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Students' Mindset to Adopt AI Chatbots for the Effectiveness of Online Learning

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Abstract

The rapid incorporation of Artificial Intelligence (AI) technologies into higher education is shifting the focus toward understanding students' perspectives and factors affecting the adoption of AI chatbots to maximise their use in online and virtual educational environments. This study fills an important gap in the literature by examining direct and mediated relationships of key constructs such as AI perceived usefulness, AI perceived ease of use, and AI technical competency toward AI chatbot usage. This study aims to investigate students' mindsets regarding adopting AI chatbots for the effectiveness of online learning in higher education. Data were collected from 429 university students and analysed using the partial least squares-based structural equation modelling (PLS-SEM) technique. The results revealed that perceived usefulness (PU), perceived ease of use (PEU), and tech competency (TC) have a significant impact on AI capability. Subjective norm (SN) has no significant impact on AI chatbot capability. The capability of AI chatbots significantly influences the adoption of AI chatbots for learning effectiveness. The findings indicated that AI chatbot capability mediates the effect of PU, PEU, and TC on the adoption of AI chatbots; however, there is no mediating effect in the relationship between SN and AI chatbot capability. Facilitating conditions moderate the effect of PU and TC on AI chatbot capability. This research addresses a new insight into AI chatbot adoption within the context of higher education, particularly demonstrating the mediating and moderating function of AI chatbot capability and adoption on students' PU, PEU, and understanding of tech-competent concepts.

Keywords AI chatbot capability, Tech competency, Learning effectiveness, Students, Higher education

Introduction

AI is a cutting-edge technology that has the potential to radically change the education, banking, tourism, and healthcare sectors. The global spending on AI-related technologies across all sectors and industries is estimated to be around 154 billion US dollars in 2023 [10]. The changing attitudes of students toward their studies have been propelled by the quick incorporation of AI technology into education, particularly the use of AI chatbots [131]. Chatbots are affordable tools that enable students to engage in accessible, comfortable, and feasible platforms for online learning [30, 81]. These tools

The previous research has mostly discussed AI chatbots' functional aspects and their possible advantages within the sphere of higher education [18, 61]. Oydna et al. [81] and Demyanova [30] have highlighted how AI chatbots serve as cost-effective tools that provide students with accessible, personalised learning environments. Additionally, research has touched upon technological competence as a crucial factor influencing AI adoption [17]. However, these studies primarily focus on technical attributes while overlooking the broader contextual and behavioural dynamics that shape chatbot usage in education. Additionally, Boubker [17] has explained technological competence as a crucial factor influencing AI adoption. Jin et al. [49] provided a global perspective on institutional adoption policies and guidelines for generative AI in higher education, emphasizing the importance of ethical governance and educational integration strategies. Akpan et al. [12] explored the dynamics of human–chatbot interaction in education and research, highlighting the role of conversational and generative AI in enhancing learning experiences and research efficiency. However, Lin and Yu [61], Boubker [17], Casheekar et al. [18], Jin et al. [49], and Akpan et al. [12] have primarily focused on technical attributes while overlooking the broader contextual and behavioural dynamics that shape chatbot usage in education.

Although previous studies have pointed out the usefulness of AI tools in educational processes, they tend to ignore the cognitive, behavioral, and contextual aspects that influence the use of these technologies by students. In particular, the level of perceived usefulness, perceived ease of use, subjective norms, and technological competence concerning AI chatbots have not been adequately addressed in the literature. Limited studies have examined the relationships between core constructs of the technology acceptance model (TAM), such as PU, PEU, SN, and TC, concerning AI chatbot usage in education. In addition, there are limited empirical studies on the relationships between the constructs of the technology acceptance model (TAM) and the use of AI chatbots to support learning efficacy in higher education institutions. The importance of this study is in its impact on the future of education.

Addressing these gaps is crucial because AI chatbots have the potential to foster inclusive education by providing scalable solutions that meet diverse learners' needs [12]. Understanding the factors influencing chatbot adoption can help overcome barriers such as technological skill issues, lack of assistance, and educational inequities. Oydna et al. [81] stated that AI chatbots have the potential to enhance inclusion in education through the provision of scalable solutions that cater to the various needs of learners. However, failing to address the adoption barriers could worsen inequities and restrict the widespread use of these technologies. In addition, such an uncontrolled use of AI chats without proper supervision or control can damage other areas of human functioning such as problem-solving, critical thinking, and communication [125]. This study contributes to extending TAM to encompass behavioral, perceptual, and contextual factors specific to AI chatbot adoption in higher education. This study explores the effect of PU, PEU, SN, and TC on students' acceptance and effective utilization of AI chatbots for learning.

Although previous research has examined the usability and educational consequences of AI chatbots [30, 38], they do not consider the joint aspects of behavior and context that promote usage. For instance, Lin and Yu [61] discussed PEU and PU but did not consider other important concepts, such as SN and TC. Similarly, Boubker [17] addressed technological competence but did not relate it to wider adoption issues. This research extends these studies by using TAM to explore the analysis of the adoption of AI chatbots for the effectiveness of online learning in higher education. The gap lies in understanding the behavioral, perceptual, and contextual factors that affect the students in adopting AI chatbots for learning. Specifically, (i) how the PU, PEU, SN, and TC influence their acceptance of AI chatbots and (ii) the lack of a comprehensive framework involving TAM in the adoption of AI chatbots for learning in higher education.

This study aims to determine the determinants of students' effective utilization of AI chatbots in the educational process. It aims to enhance the existing body of knowledge on AI Chatbot adoption by providing a framework that depicts how PU, PEU, SN, and TC promote the use of AI Chatbots for learning effectiveness in higher education. This study is novel in applying TAM in the context of AI chatbot adoption within the higher education sector. It encapsulates behavioural, perceptual, and contextual factors to provide a comprehensive approach to understanding AI chatbot determinants. This approach is different from traditional applications of TAM because it focuses on the specific use of AI penetration in education.

This study shall fill these gaps through the elaboration of the TAM model to encompass specific contextual dimensions that characterise AI chatbot learning in higher education institutions. The study suggests best practices for the use of AI chatbots for educational purposes to policymakers, educators, and technology providers. The study has the goal of further expanding the ongoing debate on AI technologies with a focus on education, fostering more comprehensive and effective learning approaches. Section two of this study discusses relevant literature and the technology acceptance model (TAM) in the context of AI chatbots for online learning effectiveness. Section three outlines the research methodology. Sections four and five present the empirical findings and discuss the implications of the results. The study concludes with limitations and recommendations for future research.

Literature review AI chatbots in higher education

AI Chatbots are seen to be revolutionizing educational processes within higher education institutions. Students are provided with learning opportunities that are unique to their personal needs, increase participation, and receive immediate answers to questions [12]. These tools are especially beneficial to learners as their infrastructure enables limitless expansion which has increased in the last few years [49]. The effectiveness of AI chatbots is strengthened by factors such as users' technological skills, individual attitudes, and available resources at the institution [61]. The adoption of AI chatbots in higher education has focused attention more on their functionalities like automated tutoring systems and effective communication of information [18]. Research has proven that these tools enhance an individual learner's efficiency in learning through the provision of individualized instructional materials [30]. Additionally, these types of AI Chatbots can be effective in enhancing independent learning abilities among students by promoting self-directed learning activities [131]. TAM is a popular framework used to study the determinants of technology acceptance, but the use of TAM with AI chatbots in education is limited. Lin and Yu [61] explored PEU and PU in the adoption of AI chatbots but did not consider SN or TC. Boubker [17] pointed out the significance of technological competence but did not connect it to adoption issues. These gaps indicate to investigation of robust frameworks that combine behavioral, perceptual, and contextual facets. Institutional adoption policies and frameworks for the use of generative AI in higher education concern governance and ethical issues [49]. Akpan et al. [12] also argue that the interaction between human users and educational chatbots is pivotal to engaging learners and enhancing research productivity. The integration of these insights with TAM provides a more holistic understanding of chatbot adoption in educational settings.

