therefore, this research can propose:
H7: Perceived usefulness impacts intention to use an AI chatbot

3. Research Methodology

Targeting students from Malaysian public universities, we will create a well-structured questionnaire based on Mikalef and Krogstie's (2020) recommendations to gather data for this study. Purposive sampling will be used to guarantee that the data gathered is highly representative. Despite being a non-probability technique, purposive sampling is frequently employed in research because of its capacity to filter questions and choose relevant respondents (Robinson, 2023). This approach will enable the study to identify and analyze the most relevant participants.

Students from different public universities in Malaysia will be the focus of the study, which aims to investigate their behavioral intention towards using AI chatbots. This is an area that has received less attention in prior research, especially when looking at developing nations. To reach these participants, the research team will utilize multiple online platforms, including social media, WhatsApp, and email. The questionnaire will be developed using Google Forms. Respondents will be free to leave the survey at any moment while filling out the questionnaire, and participation will be completely voluntary.

The process will be conducted in two separate stages to guarantee the correctness and dependability of the data collection process. In the first round, a group of students from a reputable university in Penang, Malaysia, as well as two academics from the Business School with expertise in technology management, will review the questionnaire. Their feedback will be used to refine the questionnaire, ensuring that the wording is clear, relevant, and easily understood by the target respondents. Any necessary revisions will be made based on their suggestions to enhance the overall quality and comprehensibility of the instrument. Once the clarity and validity of the questionnaire are confirmed, the final version will be prepared using Google Forms and distributed to students enrolled in various public universities across Malaysia. The G*Power statistical program was used to calculate the minimal sample size needed for the investigation. The results indicated that a minimum of 68 responses is necessary to conduct the planned analysis effectively. However, the study intends to gather a larger sample size than is necessary in order to increase the robustness and generalizability. For the measurement scales, this study will employ a 7-point Likert scale to assess the dependent variable, while a 5-point Likert scale will be used to collect data for the independent variables. This scaling approach is chosen to enhance the granularity and reliability of the participants' responses.

This study will include two screening (filtering) questions at the start of the questionnaire to guarantee the selection of suitable participants. Participants who meet the criteria based on these questions will be considered suitable for inclusion in the study. The first screening question will ask: "Are you currently studying at a public university?" Only participants who respond "Yes" will be allowed to proceed to the next stage of the survey. The second screening question will ask: "Have you used an AI-supported chatbot to assist in your studies?" Participants who respond "No" will be permitted to complete the full questionnaire. These filtering questions are designed to ensure that all respondents are students from public universities who have not

previously used AI-supported chatbots for academic assistance. By applying this screening mechanism, the research team aims to maintain the focus on the intended target group and ensure the collection of relevant, high-quality data for meaningful analysis.

Moreover, to improve the contextual understanding and dependability of the data gathered, this study will incorporate five demographic questions designed to gather background information from respondents. These demographic questions will cover Gender, Age, University Name, Education Level, and Monthly Family Income. Gathering this information will help outline the socioeconomic and educational characteristics of the student participants, providing a meaningful backdrop for interpreting the study's findings and facilitating deeper insights into potential variations in responses across different demographic groups.

In developing the questionnaire to measure both endogenous and exogenous variables, this study will adapt established items from previous scholarly works. Specifically, to assess Task Characteristics, three items will be adapted from Lu & Yang (2014). Similarly, to evaluate Technology Characteristics, three items will be drawn from the work of Rahi et al. (2020). To measure TTF, four items will be modified based on the instrument used by Wu & Chen (2017). Furthermore, to examine Perceived Usefulness and Perceived Ease of Use, four items for each construct will be adapted from Sun et al. (2025). Lastly, the construct of Intention to Use AI Chatbots will be evaluated using three items adapted from Chanda et al. (2025).

Since this research will utilize a single-source data collection method, there is a potential risk of common method variance (CMV), which could introduce bias into the results. To address this concern, the Variance Inflation Factor (VIF) test will be employed, as recommended by Kock (2015), to assess whether CMV is present in the collected data. To analyze the data and test the hypothesized relationships, this study will utilize PLS-SEM. PLS-SEM has a number of benefits over CB-SEM, especially when used in exploratory research settings. It works especially well with small sample sizes, complex models combining emerging or underdeveloped ideas, and non-normally distributed data (Hair et al., 2022). The study will first evaluate the validity and reliability of the data gathered using PLS-SEM to make sure it is appropriate for hypothesis testing. Key indicators such as factor loadings, Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) will serve as the foundation for this assessment. To be considered reliable and valid, these values must meet or exceed the established thresholds of 0.5 for factor loadings, 0.7 for CA, 0.7 for CR, and 0.5 for AVE, as outlined by Hair et al. (2017). If these criteria are met, the study will proceed to test the hypothesized relationships.

