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Integrating AI chatbots for enhancing academic support in business education: A SEM-Based study toward sustainable learning

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ABSTRACT

Artificial Intelligence (AI) chatbots are transforming academic support in higher education by delivering personalized, real-time assistance to students. In business education, where students often face difficulties accessing timely academic and administrative support, AI chatbots present innovative, scalable, and equitable solutions that promote more inclusive and sustainable learning environments. This study investigates factors influencing business students' intentions to adopt AI chatbots as virtual academic assistants, which integrates both academic and administrative functionalities, using the Stimulus–Organism–Response (SOR) framework. It examines the interaction among Perceived Ease of Use (PEOU), Perceived Usefulness (PEU), Personal Innovativeness (PIN), Anthropomorphism (ANM), Perceived Information Quality (PIQ), Trust (TRUT), Satisfaction (SAT), and Intention to Use (INT). Data from 290 business management students were analyzed using Structural Equation Modeling (SEM). Results reveal that PEOU, PEU, ANM, and PIQ positively influence SAT and TRUT, which in turn significantly predict students' behavioral intentions to adopt AI chatbots. These findings indicate the importance of usability, humanlike features, and high-quality information in fostering trust and satisfaction. The study contributes to the literature on sustainable education innovation and offers practical implications for business educators aiming to integrate AI-driven solutions into academic support services, thus promoting more effective, accessible, and student-centered learning environments.

1. Introduction

In current years, the fast-growing artificial intelligence (AI) field has increased the use of virtual assistants and chatbots across various fields, including the education sector (Chan, 2023; Rusmiyanto et al., 2023). Chatbots are AI-based applications capable of recognizing and responding to students' inputs. They have gained much popularity because they support students' educational needs,

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particularly in higher-level education institutions (Dahri, 2024). In particular, business and management programs are integrating chatbots to meet the growing demand for scalable, flexible, and technology-enhanced education delivery. These AI applications, also called virtual assistants, when designed and behave to users input in natural language, are inclined toward student engagement and support services in educational institutions (U. A. Khan & Alamäki, 2023; Y. Wu, 2023). Chatbots perform various roles, such as counsellors, academic guides, and support systems, thereby augmenting traditional educational methods and addressing issues of scalability and accessibility in universities (Bilquise et al., 2023; Iancu & Iancu, 2023; Kooli, 2023).

Nowadays, Education increasingly relies on technology to prepare more personalized learning knowledge, and the role of AI chatbots has expanded to include tutoring, mentoring, and feedback mechanisms, which mimic aspects of human teaching (Bilquise et al., 2023). Unlike conventional digital learning tools, chatbots possess the unique capability of interacting with students in a manner that resembles natural conversation, driven by advances in Natural Language Processing (NLP) technologies. These features make them particularly suited for tasks requiring frequent and immediate interaction, enabling the students to receive real-time responses to their academic queries (Liang et al., 2023; Lim et al., 2023; Y. Wu, 2023). Business students, who often juggle coursework, internships, and case-based learning activities, particularly benefit from anytime support provided by AI chatbots. In a higher education context, where student-to-instructor ratios can be imbalanced, chatbots hold promise as a tool to bridge the gap by offering immediate support outside of scheduled classroom interactions (Araujo, 2018; N.-Y. Kim et al., 2019; Kooli, 2023).

Recent studies highlight that integrating AI chatbots fosters students' sustainable learning experiences by enhancing engagement, promoting autonomy in learning, and providing continuous academic and administrative assistance, contributing to better educational outcomes and satisfaction (Bouteraa et al., 2024; Chang et al., 2023). Within business education, these tools also align with "sustainable development goals (SDGs)", particularly "Goal 4 (Quality Education) and Goal 9 (Industry, Innovation, and Infrastructure)", by promoting innovation and equitable access to academic support. Chatbot provides many advantages in the education sector, making the education business more efficient (Caratiquit & Caratiquit, 2023; Guo et al., 2023). Chatbots have significantly reduced the costs associated with staff-driven support in universities. Now, these chatbots offer valuable, innovative, and scalable student services (Dahri, Yahaya, & Al-Rahmi, 2024). Two main types of chatbots are used in education: i) Service-oriented chatbots and 2) teacher-oriented chatbots (Perez-Ortiz et al., 2021; Rahim et al., 2022). Service-oriented chatbots are utilized in administrative tasks, such as assisting students with queries about enrollment, admissions, and library services, whereas teacher-oriented chatbots act as classroom assistants, facilitating student engagement and providing personalized feedback on learning activities (Rahim et al., 2022; Vázquez-Cano et al., 2023). The popular chatbots are Bard (Rudolph et al., 2023), ChatGPT (Fitria, 2023), and ADA (Labadze et al., 2023). They support different educational needs, such as personal tutoring, writing text, making creative content, and giving feedback. ChatGPT, launched by OpenAI in 2022, is among the most widely adopted AI-powered educational tools and has quickly gained prominence in higher education for its ability to generate contextually relevant and humanlike responses. It is frequently used to assist students in brainstorming, answering course-related questions, summarizing academic texts, and even writing essays (Foroughi et al., 2023; Mogavi et al., 2023). Its popularity is attributed to its ease of use, perceived learning value, and hedonic motivation, although concerns about accuracy and reliability in academic contexts remain (Khademi, 2023; Rahsepar et al., 2023). Other chatbots, such as Replika and Socratic, are used for emotional support and help with learning through AI (Labadze et al., 2023). Games like Habitica encourage learners by managing tasks and giving rewards, while tools like Piazza improve teamwork and conversations (Labadze et al., 2023). These chatbots offer great benefits, such as ubiquitous access, a personalized learning experience, increased engagement, and reduced costs in administrative functions (Labadze et al., 2023; Okonkwo & Ade-Ibijola, 2021). However, data privacy, ethical issues, accuracy, and the risk of over-reliance on AI are some of the challenges that need to be taken into consideration for mindful integration into educational systems. Despite these limitations, chatbots continue to empower students and educators, fostering an inclusive and interactive learning environment (Okonkwo & Ade-Ibijola, 2021). it is important for business and management education, where time-sensitive learning, quick decision-making, and real-world problem-solving are key expectations from students. These functionalities of chatbots assist students in their daily lives and make them easier and more convenient to adopt to meet their unique requirements. The chatbot marketplace size is expected to increase from €5.70 billion in 2024 to €60.50 billion by 2035, with a CAGR of 23.94 % over the forecast period 2024–2035 as trends shown in Fig. 1.

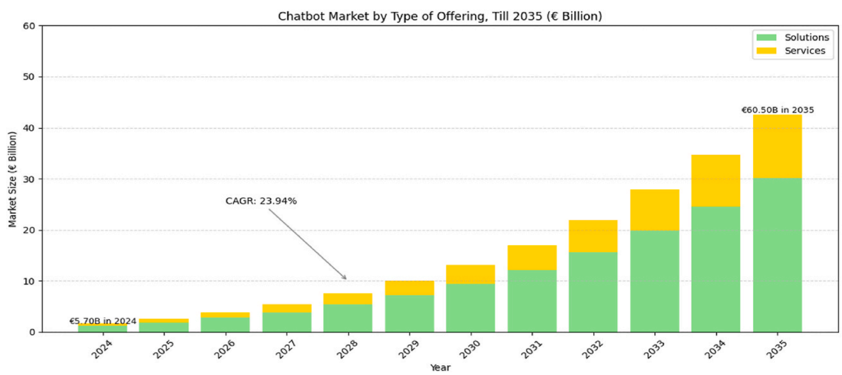

Fig. 1. AI Chatbot overview (source: https://www.rootsanalysis.com/chatbot-market).

Saudi universities have, over the years, incrementally introduced AI chatbots in support services to upgrade students' experience through virtual assistance. Such chatbots optimize access to resources, provide timely help, and perform a myriad of administrative and academic activities. Universities in Saudi Arabia created an academic assistant chatbot that gives students instant answers to their queries, allowing them to quickly access library resources and research topics (Dahri, Yahaya, Al-Rahmi, Vighio, et al., 2024). The present study investigates student perceptions of one such AI chatbot developed at Al-Jouf University, an institution-specific virtual assistant chatbot that provides both academic and personalized, curriculum-aligned academic support and administrative support for business and management students. This customized chatbot integrates key educational functions such as real-time Q&A, course-specific tutoring, and personalized feedback, making it more pedagogically relevant compared to generic AI tools. Such initiatives reflect a growing trend in Saudi higher education, especially within business and management faculties, where chatbots promote efficiency and enable personalized learning experiences that cater to the individual needs of future business leaders. This chatbot is an example of how AI-driven tools can help in resource discovery by providing personalized assistance to support the learning process of students. Apart from answering questions, the university assistant chatbot helps students navigate through library systems, find relevant materials, and even suggest resources based on user history, which makes the learning process more engaging and accessible (Annamalai et al., 2023; Chocarro Eguaras et al., 2021).