AI chatbot effectiveness in online learning AI chatbots have become revolutionary tools to improve online learning. Chatbots help learners by personalizing content, and providing instant feedback, and support [12]. AI Chatbots provide learning requirements and facilitate self-managed learning by customizing content for everyone, thus improving academic performance [30]. Yuan and Liu [131] stated that chatbots enable communication between students and instructors, which helps students stay focused and motivated. As Lin and Yu [61] argued the effectiveness of AI Chatbots is closely related to the students' technological proficiency along with their PEU and PU. Oydna et al. [80] posited that chatbots serve a very important role in modern education, as they help students access learning materials without difficulties and instantly answer their questions. Nevertheless, the study stresses certain challenges such as low levels of technological competencies and poor training that impede the adoption and effective use of AI chatbots [72]. Even with these issues noted, AI chatbots are acknowledged for having the ability to improve the quality of online learning by delivering information creatively and effectively [18]. Akpan et al. [12] argued that human chatbots can provide substantial benefits to learning. There is a need to ensure that AI chatbot platforms are integrated properly into the educational systems, together with training and support. This study emphasizes the importance of determining how variables such as PU, PEU, SN, and TC impact AI chatbot adoption for improved online learning.

Theoretical frameworks supporting AI chatbot adoption

This study used the concept of TAM [66] to evaluate students' adoption of AI chatbot technology for online learning effectiveness in higher education. According to TAM, the two key elements that influence an individual's intention to use technology are perceived usefulness (PU) and perceived ease of use (PEU) [92, 117]. While the TAM primarily considers individuals' perceptions of usefulness and ease of use, subjective norms, tech competency, and facilitating conditions consider the influence of societal factors on technology adoption [113]. Perceived usefulness in the context of online learning refers to the degree to which students think that online learning can assist them in achieving their learning objectives. Online learning may be viewed as a practical approach for certain students to get access to course materials, work with peers, and get teacher feedback [45, 132]. Nonetheless, students may believe that online learning has a negative influence on their intention to adopt it because they perceive it as a poor alternative to in-person interactions. Conversely, the idea of perceived ease of use refers to how students view the usefulness of online learning. Tang et al. [118] indicated that if students find AI chatbots easy to use, they are more likely to adopt them for learning effectiveness.

Factors influencing AI chatbot adoption in education

In online learning settings, subjective norms reflect how peers, instructors, and other influential individuals perceive and expect the use of AI chatbots for education purposes. The concept of technology competence recognizes that users' AI chatbot capability and proficiency can influence the adoption of AI chatbots for online learning effectiveness. Students who are more confident and proficient with technology may use AI-driven technology for online learning platforms [103]. Facilitating conditions are external factors that can either support or hinder the use of online learning resources [1]. Yang et al. [130] indicate that facilitating conditions can influence an individual's perceptions of the benefits and utilization of technology. Hence, TAM expanded the model that provides not only individuals' perceptions of usefulness and ease of use, but also social influences, tech competency, and facilitating conditions, resulting in a sophisticated knowledge of the factors influencing AI chatbot for learning effectiveness in higher education.

Studies on AI chatbots in education

The use of AI chatbots reveals the capability to improve learning outcomes by offering immediate assistance, personal attention, and motivating students in online learning settings. Table 1 shows the issues addressed by the literature of 10 articles from 2020 to 2024 in the area related to AI chatbots highlighting the teaching and learning effectiveness in higher education institutions. Pérez-Núñez, [86], and Chen et al. [23] reported on AI applications in the form of AI-driven writing generator tasks and AI student assistants which have advanced the role of chatbots from answering questions to more interactive and usable roles within the education sector. Roca et al. [102] and Essel et al. [31] show the contextual deployment of chatbots with most of the regional results having effective implications on regions where they are implemented (e.g., Spain and Ghana). This is different from the previous studies that were mostly obsessed with the outcomes of the students [85, 102], Merelo et al. [70] appreciated the fact that teachers also have concerns about the adoption of chatbot technology. Wollny et al. [128] and Pérez et al. [85] performed a general overview of chatbot applications but did not show the concentration on methods that recent works such as Mendoza et al. [69] highlighted how to professionally undertake chatbot development. On the other hand, Chen et al. [23] and Roca et al. [102] contribute to the dialogue by using experimental and quantitative approaches.

There are differences between the current research and the previously mentioned studies. This study adds the expanded TAM framework application, subjective norms impact evaluation, and moderating role of facilitating conditions from perspectives of higher institutions in Malaysia. This study extends the TAM model by incorporating the AI chatbot capability as a mediator between perceived usefulness and ease of use and the adoption of AI chatbots for better online learning outcomes. This is contrary to many studies, in which subjective norm is not associated with AI chatbot capability which indicates a trend toward utilitarian constraints instead of social burdens. This study adds the facilitating conditions as an important moderator that enhances the relationship between perceived usefulness and tech competency as well as adoption thereby contributing to the understanding of the educational environmental context that makes for the appropriate usage of the chatbot. In the past, the research has focused on qualitative methods, empirical studies, review approaches, and case study approaches. However, in this particular work, the aim is to quantitatively assess the students' perceptions toward the use of AI chatbots in increasing learning effectiveness in higher education. This assessment emphasizes the increasing sophistication, methodological rigor, and relevance of chatbot studies in the field of education while recognizing the outstanding issues that still need to be further investigated.

Hypotheses development

Perceived usefulness

Perceived usefulness (PU) accounts as one of the components of the technology acceptance model (TAM), which argues that the adoption of a technology by a user is determined by the user's beliefs in the technology's tangible functions and effectiveness [28, 64]. TAM has been the major explanatory theory in the field of adoption of new technologies owing to its application across multiple areas such as e-learning, the use of digital devices, and AI-based applications [87]. PU deals with the extent to which an individual feels that a given system or technology has the potential to improve either their work or productivity. It is one of the fundamental parameters of the TAM [28, 36] which has been used in many fields concerning technology acceptance. Regarding AI chatbots, perceived usefulness constitutes an aspect that primarily influences user acceptance and continuous usage. The word chatbots is likely to have high perceived usefulness, provided their design is equipped with sophisticated functionalities [129] such as natural language processing (NLP), machine learning (ML), and tailored services as these achieve task completion quickly and efficient service response. Students are more likely to be motivated to learn using AI chatbots when they believe that AI-driven technologies are useful [1]. Bahaddad [14] described that the ability of the chatbots to respond accurately and

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Table 1 Studies on AI chatbots in education

No.	Sources	Application	Country	Basic theories	Method	Population size	Focus Area	Results
1	Pérez-Núñez [86]	AI-driven task generation in Spanish teaching	Spain	Constructivist learning theory	Qualitative study	25 Spanish language instructors	ChatGPT in Spanish language instruction	Investigated the influence of AI-designed task generation for Spanish language instruction and found more variety of tasks and more efficient lesson planning by the teachers
2	Merelo et al. [70]	Chatbots in classrooms from teachers' views	Spain, Greece	UTAUT	Mixed-methods	78 teachers	Chatbots and messaging platforms in classrooms from teachers' perspectives	Examined teachers' use of chatbots, pointing out functional advantages e.g., overcoming communication barriers and issues, and training
3	Roca et al. [102]	Uses of chatbot for course assessment	Spain	TAM	Quantitative study	200 students	Engagement of students and learning in education	Increased motivation and learning outcomes of students
4	Lin & Yu [61]	Chatbot use in education	Global	Diffusion of Innovations Theory	Bibliometric analysis	Analyzed more than 1500 publications	The trends of research chatbot applications	Recognized important dimensions: activity or verbal interaction, learning outcomes, and extent of the project
5	Chen et al. [23]	AI student assistants	USA	Cognitive Load Theory	Experimental study	90 students	Chatbot design for student success	Discovered heightened levels of interest in the students and cut down on paperwork requirements
6	Nee et al. [76]	The potential of chatbots	Global	Engagement Theory	Literature review	Reviewed 160 studies	Chatbot research directions	Identified the patterns, problems and opportunities for future research
7	Essel et al. [31]	Virtual teaching application	Ghana	Self-Efficacy Theory	Mixed-methods	400 students	Higher education chatbot applications	Increase the academic performance of students and the level of satisfaction with learning
8	Mendoza et al. [69]	Application of Chatbot	Mexico	Constructivist Learning Theory	Case study	120 students	Chatbot development for learning	Enhanced feedback for students and reduction in the handling of repetitive questions
9	Wollny et al. [128]	Chatbots in education	Global	UTAUT	Systematic review	Reviewed 85 studies	Uses of Chatbots for the advancement of education	Identified the big potential but also the challenges in terms of customization and scalability

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Table 1 continued

No. (	Sources	Application	Country	Basictheories	Method	Populationsize studies	FocusArea	Results
10	Pérezet al.[85]	Rediscoveryof chatbot usein education	Global	TAM	Systematicliterature review	120 reviewed	Typesand purposes of AIchatbots in teaching	Classifieddifferenttypes of chatbotsbasedon their objectivesand in whichcircum - stancestheyareemployedpar - ticularlyin interactivelearning

appropriately enhances the level of user satisfaction and engagement. Furthermore, developments in AI algorithms enable chatbots to keep optimizing how they communicate through a simpler and more precise approach, allowing greater user trust and satisfaction [9]. PU assesses an individual's perceptions using AI chatbots for online learning platforms. As a result, this study proposed that:

H1 Perceived usefulness has a significant impact on AI chatbot capability.