Moreover, the HTMT criterion, which compares each construct to all others to see how much overlap exists between them, will be used in this study to evaluate discriminant validity. Henseler et al. (2015) state that when all HTMT values fall below the 0.90 criterion, demonstrating that the constructs are empirically different from one another, discriminant validity is deemed acceptable. Finally, the PLS-Predict technique will be used in this study to assess the research model's prediction accuracy within the PLS-SEM framework. PLS-Predict is especially well-suited for producing individual-level predictions at the item and construct levels, as described by Shmueli et al. (2019). To thoroughly verify the model's prediction ability, the methodology combines a 10-fold cross-validation approach with the PLS-Predict assessment procedure. It is especially effective when applied to datasets with sample sizes exceeding 200. The analysis will follow the guidelines and procedures recommended by Shmueli et al. (2019) to ensure methodological rigor and accuracy.

4. Implications of the Study

Based on the findings of this study, there are likely to be both theoretical and managerial implications that may offer valuable insights for stakeholders and future researchers alike. From a theoretical perspective, this study investigates the adoption behavior of AI-supported technologies, specifically chatbots, among public university students for academic assistance in developing countries, an area that has been largely overlooked in prior research. Consequently, the findings are expected to enrich the existing literature on AI-chatbot adoption by introducing fresh perspectives and empirical evidence. Furthermore, this study proposes a research model that integrates the TAM and TTF theory, a combination that has rarely been applied in earlier studies focused on AI-chatbot adoption in the context of higher education. This integrative approach not only addresses theoretical gaps but also offers a robust framework for understanding the unique adoption patterns of university students. Therefore, the theoretical contribution of this study is poised to be notably significant,

laying the groundwork for future investigations in this domain.

On the practical side, this study is expected to yield several valuable implications. Based on the findings, university authorities may gain a clearer understanding of why students tend to overlook or underutilize AI chatbots for academic assistance. This insight may help institutions refine their strategies and improve the integration of AI chatbot support in ways that better align with student needs and preferences. In addition, the results of this study may be beneficial for AI chatbot developers by highlighting potential shortcomings in existing systems. These insights may guide the enhancement of future chatbot features, ensuring they are more tailored and effective for educational settings. Lastly, policymakers may also benefit from this study by gaining a deeper understanding of how policy frameworks can support stakeholders involved in the development and implementation of AI chatbots in higher education. By aligning policy support with the needs of both developers and educational institutions, the efficiency and effectiveness of AI chatbot systems can be significantly improved. As a result, this collaborative and evidence-driven approach may have the potential to maximize the impact of AI chatbot technologies in delivering meaningful academic support to university students.

5. Conclusion

In an era where AI is increasingly integrated into educational support systems, AI-powered chatbots have emerged as vital components of digital transformation in higher education. These intelligent systems simulate human-like interactions and are designed to assist students, faculty, and administrative staff by delivering timely, personalized, and automated support across a wide array of academic and administrative functions. In educational contexts, AI chatbots are commonly used to facilitate academic advising, respond to frequently asked questions, guide students through enrollment processes, provide information on course schedules, and even support learning by offering explanations, reminders, and feedback. Even with these encouraging uses, students frequently have doubts about AI chatbots' efficacy, especially when it comes to offering individualized, need-based assistance.

Concerns about the usefulness, ease of use, and overall relevance of such technology contribute to a relatively low adoption rate, especially in developing countries like Malaysia. This is particularly evident among students in public universities, where digital transformation may progress at a slower pace due to infrastructural and contextual limitations. Therefore, the purpose of this study is to look at what factors influence public university students' intentions to use AI chatbots. Data will be gathered from students at several public universities in Malaysia using a purposive sampling technique. PLS-SEM, a commonly used quantitative method in social science research that works particularly well for exploratory investigations involving complicated models, will be used to examine the data that will be gathered in this study. The study may suggest theoretical and managerial implications in light of the findings of this study. The results are expected to offer valuable insights to both stakeholders and researchers. For stakeholders, the results may be useful in determining how to improve student interaction with chatbots that are powered by AI in classrooms. For researchers, the study may provide a deeper understanding of students' behavioral intentions regarding the adoption of emerging technologies in academic support systems.