Various Saudi universities have adopted similar AI chatbot technologies to support broader academic and administrative functions. These chatbots are particularly beneficial for new students, who may find navigating university services challenging (Dahri, Yahaya, Al-Rahmi, Vighio, et al., 2024). Such initiatives reflect a growing trend in Saudi higher education, where chatbots promote efficiency and enable personalized learning experiences that cater to individual needs. This integration of AI tools aligns with global educational trends emphasizing the role of technology in improving accessibility and student engagement within university environments (Bansal et al., 2024).

Numerous studies highlight the potential of chatbots in improving educational outcomes and addressing challenges in higher education. Chatbots are seen as potential solutions to issues such as inadequate student-instructor interactions, particularly in contexts where large class sizes limit individual student attention and where higher education institutions often have high student-to-instructor ratios, making it difficult for instructors to address individual student needs properly (Dahri, Yahaya, Al-Rahmi, Vighio, et al., 2024). In such environments, chatbots can serve as a supplemental instructional resource, providing students with instant responses to their questions, similar to what they might receive from an instructor in a one-on-one setting (Soomro et al., 2024). In addition to enhancing student engagement, chatbots benefit educators by enabling them to track students' progress and monitor areas where students may require additional support. As noted by (Akinyemi et al., 2023), the enhanced computing power and widespread availability of mobile devices have further facilitated the deployment of chatbots in education. This is not a result of technology but a response to the rising need for more accessible, scalable, and personalized learning resources aligned with the learning styles of the current generation of students. Furthermore, progress in NLP enables chatbots to better interpret and produce answers that relate to the students' questions, which creates a more user-friendly and interactive learning environment (Sajja et al., 2024).

Chatbots can improve the delivery of educational services; therefore, educational institutions are paying attention to them to update and advance the teaching methods in the process. According to Pappagallo (Pappagallo, 2024), problems of traditional learning settings, such as too little in-person interaction and rigid academic and administrative support systems, might also be reduced due to chatbots. Through their use as virtual assistants, chatbots allow education establishments to improve the student satisfaction levels by providing round-the-clock support, reducing the on-site staff requirements, and offering services beyond the confines of their traditional support environments (Vonitsanos et al., 2024; Waleed et al., 2023). In business programs, this flexibility is essential for catering to students pursuing professional certifications, internships, or part-time jobs. Given the fact that educational institutions increasingly implement AI-driven technology, there is a need to understand the factors responsible for the willingness of students to interact with such virtual assistants, particularly in relation to perceived ease of use, usefulness, trust, and Satisfaction.

The SOR model can be considered as a base frame of reference for the analysis of AI chatbot adoption in higher education (Cho et al., 2019). According to the SOR model, internal states like trust and Satisfaction are dependent on stimuli in the form of chatbot interactivity, anthropomorphism, and information quality that motivate the response intention to adopt. At the same time, TAM (Davis, 1989) highlights that "perceived ease of use (PEOU) and perceived usefulness (PEU)" are important factors in accepting technology. Kukanja (2024) emphasize that user attitudes, trust, and contextual readiness play a significant role in determining AI adoption outcomes across various sectors, including education and hospitality. This study looks at how chatbot features, such as being interactive, easy to use, useful, and smart, affect students' trust, satisfaction, and willingness to use them. These ideas are especially important in schools, where knowing how to build trust and satisfaction can greatly impact students' use of AI tools (Venkatesh & Davis, 2000). Particularly in business education, fostering trust in technology is crucial for developing future managers and entrepreneurs who will increasingly rely on AI in the business environment. It was on the back of these trends that this research assessed the factors that determine the acceptance of AI chatbots as academic virtual assistants in Malaysian higher education institutions. This research demonstrated that PEOU, PEU, perceived intelligence (PIN), anthropomorphism (ANM), trust (TRU), perceived information quality (PIQ), interactivity (INT), and Satisfaction (SAT) were the predictors of the intention to use AI chatbots. This research uses SOR theory and TAM model ideas to show how these factors work together to affect students' acceptance and use of chatbots. This information is helpful for teachers and technology developers who want to use AI to improve education.

The main aim of this study is to investigate the factors that influence the adoption of AI chatbots as a virtual assistant in Saudi higher education institutions. This study seeks to understand how these factors affect students' behavioral intentions to adopt AI chatbots in educational settings. To accomplish the aim, these objectives need to be focused. 1) To investigate the impact of PEOU, PEU, and PIN on TRU and SAT with AI chatbots as academic virtual assistants. 2) To evaluate how ANM, PIQ, and INT influence students' trust and Satisfaction in using AI chatbots in higher education. 3) To examine the relationships between trust, Satisfaction, and behavioral intention to adopt AI chatbots (BIAC) as virtual assistants among students in higher education institutions.

2. Theoretical background and Hypothesis Development

The study design of this proposed framework relies on two models: the "Stimulus-Organism-Response Theory and the Technology Acceptance Model". The theories clarify the determinants of the behaviour of business students to accept AI chatbots as virtual academic assistants within a higher education context. The S-O-R theory, established by Mehrabian and Russell in 1974, provides a framework to explain how environmental stimuli can affect the internal state of people and then subsequently their behavior. In this theory, stimuli (S) are environmental cues or exogenous factors that affect the organismic state of the person, which then includes emotional and cognitive reactions. These organismic reactions then become the behavior (R) of the person. S-O-R theory has also been widely used in many areas such as consumer behavior and user experience research, to explain how environmental characteristics affect decision-making processes (O'Donovan, 2017).

The PEOU, PEU, PIN, ANM, PIQ, and INT constructs are external stimuli (S) according to the context of this study. They encapsulate the way the students view the AI chatbot as an online assistant. These are PEOU and PEU of TAM, PIN, ANM, PIQ, and INT as contributors to functionality and appeal for the chatbot. Collectively, these stimuli influence students' internal states of trust and Satisfactions (O), which in turn go on to influence their behavioral intentions regarding the adoption of the chatbot (R) as a study support tool (Kühn & Petzer, 2018).

In addition, the TAM, developed by Davis in 1989, is one of the most widely used models to predict user acceptance of technology. TAM postulates that PEOU and PEU are the prime factors that influence users' attitudes toward technology, which then influence their behavioral intentions. PEOU is defined as the degree to which a user believes that the system will be utilized with minimal effort, and perceived usefulness is the degree to which a user believes that the use of specific technology will enhance his or her performance. It is assumed in the S-O-R model that these two constructs are crucial to drivers affecting organismic states such as trust and satisfaction toward the AI chatbot.

This study expands TAM by considering additional constructs that bring out the unique chatbot features in terms of the PIN of the chatbot, ANM, PIQ, and INT; these variables may be important as they help the assessment of how well the AI chatbot might be meaningfully connect with students thereby enhancing both trust and Satisfaction. Specifically, trust is an essential feature of the technology adoption that defines the extent of users' beliefs in the safety and security of the chatbot (Gefen et al., 2000). Satisfaction would then be another vital result that incorporates user satisfaction with the performance of the chatbot.

Fig. 2 depicts the novel research model of S-O-R theory for analyzing the adoption of AI chatbots for business education (J. Kim & Lennon, 2013; Tsai & Bagozzi, 2014). The integration of the theoretical framework and hypothesis relationships, as depicted in Fig. 3, would therefore be more feasible for deeper understanding of factors determining the acceptance of AI chatbots among students; this can lead to beneficial inputs for educational institutes trying to boost engagement and support services using the same chatbot technology (Jacoby, 2002).

2.1. PEOU, trust, and satisfaction

According to Davis (1989), PEOU is defined as the degree to which a person believes that the use of a particular system or technology will require little effort (Jeong & Chung, 2022). The ease of use of AI chatbots in education is very important since it determines how much users trust and are satisfied with the technology. When students perceive the chatbot as easy to navigate and use, they are more likely to trust the chatbot's capabilities and feel satisfied with their interactions (Al-Adwan et al., 2023; Dahri, Yahaya, Al-Rahmi, Aldraiweesh, et al., 2024). Trust is a greater determinant of technology adoption, particularly in an academic environment where students use chatbots for learning and guidance. Earlier findings indicate that users trust a system the more easily they are able to interact with it and consequently find reliable and accurate information (Bedué & Fritzsche, 2022; Hasija & Esper, 2022). This impact is especially notable in chatbots because ease of use enables students to concentrate on business study without having to struggle with technical issues (Bedué & Fritzsche, 2022; Huang et al., 2022; Stöhr et al., 2024). Hence, it is hypothesized that perceived ease of use has a positive effect on trust in the chatbot. Similarly, Satisfaction reflects a user's contentment with the chatbot's performance, largely

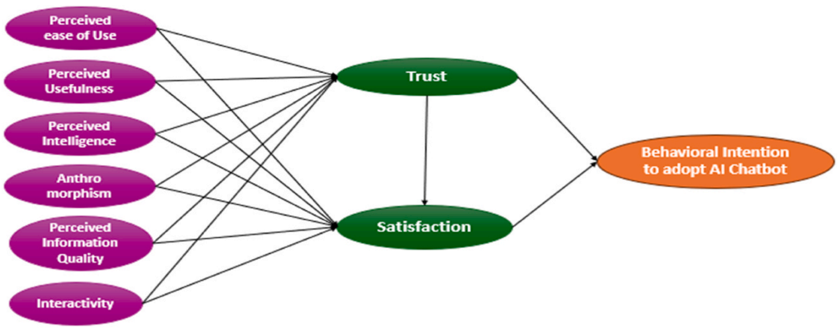

Fig. 2. Proposed research model.