Perceived ease of use

Perceived ease of use (PEU) is one of the fundamental elements of TAM, which argues that the learning and use characteristics of any system are significant factors in the acceptance and implementation of technologies [28, 62, 73]). In the setting of PEU within the context of interaction with AI chatbots, it refers to the intuitive design of the interface and users' ability to find the functions of the chatbot to further reach their goals in the chatbot interaction. Perceived ease of use in AI chatbot interaction relates to the extent to which a user finds it easy to operate a chatbot, utilize its features, and retrieve desired information [104]. Previous studies have found that the more user-friendly a chatbot is, the more users tend to use it and value its benefits [129]. The extent to which an individual believes that AI Chatbots can accomplish tasks is determined by the utilization of the services. Such features include conversation, problem-solving, customization, and adaptability and are dependent on how easy it is for the audience to interact with and employ the chatbot. Previous studies have shown that if a user-friendly interface is provided for a complex chatbot, the users will be able to perform complicated tasks and this will positively impact their perception of the quality of the chatbot [14]. The excessive sophistication of AI chatbots incentivizes developers with regards to offering users advanced functionalities, but the interface does not pose the same challenges when having non-expert users who tend to be scared of advanced systems without a user-friendly environment [10]. As a result, this study suggested that:

H2 Perceived ease of use has a significant impact on AI chatbot capability.

Subjective norm

The adoption of technology, particularly AI chatbots, has been largely influenced by subjective norms as highlighted by numerous behavioral studies [47]. Subjective norms are the perceived social pressures from peers and communities that encourage or discourage individuals from engaging in certain behaviors [2, 94]. In the context of higher education, these norms can be developed through pursuing encouragement and support from fellow students in the same class or parentheses or through working in divided groups to convince the class of the need to use the tool. Classmates tend to be important stakeholders in developing subjective norms concerning the use of AI chatbots. Sutrisno et al. [116] pointed out that students who seek to use technology but lack experience in their peer groups who share the same interests are more likely to rely on peer advocacy. Powerful models in society including the students' instructors and teachers play an important role in the introduction of new educational technologies. Stöhr et al. [114] stated that students are likely to seek the assistance of chatbots because they believe that most students around them are using such tools. Thus, their faith in the tool's capability only grows. Instructors are recognized to be great power brokers in most cases, and they usually facilitate information communication technology (ICT) tools. For instance, when instructors promote the use of AI chatbots claiming they are useful for students' learning, this greatly increases the chances of students using these systems. Zhang et al. [133] provide evidence of the need for instructors' endorsement to modify students' perception of chatbot tool effectiveness and reliability. When teachers use chatbots to teach students and encourage them to use them, students are more willing to consider them as an integral part of the learning process. Study groups constitute another critical domain for subjective norms, as group behavior is often the better determinant of individual behavior in such groups. The use of AI chatbots in study groups encourages further academic support in the form of these tools. Ayanwale and Molefi [13] stated that group structure and social practices considerably shape the decision of individuals to adopt technology. Thus, this investigation suggested that:

H3 Subjective norm has a significant impact on AI chatbot capability.

Tech competency

According to TAM, the perception of PU and PEU by the users is a major consideration of a specific technology being adopted [28, 106]). Here, tech competency (TC) is pivotal, as it can influence both PU and PEU. For instance, tech-savvy users are more competent in comprehending, operating, and deploying some advanced technological tools including AI chatbots. With AI chatbots for online learning, TC is significant in shaping the education community's view of ability and the application value of these systems [52]. In this sense, educators who have high-tech perception will try to express the AI chatbots according to learning outcomes and use them thoughtfully across the instructional processes. TC refers to the capability of individuals or organizations to proficiently employ technological tools, systems, and processes toward fulfilling desired objectives [105]. It includes the understanding of concepts, possessing talent in the digital world, and applying this knowledge to actual scenarios. Pathak et al. [82] stated that when concerning AI chatbots, an understanding of technology affects interactivity, management, and perception of the capabilities, toward its tech competency. When tech competency is associated with organizations, AI chatbots stand to be fully exploited through advanced features like *natural language processing (*NLP), machine learning (ML), and automation [101]. Xiao and Yu [129] demonstrated that organizations with greater tech competency are more capable of applying and managing AI chatbot systems. Such organizations can better incorporate chatbots within their current dissemination systems thereby enhancing the level of productivity of the chatbot. Competent employees can also provide a higher level of instructions to the chatbots thus making them perform higher level cognitive tasks like prediction making and decision making. Competency in technology has a role in the customization of AI chatbots for a particular purpose within an organizational structure [6]. More competent users can make the chatbot programs interact with users more intelligently and less mechanically rather than only changing the program functions and system responses. Hence, tech competency is based on the core constructs of TAM because tech competency alters the perceptions of AI chatbots both in terms of ease of use and usefulness. Consistent with the previous studies, we assume that increasing tech competency aids people in interacting with AI chatbots, and contributes to better adaptive, intelligent, and useful performance of AI chatbots in other contexts such as online learning. Therefore, we postulated that:

H4 Tech competency has a significant impact on AI chatbot capability.

AI chatbot capability

In the context of TAM, the adoption of technology is the most important aspect. Actual use of technology is greatly determined by the AI chatbot capability (ACC) because the chatbot's ability to interact intelligently and effectively improves and is easier to adopt. In the realm of online education, where students encounter obstacles such as lack of interest, and insufficient individualized support, the use of AI chatbots can be beneficial in increasing participation, offering immediate responses, and encouraging tutorials [48]. AI is changing our lives in diverse ways, one of the areas that offer immense possibilities is education. AI has been integrated into education in the form of chatbots that cater to the needs of learners, boost participation, and improve learning efficiency in an online setting. Kerimbayev et al. [52] pointed out that AI chatbots are good at monitoring progress and giving feedback from sources which leads to individualized learning. Mohebbi [75] examined the effects of AI chatbots on self-directed learning and retention of information, which is important for effective online learning. Garcia-Varela et al. [37] stated that students who were provided time to interact with an AI chatbot reported being more active and asserted that they would be successful in completing their assignments. AI chatbot capabilities include NLP, understanding of the context, functionalities, the feedback system, and being receptive to any dynamism. Ait Baha et al. [7] stated that the NLP capabilities of AI chatbots improve their effectiveness, especially in how students interact with the system. Student progress monitoring and evidence-based recommendations and responses for continuous learning are more efficiently achieved through AI chatbots. This effectiveness of AI chatbots for online learning is a crucial factor that has been highlighted in several works on human–computer interaction design. Besides, AI chatbots promote independent progress, prompting active participation of learners, and enhancing the long-term memory auxiliary effect [133]. Students who interacted with chatbots were more engaged and felt they would positively complete their tasks [25]. Hence, this hypothesis posits that the likelihood of students using AI chatbots in learning increases with AI chatbots'' ability to handle NLP, context analysis, feedback provision, and flexibility. Therefore, we suggested that:

H5 AI chatbot capability has a significant impact on the adoption of AI chatbot for online learning effectiveness.