References

Al-Abdullatif, A. M. (2023). Modeling Students' Perceptions of Chatbots in Learning: Integrating Technology Acceptance with the Value-Based Adoption Model. *Education Sciences*, *13*(11), 1151. https://doi.org/10.3390/educsci13111151

Al-Emran, M. (2021). Evaluating the Use of Smartwatches for Learning Purposes through the Integration of the Technology Acceptance Model and Task-Technology Fit. *International Journal of Human–Computer Interaction*, *37*(19), 1874–1882. https://doi.org/10.1080/10447318.2021.1921481

Al-Mamary, Y. H., Alfalah, A. A., Alshammari, M. M., & Abubakar, A. A. (2024). Exploring factors influencing university students' intentions to use ChatGPT: analyzing task-technology fit theory to enhance behavioral intentions in higher education. *Future Business Journal*, *10*(1), 119. https://doi.org/10.1186/s43093-024-00406-5

Almusawi, H. A., & Durugbo, C. M. (2024). Linking task-technology fit, innovativeness, and teacher readiness

using structural equation modelling. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-12440-x

Al-Rahmi, W. M., Al-Adwan, A. S., Al-Maatouk, Q., Othman, M. S., Alsaud, A. R., Almogren, A. S., & Al-Rahmi, A. M. (2023). Integrating Communication and Task–Technology Fit Theories: The Adoption of Digital Media in Learning. *Sustainability*, *15*(10), 8144. https://doi.org/10.3390/su15108144

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in human behavior, 85,* 183-189.

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets Electronic Markets, 31*(2), 427–445. https://doi.org/10.1007/s12144-024-06072-8

Ayanwale, M. A. (2024). Using Diffusion Theory of Innovation to Investigate Perceptions of STEM and Non-STEM Students' Adoption of Chatbot Systems in Higher Education: A Multiple Group Analysis. *IEEE Global Engineering Education Conference (EDUCON)*.

Ahmad, S. F., Alam, M. M., Rahmat, M. K., Mubarik, M. S., & Hyder, S. I. (2022). Academic and administrative role of artificial intelligence in education. *Sustainability, 14*(3), 1101.

Alturki, U., & Aldraiweesh, A. (2022). Adoption of Google Meet by Postgraduate Students: The Role of Task Technology Fit and the TAM Model. *Sustainability*, *14*(23), 15765. https://doi.org/10.3390/su142315765

Ayanwale, M. A., & Ndlovu, M. (2024). Investigating factors of students' behavioral intentions to adopt chatbot technologies in higher education: Perspective from expanded diffusion theory of innovation. *Computers in Human Behavior Reports*, *14*, 100396. https://doi.org/10.1016/j.chbr.2024.100396

Bilquise, G., Ibrahim, S., & Salhieh, S. M. (2024). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies*, *29*(5), 6357–6382. https://doi.org/10.1007/s10639-023-12076-x

Belda-Medina, J., & Calvo-Ferrer, J. R. (2022). Using chatbots as AI conversational partners in language learning. *Applied Sciences, 12*(17), 8427.

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the association for information systems, 8*(4), 3.

Chang, D. H., Lin, M. P. C., Hajian, S., & Wang, Q. Q. (2023). Educational design principles of using an AI chatbot that supports self-regulated learning in education: Goal setting, feedback, and personalization. *Sustainability, 15*(17), 12921. https://doi.org/10.3390/su151712921

Chanda, R. C., Vafaei-Zadeh, A., Hanifah, H., & Ramayah, T. (2025). Artificial intelligence teaching assistant adoption in university education: Key drivers through the ability, motivation, and opportunity framework. *Education and Information Technologies, 30*(2). https://doi.org/10.1007/s10639-025-13360-8

Dahri, N. A., Yahaya, N., Al-Rahmi, W. M., Almogren, A. S., & Vighio, M. S. (2024). Investigating factors affecting teachers' training through mobile learning: Task technology fit perspective. *Education and Information Technologies, 29*(3). https://doi.org/10.1007/s10639-023-12434-9

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly,* 319–340.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213-236.

Gupta, P., & Yadav, S. (2022). A TAM-based Study on the ICT Usage by the Academicians in Higher Educational Institutions of Delhi NCR. *Data Engineering and Communications Technologies, (111)*. https://doi.org/10.1007/978-981-16-9113-3_25

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (2nd ed.)*. Sage Publications.

Hair, J. F., Thomas, G., Hult, M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (3rd ed.)*. Thousand Oaks, CA: Sage.

Henseler, J., Ringle, C., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-based Structural Equation Modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135.

Hwang, G.-J., & Chang, C.-Y. (2023). A review of opportunities and challenges of chatbots in education. *Interactive Learning Environments, 31*(7), 4099–4112.