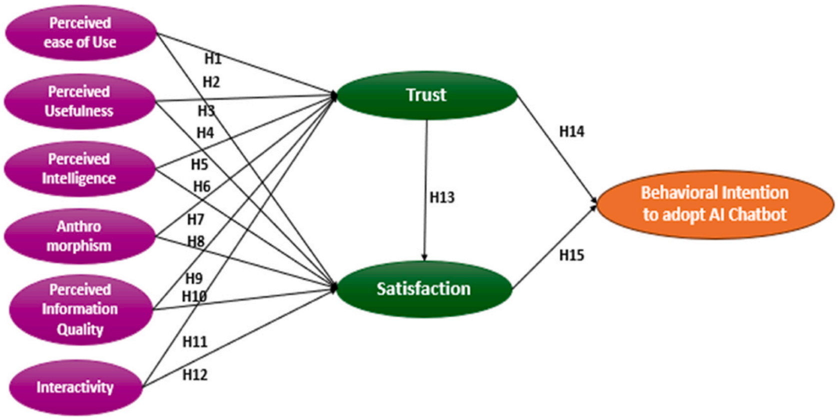

Fig. 3. Hypothesis development.

influenced by the user's perception of the chatbot's ease of use (Ashfaq et al., 2020; Chatterjee & Bhattacharjee, 2020). Students who find the chatbot easy to use are more likely to have a positive experience, leading to higher satisfaction levels. Literature supports the notion that perceived ease of use positively impacts Satisfaction by reducing the cognitive effort required to interact with the system, thereby enhancing user experience (Huang et al., 2022; Nguyen & Sidorova, 2018; Park & Kim, 2023).

H1. PEOU has a positive effect on TRU.

H2. PEOU has a positive effect on SAT.

2.2. PEU, trust, and satisfaction

PEU, which forms an important element of TAM, is how much a person perceives that employing a particular system will enhance their performance (Grover et al., 2019). In the context of AI chatbots in business education, perceived usefulness represents students' belief that the chatbot can effectively support their academic tasks, provide relevant information, and contribute to their learning outcomes (Bilquise et al., 2023). Research indicates that when students perceive a chatbot as useful, they are more likely to trust it, as its usefulness reflects its capability to effectively meet their academic needs (Al-Abdullatif, 2023). When users recognize the practical value of the chatbot, they tend to develop trust in its capabilities and reliability, particularly in delivering accurate and helpful information for their educational pursuits (Al-Abdullatif, 2023; Bilquise et al., 2024). In addition, perceived usefulness directly influences Satisfaction, as it shapes users' perceptions of the chatbot's effectiveness in assisting their academic activities. Satisfaction arises when the chatbot fulfils the user's expectations regarding academic support and enhances their learning experience. According to (Bilquise et al., 2024), when users perceive technology as valuable and beneficial, they are more likely to feel satisfied with its use. In an educational setting, if students believe that the chatbot adds value to their academic activities, their Satisfaction with the system is likely to increase. This positive effect of perceived usefulness on Satisfaction has been widely supported in educational technology research (Bilquise et al., 2024; Rahim et al., 2022). Based on this, the following hypotheses are developed:

H3. PEU has a positive impact on TRU.

H4. PEU has a positive effect on SAT.

2.3. PIN, trust, and satisfaction

PIN refers to the extent to which users believe that a technology or system can exhibit intelligent behavior, such as empathetic context, learning from interactions, and providing relevant responses PIN refers to how much users believe that a technology or system can exhibit smart behavior, that is, by understanding the context, learning through interactions, and providing useful answers (Ho & MacDorman, 2010). In the context of AI chatbots in higher education, perceived intelligence is critical because it determines students' trust in the system's capabilities. Chatbots that demonstrate humanlike intelligence, including adaptive and responsive behavior, tend to foster higher trust among users, as they are seen as reliable and capable of meeting user needs effectively (McGinn et al., 2019; Petisca et al., 2015; Weiss & Bartneck, 2015). Research has shown that when students perceive a chatbot as intelligent, they are more inclined to trust it, as they believe it can accurately understand their inquiries and provide meaningful assistance (Dahri, Yahaya, Al-Rahmi, Aldraiweesh, et al., 2024; Y.-F. Lee et al., 2022). Perceived intelligence also plays a key role in influencing Satisfaction with the chatbot. Satisfaction in this context arises when students feel that the chatbot's responses are accurate, insightful, and contextually relevant, indicative of intelligent behavior (Dwivedi et al., 2021). When students perceive the chatbot as intelligent, they are more likely to feel satisfied with the interaction, as the chatbot's ability to respond intelligently can reduce cognitive effort and enhance the overall learning experience (Pillai & Sivathanu, 2020). This is particularly significant in educational settings where students seek timely and contextually accurate study assistance. Therefore, the following hypothesis is proposed:

H5. PIN has a positive impact on TRU.

H6. PIN has a positive effect on SAT.

2.4. ANM, trust, and satisfaction

ANM is the tendency to believe that things that are not anthropological, such as AI chatbots, possess human-like features or attributes (Araujo, 2018; Bartneck et al., 2009; Singh et al., 2021). In the case of AI chatbots in higher education, anthropomorphism is an important factor in influencing the perceptions of students, as it makes the chatbot conversations more personal and interactive (Araujo, 2018; Moussawi et al., 2023). When users experience a chatbot as having humanlike attributes—like being able to understand emotions or respond with empathy—they are more likely to trust it. Evidence indicates that anthropomorphizing chatbots through the use of features such as natural language replies, tone shifts, and even facial expressions builds trust among users by making the system feel familiar and relatable (Alsaggaf & Althonayan, 2018; S. Lee et al., 2011; Vinhas Da Silva & Faridah Syed Alwi, 2006). Additionally, anthropomorphism boosts Satisfaction by making the interaction more pleasant and engaging, which ultimately contributes to higher levels of user satisfaction. Humanlike behaving chatbots are more likely to receive positive emotional reactions from users because they mimic social interaction in a way that is satisfying and comforting (Alabed et al., 2022; Li & Sung, 2021; Tian et al., 2024; Złotowski et al., 2015). In the context of education, personalized and responsive chatbots are more acceptable to students, given that such characteristics lead to a better user experience (Li & Sung, 2021; Sheehan, 2018; Tian et al., 2024). For example, an anthropomorphized chatbot with empathy and adaptive responses according to the student's requirements can increase Satisfaction by emulating supportive behaviors commonly anticipated in human interaction (Bilquise et al., 2024). On this basis, the following hypothesis is formulated:

H7. ANM has a positive effect on TRU.

H8. ANM has a positive effect on SAT.

2.5. PIQ, trust, and satisfaction

PIQ refers to how much users think the information given by a technology system is accurate, relevant, timely, and useful (Aggarwal & Rahul, 2017; Wang & Lin, 2017). In the context of AI chatbots in higher education, perceived information quality is particularly relevant, as students depend on chatbots to provide reliable and accurate responses. High-quality information fosters trust because users are more likely to trust a chatbot that delivers precise, credible, and useful information (Jayadi & Murwani, 2022). When students perceive the chatbot as a reliable source, their trust in the system grows, believing it will effectively meet their informational needs (Jayadi & Murwani, 2022). In addition to trust, perceived information quality significantly impacts Satisfaction. When students experience a high level of "information quality" from the chatbot, they are more likely to feel satisfied with their interactions, as the chatbot provides value and meets their academic expectations (Ashfaq et al., 2020; Chen et al., 2023). Satisfaction arises when students perceive that the chatbot is a dependable tool that contributes to their learning, helping them find accurate answers quickly. Research suggests that perceived information quality enhances user satisfaction by reducing the cognitive effort required to find reliable information and improving the overall interaction experience (Jayadi & Murwani, 2022). Consequently, the following hypothesis is formulated:

H9. PIQ has a positive impact on TRU.

H10. PIQ positively influences SAT.

