INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN ACCOUNTING, FINANCE AND MANAGEMENT SCIENCES

OPEN ACCESS JOURNAL

Vol 16, Issue 2, (2026) E-ISSN: 2225-8329

Influential Factors of Accounting Students' Intentions to Use ChatGPT: An Analysis Using Structural Equation Modelling (SEM)

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DOI Link: http://dx.doi.org/10.6007/IJARAFMS/v16-i2/28057

Published Online: 12 April 2026

Abstract

This study examines the levels of acceptance and actual use of AI tools in Malaysian accounting education within the global trend toward digitalized teaching and learning systems. This study explores the factors influencing ChatGPT acceptance among Malaysian accounting students using the Technology Acceptance Model (TAM), including perceived ease of use, perceived usefulness, result demonstrability, and technological self-efficacy. A self-reported questionnaire survey was conducted, and hypothesis testing was performed using Smart PLS. The study found perceived ease of use, perceived usefulness, result demonstrability, and technological self-efficacy were significantly associated with students' intention to use ChatGPT. These findings are particularly relevant to accounting educators, who can use AI to empower students to have a voice and approach learning practically, with socio-cultural considerations. As AI integrates into the educational landscape, stakeholders in curriculum development, policymakers, and educators will benefit from understanding the most effective AI application in practice that minimizes digital gaps while simultaneously fostering independent technological skills alongside accounting skills. In addition, the findings will apply globally to academics and practitioners seeking to integrate AI-based systems into the teaching and learning process and to encourage a world in which AI can both improve student performance in the learning environment and transform students into competent professionals in the emerging world of work, especially in the accounting field.

Keywords: ChatGPT, Perceived Ease of Use, Perceived Usefulness, Result Demonstrability, and Technological Self-Efficacy

Introduction

According to the 4IR (Malaysia's National Fourth Industrial Revolution) policy, Malaysia aims to raise 30% of the nation's output by the end of 2030 across all sectors. Integrating automation and AI is a way to achieve this mission. As professional change agents of this transformation, accounting professionals facilitate increased of productivity, efficiencies, and economic growth opportunities. On average, accounting professionals are always ahead of the curve, thanks to access to real-time data and information. Thus, critical positioning in today's rapidly evolving society enables them to make accurate assessments and implement practical solutions for their stakeholders. Therefore, those professionals who can adapt to future trends enabled by AI and automation may be in a better position to drive changes in their professional environments and the broader accounting industry (Business Today, 2023). There is a need to implement AI in Malaysia through collaboration.

The Purpose of the study was to assess perceptions and implementation of an AI tool, ChatGPT, in Malaysian accounting education. It explores how students perceive the tool's learnability and usability relative to their accounting curriculum. For instance, is it a product that is so easy to use and learn more about, and to learn from ChatGPT through its interface and conversational elements? Is it a product from which one could learn more and use through lesson feedback, practice problem generation, and online answer creation? Furthermore, the study addresses the idea of learnability relative to the possibility of learning from such robust AI, since in the world of accounting, AI is an excellent example of a product that can become more understandable the more one learns about it. Finally, as technology self-efficacy naturally affects the use and learning of AI products, this study examines this variable as a secondary theme to understand the technology theme at hand better. Ultimately, this study investigates all of these avenues to determine relative relevance and frequency in understanding how and why ChatGPT may or may not be used and accepted by Malaysian accounting students. Results will provide educators and policymakers with further insight into target programs and the necessary interventions for their proper implementation in the curriculum.

This study aims to add to the emerging body of literature on ChatGPT and AI tools in professional learning from a Malaysian perspective; to explore accounting students' attitudes towards ChatGPT for Accounting as an AI tool; and to extend TAM's applicability to AI for accounting in Malaysia. TAM serves as a theory to be developed in a Malaysian context. The research is enlightening regarding understanding multi-variable interactions around applying TAM with AI instruments in accounting pedagogy. This research builds on prior works such as Chawla et al. (2024) to explore the accounting students' lived experiences, especially from the socio-cultural, technological diversity, and geographic disparity angles that exist within Malaysia. These, among other reasons, frame this study, such as that there exists within the world of educational data analytics limited published evidence in Malaysia (Luqman Hakim & Fuad Nizam, 2023; PricewaterhouseCoopers, 2020).

Literature Review and Hypotheses Development

Underpinning theory: Technology Acceptance Model

The Technology Acceptance Model (TAM) was a robust framework for understanding and predicting how individuals adopt and use technologies (Kim, Chow, Park, & Liu, 2023; Nadal, Sas, & Doherty, 2020). In the late 1980s, Fred Davis proposed TAM as a psychological model to explain the factors affecting users' commitment to adopt and use information technology (Davis, 1986). TAM originated in the theory of reasoned action and the theory of planned behavior, which claimed that an individual's behavioral intention is the main cause of their actual behavior (Ferizaj, Perotti, Dahms, & Heimann-Steinert, 2024; Kwan, Yeung, Lee, & Lou, 2023). TAM argues that perceived usefulness and ease of use influence individuals' objectives to embrace and use a specific technology when considering technology acceptance. However, the TAM does not have a reliable theory and method to identify perceived usefulness and perceived ease of use as external variables (Bagozzi, 2007). The model should explain how a user believes a new technology is valuable and easy to use.

This first TAM can explain 40% of the variables' intention to use and usage patterns, and it excludes factors such as social influences, personal values, and habits (Venkatesh & Bala, 2008). They proposed extending the Technology Acceptance Model 2 (TAM 2), considering the social influence and cognitive instrumental processes that impact perceived usefulness. The social influence process includes subjective norms, voluntariness, and image dimensions. Other dimensions, such as output quality, result demonstrability, perceived ease of use, and job relevance, have been added under the cognitive instrumental process.