Mediating effect of AI chatbot capability TAM provides a basis for understanding how AI chatbot capability can influence PU by delivering fast answers and adapting the learning experience based on the students' needs. Students are bound to benefit from NLP endowed chatbots that comprehend the questions posed by students and evolve with suitable answers thereby enhancing the learning experience [89]. These chatbots can assist students with different kinds of feedback depending on their progress which in turn helps students to achieve better results. The most critical aspect of technology acceptance is the perceived usefulness of the system. Past research has shown that AI chatbots impact this perception positively by offering quick responses, individualized help, and ongoing tutoring [25]. There is a direct relationship between the features of the chatbot and the students' outlook toward its usefulness in improving their learning. Advanced features of chatbots with attractive graphical user interfaces and connective interactions also facilitate this process by reducing the level of learning difficulties and the adoption of new technologies [54]. Students adopting AI chatbots are often influenced by the presence of others around them using the AI chatbots to great effect. AI chatbots using this capability also strategically reinforce the use of social norms of utilizing the AI chatbot in an educational setting by creating an enjoyable and effective learning experience [62]. There will be a greater inclination toward the utilization of AI chatbots among students who possess higher capabilities with technology, although the capabilities of the chatbot can help overcome this challenge for the lower end of the spectrum. Bahaddad [14] stated that effective AI chatbots can change based on requests and learning new things encourages the use of AI chatbots across all expertise levels. Therefore, we suggested that:

H6 AI chatbot capability mediates the effect of (a) perceived usefulness, (b) perceived ease of use, (c) subjective norm, and (d) tech competency on the adoption of AI chatbots for online learning effectiveness.

Moderating effect of facilitating condition

According to the TAM construct, facilitating conditions encompass relevant technology variables that are external to an individual's use of a given technology such as the internet, computer facilities, and auxiliary material [21]. Facilitating conditions are essential moderators in the relationship between TC and PEU on the acceptance of AI chatbots. Liu et al. [63] provide evidence that facilitating resources enables PEU for technology in their adoption. Facilitating conditions are useful for nonICT proficient AI and actual users as they enhance the connection between TC and the real usage of AI chatbots [54]. Perceived usefulness is an important determinant of chatbot adoption [4]. The availability of facilitating conditions such as internet connections and robust IT infrastructure is imperative in enhancing the use of AI chatbots [133]. Advanced functions can be accessed if users know how to use a computer and the application [3]. The facilitating conditions also moderate the effect of PEU, which is how easily the AI chatbots are considered by users. Liu et al. [63] showed that when users have a sophisticated support system, the effect of PEU on the adoption of chatbots is strong, which encourages users to leverage the technology. Leng et al. [60] indicated that social influences are amplified when the supporting structures exist. AI-powered chatbots tend to be more readily accepted by those who are highly competent in technology [54] but enabling conditions offer sufficient reinforcement to those who are less competent so that they can realize good chatbot capability. Facilitating conditions such as instructional materials and training serve as essential moderators [19] of the relationship between technology competency and AI chatbot utilization. Thus, we postulated that:

H7 Facilitating condition moderates the effect of (a) perceived usefulness, (b) perceived ease of use, (c) subjective norm, and (d) tech competency on the AI chatbot capability.

Research Gaps and Contribution of the Study

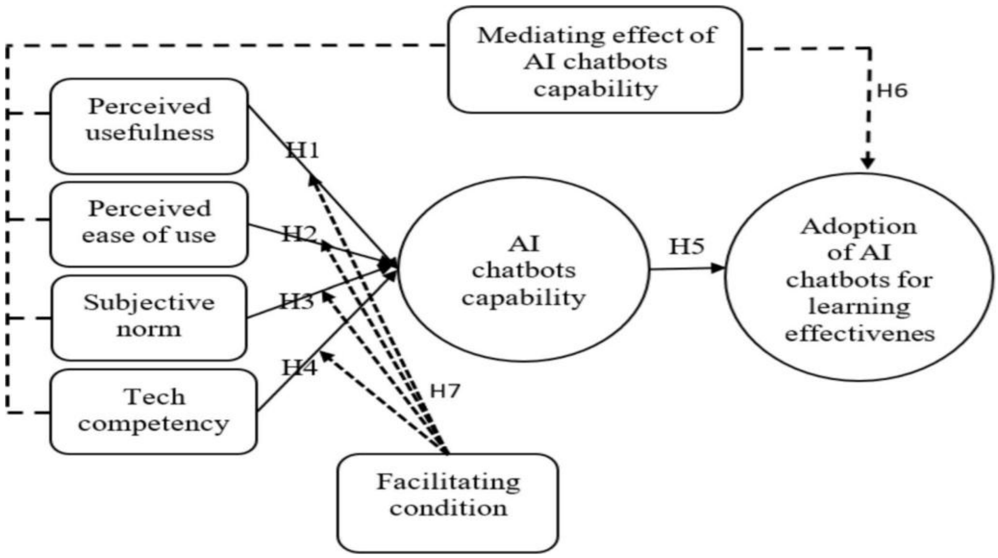
There are some gaps within the research regarding AI chatbots in education that requires focus. Casheekar et al. [18] and Demyanova [30] have concentrated on the functional benefits of AI chatbots but they tend to overlook behavior, cognitive processes, and selfcontext that affect the student's acceptance and use of AI chatbots effectively. Most studies on the adoption of AI chatbots in higher education have focused on PEU and PU [61], while SN and TC have received limited attention. These variables are paramount to gaining a deeper understanding of adoption behavior. There is no empirical evidence from existing literature integrating the TAM constructs to explain the adoption of AI chatbots for learning effectiveness [17]. However, there is a lack of literature on how AI chatbots can mitigate educational inequities and develop required skills such as critical thinking and communication without fostering an over-reliance on technology [46, 125]. This study has some notable contributions. The study forms a model based on PU, PEU, SN, and TC that investigates the effectiveness of AI chatbot adoption for learning online. The research examines the adoption of AI chatbots from cognitive, behavioral, and contextual aspects to better understand how students engage with such technologies. The study fills a significant gap by using empirical evidence to examine the key constraints of TAM and TPB with AI chatbot adoption in higher education and other domains. Furthermore, the study provides a practical guide to educators, policymakers, and technology providers on how to adequately and responsibly implement AI chatbots. Such efforts will in turn help foster inclusive and effective learning that utilizes the advancements of AI chatbot technology while upholding some critical aspects of human intelligence. By evaluating the obstacles to AI chatbot adoption, the study aids in improving innovative and inclusive educational practices in the higher education sector.

Conceptual model

This research applied the theory of TAM [28] one of the most popular theoretical concepts for explaining users' adoption of new technologies [92]. This study combines the TAM [28] and the TPB [2] in formulating a management model that explains the adoption of AI chatbots for online learning in a tertiary education context. The study attempts to close the gap between user perceptions, behavioral influence, and their context using selected components from the TAM model (PU, PEU, TC, and FC) and SN, perceived behavior of AI, and intention from the TPB model. One of the key constructs of TAM is PU, which has a direct relationship with users' behavioral intentions. AI chatbots enhance student learning by providing personalized and timely assistance; hence, students are willing to engage with AI chatbots [61]. PEU is interpreted as a user's perceived effort or lack of effort needed when using a particular technology. PEU is significant in the adoption of educational technologies as many users tend to lean toward aids that demand the least amount of effort to learn. Students are more likely to use chatbots with easy and friendly interfaces and interactions [11]. TC denotes the users' ability to use digital technologies. TC already integrates some aspects of user self-efficacy into the more functional TAM model. The PEU and PU of AI chatbots can be improved when students have adequate digital competencies [17]. FC is the provision of the necessary support and resources to effectively use a particular technology. FC adds to TAM an external dimension to the adoption challenge. Students adopting AI chatbots for online learning need reliable infrastructure and technical support [78].

SN focuses on the social expectations that discourage or encourage an individual to engage in behavior. In this regard, SN embodies the actions of students, their peers, instructors, and educational institutions to adopt AI chatbots [126].