2.6. INT, trust, and satisfaction

INT depicts the extent to which users can interact with an environment and experience a two-way exchange of communication (Arghashi & Yuksel, 2022). For AI chatbots, especially in the educational environment, interactivity is a necessity to offer an engaging and interactive experience. Highly interactive chatbots enable users to have meaningful conversations, responding based on inputs from users and developing a customized interaction experience. It has been evidenced that increased interactivity positively affects trust since it increases the feeling that the system is responsive and active in attending to user requirements (Bao et al., 2016; G. Wu et al., 2010). Such responsiveness aids in establishing trust due to its simulation of human conversation patterns, thus making users more confident in the reliability and relevance of the chatbot. Interactivity also greatly improves Satisfaction by making the experience more satisfying and fun to engage in. When a chatbot is interactive, it can return answers to users' questions in a manner that is stimulating, thus improving satisfaction with the technology by the users (Croxton, 2014; Ting et al., 2021). Interactive college chatbots can engender Satisfaction by responding instantaneously and resolving personal user inquiries, so students feel assisted and comprehended (Croxton, 2014; G. Wu et al., 2010). A chatbot's capacity to engage in conversation with users, resolve inquiries, and react in real-time satisfies users' demands and heightens their perception of the system's utility and performance. Under this premise, therefore, the following hypothesis is formulated:

H11. INT positively influences TRU.

H12. INT positively influences SAT.

2.7. Trust, satisfaction, and behavioral intention to adopt AI chatbots

Trust is fundamental in influencing users' experience of technology and their likelihood of adopting it (Horst et al., 2007). Within the context of AI chatbots in higher education, trust reflects the belief that the chatbot is reliable, competent, and has the users' best interests in mind. When students trust a chatbot, they are more likely to be satisfied with their experience, as trust reduces uncertainties and enhances perceived value during interactions (Pesonen, 2021). This feeling of trust creates a positive feedback cycle, resulting in a greater degree of Satisfaction by causing users to believe that they are interacting with reliable and trustworthy technology (Toader et al., 2019). Furthermore, trust is an important predictor of the behavioral intention to embrace AI chatbots, as users are more inclined towards using technology, which they consider trustworthy (Ayanwale & Ndlovu, 2024; Emon et al., 2023). Belief in the capability of the chatbot to yield correct and relevant information, protect user privacy, and display consistent functioning promotes a feeling of security, which encourages users to embrace the technology. Such trust, particularly within an educational environment, can minimize new technology perceived risk, thus enhancing the readiness of students to incorporate chatbots in their learning processes (Ayanwale & Ndlovu, 2024; Bilquise et al., 2023). Thus, the following hypothesis is formulated:

H13. TRU has positively impacted the SAT.

H14. TRU positively impacted BIAC.

2.8. Satisfaction and behavioral intention to adopt AI chatbots

Satisfaction is a critical factor influencing users' behavioral intention to adopt a new technology, as it reflects a user's overall positive experience when interacting with the system (Ashfaq et al., 2020). In the context of AI chatbots, particularly those used in higher education, Satisfaction arises when users feel that the chatbot effectively meets their needs, provides accurate information, and contributes positively to their learning experience (Eren, 2021). Research suggests that when users are satisfied with technology, they are more likely to continue using it and integrate it into their routines (Eren, 2021). This positive experience reinforces users' intention to adopt and continue using the chatbot, especially when it is perceived as a valuable tool in academic settings (Huang et al., 2022). Therefore, the subsequent assumption is proposed:

H15. SAT positively affects the BIAC.

3. Research methodology

We implemented a quantitative research method to examine the influence of trust, Satisfaction, and other factors on students' behavioral intention to adopt an AI chatbot (Creswell & Creswell, 2017). The data collection took place between April 1st and July 30th, 2024. A total of 350 questionnaires were distributed to students enrolled in business and management programs at Al-Jouf University. Participation in the study was limited to students who had interacted with the university's AI-powered academic support chatbot, which was specifically developed and deployed internally by the university to assist students with academic and administrative inquiries and for their learning support. This institutional chatbot provided a range of student-centered functionalities, including anytime access to course-related information, personalized academic assistance, instant responses to frequently asked questions, and support in navigating university systems such as the LMS and academic calendar. The chatbot was a customized solution integrated with university systems to enhance learning outcomes and student satisfaction within the faculty. The design and deployment of this AI solution aimed to enhance both student satisfaction and learning outcomes by offering scalable, equitable, and context-specific academic support. Out of 350 distributed surveys, 300 responses were received. After excluding incomplete and invalid responses, 290 valid questionnaires were retained for final analysis using Structural Equation Modeling (SEM). Demographic descriptions of the respondents are depicted in Table 2. The measurement survey questionnaire consisted of 45 items (we used "five-point Likert scale 1 = SD, Strongly Disagree and 5 = SA, Strongly Agree", See Appendix A for survey items), i.e., PEOU (5 items), PEU (5 items, $\alpha = 0.86$), PIN (5 items), ANM (4 items), TRU (4 items), SAT (5 items), and BIAC (4 items). The instrument comprised various constructions derived from the theoretical model of AI chatbots; see adopted references in Table 1. We engaged four field experts to review and give feedback on the content, showing proper meaning and aligned with our study objective for content validity.

Table 1
Items, no of items, Reliability results and sources.

Constructs	No of items	Reliability	References
PEOU	PEOU01-PEOU05	0.89	Almulla (2022)
PEU	PEU01-PEU05	0.75	Almulla (2022)
PIN	PIN01-PIN05	0.88	Pillai & Sivathanu (2020)
ANM	ANM01-ANM04	0.89	Martín-García et al. (2019)
PIQ	PIQ01-PIQ04	0.83	Kollo et al. (2024)
INT	INT01-INT04	0.80	Martín-García et al. (2019)
TRU	TRU1-TRU04	0.81	Lu & Ho (2020)
SAT	SAT01-SAT05	0.78	Lu & Ho (2020)
BIAC	BIAC01-BIAC04	0.89	Kollo et al. (2024)

After that, we conducted a pilot test with 60 students, establishing the tool's reliability and yielding Cronbach's alpha values above 0.7 (see Table 1). This is for pilot test results and adoption of the source of items, which show good reliability results (Bell et al., 2022). We used "structural equation modelling (SEM)" techniques using the SmartPLS application for further data analysis. We used both SEM analysis techniques, as mentioned in the SEM analysis steps in Fig. 4: Measurement model (MM) for reliability and validity, and the structural model (SM) to test hypothesized relationships (J. Hair Jr et al., 2021; Sarstedt et al., 2021).

4. Findings

4.1. Participants' data analysis

The total number of participants in the study was 290 university students, predominantly male (276; 95.1 %), with only 14 (4.9 %) female students. In terms of age, the majority were young adults aged 20–30 years (268; 92.3 %), while 22 participants (7.7 %) were between 31 and 40 years old. Regarding educational qualifications, most students held a bachelor's degree (223; 76.9 %), followed by those with a master's degree (50; 17.3 %), and a smaller group with a PhD (17; 5.8 %). Academic distribution revealed that 201 students (69.2 %) were from the Department of Business, 67 (23.1 %) from Administration, and 22 (7.7 %) from Management.

To assess chatbot familiarity and exposure, students were also asked about their AI chatbot usage experience, frequency, duration, and preferences. A significant proportion of participants (265; 91.4 %) reported having a positive or highly positive experience with AI chatbots. Regarding frequency of use, 198 students (68.3 %) used AI chatbots daily, and 62 (21.4 %) used them a few times a week, showing a strong engagement rate.

When asked about preferred chatbots, ChatGPT emerged as the most frequently used platform (221; 76.2 %), followed by Google Bard (38; 13.1 %), Replika (10; 3.4 %), and Socratic (6; 2.1 %). Academic support (139; 47.9 %) and writing assistance (84; 29.0 %) were the most common purposes of use, with others using them for information search (42; 14.5 %), emotional support (10; 3.4 %), and miscellaneous needs (15; 5.2 %). In terms of duration per session, the vast majority (278; 95.9 %) used chatbots for less than 30 min, suggesting focused, task-driven use. Additionally, 253 students (87.2 %) had been using chatbots for more than six months, indicating a mature adoption pattern.

4.2. Measurement model (MM) analysis: factor loadings

To measure the model's reliability and validity through convergent validity with the constructs, first, we examined the factor loading and "variance inflation factor (VIF)" results (Stensen & Lydersen, 2022). Factor loadings represent the correlation or shared

Table 2
Demographic information of schoolteachers.