Subsequently, Venkatesh and Bala (2008) introduced Technology Acceptance Model 3 (TAM 3) which focuses on perceived ease of use, such as computer self-efficacy, computer anxiety, computer playfulness, perceived external control, perceived enjoyment, and objective usability.

Hence, understanding how social factors influence perceived usefulness and perceived ease of use assists users in planning and implementing strategies to increase new technology acceptance and usage is essential. Given the above literature, this study uses the TAM to examine the factors influencing the intention to use the ChatGPT in Malaysian accounting education as evidenced by other past studies (Baek & Kim, 2023; Lai, Cheung, & Chan, 2023; Saif, et al., 2024).

Intention to use (ITU)

Intention to use represents users' willingness and effort to perform the underlying behaviour. Users are more interested in adopting ChatGPT when they know its prospects for improving communication, completing tasks, and increasing user experience (Shahzad, Xu, & Javed, 2024). It's about exposure to ChatGPT in everyday life, from ideation and writing to personal and professional projects (Parveen et al., 2024). For many, it starts with a referral from a friend, colleague, or social acquaintance in their community. Thus, success stories and positive reviews from initial users spread to others, creating informed awareness of ChatGPT's advantages and an expected, positive environment for implementation. The more educated people are about ChatGPT's potential and benefits, the more likely they are to implement it. It is essential to understand ChatGPT's utilisations, attributes, and how it can be incorporated into day-to-day operations. Recent findings showed that ChatGPT students demonstrated improved performance in understanding the materials, user flow, and functionality (Sun, Boudouala, Zhu, & Li, 2024; Limna, et al., 2023). Most of the instructors and learners positively perceived the implementation of ChatGPT. Hence, users' intention to adopt ChatGPT relates to the following factors:

Perceived Ease of Use (PEOU)

Perceived ease of use refers to the user's sense of how straightforward it is to utilize technology (Akritidi, Gallos, Koufi, & Malamateniou, 2022). Past technology adoption studies have employed perceived ease of use and usefulness because these factors significantly affect users' intentions to use technological tools (Acosta-Enriquez, Ballesteros, Jordan, & Tirado, 2024).

Perceived ease of use is related to human-computer interaction and general user experience. If users find ChatGPT instinctive, user-friendly, and interactive, they are more likely to perceive its ease of use. A well-developed interface, clear guides, and instinctive connection flow provide a pleasant user experience (Jo, 2023). It will encourage a feeling of confidence and comfort to increase users' intention to adopt ChatGPT. In addition, the efficiency and effectiveness of ChatGPT in producing relevant responses increase the perceived ease of use. If users continuously receive correct and helpful information through inquiry with ChatGPT, they are more likely to perceive its ease of use. ChatGPT's capability to apprehend user inquiry, produce logical outputs, and adapt to different conditions increases its usability and optimum influences adoption intention (de Andres-Sanchez & Gene-Albesa, 2023).

Perceived Usefulness (PU)

The TAM defined perceived usefulness as the trusted usefulness of a new technology to achieve a job (Venkatesh & Bala, 2008). It refers to the user's confidence that the technology will make their jobs easier or improve their performance (Akritidi, Gallos, Koufi, & Malamateniou, 2022). Constructive experiences with ChatGPT regarding accurate responses and well-organized job completion will increase users' perception of its usefulness (Shahzad, Xu, & Javed, 2024). Transparent dissemination about the perceived usefulness of technologies in the areas of tangible advantages and convenience will increase acceptance (Kim, 2024). In addition, transparent and trustworthy security measures play an essential role in gaining confidence and trust among users. With proper training and subsequent support, one will feel more confident and capable with using technology. Therefore, the intervention should be specific to user concerns to foster buy-in. The potential problems that could limit TAM's universal appropriateness for all users are accessibility and the digital divide, which could lead to rejection. Therefore, as a technology acceptance aid, the research suggests that intervention specificity, equity of resources, and usability and safety factors are reliable (Kim, 2024).

Perceived Output Quality (OQ)

According to the TAM, the quality of output is the expectation of work someone accomplishes by utilizing something new (Venkatesh & Bala, 2008). When this is the case, if people think this form of technology produces higher-quality output, it will be considered valid, and the resulting intention to use it will increase. The higher the quality of technology presented to the general population, the more likely they are to explore newer technologies and expand their area of work (Gupta, 2024). This often helps them get what they need, which in turn affects their perceptions of ease of use and usefulness. ChatGPT's enhanced quality could affect users' enhanced intentions to use this technology. In addition, the service quality will influence the users' intention to adopt AI technology. Output quality is ascertained by reliability, accuracy, and short service time, which impacts user performance expectancy towards AI's perceived usefulness.

Management support may increase subordinates' sense-making regarding output quality and results (Montarargot & Lahouel, 2018). With managerial dedication and commitment, subordinates would enjoy the full advantages of new technology. If management demonstrates positive attitudes toward new technology, subordinates' perceived favour toward the latest technology will likely positively impact via social influence procedures (Wong et al., 2022).

Increasing research has focused on service quality, as it significantly influences customer satisfaction and loyalty, which positively impacts desired attitudinal, behavioural, and financial results (Fassnacht & Koese, 2006). Hence, organizations need a good knowledge of how customers consider and assess quality to deliver excellent service (Yi & Gong, 2008).

Perceived Result Demonstrability (RD)
The TAM defined the perceived result demonstrability as the ability to show results from adopting technology (Venkatesh & Bala, 2008). Moore and Benbasat (1991) identified result demonstrability as a key dimension of social influence affecting consumers' behavioural intentions. They explained result demonstrability as the degree to which the intention of using a specific technology product or service is communicable as part of cognitive instrumental processes. This idea is further developed by Gow et al. (2019), who observe that intention to use also correlates significantly with the demonstrability of results. In addition, result demonstrability stems from current users speaking with others, prospective users, about their good experiences. It relates to the social (an external contextual force) component of Bandura's (1986) social cognitive theory.