Students' motivation to interact with AI chatbot technologies can be influenced by social acceptance. Supportive behavior considers both internal and external constraints in executing a behavior and the ease or difficulty experienced in performing it. Supportive behavior strengthens the model through perceived ease of control over the adoption of AI chatbots. It captures both internal competencies such as technological ability and external aids such as access to resources and support, making it one of the most important determinants of adoption behavior [78]. Behavioral intention refers to the factors that have the potential to motivate an individual to engage in a particular action. Understanding the various factors that influence students' intentions toward the adoption of AI chatbots is useful information for educational institutions to promote engagement and adoption [111].



According to the theory of TAM, technology will be utilized if two key aspects such as PU and PEU influence an individual's intention to use technology. These factors shape perceptions about the technology, behavioral intention to engage with it, and the usage itself. In this research, the adoption of AI chatbots is explained comprehensively by integrating it with TAM with SN, TC, FC, and AI chatbot capability (ACC). SN pertains to the kind of social influence that results in considerable changes in users' behavioral intentions especially in a working or learning environment [126]. The use of SN reflects other elements and positively enhances the scope of TAM since it explains internal circumstances. TC is concerned with the level of efficiency achieved using ACC, and if users consider the system user-friendly and useful, TC is likely to enhance ACC. FC focuses on other resources, such as infrastructures and technical support, which are critical in determining the users' intention to adopt technology [78]. FC fills the gap left by TAM, which concerns individual perceptions only.

ACC is an important component of the model as it is the usage of an AI chatbot's voice, real-time assistance, and interactive elements. In this study, the model excludes some of the TAM determinants such as attitude toward use which makes the model more complex. The previous studies show that attitude often overlaps with PU and PEU and therefore is of less importance to extended models [11, 111]. This study investigates incorporating ACC with other constructs that are specific to artificial intelligence tools within the context of the mediator chains model, which provides a robust explanation for the users' adopt chatbot capability and actual use of chatbots for the effectiveness of online learning in higher education. The inclusion of SN, TC, and FC has a relation to the real aspects of technology adoption and may provide useful insights to organizations using AI chatbots. By focusing on AI chatbot adoption, this study expands the applicability of TAM to a domain where these technologies are being used widely. This emphasizes the originality of the study and its approach to testing ACC. Previous studies that explored TAM rarely addressed this issue.

Based on the review of literature and theoretical foundation, this study proposed the following conceptual model (Fig. 1). In addition, the study provides mathematical models that examine the relationship based on the given constructs.

Fig. 1 Conceptual model

$$AAC = \beta_0 + \beta_1 PU + \beta_2 PEU + \beta_3 SN + \beta_4 TC + \beta_5 ACC + \varepsilon \quad (1)$$

$$AAC = \beta_0 + \beta_1 ACC + \beta_2 FC + \beta_3 (ACC \times FC) + \varepsilon \quad (2)$$

Hence, ACC = AI Chatbot Capability, PU = Perceived Usefulness, PEU = Perceived Ease of Use, SN = Subjective Norms, TC = Tech Competency, β_0 = Intercept, β_1, β_2, β_3, β_4 = Coefficients for the independent variables, and ε = Error term.

The first model examines the effects of PU, PEU, SN, TC, and ACC on AI chatbots (AAC). The equation integrates the direct relations and the mediating impact of ACC. The second model explores the effect of FC in the relationship between ACC and AAC. This moderation effect is evaluated through the interaction term (ACC × FC). Lastly, we employed the structural equation modeling (SEM) technique in the study to estimate all the relations. This technique integrates the mediation and moderation models.

Methodology

Sample and data collection

A survey was carried out on 500 randomly selected face-toface respondents from February to April of 2024. This survey was conducted to anonymously address students' propensities to AI chatbot adoption for online learning effectiveness in higher education. Not a single detail of personal information was recorded focusing entirely on anonymity. The data collected were kept safely and maintained privately to avoid any risks to respondents' interests. The participants consisted of university students pursuing Bachelor, Master, and Ph.D. degrees at three major public universities in Malaysia. The non-probability purposive sampling was a suitable choice for this study which aims to investigate the students' likelihood of adopting AI chatbots for online learning in higher education. Etikan et al. [32] noted that non-probability purposive sampling is one of the most common techniques for choosing respondents with knowledge or experience with a specific research problem. In this case, it was appropriate to select university students who are completing Bachelors, Masters, and PhDs as they form a significant part of higher education and have experienced a digital learning environment that encompasses chatbot technologies. This non-probability sampling technique enables researchers to purposefully choose respondents with specific characteristics and guarantees the completeness and relevancy of the data collected [84]. Targeting students from three major public universities in Malaysia ensures that the sample portrays the different ranges of academic and institutional diversity which is important in understanding the multiple factors that impact AI chatbot adoption. For instance, non-probability purposive sampling is useful in situations where random sampling does not guarantee the retrieval of respondents who can contribute meaningfully to the research [83]. To achieve the research objective, non-probability purposive sampling is best suited for studies where respondents are expected to have adequate knowledge and insight into the technologies being studied to ensure their adoption [124].

In preparation for the survey deployment, we performed a pretest and a pilot study to measure the validity and reliability of the questionnaire. A pretest is administered during this stage to pinpoint problems regarding the relevance, clarity, and comprehensiveness of the items included within the questionnaire, ensuring they are appropriate for the population of interest [93]. Following this, a pilot study was conducted to test the internal consistency, reliability, and construct validity of the instrument. This method is crucial in instrument refinement and improving the precision and effectiveness of the instrument for the primary study [50]. Such measures are fundamental to reduce response bias and improve the data quality during the actual survey. First, six specialists were engaged to scrutinize the questionnaire, who are experts in the use of AI chatbots for Education. This expert assessment highlighted some of the limitations, such as; having some questions that were repeated, some items that were too broad, vagueness, and bias. Therefore, the respective parts of the questionnaire were improved. Afterward, a pilot study was undertaken and Cronbach's alpha results for all variables were above the threshold of 0.70 which indicates that the questionnaire was reliable and internally consistent. Cronbach's alpha is the most used statistic to assess the internal reliability of a scale [77]. According to Kline [56], Kline [55], Trabelsi et al. [123], Hair et al. [42], and Hair et al. [40], Cronbach's values greater than 0.70 are suitable for exploratory research, and higher cutoff values are usually recommended for confirmatory research. From a total of 500 distributed questionnaires, 436 responses were received. To remove bias from non-response, we attempted to understand the extent of missing data and the factors associated with it. Analysis was performed using only 429 valid responses after excluding seven missing responses, resulting in a response rate of 85.8%. In conducting this research G*Power analysis indicates that at least 113 samples are desirable for a statistical power of 0.80 [33]. Thus, the 429 valid samples are sufficient to inform the analysis of the coefficients in the present study.

Measurement instrument

The questions in this study were carefully adapted from previous studies to evaluate several important constructs. Tech competency was evaluated using four items from Chung et al. [26], and subjective norms were measured using four items from Kim et al. [53]. Four questions from

Razami and Ibrahim [99] were modified to assess facility conditions, while eight questions from Sukendro et al. [115], Maheshwari [67], Al-Abdullatif and Alsubaie [8] were selected to measure perceived usefulness and ease of use. Additionally, AI chatbots capability was assessed with six items adapted from Tian et al. [121], and four reformed questions from Maheshwari [67], Tian et al. [8, 121]), and Schei et al. [109] were used to measure the adoption of AI chatbots for students' online learning effectiveness. A five-point Likert scale from strongly disagree to strongly agree was applied to each statement to assess content validity and ensure that responses were not biased [99]. The use of this scale ensures clarity and consistency in measuring the participants' views. This design helps in accurately evaluating the factors that influence AI chatbot capability and Al chatbot adoption for students' online learning effectiveness.