Items	Characteristic	Count	%
Age (years)	20–30	268	92.3 %
	31–40	22	7.7 %
Gender	Male	276	95.1 %
	Female	14	4.9 %
Educational Qualification	Bachelor's Degree	223	76.9 %
	Master's Degree	50	17.3 %
	PhD/Doctorate	17	5.8 %
Department	Business	201	69.2 %
	Administration	67	23.1 %
	Management	22	7.7 %
Most Frequently Used Chatbot	ChatGPT	221	76.2 %
	Google Bard	38	13.1 %
	Replika	10	3.4 %
	Socratic	6	2.1 %
	Other	15	5.2 %
Frequency of AI Chatbot Use	Daily	198	68.3 %
	A few times a week	62	21.4 %
	Occasionally	20	6.9 %
	Rarely	7	2.4 %
	Never	3	1.0 %
Main Purpose of Use	Academic support	139	47.9 %
	Writing assistance	84	29.0 %
	Information search/general queries	42	14.5 %
	Emotional support or conversation	10	3.4 %
	Other	15	5.2 %
AI Chatbot Experience	Positive/Highly Positive	265	91.4 %
	Neutral/Negative	25	8.6 %
Chatbot Usage Duration	<30 min per session	278	95.9 %
	>30 min per session	12	4.1 %
Length of Chatbot Use	More than 6 months	253	87.2 %
	Less than 6 months	37	12.8 %

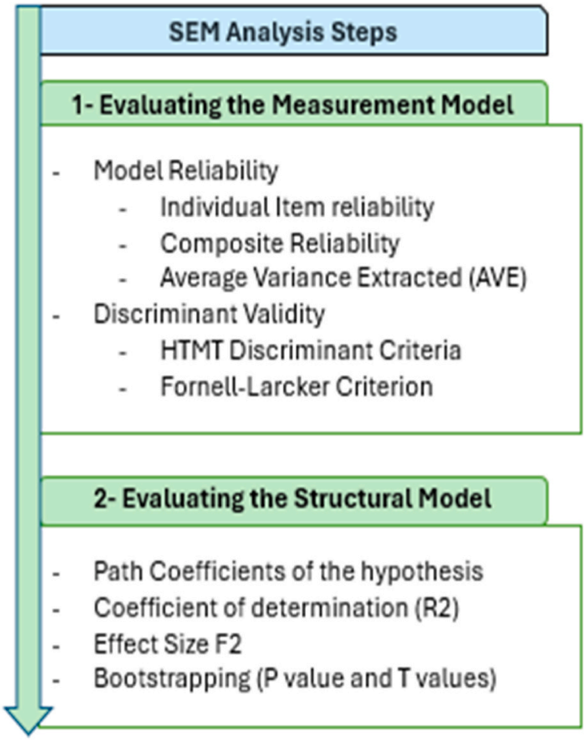

Fig. 4. PLS-SEM steps (Source: adapted from (Fehan & Aigbogun, 2021)).

variance between observed items and their underlying latent constructs. Higher loadings (typically >0.70) indicate stronger associations.

Mathematical Formulation:

$$\lambda_i = \frac{\mathrm{Cov}(X_i, \eta)}{\sqrt{\mathrm{Var}(X_i) \cdot \mathrm{Var}(\eta)}} \tag{01}$$

Where:

λ_i: Factor loading for item i
X_i: Observed variable
η: Latent construct
$\mathrm{Cov}(X_i, \eta)$: Covariance between X_i and η
$\mathrm{Var}(X_i)$: Variance of X_i
$\mathrm{Var}(\eta)$: Variance of η

whereas the VIF measures the degree of multicollinearity among predictor variables in a regression model. A VIF value below 3 is typically considered acceptable.

Mathematical Formulation:

$$VIF_i = \frac{1}{1 - R_i^2} \tag{02}$$

Where:

VIF_i: Variance Inflation Factor for predictor i
R_i^2: Coefficient of determination for predictor i regressed on all other predictors

The factor loading and VIF results of the study are presented in Table 3 indicate that most items have strong factor loadings, generally above the threshold of 0.70, which suggests a high level of convergent validity within the constructs (F. Hair Jr et al., 2014; Prihadi et al., 2012). Items across various constructs, including ANM, BIAC, INT, PEOU, PEU, PIN, PIQ, SAT, and TRUT, demonstrate loadings ranging from 0.70 to 0.89. Specifically, ANM04, PEOU03, and INT02 exhibit particularly high factor loadings (0.89, 0.87, and

0.87, respectively), indicating strong correlations with their respective constructs (Stensen & Lydersen, 2022). Additionally, the VIF values for most items are below 3, suggesting that multicollinearity is not a significant concern within the measurement model. These results show high factor loadings and acceptable VIF values across the constructs indicate that the MM demonstrates adequate reliability and validity.

"Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE)" also show convergent validity analysis for the constructs presented in Table 4. Cronbach's Alpha measures internal consistency, assessing how closely related a set of items are as a group.

Mathematical Formulation:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum \sigma^2}{\sigma_T^2}\right) \tag{03}$$

Where:

k = Number of items,
σ2 = Variance of each item,
σT2 = Total variance.

While the CR measures the internal consistency and reliability of the latent construct.
Mathematical Formulation:

$$CR = \frac{\left(\sum \lambda_i\right)^2}{\left(\sum \lambda_i\right)^2 + \sum \theta_i} \tag{04}$$

Where:

λi = Standardized loadings,
θi = Error variances.

Moreover, The AVE measures the amount of variance captured by a construct relative to the variance due to measurement error.
Mathematical Formulation:

$$AVE = \frac{\sum \lambda_i^2}{n} \tag{05}$$

Where:

λi^2 = Squared factor loadings,
n = Total number of indicators.

Table 3
Factor loading and VIF results.

Item	Factor loadings	VIF	Item	Factor loadings	VIF
ANM01	0.84	2.08	PEU04	0.76	1.89
ANM02	0.85	2.26	PEU05	0.71	1.26
ANM03	0.88	2.67	PIN01	0.76	1.67
ANM04	0.89	2.53	PIN02	0.86	2.05
BIAC01	0.70	1.38	PIN03	0.72	1.97
BIAC02	0.82	1.61	PIN04	0.72	1.59
BIAC03	0.82	1.59	PIN05	0.77	1.41
BIAC04	0.74	1.21	PIQ01	0.73	1.35
INT01	0.85	2.38	PIQ02	0.82	1.90
INT02	0.87	2.64	PIQ03	0.73	1.56
INT03	0.83	2.18	PIQ04	0.81	1.36
INT04	0.86	2.39	SAT01	0.78	1.74
PEOU01	0.73	1.42	SAT02	0.72	1.29
PEOU02	0.86	2.81	SAT03	0.82	1.94
PEOU03	0.87	3.02	SAT04	0.70	1.45
PEOU04	0.85	2.61	SAT05	0.78	1.63
PEOU05	0.85	2.75	TRUT01	0.81	1.68
PEU01	0.75	1.57	TRUT02	0.81	1.71
PEU02	0.82	2.02	TRUT03	0.70	1.29
PEU03	0.78	2.11	TRUT04	0.77	1.50

Table 4
Convergent validity analysis.

Constructs	Cronbach's alpha	CR	AVE
ANM	0.89	0.92	0.75
BIAC	0.72	0.83	0.55
INT	0.88	0.92	0.73
PEOU	0.89	0.92	0.69
PEU	0.81	0.87	0.57
PIN	0.82	0.86	0.55
PIQ	0.76	0.84	0.57
SAT	0.8	0.86	0.56
TRUT	0.76	0.85	0.59

The results indicate that most constructs meet the acceptable thresholds for reliability and validity (Almogren et al., 2024; Dahri et al., 2023; Nasir et al., 2021; Sadiq & Adil, 2021). Specifically, Cronbach's alpha values for the constructs range from 0.72 to 0.89, with ANM demonstrating the highest reliability ($\alpha = 0.89$) and BIAC the lowest ($\alpha = 0.72$). All constructs exceed the proposed CR threshold values of 0.70, indicating good internal consistency, with ANM again performing the best (CR = 0.92). The AVE values, ranging from 0.55 to 0.75, suggest that all constructs exhibit sufficient convergent validity, as they are above the minimum threshold of 0.50, except for BIAC (AVE = 0.55) and PEU (AVE = 0.57), which are marginally below (J F Hair et al., 2010). Overall, these results affirm the constructs' reliability and validity, supporting their use in the study.

4.3. Discriminant validity analysis

The discriminant validity assessment was conducted using the "Heterotrait-Monotrait ratio (HTMT) and Fornell-Larcker method", with results provided in Tables 5 and 6. HTMT assesses discriminant validity by comparing the mean of inter-construct correlations to intra-construct correlations.

Mathematical Formulation:

$$HTMT = \frac{\text{Mean of inter-construct correlations}}{\text{Mean of intra-construct correlations}} \quad (06)$$

However, the Fornell-Larcker Criterion ensures that the square root of AVE for each construct is higher than its correlation with other constructs.

Mathematical Formulation:

$$\sqrt{\{AVE\_i\}} >^{''}\{Correlation\}\_\{ij\} \quad \forall i \neq j] \quad (07)$$

Where:

AVE_i = Square root of the average variance extracted for construct i,
$Correlation_{ij}$ = Correlation between constructs i and j.

In Table 5, the HTMT ratios for all pairs of constructs are well below the threshold value of 0.85, indicating that constructs are adequately distinct (Henseler et al., 2015). Notably, the highest HTMT values observed were between INT and SAT (0.86) and between INT and TRUT (0.84), suggesting a moderate correlation yet still maintaining discriminant validity (Henseler et al., 2015).