It's critical to note that result demonstrability is related to perceived ease of use, perceived usefulness, and output quality. One of the most readily acknowledged characteristics of ChatGPT is perceived ease of use. ChatGPT is accessible via a web browser on any web-responsive device, and it is available as an app on any web-responsive computer, tablet, or smartphone, all of which indicate perceived ease of use (PEOU). In addition, its accessibility is evident in how easily one can access it via direct communication prompts, making it useful for college students in educational settings. Thus, they can configure and adapt it to their preference and learning efficiencies, as articulated by perceived usefulness (PU) (Le et al., 2024).

Undergraduates are prone to adopting ChatGPT-type virtual assistants because they feel it benefits them to improve learning effectiveness (Hsu et al., 2023). In addition, the response quality of ChatGPT, as accurate and topical, is necessary for successfully rendering physical learning benefits since it assists students in essay writing and problem-solving/coding assignments as a supplemental resource to expand comprehension and comprehension-based skills in the learning process (Le et al., 2024).

Furthermore, since this usefulness emerges in precise, communicable results, it constitutes a yet-to-be-supported assertion from this hypothesis; note how this supports the intent to use ChatGPT among university students. However, the intention-to-use construct, as defined by ChatGPT, can be supported by only a limited number of antecedents; without the mediation of result demonstrability, it fails to assess value through a mediating variable. In fact, there's a gap in the literature regarding the lack of empirical studies evaluating the role of results' demonstrability as a mediating variable guiding the intention to use them. Thus, this study will address this gap by assessing the demonstrability of mediated effects on intention to use in relation to PEOU, PU, and OQ. Therefore, this study proposes the following hypothesis:

H1: The relationship between Perceived Ease of Use (PEOU) and Intention to Use (ITU) will be mediated by Result Demonstrability (RD)
H2: The relationship between Perceived Usefulness (PU) and Intention to Use (ITU) will be mediated by Result Demonstrability (RD)
H3: The relationship between Perceived Output Quality (OQ) and Intention to Use (ITU) will be mediated by Result Demonstrability (RD)

Perceived Technology Self-Efficacy (PTSE)
Self-efficacy refers to people's judgment of their ability to arrange and perform a set of intended and essential actions to achieve expected performance. It is concerned with the judgment of what an individual can do with whatever skills they own (Bandura, 1986). Self-efficacy determines human behaviour by driving effort and an unceasing desire to accomplish tasks, enabling one to overcome challenges in the face of difficulty and failure. In the context of technology, self-efficacy refers to users' judgment regarding their capability to perform what is successfully executed through the technology service process, as it requires a fundamental knowledge of computers and internet usage (Yi & Gong, 2008). It is a critical construct for understanding students' learning and engagement, a significant factor influencing students' intentions to engage in specific activities. Regarding behaviour, self-efficacy can shape an individual's choice of activities, including the likelihood of adopting tools like ChatGPT (Latip et al., 2020; Wong et al., 2022).

Self-efficacy does not refer to one's skill but instead to one's perception of one's ability to accomplish a task with the skills, knowledge, and experience already acquired. According to Robbins and Judge (2018), four sources of self-efficacy are enactive mastery, vicarious modelling, verbal persuasion, and arousal. The most definitive source to bolster self-efficacy is enactive mastery, appropriately, one's acquisition of relevant experiences and subsequent successful outcomes. Students who have similar tasks or experiences to their benefit, and who have used ChatGPT or other AI-based tools before and completed their tasks, are more likely to believe they can do the same again. The intention to use and subsequent adoption stem from confidence. Likewise, vicarious modelling is the second most reliable source. Undergraduate students, in this case, are more likely to feel they can do something if they've seen someone just like them do it. From that perspective, they conclude they can do the same.

Persuasive power increases from verbal persuasion among this population. If someone tells undergraduates that they're capable, that they have the skills and ability to do what's necessary to succeed, especially when given the tools to empower them, they believe it and act accordingly. Finally, arousal provides a psychological and emotional boost, promoting higher self-efficacy, especially when students feel charged and "pumped up" for a task they're just undertaking. It works better when it's supported. Therefore, all sources of self-efficacy relate to intention of use and subsequent adoption of ChatGPT and similar tools (Latip et al., 2020; Yilmaz & Yilmaz, 2023; Tailor & Tailor 2025)

In the context of higher education, students' judgments about their ability to organize and execute actions required to manage and navigate IT-based learning environments effectively. This includes their beliefs about their capabilities in using IT tools such as the internet, web-based learning platforms (e.g., learning management system), instructional technologies, and ChatGPT to achieve academic success (Latip et al., 2020). Past research showed that ChatGPT significantly improved students' programming self-efficacy (Yilmaz & Yilmaz, 2023). Artificial intelligence capability in colleges and universities has been found to positively impact students' self-efficacy and creativity in studying performance (Li & Wang, 2021). Yilmaz and Yilmaz (2023) observed that the experimental students followed an algorithm for problem-solving; determining subprogram particles to agree with the algorithm resulted in querying the most relevant question. These students tried to obtain the expected output by combining the subprogram fragments' codes from the ChatGPT. During this process, students spent their time in creative thinking, querying relevant questions, algorithmic thinking, critical thinking, and problem-solving. Because of this, the students can derive the answer to the code extracts expected by querying the most relevant questions using ChatGPT. Other studies also found the experimented students who received AI training with the STEAM model (Huang & Qiao, 2024), machine learning training (Rodriguez et al., 2019), and the use of voice assistant (Hsu et al., 2023) significantly increased students' computational thinking skills (i.e., result demonstrability), hence increasing the intention to use AI.