Koh, L. Y., Lee, J. Y., Wang, X., & Yuen, K. F. (2023). Urban drone adoption: Addressing technological, privacy,

and task–technology fit concerns. *Technology in Society*, *72*, 102203. https://doi.org/10.1016/j.techsoc.2023.102203

Kamalov, F., Santandreu Calonge, D., & Gurrib, I. (2023). New era of Artificial Intelligence in education: Towards a sustainable multifaceted revolution. *Sustainability, 15*(16), 12451.

Khan, R. A., & Jawaid, M. (2020). Technology-enhanced assessment (TEA) in the COVID-19 pandemic. *Pakistan Journal of Medical Sciences, 36*, S108. https://doi.org/10.12669/pjms.36.COVID19-S4.2795

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International *Journal of e-Collaboration, 11*(4), 1-10.

Lin, X. (2024). Factors Influencing College Students' Use of AI Chatbots for Learning Empirical Study based on the TAM extended model. *2024 5th International Conference on Artificial Intelligence and Electromechanical Automation (AIEA)*, 151–159. https://doi.org/10.1109/AIEA62095.2024.10692550

Lo Presti, A., De Rosa, A., & Viceconte, E. (2021). I want to learn more! Integrating technology acceptance and task–technology fit models for predicting behavioral and future learning intentions. *Journal of Workplace Learning*, *33*(8), 591–605. https://doi.org/10.1108/JWL-11-2020-0179

Lu, H.-P., & Yang, Y.-W. (2014). Toward an understanding of the behavioral intention to use a social networking site: An extension of task-technology fit to social-technology fit. *Computers in Human Behavior*, *34*, 323–332. https://doi.org/10.1016/j.chb.2013.10.020

Maheshwari, G. (2024). Factors influencing students' intention to adopt and use ChatGPT in higher education: A study in the Vietnamese context. *Education and Information Technologies*, *29*(10), 12167–12195. https://doi.org/10.1007/s10639-023-12333-z

Mello, R. F., Freitas, E., Pereira, F. D., Cabral, L., Tedesco, P., & Ramalho, G. (2023). Education in the age of generative AI: Context and recent developments. *arXiv preprint arXiv:2309*.12332.

Monserrat, M., Mas, A., Mesquida, A. L., & Clarke, P. (2022). Investigating the use of artificial intelligence (AI) in educational settings: A systematic review. *Communications in Computer and Information Science, 1646*, 3–17.

Mikalef, P., Krogstie, J., 2020. Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *Eur. J. Inf. Syst., 29*(3), 260–287. https://doi.org/10.1080/0960085X.2020.1740618.

Myin, M. T., & Watchravesringkan, K. (2024). Investigating consumers' adoption of AI chatbots for apparel shopping. *Journal of Consumer Marketing*, *41*(3), 314–327. https://doi.org/10.1108/JCM-03-2022-5234

Ng'ambi, D., Brown, C., Bozalek, V., Gachago, D., & Wood, D. (2016). Technology-enhanced teaching and learning in South African higher education–A rearview of a 20-year journey. *British Journal of Educational Technology, 47*(5), 843–858. https://doi.org/10.1111/bjet.12485

Pillai, R., Sivathanu, B., Metri, B., & Kaushik, N. (2024). Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education. *Information Technology & People*, *37*(1), 328–355. https://doi.org/10.1108/ITP-02-2021-0152

Rahi, S., Khan, M. M., & Alghizzawi, M. (2020). Extension of technology continuance theory (TCT) with task technology fit (TTF) in the context of Internet banking user continuance intention. *International Journal of Quality & Reliability Management*, *38*(4), 986–1004. https://doi.org/10.1108/IJQRM-03-2020-0074

Rahman, M. K., Ismail, N. A., Hossain, M. A., & Hossen, M. S. (2025). Students' mindset to adopt AI chatbots for the effectiveness of online learning in higher education. *Future Business Journal*, *11*(1), 30. https://doi.org/10.1186/s43093-025-00459-0

Robayo-Pinzon, O., Rojas-Berrio, S., Rincón-Novoa, J., & Ramírez-Barrera, A. (2023). Artificial intelligence and the value Co-creation process in higher education institutions. *International Journal of Human-Computer Interaction*, *40*(20), 1–17.

Rapp, A., Curti, L., & Boldi, A. (2021). The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots. *International Journal of Human-Computer Studies*, *151*, 102630.

Robinson, R.S. (2023). Purposive Sampling. *Encyclopedia of Quality of Life and Well-Being Research*. Springer, Cham. https://doi.org/10.1007/978-3-031-17299-1_2337.