Similarly, Table 6 reinforces these findings with the Fornell–Larcker Discriminant Validity method (Fornell & Larcker, 1981), where the HTMT ratios also remain below the threshold, with the highest ratio again observed between INT and ANM (0.96) and INT and SAT (0.73). The results from both tables confirm that the constructs are sufficiently independent, supporting the overall validity of the measurement model (Fornell & Larcker, 1981). This indicates that the constructs gain unique aspects of the phenomenon under study, allowing for reliable interpretations of their relationships within the research framework.

Table 5
HTMT discriminant validity.

	ANM	BIAC	INT	PEOU	PEU0	PIN	PIQ	SAT	TRUT
ANM									
BIAC	0.78								
INT	0.85	0.8							
PEOU	0.69	0.71	0.7						
PEU0	0.64	0.71	0.68	0.56					
PIN	0.1	0.14	0.09	0.09	0.12				
PIQ	0.74	0.72	0.81	0.67	0.79	0.12			
SAT	0.84	0.83	0.86	0.77	0.7	0.1	0.78		
TRUT	0.84	0.72	0.63	0.76	0.75	0.15	0.79	0.76	

Table 6
Fornell–Larcker discriminant validity.

	ANM	BIAC	INT	PEOU	PEU	PIN	PIQ	SAT	TRUT
ANM	0.86								
BIAC	0.64	0.74							
INT	0.96	0.65	0.85						
PEOU	0.62	0.59	0.63	0.83					
PEU	0.54	0.55	0.57	0.48	0.75				
PIN	0.09	0.08	0.07	0.03	0.1	0.74			
PIQ	0.65	0.56	0.7	0.57	0.64	0.08	0.76		
SAT	0.72	0.83	0.73	0.84	0.57	0.06	0.64	0.75	
TRUT	0.81	0.84	0.77	0.65	0.59	0.13	0.64	0.81	0.77

4.4. Analysis of R-squared and F-squared values

The analysis of R^2 and f^2 values provide important understandings into the explanatory power and effect sizes of the structural model in this study. R2 measures the proportion of variance in the dependent variable explained by the independent variables.

Mathematical Formulation:

$$R^2 = \frac{\text{Explained Variance}}{\text{Total Variance}} \tag{08}$$

Whereas Effect size f2 measures the impact of a specific predictor variable on the dependent variable.

Mathematical Formulation:

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}} \tag{09}$$

The R^2 values presented in Table 7 indicate a substantial explanatory power for the construct SAT ($R^2 = 0.84$), suggesting that the model justifications for a significant proportion of the variance in this construct. Conversely, the constructs Trust and BIAC exhibit moderate and substantial R-squared values (0.72 and 0.77, respectively), indicating a respectable level of variance explained but suggesting additional factors may influence these constructs (Joseph F Hair et al., 2019). Effect sizes f^2 provides a measure of the strength of relationships between key constructs in the study on adopting Chatbots as academic virtual assistants. According to Cohen's guidelines, which classify effect sizes as weak, medium, or large (Cohen, 1988) as shown in Table 8, we provided the f-square analysis that indicates the effect sizes of Satisfaction (SAT) and Trust (TRUT) on Behavioral Intention to Adopt chatbot (BIAC). For SAT - > BIAC, an f-square of 0.250 suggests a medium effect, highlighting that higher Satisfaction significantly boosts adoption intentions. The path TRUT - > BIAC has a large effect (f-square = 0.370), underscoring trust as a key factor in influencing adoption. Similarly, TRUT - > SAT shows a large effect ($f^2 = 0.350$), emphasizing that trust enhances Satisfaction, which supports BIAC. These results supported with past research on the importance of trust and Satisfaction in technology adoption decisions (Cohen, 1988).

4.5. Analysis of direct effects

Table 9 and Fig. 5 presents the findings of hypothesis analysis and confirms a significant network of relationships among the constructs (J. F. Hair Jr et al., 2017), with all hypotheses accepted and supported by the data as highlighted in Fig. 4. The direct effects indicate that the ANM construct significantly influences both SAT and TRUT, with the highest positive impact on TRUT (β = 0.900). Additionally, INT positively affects SAT (β = 0.310) while negatively influencing TRUT (β = −0.380), highlighting the intricate substantial support for several key associations' intention and trust in this context. Notably, PEOU demonstrates a substantial positive effect on SAT (β = 0.510) and a moderate positive effect on TRUT (β = 0.180), suggesting that PEOU is significant for SAT and TRU. The effects of PEU on SAT (β = 0.186) and TRUT (β = 0.160) further reinforce the importance of user experience in shaping outcomes. Meanwhile, PIN also exhibits significant effects on SAT and TRUT. The pathways from SAT and TRUT to BIAC also reflect significant positive impacts (β = 0.420 and β = 0.500, respectively), demonstrating their important roles in leading behavioral intentions. These findings affirm the importance of user perceptions in increasing Satisfaction, trust, and behavioral intentions.

Table 7
R-Squared values.

Constructs	R-square	R-square adjusted	Effect	Benchmark
SAT	0.84	0.84	Substantial	"0.75 => Substantial
TRUT	0.72	0.72	Moderate	0.50 => Moderate
BIAC	0.77	0.77	Substantial	0.25 => Weak (Hair et al. (J. F. Hair Jr et al., 2017))"

Table 8
F-square values.

Paths	f-square	Effect	Benchmark
SAT - > BIAC	0.250	Medium	The following threshold values for effect sizes are based on (Cohen, 1988)
TRUT - > BIAC	0.370	Large	Small (S): f2=>0.02
TRUT - > SAT	0.350	Large	Medium (M): f2=>0.15
			Large (L): f2=>0.35

Table 9
Analysis of direct effects.

Hypothesis	Original sample	T statistics	P values	Decision (Accepted Y/N)
ANM - > SAT	−0.270	02.640	0.010	YES
ANM - > TRUT	0.900	06.500	0.000	YES
INT - > SAT	0.310	02.850	0.000	YES
INT - > TRUT	−0.380	02.740	0.010	YES
PEOU - > SAT	0.510	13.960	0.000	YES
PEOU - > TRUT	0.180	03.910	0.000	YES
PEU - > SAT	0.186	03.326	0.001	YES
PEU - > TRUT	0.160	03.780	0.000	YES
PIN - > SAT	0.330	02.720	0.001	YES
PIN - > TRUT	0.290	03.760	0.000	YES
PIQ - > SAT	0.149	03.424	0.001	YES
PIQ - > TRUT	0.120	02.790	0.010	YES
SAT - > BIAC	0.420	05.660	0.000	YES
TRUT - > BIAC	0.500	06.740	0.000	YES
TRUT - > SAT	0.450	08.790	0.000	YES

5. Discussion

This study explored the factors influencing students' acceptance of AI chatbots as academic virtual assistants within the context of business education. As digital transformation becomes increasingly important in business schools, understanding how students perceive and adopt AI-driven tools is critical. This study focused on six key variables—"Perceived Ease of Use (PEOU), Perceived Usefulness (PEU), Perceived Intelligence (PIN), Anthropomorphism (ANM), Perceived Information Quality (PIQ), and Interactivity (INT)—and examined their effects on Trust (TRUT), Satisfaction (SAT), and Behavioral Intention to Adopt AI Chatbots (BIAC)". The findings offer important insights into how business education institutions can use and adopt AI chatbots to enhance learning outcomes, productivity, and student engagement.

The results confirm that Perceived Ease of Use (PEOU) has a significant positive impact on both Trust and Satisfaction, consistent with technology acceptance model (TAM) studies (Kumar & Krishnan, 2020; Park & Kim, 2023; Rahman et al., 2025; Steiss et al., 2024). However, in the context of this study, these findings are particularly meaningful as the AI chatbot under investigation, developed internally by the university, offers both academic and administrative support through a single platform. This dual

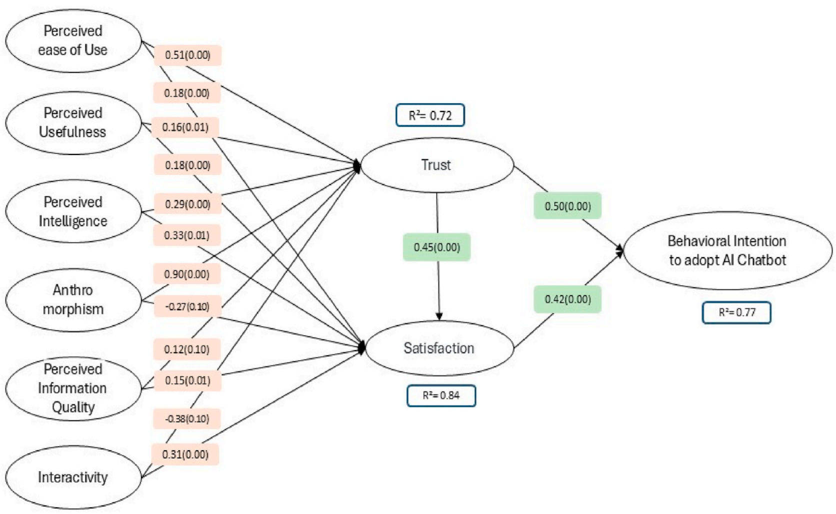

Fig. 5. Hypothesis results.

functionality distinguishes it from earlier educational technologies that served more fragmented purposes, such as Learning Management Systems (LMS) or helpdesk portals. Students in business education, often balancing complex and deadline-driven workloads, benefited from the chatbot's real-time assistance and intuitive interface, leading to higher satisfaction and trust (Dahri, Yahaya, Al-Rahmi, Vighio, et al., 2024; Grover et al., 2019). The chatbot's integration of conversational AI reduced effort and improved access to learning materials and institutional services, thus enhancing its perceived usefulness (PU), an observation supported by recent studies on intelligent virtual assistants (Foroughi et al., 2023; Rahman et al., 2025). Unlike traditional tools that require structured navigation, this multifunctional chatbot enables natural, task-specific interactions, which is especially valuable in high-pressure learning environments.