Therefore, this study also aims to investigate the mediating effect of result demonstrability on the relationship between PEOU, PU, and output quality and perceived self-efficacy and their association with intention to use. To achieve this, the study proposes the following three hypotheses:

H4: The relationship between Perceived Ease of Use (PEOU) and Perceived Technology Self-Efficacy (PTSE) will be mediated by Result Demonstrability (RD)
H5: The relationship between Perceived Usefulness (PU) and Perceived Technology Self-Efficacy (PTSE)will be mediated by Result Demonstrability (RD)
H6: The relationship between Perceived Output Quality (OQ) and Perceived Technology Self-Efficacy (PTSE)will be mediated by Result Demonstrability (RD).

Mediation of Perceived Ease of Use, Perceived Usefulness, and Output Quality by Result Demonstrability and Perceived Technology Self-Efficacy (H7-H9)

The Technology Acceptance Model (TAM) has been widely utilized to investigate users' acceptance of new technologies, proposing that perceived ease of use (PEOU) and perceived usefulness (PU) are pivotal in that context (Davis, 1986; Venkatesh & Bala, 2008). Nevertheless, the latest literature highlights alternative constructs, including result demonstrability and perceived technology self-efficacy, as important mediators influencing users' intention to use (ITU) innovative technologies (Gow, Wong, & Lim, 2019; Latip et al., 2020).

Demonstrability of results (RD) captures the idea of users deriving utility from seeing tangible and witnessable benefits from a technology (Moore & Benbasat, 1991). Previous research revealed that users' acceptance and intention to use that technology significantly increase when they sense it generates visible and valuable output (Gow et al., 2019). Likewise, perceived technology self-efficacy refers to an individual's belief in their ability to successfully use technology (Bandura, 1986; Yi & Gong, 2008). Studies show that users with higher levels of PTSE are more likely to engage with technology and utilize it within their activities (Rodriguez et al., 2019; Yilmaz & Yilmaz, 2023).

The mediation effect of RD and PTSE has been claimed in studies regarding digital adoption. For example, when users feel that technology offers better output quality and evident benefits, they will be more likely to use it (Gupta, 2024). Additionally, when users think they can use technology effectively, it helps adoption (Navarro et al., 2023). Such sentiments resonate with evidence from previous studies of ChatGPT adoption (Le et al., 2024; Hsu, Chang, & Lin, 2023) that the mental model of continued technology use is built by positive evaluations of the ease, usefulness, and output from the AI-powered tools, which in turn further increase technology self-efficacy leading to a stronger intention to use.

Despite an extensive body of research on TAM, the mechanism of the composite mediator of RD and PTSE collectively impending the relationship of the key antecedents (PEOU, PU, and OQ) and ITU is still lacking. Although previous studies have examined each of these individually, the combined effect of these factors influencing ChatGPT adoption, particularly in an AI-driven context, has scarcely been explored (Le et al., 2024; Navarro et al., 2023). Filling this gap is essential for developing more effective models of technology acceptance and improving strategies for increasing the rate of technology adoption, whether it pertains to use in education or professional settings. Accordingly, the following hypotheses are proposed:

H7: The relationship between Perceived Ease of Use (PEOU) and Intention to Use (ITU) will be mediated by Result Demonstrability (RD) and Perceived Technology Self-Efficacy (PTSE).
H8: The relationship between Perceived Usefulness (PU) and Intention to Use (ITU) will be mediated by Result Demonstrability (RD) and Perceived Technology Self-Efficacy (PTSE).
H9: The relationship between Perceived Output Quality (OQ) and Intention to Use (ITU) will be mediated by Result Demonstrability (RD) and Perceived Technology Self-Efficacy (PTSE).

Mediation of Result Demonstrability by Perceived Technology Self-Efficacy
It is noted that result demonstrability is one of the most critical determinants of technology adoption because users are more likely to use technologies if they can see the benefits that the technology brings (Venkatesh & Bala, 2008; Gow et al., 2019). However, result demonstrability is not the sole driver for adopting the technology, as another factor in the technology application adds to strengthening this relationship, i.e., the PTSE (perceived technological self-efficacy). According to Bandura (1986), self-efficacy influences motivation and behavioural intention, indicating that individuals with high PTSE tend to believe in demonstrable results and use technology effectively (Latip et al., 2020; Wong, Teoh & Saleh, 2022).

This mediating role is supported by empirical evidence (Navarro et al., 2023). Prior research has found that if people are aware of the benefits technology brings but feel as though they do not know how to perform the actions to benefit from the technology, they are less likely to adopt it (Romero-Sánchez & Barrios, 2022). However, when PTSE is high, the perceived demonstrability of the results of technology increases ITU significantly (Hsu et al., 2023). Based on these understandings, we hypothesize:

H10: The relationship between Result Demonstrability (RD) and Intention to Use (ITU) will be mediated by Perceived Technology Self-Efficacy (PTSE).

Direct Effects of Result Demonstrability and Perceived Technology Self-Efficacy on Intention to Use (H11-H12)

In addition to acting as mediators, RD and PTSE have directly influenced ITU. With result demonstrability, ITU is increased with tangible proof that the technology works (Moore & Benbasat, 1991). The more a technology is seen as beneficial and applicable to user needs, the more users are likely to adopt it (Gow et al., 2019; Yuan et al., 2021). This phenomenon has been validated across several fields, including AI-based products, where users are more inclined to incorporate AI into their practices if they observe distinct benefits (Jo, 2023).