Common method bias

A variance inflation factor (VIF) above 3.3 [57] denotes the presence of common method bias (CMB) in a model. On the other hand, the model is regarded as free of CMB if all VIF results from the collinearity test are equal to or lower than 3.3 [95]. According to the VIF results below 3.3, CMB is not a problem (Table 3). Skewness and kurtosis values were analyzed and the results between −1.5 to 1.5 and −2.0 to 2.0 indicated that the data was normal [96, 110]. According to Podsakoff et al. [91], Harman's single-factor test represents a simple approach to detecting CMB. It requires all items in a dataset to be submitted for factor analysis without any rotational extraction. If one factor accounts for large amounts of variance, it is reasoned that CMB is probably a problem [96]. Thus, to determine the potential presence of CMB, we employed Harman's single-factor model. All items were evaluated utilizing exploratory factor analysis and subjected to nonrotating principal components factor analysis. We have accustomed all the items around one factor, which was found to explain 31.23% of the variance which is lower than the acceptable threshold of 50% [90, 91]. Thus, it follows that there is no CMB in the present study.

Data analysis

This study used SPSS 24.0 for the demographic analysis, and SmartPLS 4.0, a covariance-based structural equation modeling technique [107], for data analysis and predicting the relationships between variables in the research model. By using the partial least square (PLS) technique, this research aims to determine how students are likely to adopt AI chatbots and their consequent effect on the effectiveness of online learning. PLS is known to cater perfectly to predictive studies as it seeks to attain maximization of the variance explained by the dependent variables [24, 41]. Since it has already been established, the use of AI chatbots among students in higher education learning institutions is still a developing concern. PLS provides convenience in addressing exploratory constructs and relationships which may be less advanced when it comes to literature [108]. PLS is also capable of obtaining valid findings with small datasets. Furthermore, PLS is suitable for this research model since it is tolerant of nonlinear patterns that do not comply with normal distributions and places no restrictions on the nature of the data collected [68, 108]. In this study, PLS emphases on prediction and application align with the practical orientation of the research objectives. Perceived usefulness, AI chatbots, and facilitating conditions are key variables that are included within the model designed to regulate the effects of the AI chatbots. PLS provides the most approachable model in examining indirect effects and interaction terms adding to the completeness of the hypothesized links [41]. A two-stage PLS technique was used in this investigation, which is a measurement model and structural model assessment [40]. The structural model was used in the second stage to test the hypotheses using the bootstrapping approach.

Results Demographic information

The results indicated that female respondents were 60.6% and male respondents were 39.4%. The results revealed that the largest age group is 22–25 years old, with 38.7%, followed by 26–29 years old with 23.6%. Business administration has the highest enrollment at 32.8%, while rural areas have more residents at 56.3% compared to Urban areas at 43.8%. In terms of category of study, the majority of the respondents, 47.3%, are pursuing bachelor's degrees, followed by 31.1% enrolled in master's or M.Phil. programs, and 21.6% pursuing PhD. The proficiency levels of individuals in technology skills showed that the majority, 70.2% have moderate technology skills, while 22.6% possess high-level skills, and 7.2% have low-level skills. In terms of internet access, the highest number of respondents access the internet through mobile hotspots (54.7%) than through home Wi-Fi (45.3%). The frequency of using the Internet, the majority (58.8%) use the Internet for 5–10 h daily, while 27.5% use it for less than 5 h, and 13.8% vary their usage depending on the situation. Among the students, 64.2% are nationals, while 35.8% are international students. The summary of the demographic profile is shown in Table 2.

Measurement model analysis

The factor loadings in this study ranged from 0.722 to 0.932 (Fig. 2), all of which are higher than the minimum threshold [40]. To meet the convergent validity, composite reliability (CR) and average variance extracted (AVE) should be 0.70 [40]. The AVE values in this study ranged from 0.554 to 0.807, and the CR values ranged from 0.732 to 0.891 (Table 3). These results indicate that the study meets the standards for convergent validity. Additionally, the variance inflation factor (VIF) values ranged from 1.300 to 3.150, all below the critical threshold of 3.3 [57]. These findings corroborate the adequacy of the measurement model applied in this research, validating that the constructs are good enough for more analysis.

Table 2 Demographic information

Characteristics	Frequency	%
Gender		
Male	169	39.4
Female	260	60.6
Age		
19–21 years	79	18.5
22–25 years	166	38.7
26–29 years	101	23.6
Above 30 years	83	19.2
Enrollment in faculty		
Arts and Social Sciences	52	11.9
Business Administration	141	32.8
Faculty of IT	57	13.4
Faculty Engineering	68	15.9
Faculty of Sciences	47	10.9
Faculty of Education	64	15.0
Area of residence		
Rural	241	56.3
Urban	188	43.8
Category of study		
Bachelor	203	47.3
Master/ M.Phil	133	31.1
PhD	93	21.6
Technology skills level		
High	97	22.6
Moderate	301	70.2
Low	31	7.2
Internet access		
Home Wi-Fi	194	45.3
Mobile hotspot	235	54.7
Frequency of using the Internet		
Below 5 h daily	118	27.5
5–10 h daily	252	58.8
Depend on situation	59	13.8
Types of Students		
National	275	64.2
International	154	35.8

Once the convergent validity was achieved, the next step was to check for the discriminant validity of the model. Based on the explanation provided by Fornell and Larcker [35], the discriminant validity of constructs is ascertained when the square root of the AVE for each construct is greater than the correlations among the latent constructs. Furthermore, Franke and Sarstedt [34] stressed that a Heterotrait-monotrait (HTMT) value of less than 0.90 is considered discriminant validity. In this

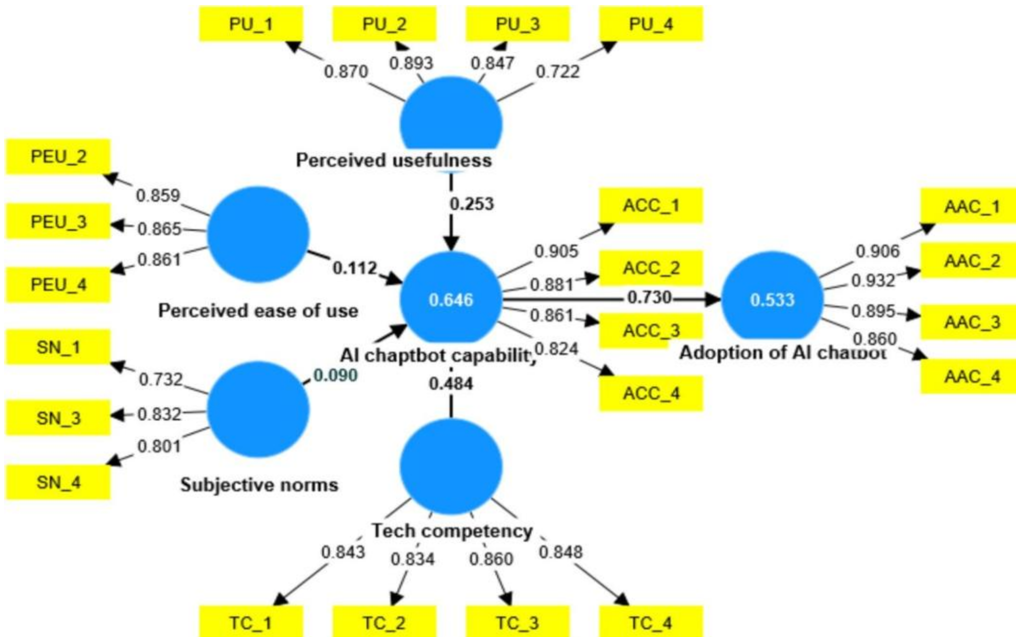


Fig. 2 Measurement model

study, the HTMT values, as explained in Table 4, were all below 0.90, therefore, satisfying the criterion for discriminant validity. Therefore, these findings imply that the model effectively demonstrates the discriminant validity of the assessed constructs and items associated with them.

Structural model analysis

The structural model was exposed to hypothesis testing using the bootstrapping method. According to Table 5, the results revealed a significant link between perceived usefulness and AI chatbot capability ($\beta = 0.253$, $t = 4.875$, $p < 0.01$). Similar to this, perceived ease of use significantly influenced AI chatbot capability ($\beta = 0.112$, $t = 2.014$, $p < 0.05$), but the subjective norm has no significant impact on AI chatbot capability ($\beta = -0.090$, $t = 1.723$, $p > 0.05$), therefore, H1, H2 are accepted and H3 is not accepted. Tech competency has a significant impact on AI chatbot capability ($\beta = 0.484$, $t = 9.173$, $p < 0.01$), thus, H4 is accepted. AI chatbot capability has a significant impact on AI chatbot adoption for online learning adoption ($\beta = 0.730$, $t = 21.190$, $p < 0.01$), as a result, H5 is accepted (Fig. 3).