Moreover, Perceived Intelligence (PIN) was found to have a significant positive influence on both Trust and Satisfaction, reinforcing its critical role in shaping user perceptions of AI chatbots. In the context of business education, students often expect AI systems to reflect intelligent behavior akin to real-world decision-making scenarios. When chatbots demonstrate the ability to understand context, provide relevant responses, and adapt to user needs, they are perceived as more credible and effective learning tools (Bitkina et al., 2020; Meng et al., 2022). Seeger et al. (2021) emphasized that intelligent system behavior fosters user confidence and emotional engagement, which in turn enhances trust and satisfaction. As AI chatbots increasingly mimic humanlike cognition through natural language processing and contextual reasoning, users begin to attribute competence and reliability to the system, factors that are crucial for sustained engagement in educational environments (Casheekar et al., 2024; Chandra et al., 2022). In this study, the university-developed chatbot's intelligent responses, offering timely academic support and adaptive guidance, contributed to students' perception of its reliability and value. This underscores the importance of embedding perceived intelligence as a design principle in AI-powered educational tools, particularly in domains where analytical and cognitive support is essential, such as business education.

Anthropomorphism (ANM) was also found to have a significant positive influence on both Trust and Satisfaction. The integration of humanlike attributes, such as conversational tone, empathy, and personalized responses, enhances the emotional resonance of AI chatbots, making interactions feel more natural and engaging. This emotional connection plays a pivotal role in reducing psychological distance between the user and the technology, thereby encouraging sustained use and deeper trust (Bilquise et al., 2023; Seeger et al., 2021). In business education, where communication, interpersonal skills, and emotional intelligence are vital, anthropomorphic features help align chatbot interaction with real-world professional expectations. Students are more likely to perceive AI chatbots as collaborative partners rather than mechanical tools when these systems exhibit humanlike behavior, such as addressing users by name, maintaining conversational continuity, or expressing encouragement (M. I. Khan et al., 2025; Rapp et al., 2024). This finding reinforces earlier research, Blut et al. (2021), Cheng et al. (2022), Truong and Chen (2025), and Zheng et al. (2023), suggesting that anthropomorphism can increase user engagement, perceived system warmth, and overall satisfaction. In the context of this study, the university's AI chatbot leveraged subtle anthropomorphic design elements to deliver a supportive and humanized user experience, particularly important in scenarios where students seek academic guidance outside traditional classroom hours. Thus, ANM emerges as a key design feature that can bridge emotional gaps in digital learning environments and enhance the acceptability of AI-driven educational tools.

In the context of AI chatbots, Perceived Information Quality (PIQ) also emerged as a significant predictor of both Trust and Satisfaction, reinforcing its role as a foundational element in students' evaluation of AI chatbot effectiveness. High-quality, accurate, and timely responses enhance the perceived credibility of the system, encouraging continued use and reliance on the chatbot for academic and administrative tasks. As students in business programs often make quick, high-stakes decisions based on information retrieved, the reliability of chatbot-delivered content directly influences their learning efficacy and satisfaction (Jayadi & Murwani, 2022). This finding aligns with previous literature emphasizing that the trustworthiness of AI systems hinges on the consistency and precision of the information they provide (Basharat & Shahid, 2024; Blut et al., 2021; Salloum, 2024). In the context of university education, students are more likely to trust chatbots that supply coherent, relevant, and context-specific content, especially when engaging with curriculum-related queries, resource recommendations, or administrative guidance (Dahri et al., 2025). Moreover, PIQ acts as a crucial stimulus in the S-O-R framework, shaping users' internal states such as trust and satisfaction, which in turn influence their behavioral intentions. The university-developed chatbot in this study was designed to deliver curriculum-aligned responses, integrating with institutional databases to enhance accuracy and contextual relevance. This integration likely contributed to the positive evaluations of PIQ by users and underscores the importance of information quality in the successful adoption of intelligent educational technologies.

Whereas, the Interactivity (INT) demonstrated a significant positive influence on Satisfaction, reinforcing prior research that highlights how dynamic, responsive interactions enhance user engagement and perceived system effectiveness (Bao et al., 2016; J. Wu & Chang, 2005). In the context of business education, interactive chatbots can simulate real-time academic support, making learning more immediate, personalized, and learner-centered. This aligns with pedagogical goals that value active learning and prompt feedback. However, the findings also suggest that while interactivity increases satisfaction, it may not directly build Trust, and in some cases, excessive interactivity might even undermine it. This outcome indicates that overly complex or ambiguous responses can create friction, especially when users expect direct, concise answers. Business students, often engaged in time-sensitive tasks, may find that complicated chatbot dialogues detract from usability and reduce confidence in the system's reliability. Therefore, a balance must be maintained between responsiveness and clarity. These insights contribute to existing literature by highlighting that interactivity, although essential for engagement, must be carefully calibrated to avoid cognitive overload or decision fatigue. The dual academic and administrative functionality of the university's chatbot may also influence how students perceive interactivity, valuing it in learning tasks but expecting simplicity in service-related queries. This highlights the need for adaptive interface design that tailor's interactivity based on task type and user intent.

Trust and Satisfaction were noted to have a strong and positive impact on students' Behavioral Intention to Adopt AI Chatbots

(BIAC), affirming previous research in technology acceptance studies (Almogren et al., 2024; Jayadi & Murwani, 2022). This correlation highlights the significance of emotional and cognitive assurance in facilitating extended application of AI-based learning technologies. Within business education, professionalism, efficiency, and result-driven tools are essential-trust and satisfaction are imperative facilitators of long-term technology adoption. More generally, this research illustrates that factors like Perceived Ease of Use, Usefulness, Intelligence, Information Quality, and Anthropomorphism all influence students' willingness to incorporate chatbots into their educational habits. The university's chatbot, uniquely designed to serve both instructional and administrative needs, exemplifies how a multi-functional AI solution can meet the multifaceted demands of business students by offering reliable, relevant, and support.

This study extends the existing technology adoption literature by illuminating the specific expectations, behaviors, and contextual factors influencing AI adoption in business higher education. It contributes theoretical insight into how cognitive and affective drivers interact in AI-driven learning environments. For developers and academic leaders, these findings offer actionable recommendations: focus on building intuitive, trustworthy, and high-utility AI systems that align with the pedagogical and practical needs of digitally savvy business students. Such tools not only improve academic performance but also enhance learners' decision-making, self-regulation, and digital competencies, skills critical to succeeding in future business.

5.1. *Theoretical and practical implications*

This study contributes meaningfully to the broader discourse on AI integration in education by advancing the foundational constructs of the Technology Acceptance Model (TAM) and the Stimulus–Organism–Response (SOR) theory. While TAM has traditionally emphasized perceived ease of use and usefulness, this research enriches the model with advanced socio-cognitive dimensions such as perceived intelligence, anthropomorphism, and interactivity elements that are increasingly relevant in human–AI interactions. These extensions help bridge the gap between functional efficiency and user emotion, highlighting how trust and satisfaction are co-constructed through both technological performance and engagement. Moreover, this study responds to ongoing calls in the literature to explore AI adoption not merely as a technological trend, but as a behavioral and emotional experience. By doing so, it sheds light on how digital learning assistants can move beyond task automation to become relational tools that foster cognitive engagement and motivation, an area still underexplored in educational technology research.

From a practical perspective, the results provide useful insights for educational institutions, edtech developers, and courseware designers. With more and more students depending on AI systems for support in their academic work, it is crucial to design chatbots that are not just smart and effective but also context-sensitive and emotionally appealing. Functionality such as natural language processing, real-time assistance, and dual-functionality support (academic and administrative) positions AI chatbots to have the singular ability of augmenting learning experiences as well as institutional scalability. Educators and university administrators can utilize such tools in order to oversee large class sizes, enable ubiquitous support, and deliver personalized pathways of learning, without adding instructional burden. Equally, developers are encouraged to create AI interfaces that strike a balance between interactivity and simplicity, consistent with the particular behavior patterns and expectations of today's digital-native learners.