Likewise, another major predictor of ITU is PTSE (Navarro et al., 2023; Kim, 2024). People who engage in PTSE are accustomed to trying out new technologies and, in time, learning how to incorporate them into their daily lives. This is widely adopted based on such perceptions (Shahzad, Xu, & Javed, 2024). For instance, where student perceptions of AI adoption are concerned, those who possess good levels of PTSE are more likely to engage in using AI-connected technologies like ChatGPT for educational use (Huang & Qiao, 2024; Le et al., 2024).

In addition, studies show that PTSE increases self-efficacy for using new technology and establishes a positive perception of demonstrability. If people believe they will get the most out of the technology, they're more likely to appreciate its tangible benefits. Thus, the mutual connection further validates PTSE and RD as connected predictors of ITU growth and important constructs for technology adoption.

Despite prior literature suggesting RD and PTSE as antecedents of ITU, champions of their facilitation, in technology-mediated learning and interactive settings need to establish more grounded support for their direct impacts in AI technology classrooms. For example, RD facilitates ITU based on effective results; however, few studies have explored RD's competing independent vs. dependent constructs in emerging AI technology (Jo, 2023; Yuan et al., 2021). In addition, the literature suggests that PTSE is a precursor to ITU; however, an independent direct impact of ChatGPT and PTSE has yet to be determined (Navarro et al., 2023). Therefore, this study aims to address this gap by evaluating the presence of each for ITU. Thus, the following hypotheses will be tested:

H11: Result Demonstrability (RD) significantly impacts Intention to Use (ITU).
H12: Perceived Technology Self-Efficacy (PTSE) significantly impacts Intention to Use (ITU).

Research Methodlogy

The study uses a questionnaire survey for data collection. Two hundred and fourteen students were approached to answer the questionnaires. Questionnaires were distributed using convenience and snowball sampling methods through various social media platforms such as WhatsApp, Facebook, WeChat, and Instagram. **Table (i)** provides the respondents' profiles:

Table (i)
Respondents' Profiles

Demographic	Frequency	Percentage
Gender		
Male	73	34
Female	141	64
Type of University		
Public University	39	18
Private University	172	80
Others	3	2
Experience with ChatGPT		
No	28	13
Yes	186	87

Instrumentation

Various instruments were used to test the variables. They are adapted and adopted from other studies in the literature. By doing so, it helps to ensure the appropriateness and reliability of the instruments. The instruments utilized in the study were carefully chosen and modified from established sources:

- Perceived Ease of Use (PEOU) (5 items) (Noted: This variable was named as "PEOU in Web-based learning system" in (Tarhini et al, 2017)
- Perceived Usefulness (PU) (4 items) (Noted: This variable was named as "PU in Web-based learning system" in Tarhini et al, 2017)
- Perceived Output Quality (OQ) (3 items) (Noted: This variable was named as "Output Quality" in Venkatesh & Bala, 2008);
- Perceived Result Demonstrability (RD)(4 items) (Noted: This variable was named as "Result Demonstrability" in Venkatesh & Bala, 2008);
- Perceived Technology Self-Efficacy (PTSE) (4 items)(Noted: This variable was named as "Computer Self-Efficacy in Venkatesh & Bala, 2008);
- Intention to use ChatGPT (ITU) (4 items) (Note: This variable was named as "Behavioural intention" in Tarhini et al, 2017)

A meticulous selection and adaptation process was undertaken to ensure the instruments used in the study were valid and consistent, assuring that the targeted constructs would be measured robustly.

Data Analysis

Internal Consistency and Convergent Validity

Internal consistency is verified through Cronbach's Alpha, rho A, and composite reliability (CR). Based on Table 1, all constructs fulfill the threshold level of at least 0.70 (Hair et al., 2019). Convergent validity implies the degree to which indicators correlate to the latent variable they intended to proxy (Santhanamery & Ramayah, 2014). In Table 1, the last column shows the convergent validity of the reflective constructs being assessed using average variance extracted (AVE), while factor loading results are presented in the first column. Factor loadings, AVE of higher than 0.50, and composite reliability (CR) values higher than 0.70 are acceptable (Hair et al. 2022). All the constructs' AVE, factor loading, and CR values are higher than required to fulfill the convergent validity.

Table 1
Internal Consistency and Convergent Validity Assessments

Construct	Item	Loading	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Perceived Ease of Use (PEOU)	A1	0.796	0.876	0.879	0.909	0.668
	A2	0.828				
	A3	0.819				
	A4	0.798				
	A5	0.845				
Perceived Usefulness (PU)	B1	0.847	0.912	0.916	0.934	0.738
	B2	0.879				
	B3	0.857				
	B4	0.848				
	B5	0.863				
Perceived Output Quality (OQ)	C1	0.868	0.833	0.853	0.899	0.747
	C2	0.855				
	C3	0.871				
Perceived Result Demonstrability (RD)	D1	0.790	0.824	0.837	0.883	0.654
	D2	0.750				
	D3	0.844				
	D4	0.847				
Perceived Technology Self-Efficacy (PTSE)	E1	0.802	0.824	0.846	0.883	0.655
	E2	0.860				
	E3	0.714				
	E4	0.852				
Intention to use ChatGPT (ITU)	F1	0.811	0.869	0.875	0.911	0.718
	F2	0.820				
	F3	0.868				
	F4	0.889				

Discriminant Validity
Discriminant validity results show how indicators are different across constructs and are assessed through the Fornell & Larcker's Criterion (Fornell and Larcker, 1981) cross-loading (Chin 1998) and Heterotrait-Monotrait (HTMT) ratio of correlations (Henseler et al., 2015).