AI chatbot capability mediate the effect of perceived usefulness ($\beta = 0.185$, $t = 4.654$, $p < 0.01$), perceived ease of use ($\beta = 0.082$, $t = 1.996$, $p < 0.05$), and tech competency ($\beta = 0.353$, $t = 8.993$, $p < 0.01$) on AI chatbot adoption for online learning effectiveness, but there is no mediating effect of the subjective norm ($\beta = 0.066$, $t = 1.623$, $p > 0.05$) on AI chatbot adoption. Hence, the results indicated that facilitating conditions moderate the effect of perceived usefulness and tech competency on AI chatbot capability (Fig. 4). Facilitating conditions act as a key facilitator increasing the effect of perceived usefulness and tech competency on AI chatbots' role in enhancing the effectiveness of online learning. As a result, infrastructural provision and contextual support are necessary to increase the effectiveness of AI chatbots in education. According to PLS analysis, the blindfolding procedures were used in the current investigation to assess the structural model's predictive relevance (Q^2) and effect size (f^2). The outcomes showed that the model had a good ability to predict the variables. For example, R^2 values for AI chatbot capability and AI chatbot adoption were found to be 0.646 and 0.533, respectively. To examine the strength of the association between the variables, effect size (f^2) values were also evaluated. According to Cohen [27], a f^2 value of 0.35 denotes a significant impact size, whereas a value of 0.02 denotes a modest effect size. The results showed that perceived usefulness (0.139), perceived ease of use (0.215), subjective norm (0.108), tech competency (0.113), and AI chatbot capability (0.356) all had significant f^2 values.

Table 3 Convergent validity

Characteristics	**Skewness**	**Kurtosis**	**VIF**	**FL**	**CA**	**AVE**
Perceived usefulness					0.855	0.698
AI chatbots save me time by providing quick answers to my academic questions	–0.241	0.249	2.294	0.870		
Using AI chatbots helps me understand complex concepts in my studies more effectively	–0.336	0.088	2.822	0.893		
I find that AI chatbots offer useful resources that enhance my learning experience	–0.211	–0.195	2.187	0.847		
AI chatbots increase my motivation in online learning environments	1.109	1.449	1.521	0.722		
Perceived ease of use					0.827	0.743
The interface of the AI chatbot is easy to understand	–0.775	–0.349	1.799	0.859		
I find it easy to access and use the AI chatbot for my academic needs	0.165	– –0.191	– 2.075	0.865		
The instructions provided by the AI chatbot are clear and easy	0.285	0.277	1.845	0.861		
Subjective norm					0.732	0.554
Most of my classmates encourage me to use AI chatbots for assistance in my studies	–0.443	– –0.260	1.300	0.732		
My instructors advocate the use of AI chatbots as helpful tools for learning	0.224	– –0.107	1.467	0.832		
In my study groups, using AI chatbots is a common practice	0.217	0.468	1.362	0.801		
Tech competency					0.868	0.716
I feel confident in my ability to use AI chatbots for my learning needs	–0.468	0.588	1.944	0.843		
I am familiar with AI chatbots, that support my education	–0.133	0.686	1.964	0.834		
I have the necessary skills to effectively interact with AI chatbots	–0.255	0.573	2.535	0.860		
I easily adapt to new technology AI chatbots in my academic environment	–0.217	0.517	2.415	0.848		
AI chatbot capability					0.891	0.753
AI chatbots provide accurate and relevant responses to my questions	–0.321	0.008	2.984	0.905		
I believe AI chatbots can understand the context of my inquiries effectively	–0.513	0.275	2.595	0.881		
AI chatbots enhance my learning experience by providing useful information and resources	–0.455	0.400	2.416	0.861		
I find the interaction with AI chatbots to be engaging and user-friendly	–0.416	0.577	1.938	0.824		
AI chatbot adoption					0.820	0.807
I believe that using AI chatbots improves my learning effectiveness	–0.166	––0.064	–3.150	0.906		
I find it easy to interact with AI chatbots	0.310	–0.425	–2.575	0.932		
I feel confident using AI chatbots as part of my learning process	0.125	0.561	2.39	0.895		
AI chatbots provide timely and relevant support for my academic needs	–0.352	–0.417	2.355	0.861		

Variance inflation factorL), A), Composite(CR), and Average variance (VIF), Factor loading (F Cronbach's reliability extracted (AVE) alpha (C

Table 4 Discriminant validity

Fronell-Larcker criterion	**ATT**	**MOL**	**PEU**	**PU**	**SN**	**TC**
AI chatbot capability	0.868					
Adoption of AI chatbot	0.73	0.898				
Perceived ease of use	0.624	0.485	0.862			
Perceived usefulness	0.654	0.602	0.712	0.836		
Subjective norms	0.565	0.47	0.522	0.54	0.789	
Tech competency	0.744	0.588	0.588	0.564	0.579	0.846
Heterotrait-monotrait (HTMT)						
AI chatbot capability	–					
Adoption of AI chatbot	0.804					
Perceived ease of use	0.721	0.552				
Perceived usefulness	0.739	0.676	0.833			
Subjective norms	0.712	0.581	0.688	0.698		
Tech competency	0.842	0.655	0.687	0.647	0.742	-

Table 5 Path coefficient

HP	**Relationship**	**β**	**SD**	**t-values**	**R2**	**Q2**	**f2**	**Comment**
H1	PU → ACC	0.253	0.052	4.875**			0.139	Significant
H2	PEU → ACC	0.112	0.056	2.014*			0.215	Significant
H3	SN → ACC	0.090	0.052	1.723			0.108	Not significant
H4	TC → ACC	0.484	0.053	9.173**	0.646	0.425	0113	Significant
H5	ACC → AAC	0.730	0.034	21.19**	0.533	0.477	0.356	Significant
The mediating effect of attitudes		0.185	0.04	4.653**				Significant

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H6a	PU→ ACC → AAC				
H6b	PEU→ ACC → AAC	0.082	0.041	1.996*	Significant
H6c	SN→ ACC → AAC	0.066	0.039	1.623	Not significant
H6d	TC → ACC → AAC	0.353	0.039	8.993**	Significant
Moderating effect of facilitating conditions					
H7a	FC × PU →ACC	0.212	0.065	3.261**	Significant
H7b	FC × PEU→ACC	0.033	0.098	0.336	Not significant
H7c	FC × SN →ACC	0.053	0.087	0.609	Not significant
H7e	FC × TC →ACC	0.109	0.058	1.878*	Significant

Perceived usefulness (PU), Perceived ease of use (PEU), Subjective norms (SN), Tech competency (TC), Facilitating condition (FC), AI chatbot capability (ACC), Adoption of AI chatbot (AAC), Hypothesis (HP), Beta value (β), Standard deviation (SD).
Significant level at *$p< 0.05$, **$p< 0.01$