Specifically, this study highlights how a university-developed AI chatbot that seamlessly integrates both instructional and service-oriented functionalities can serve as a comprehensive academic virtual assistant. This innovation not only supports students academically but also operationally, providing a unified interface for curriculum-aligned learning, administrative navigation, and real-time assistance. As such, this work contributes a scalable, replicable framework for higher education institutions seeking to modernize student engagement, bridge accessibility gaps, and promote digital transformation in teaching and learning.

6. Conclusion

This research explores the determinants of business students' intentions to use AI chatbots by adopting constructs like "Perceived Ease of Use (PEOU), Perceived Usefulness (PEU), Anthropomorphism (ANM), Interactivity (INT), Perceived Intelligence (PIN), Perceived Information Quality (PIQ), Satisfaction (SAT), and Trust (TRU)." A quantitative design was used, where SEM was used to examine survey data gathered from 290 students of business education, enabling an in-depth analysis of the relationships between these variables. This study was conducted in the context of the university-developed AI chatbot, designed to deliver both academic and administrative support. Results identify ease of use, perceived usefulness, perceived intelligence, and trust as the most effective factors in influencing satisfaction and intention to use AI chatbots in business education. Additionally, anthropomorphism and interactivity were identified as pivotal factors in creating a positive experience, promoting emotional engagement with AI technologies among students. The findings bring to the foreground that functional needs have to be supplemented with cognitive and emotional trust factors in creating AI systems for educational use, especially for fostering personalized and career-related learning within business education. These findings suggest that business teachers can use AI chatbots in providing personalized learning experiences, thinking support, and professional development advisement. Future studies should examine these variables in various learning environments and include novel AI features, such as predictive analytics and adaptive learning, to better see how they affect the adoption of AI and learning performance in business education.

6.1. *Limitations and future work*

This study offers significant insights into the factors influencing business students' adoption of AI chatbots for academic support; however, several limitations should be acknowledged to guide future research. Methodologically, the study employed a cross-sectional design based on self-reported survey data, which may be subject to response biases such as social desirability or inaccurate self-assessment. Furthermore, the exclusive use of Structural Equation Modeling (SEM) provides a robust but linear analytical perspective that may overlook complex, nonlinear relationships between variables. Future studies are encouraged to adopt mixed-methods approaches by integrating qualitative methods, such as in-depth interviews, focus group discussions (FGDs), or case studies, to provide richer insights into students' lived experiences with AI chatbot technologies. Additionally, advanced analytical techniques such as Artificial Neural Networks (ANNs) or hybrid SEM-ANN models could be employed to enhance predictive accuracy and uncover nonlinear patterns in behavioral intentions.

From a theoretical standpoint, the study primarily draws on the Stimulus–Organism–Response (SOR) framework and Technology Acceptance Model (TAM), which, while relevant, do not encompass all dimensions of technology adoption. Future research could benefit from incorporating or comparing alternative theoretical perspectives, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), Expectation-Confirmation Theory (ECT), or Innovation Diffusion Theory (IDT), to offer a more holistic understanding of AI chatbot adoption in educational settings. A significant design limitation lies in the focus on a specific university-developed chatbot with a fixed set of academic and administrative features. Although this chatbot was functional and contextually relevant, it lacked more advanced AI capabilities such as adaptive learning, predictive analytics, voice-based interaction, or emotional recognition. Future versions should explore these dimensions to expand functionality and increase user engagement. Additionally, incorporating real-time feedback, content curation, and multilingual support could improve its scalability and effectiveness in diverse academic contexts.

Contextually, the study was limited to a single public university with a focus on business education students, which restricts the generalizability of findings to other academic disciplines, private institutions, or culturally diverse environments. Subsequent studies should aim to include more heterogeneous samples, covering various universities, academic levels, and cultural backgrounds, to test the moderating effects of contextual variables such as institutional digital readiness, AI policy frameworks, or students' digital literacy levels.

Future research could also take a longitudinal approach to explore how students' perceptions and behavioral intentions toward AI chatbots evolve over time, especially as these technologies mature and become more integrated into academic systems. In addition, scholars should examine the pedagogical effectiveness and limitations of AI chatbot features—such as adaptive learning capabilities, predictive analytics, and automated feedback systems—while also addressing critical ethical concerns related to data privacy, algorithmic transparency, and trust in generative AI technologies. Expanding research in these directions will not only enhance the theoretical and methodological robustness of the field but also provide practical guidance for educators and policymakers seeking to implement AI-based learning tools in a responsible, effective, and student-centered manner.

CRediT authorship contribution statement

Wafa Naif Alwakid: Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Nisar Ahmed Dahri:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis. **Mamoona Humayun:** Writing – review & editing, Validation, Supervision, Software, Resources. **Ghadah Naif Alwakid:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization.

Informed consent statement

Not applicable.

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Data availability statement

Data will be made available to corresponding authors upon request.

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Conflicts of interest

The authors declare no conflict of interest.

Appendix A. Final Survey items

(Please indicate your level of agreement with each statement by ticking the appropriate box).
Scale: SD = Strongly Disagree |D = Disagree |N = Neutral | A = Agree | SA = Strongly Agree.

Construct	Items	SD	D	N	A	SA
PEOU	PEOU1: The AI chatbot is easy to use.	☐	☐	☐	☐	☐
	PEOU2: Learning to interact with the chatbot is easy for me.	☐	☐	☐	☐	☐
	PEOU3: My interaction with the chatbot is clear and understandable.	☐	☐	☐	☐	☐
	PEOU4: I find the chatbot user-friendly.	☐	☐	☐	☐	☐
	PEOU5: I can quickly become skillful at using the chatbot.	☐	☐	☐	☐	☐
PEU	PEU1: The chatbot helps me complete academic tasks more efficiently.	☐	☐	☐	☐	☐
	PEU2: The chatbot improves my academic performance.	☐	☐	☐	☐	☐
	PEU3: Using the chatbot increases my academic productivity.	☐	☐	☐	☐	☐
	PEU4: The chatbot is useful in my academic activities.	☐	☐	☐	☐	☐
	PEU5: The chatbot provides helpful support for learning.	☐	☐	☐	☐	☐
PIN	PIN1: I like to experiment with new technologies like AI chatbots.	☐	☐	☐	☐	☐
	PIN2: I am usually among the first to try new technologies.	☐	☐	☐	☐	☐
	PIN3: I find it exciting to use AI chatbot tools.	☐	☐	☐	☐	☐
	PIN4: I enjoy exploring new features in the chatbot.	☐	☐	☐	☐	☐
	PIN5: I am willing to use AI-based solutions in my academic routine.	☐	☐	☐	☐	☐
ANM	ANM1: The chatbot interacts in a human-like manner.	☐	☐	☐	☐	☐
	ANM2: The chatbot shows empathy or friendly behavior.	☐	☐	☐	☐	☐
	ANM3: I feel comfortable communicating with the chatbot.	☐	☐	☐	☐	☐
	ANM4: The chatbot seems to have a personality.	☐	☐	☐	☐	☐
PIQ	PIQ1: The chatbot provides accurate information.	☐	☐	☐	☐	☐
	PIQ2: The information from the chatbot is complete and reliable.	☐	☐	☐	☐	☐
	PIQ3: The chatbot offers up-to-date academic information.	☐	☐	☐	☐	☐
	PIQ4: The information provided by the chatbot is relevant.	☐	☐	☐	☐	☐
INT	INT1: I am interested in using the chatbot regularly.	☐	☐	☐	☐	☐
	INT2: I intend to continue using the chatbot in the future.	☐	☐	☐	☐	☐
	INT3: I will recommend this chatbot to others.	☐	☐	☐	☐	☐
	INT4: I plan to use the chatbot more frequently.	☐	☐	☐	☐	☐
TRU	TRU1: I trust the chatbot to provide accurate support.	☐	☐	☐	☐	☐
	TRU2: I feel confident in the chatbot's recommendations.	☐	☐	☐	☐	☐
	TRU3: The chatbot behaves in a reliable way.	☐	☐	☐	☐	☐
	TRU4: I trust the chatbot to support my academic work.	☐	☐	☐	☐	☐
SAT	SAT1: I am satisfied with the overall experience of using the chatbot.	☐	☐	☐	☐	☐
	SAT2: Using the chatbot meets my expectations.	☐	☐	☐	☐	☐
	SAT3: I feel positive about using the chatbot.	☐	☐	☐	☐	☐
	SAT4: I am pleased with the support provided by the chatbot.	☐	☐	☐	☐	☐
	SAT5: The chatbot is a valuable tool in my academic routine.	☐	☐	☐	☐	☐
BIAC	BIAC1: I believe AI chatbots can enhance academic learning.	☐	☐	☐	☐	☐
	BIAC2: I support the adoption of AI chatbots in education.	☐	☐	☐	☐	☐
	BIAC3: I think AI chatbots are necessary for future education.	☐	☐	☐	☐	☐
	BIAC4: I am in favor of expanding AI chatbot usage in my university.	☐	☐	☐	☐	☐

Data availability

Data will be made available on request.

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