Table 2 shows the results of Fornell & Larcker's Criterion, which required the criterion value on the diagonal to be higher than the value on the off-diagonal. All constructs have fulfilled the required Fornell & Larcker's Criterion. Cross-loading results, as in **Table 3**, also supported the discriminant validity. The cross-loadings for the respective construct they proxied (highlighted in bold for easy reference) are higher than the others. All the constructs have a Heterotrait-Monotrait (HTMT) ratio of correlation value lower than 0.85, thus further supporting discriminant validity. The results are shown in **Table 4**.

Table 2
Fornell-Larcker Criterion Results

Construct	ITU	PEOU	OQ	RD	PTSE	PU
ITU	0.848					
PEOU	0.583	0.817				
OQ	0.399	0.473	0.864			
RD	0.652	0.609	0.529	0.809		
PTSE	0.561	0.467	0.471	0.660	0.809	
PU	0.679	0.731	0.496	0.639	0.544	0.859

Note:
ITU is Intention to use ChatGPT, PEOU is Perceived Ease of Use, OQ is Perceived Output Quality, RD is Perceived Result Demonstrability, PTSE is Perceived Technology Self-Efficacy, and PU is Perceived usefulness

Table 3
Cross-loading Results

Construct /	ITU	PEOU	OQ	RD	PTSE	PU
Item	F	A	C	D	E	B
A1	0.459	**0.796**	0.298	0.459	0.310	0.518
A2	0.502	**0.828**	0.433	0.561	0.505	0.642
A3	0.446	**0.819**	0.466	0.502	0.421	0.589
A4	0.481	**0.798**	0.373	0.475	0.313	0.613
A5	0.490	**0.845**	0.346	0.480	0.335	0.614
B1	0.622	0.699	0.388	0.619	0.537	**0.847**
B2	0.594	0.647	0.479	0.566	0.437	**0.879**
B3	0.618	0.608	0.418	0.562	0.484	**0.857**
B4	0.513	0.565	0.461	0.469	0.431	**0.848**
B5	0.553	0.598	0.389	0.504	0.430	**0.863**
C1	0.317	0.452	**0.868**	0.414	0.371	0.424
C2	0.282	0.364	**0.855**	0.397	0.335	0.365
C3	0.413	0.409	**0.871**	0.535	0.489	0.480
D1	0.508	0.521	0.441	**0.790**	0.518	0.509
D2	0.395	0.367	0.307	**0.750**	0.453	0.374
D3	0.565	0.468	0.478	**0.844**	0.609	0.563
D4	0.608	0.589	0.458	**0.847**	0.541	0.587
E1	0.424	0.417	0.406	0.509	**0.802**	0.461
E2	0.519	0.444	0.400	0.590	**0.860**	0.547
E3	0.327	0.178	0.262	0.399	**0.714**	0.244
E4	0.510	0.423	0.430	0.606	**0.852**	0.457
F1	**0.811**	0.457	0.357	0.500	0.415	0.593
F2	**0.820**	0.497	0.272	0.563	0.471	0.531
F3	**0.868**	0.489	0.330	0.534	0.444	0.577
F4	**0.889**	0.526	0.391	0.603	0.557	0.604

Note:
ITU is Intention to use ChatGPT, PEOU is Perceived Ease of Use, OQ is Perceived Output Quality, RD is Perceived Result Demonstrability, PTSE is Perceived Technology Self-Efficacy, and PU is Perceived usefulness

Table 4
Heterotrait-Monotrait Ratio (HTMT) Results

Construct	ITU	PEOU	OQ	RD	PTSE	PU
ITU	-					
PEOU	0.666					
OQ	0.457	0.548				
RD	0.756	0.704	0.616			
PTSE	0.646	0.525	0.546	0.783		
PU	0.759	0.809	0.562	0.718	0.605	-

Note:
ITU is Intention to use ChatGPT, PEOU is Perceived Ease of Use, OQ is Perceived Output Quality, RD is Perceived Result Demonstrability, PTSE is Perceived Technology Self-Efficacy, and PU is Perceived Usefulness

Collinearity Test
The variance inflation factor (VIF) is used to test the presence of collinearity. The outer VIF results are shown in **Table 5**. All the indicators have a VIF value of less than 10, indicating no collinearity.

Table 5
Outer Variance inflation factor (VIF)

Item	VIF	Item	VIF
A1	1.932	D1	1.622
A2	1.976	D2	1.594
A3	1.999	D3	1.892
A4	1.908	D4	1.905
A5	2.317	E1	1.910
B1	2.293	E2	2.142
B2	2.905	E3	1.605
B3	2.507	E4	2.016
B4	3.247	F1	1.880
B5	3.251	F2	1.845
C1	2.178	F3	2.666
C2	2.104	F4	2.810
C3	1.699		

Note:
ITU is Intention to use ChatGPT, PEOU is Perceived Ease of Use, OQ is Perceived Output Quality, RD is Perceived Result Demonstrability, PTSE is Perceived Technology Self-Efficacy, and PU is Perceived Usefulness

Structural Model

Figure 1 represents the relationships between the latent variables PEOU, PU, OQ, RD, and PTSE and the target variable ITU. These relationships are matched to their respective hypotheses in **Table 6**, which also reported the values of path coefficients and their significance.