Saihi, A., Ben-Daya, M. & Hariga, M. (2025). The moderating role of technology proficiency and academic discipline in AI-chatbot adoption within higher education: Insights from a PLS-SEM analysis. *Educ Inf*

Technol, 30, 5843–5881. https://doi.org/10.1007/s10639-024-13023-0

Saihi, A., Ben-Daya, M., Hariga, M., & As'ad, R. (2024). A Structural equation modeling analysis of generative AI chatbots adoption among students and educators in higher education. *Computers and Education: Artificial Intelligence*, *7*, 100274. https://doi.org/10.1016/j.caeai.2024.100274

Sánchez-Prieto, J. C., Cruz-Benito, J., Therón, R., & García-Peñalvo, F. (2020). Assessed by Machines: Development of a TAM-Based Tool to Measure AI-based Assessment Acceptance Among Students. *International Journal of Interactive Multimedia and Artificial Intelligence*, *6*(4), 80-86. https://doi.org/10.9781/ijimai.2020.11.009

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict. *European Journal of Marketing, 53*(11), 2322-2347.

Stöhr, C., Ou, A. W., & Malmström, H. (2024). Perceptions and usage of AI chatbots among students in higher education across genders, academic levels, and fields of study. *Computers and Education: Artificial Intelligence*, *7*, 100259. https://doi.org/10.1016/j.caeai.2024.100259

Sun, P., Li, L., Hossain, M. S., & Zabin, S. (2025). Investigating students' behavioral intention to use ChatGPT for educational purposes. *Sustainable Futures*, *9*, 100531. https://doi.org/10.1016/j.sftr.2025.100531

Urbani, R., Ferreira, C., & Lam, J. (2024). Managerial framework for evaluating AI chatbot integration: Bridging organizational readiness and technological challenges. *Business Horizons*, *67*(5), 595–606. https://doi.org/10.1016/j.bushor.2024.05.004

Wang, X., Wong, Y. D., Chen, T., & Yuen, K. F. (2021). Adoption of shopper-facing technologies under social distancing: A conceptualization and an interplay between task-technology fit and technology trust. *Computers in Human Behavior*, *124*, 106900. https://doi.org/10.1016/j.chb.2021.106900

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, *67*, 221–232. https://doi.org/10.1016/j.chb.2016.10.028

Yang, T.-C., & Chen, J.-H. (2023). Pre-service teachers' perceptions and intentions regarding the use of chatbots through statistical and lag sequential analysis. *Computers and Education: Artificial Intelligence*, *4*, 100119. https://doi.org/10.1016/j.caeai.2022.100119

Yildiz Durak, H., & Onan, A. (2024). Predicting the use of chatbot systems in education: a comparative approach using PLS-SEM and machine learning algorithms. *Current Psychology*, *43*(28), 23656–23674. https://doi.org/10.1007/s12144-024-06072-8

Appendix
Measurement items

Constructs	Items	Questions	Sources
Task Characteristics	TC1	I often have to solve problems I come across while studying.	Lu & Yang (2014)
	TC2	I frequently need to gather information to support problem-solving in various courses throughout my studies.	
	TC3	I often ask for advice when dealing with problems in my courses.	
Technology Characteristics	TEC1	The AI chatbot offers prompt and efficient service.	Rahi et al. (2020)
	TEC2	The AI chatbot offers me support anytime and anywhere.	
	TEC3	The AI chatbot ensures the delivery of secure services.	
Task-Technology Fit	TTF1	AI chatbots are well-suited for my learning needs.	Wu & Chen (2017)
	TTF2	AI chatbots fit well with my educational practice.	
	TTF3	It is straightforward to identify the appropriate tool to use in AI chatbots.	
	TTF4	AI chatbots are highly effective in assisting me with completing my courses.	
Perceived Usefulness	PU1	AI-Chatbot significantly enhances the learning experience of students.	Sun et al. (2025)
	PU2	AI-Chatbot helps save time when looking up educational information.	
	PU3	AI-Chatbot gives students more ways to engage with their learning content.	
	PU4	Overall, AI-Chatbot makes it easier for students to get educational support.	
Perceived Ease of Use	PEOU1	AI-Chatbot facilitates easy access to information pertinent to educational tasks.	Sun et al. (2025)
	PEOU2	AI-Chatbot streamlines the decision-making process concerning educational activities.	
	PEOU3	Using an AI chatbot for educational inquiries demands little cognitive effort.	
	PEOU4	Overall, AI-Chatbot makes it easy for students to connect with educational resources.	
Intention to Use AI Chatbot	ITUAIC1	I intend to use the AI-supported chatbot to assist me with my coursework.	Chanda et al. (2025)
	ITUAIC2	I intend to recommend the use of the AI chatbot to others for academic support.	
	ITUAIC3	I intend to utilize the AI-supported chatbot to address issues related to my academic inquiries.	