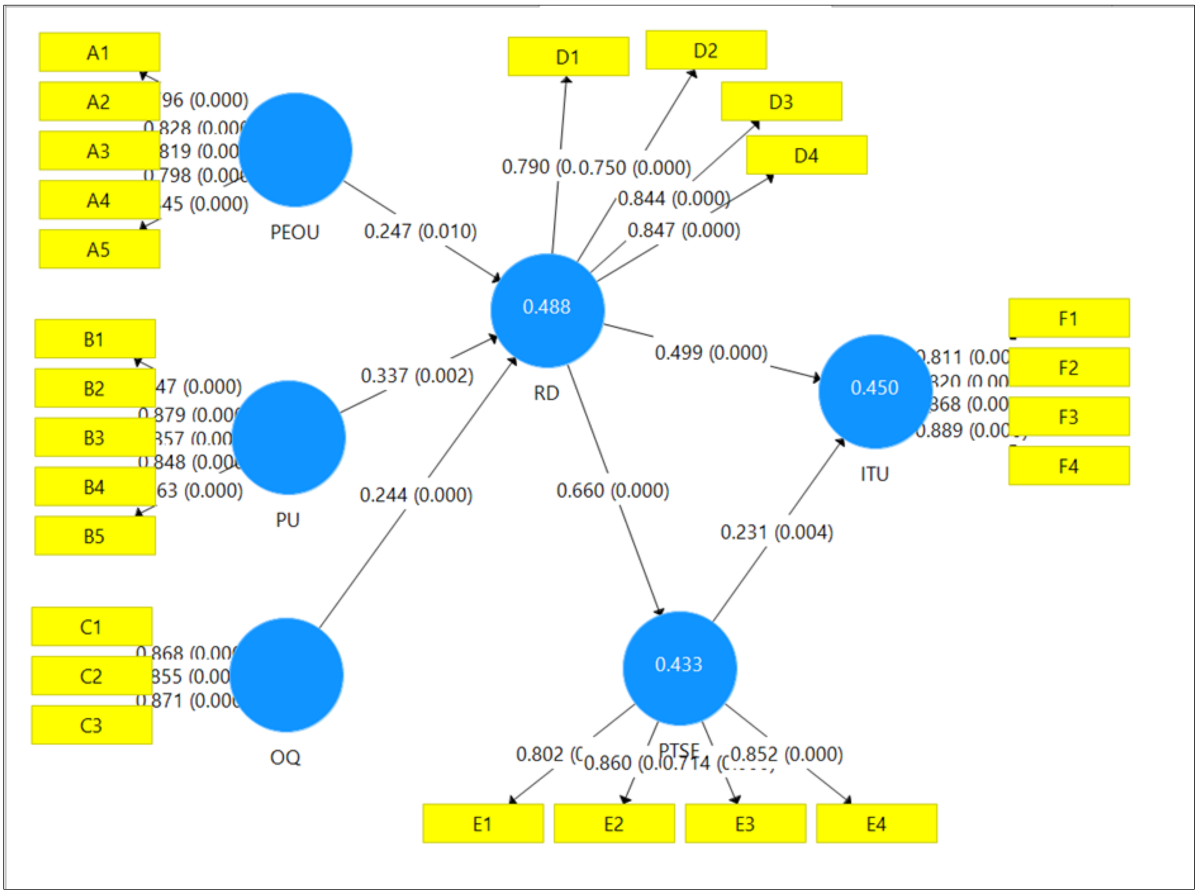

Figure 1: Structural Model

Table 6

Summary of the Hypotheses of the Study

No	Relationship	Std. Beta	Std. Error	t-value	Confidence Interval		Decision
					LL	UL	
H1	PEOU -> RD -> ITU	0.123	0.045	2.715***	0.036	0.210	Supported
H2	PU -> RD -> ITU	0.168	0.065	2.575***	0.053	0.304	Supported
H3	OQ -> RD -> ITU	0.122	0.035	3.494***	0.053	0.189	Supported
H4	PEOU -> RD -> PTSE	0.163	0.063	2.589***	0.045	0.289	Supported
H5	PU -> RD -> PTSE	0.223	0.074	2.997***	0.078	0.368	Supported
H6	OQ -> RD -> PTSE	0.161	0.044	3.627**	0.076	0.254	Supported
H7	PEOU -> RD -> PTSE -> ITU	0.038	0.021	1.757*	0.008	0.103	Supported
H8	PU -> RD -> PTSE -> ITU	0.052	0.025	2.068**	0.018	0.119	Supported
H9	OQ -> RD -> PTSE -> ITU	0.037	0.017	2.211**	0.014	0.085	Supported

No	Relationship	Std. Beta	Std. Error	t-value	Confidence Interval		Decision
					LL	UL	
H10	RD -> PTSE -> ITU	0.153	0.055	2.764***	0.061	0.281	Supported
H11	RD -> ITU	0.499	0.068	7.334***	0.360	0.631	Supported
H12	PTSE -> ITU	0.231	0.078	2.965***	0.080	0.385	Supported

Note:
*p<0.10, **p<0.05, *** p<0.01; ITU is Intention to use ChatGPT, PEOU is Perceived Ease of Use, OQ is Perceived Output Quality, RD is Perceived Result Demonstrability, PTSE is Perceived Technology Self-Efficacy, and PU is Perceived Usefulness; Std. Beta is standard Beta (coefficient), Std. Error is the standard error; LL is a lower limit; UL is an upper limit; the confidence interval is at a 5% level, and bias is corrected.

Discussion

These findings from the current research provide a different lens through which personal perceptions and confidence can influence technology-in-use intentions for a new technology. The statistical significance of PEOU, PU, OQ, and RD suggests that a more intertwined approach to rational engagement is required for this to be a truly new system accepted and operated.

The relationship between PEOU and ITU, therefore, includes a clear intent of use for end-users who find the technology easy to use and useful for meeting their specific requirements. The easier it is for one to operate the program to fulfil its needs, the more people are likely to accept this new technology. This finding corroborates the creators of TAM, who believe that ease of access to design ensures that required endeavours are not overly cumbersome (Venkatesh & Bala, 2008). Finally, these findings show that PEOU subsequently mediates PU, meaning that PEOU helps people understand usefulness, which then empowers their intentions of acceptance.

PU was identified as the most critical construct in determining ITU because people are more likely to believe and accept a technology that offers true innovation in terms of functionality and performance. This aligns with the existing literature, which notes that practical benefits are the most critical emergent factor in technological adoption (King & He, 2006). Thus, this should be championed for user use, providing benefits not only in time management and improved efficiency, but also as a decision-making resource for major decisions and when one feels most overwhelmed (Chen et al., 2020; Sundkvist et al., 2024).

Where OQ also adds to the information, users are guided by ease and usefulness from the system, and, in turn, by results. Systems that continually deliver desired results help to improve users' confidence in technology and their willingness to use it (DeLone & McLean, 2003). Thus, the information that maintains a user's focus on reliability in their output keeps them secure in the system and allows it to accept their production (Sundkvist et al., 2024; Al-Abdullatif et al., 2024). Furthermore, this study identified an additional finding: the mediating role of RD in the relationships between PEOU, PU, OQ, and ITU. RD amplifies the effectiveness of PEOU and PU at ITU, yielding clear gains from technology. The more users can visualize positive benefits (greater productivity, better results), the greater the perceived usefulness of the technology and the easier its acceptance (Gefen & Straub, 2000). This is particularly important in contexts where new technology could be misused by those for whom it's designed. Therefore, highlighting benefits not only places such evidence under a microscope but also rallies people to support it and reduces change-induced apprehension.

In another note, RD refers to circumstances in which the pre-data stage of a recently implemented technology is a breakthrough, and other system characteristics apply. This occurs with everything before technology is implemented, meaning the narrative framing (case studies, demonstrations, or user testimonials on how technology currently provides benefits in the real world). In fact, the research suggests that this could yield greater benefits for user perception, thereby encouraging implementation (Duy et al., 2025; Pang et al., 2024).

Another important finding from this investigation is the impact of PTSE on ITU. Users possessing PTSE may obtain more desirable and favourable outcomes through technology, which often puts them in advantageous situations (Compeau & Higgins, 1995). Furthermore, RD finds that increased PTSE indicates that, if users see tangible benefits from technology use, their belief that they are more qualified to do something will be greater. This highlights the idea that people know they can succeed at something with support when they see how successful others appear (Compeau et al., 1999).

The study also finds PTSE to be a mediator, so as confidence rises, one experiences reduced anxiety (negatively) for adaptation towards an uncomfortable transition/newness. Thus, for companies or universities looking to educate students/professionals on multiple systems, critical training efforts that elevate PTSE among insiders are needed, as this will be viewed as a contributor to user adoption and will most definitely yield short-term gains (Agarwal et al., 2000). Thus, since this will give students hands-on experience, it will allow universities to improve student acquisition performance (e.g., ChatGPT).

In sum, the study highlights the interrelated effect of these factors as something that has been ignored or overlooked for too long. PEOU, PU, OQ, RD, and PTSE interact to construct user behaviour and perception. The findings also suggest that the strategies for successful technology adoption should look not only at designing user-friendly systems but also at highlighting concrete benefits of the technology to build confidence with help and training for users; the approach can result in a better perception of the technology, ultimately leading to increased adoption rates.

Limitations and Recommendations for Future Research

The study has some limitations; for example, a quantitative survey has been used in this study, and even though this study found evidence for distance prediction and generalisability, this study adopted only quantitative methods for data collection and analysis, and this might have limited the depth of insights if compared to qualitative approaches to examine students' perceptions and experiences of AI in learning environments. Therefore, it might be more effective for future researchers to incorporate qualitative methods such as interviews or focus groups to gather evidence on students' panorama of learning with AI tools. Besides, the respondents in this study are only accounting students, so the results are not generalizable to other academic specializations. Future studies can be conducted across national boundaries and in different areas of specialization. Besides, they may consider deliberating the multiple-sector approach to emphasize the other perspectives on the phenomenon, and this may help provide an in-depth insight into the aspects that define AI tools like ChatGPT, which may be useful.

Future research could explore the longer-term implications of such AI tools for student learning and achievement, as a more generalizable measure of the tools' effectiveness. For example, longitudinal studies collecting panel data on the same students year after year would better illuminate such effective facilitation of student growth through AI tool implementation over time. Research into the potential of cognitive endowments, such as learning styles, would also better facilitate student buy-in and the implementation of AI tools for personalized learning solutions. However, when AI tools are supported in the classroom, there are ethical implications (i.e., privacy, bias, and algorithmic accountability) that practitioners must acknowledge. Subsequently, future research could clarify how such ethical implications affect students' perceptions of the investigated tools, and there should be a call for the ethical implementation of AI in such contexts.

Finally, it is important to note that this paper reports the findings based on the data collected from the survey conducted purely for academic purposes and it does not imply, endorse or critique behaviour, intent and organisational practices of OpenAI and its products.

Conclusion

The study's results confirm the key postulates of the TAM framework and underline the impact of perceived ease of use, perceived usefulness, and output quality on result demonstrability. The study has also examined the mediating effect of result demonstrability. The study's results provide an enriched theoretical perspective on the applicability of technology acceptance models in the educational setting with references to AI integration. Hence, subsequent research should examine the existence and persistence of the identified impacts in the long term and explore the ethical issues associated with implementing AI tools in the learning environment. Studies may also consider other forms of AI tools beyond ChatGPT and adopt more extensive samples and mixed-methods research to understand AI tools' acceptance in the learning environment. With these approaches addressed, stakeholders may respond to the call and use AI tools to enhance learning outcomes and prepare students for future life based on ICTs.

Acknowledgement

Publication of this work was supported by HELP University, Malaysia [Publication Charge Support Grant 26-03-009]

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