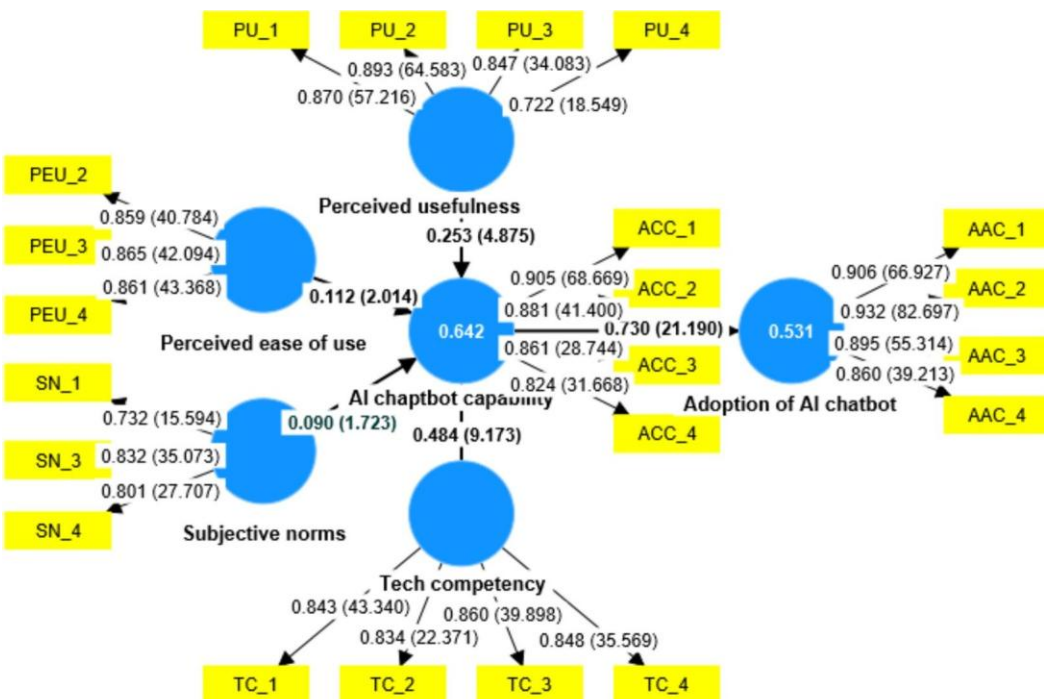
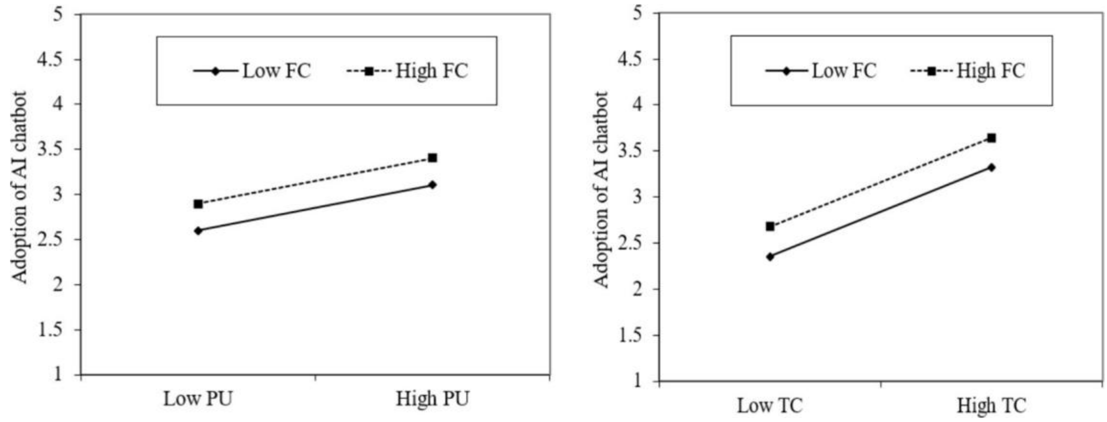


Fig. 3 Structural model

PLS-SEM predict analysis

PLS-SEM prediction is an advanced method that evaluates the predictive power of models. This method assesses the predictive relevance of the model through out of sample predictions. In this study, PLS-SEM prediction was used to evaluate the model's predictive performance, especially concerning the linkages among the PU, PEU, SN, TC, ACC, and AAC. The analysis considered several important indicators like root mean square error (RMSE), mean absolute error (MAE), and Q^2 predict values to assess



prediction performance. Hence, Q^2 prediction values for ACC and

Fig. 4 Moderating effect of facilitating conditions

Table 6 PLS-SEM predict results

Constructs	Q^2 predict	RMSE	MAE
AI chatbots capability	0.631	0.612	0.457
Adoption of AI chatbot	0.423	0.768	0.553

Table 7 Performance and t otal effects

Target Construct	Adoption of AI chatbot	
Variables	**Total Effect**	**Performance**
Perceived ease of use	0.134	62.659
Perceived usefulness	0.231	57.768
Subjective norm	0.117	58.531
Tech competency	0.511	63.502
AI chatbot capability	0.284	60.993

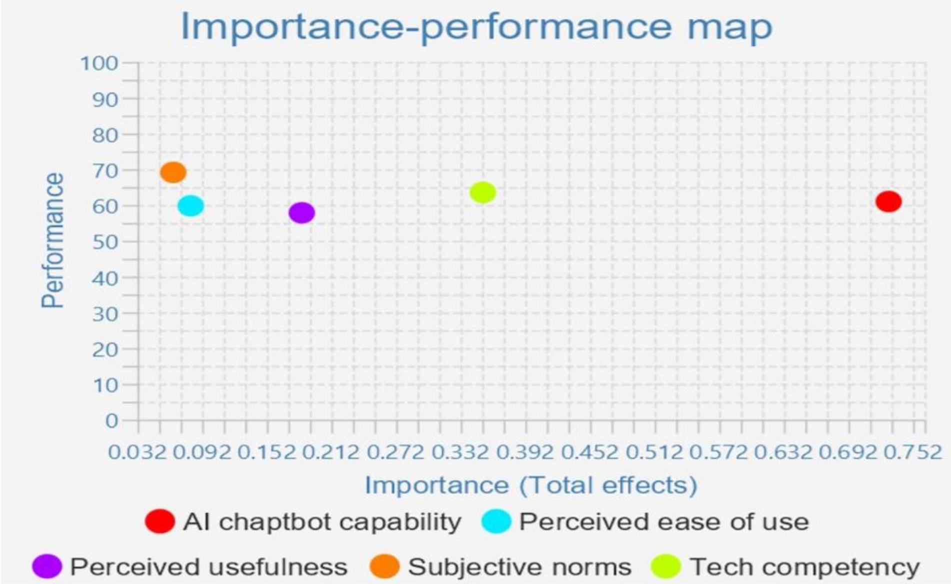
Source: Author's data analysis

AAC were determined to be 0.631 and 0.423, respectively (Table 6). The Q^2 predict values for ACC and AAC indicators are above 0.25, indicating a strong predictive capability for the adoption and effectiveness of AI chatbots in online learning.

The importance-performance matrix analysis (IPMA) identified that tech competency appeared as the crucial factor for the performance of tech competency (0.511; 63.502). The next most significant factors for the performance of AI chatbot capability were (0.284; 60.993), perceived usefulness (0.231; 57.768), perceived ease of use (0.134; 62.659), and subjective norm (0.117; 58.531). Table 7 and Fig. 5 illustrate the results of performance and total effect.

Discussion

The findings revealed that perceived usefulness has a highly significant impact on AI chatbot capability for online learning effectiveness (H1). This finding is relevant to Raza et al. [100] who found that the perceived usefulness of AI-based tools affects students' engagement and overall learning effectiveness. They argued that when students find AI chatbots as useful tools to increase learning efficiency, they tend to have a more realistic interaction with the online platforms for a higher improvement in the educational aspects. According to Ponsree and Naruetharadhol [92], students' perception of technology tools increases their academic performance. AI chatbots are useful for facilitating information retrieval and providing assistance, which encourages their adoption in digital learning environments. Antonietti et al. [11] suggested that AI tools are more likely to promote academic selfefficacy as students are willing to use such tools to complete higher order tasks. This study builds on such findings by providing evidence of the importance of the perceived usefulness of AI chatbot capability and adding to the existing literature on the acceptance of technology in education. Sharma et al. [112] used the TAM and identified perceived usefulness as a critical element that impacts a user's intention to use a particular technology. For AI-based tools, perceived usefulness has been found as an important factor in



determining users' constructs such as efficiency and ease of use for online learning [120]. Further, current studies validate the role of usefulness in the context of AI chatbots for education, which provide real-time interaction, conversational feedback, and interactive engagement in learning [7]. Furthermore, perceived usefulness also facilitates user engagement and satisfaction related to communication support needs, especially within online learning systems

Fig. 5 Importance-performance map AI chatbot adoption

[9]. Karaahmetoglu et al. [51] supported that learners' perceived usefulness plays an important evaluative role in the influence of AI chatbots deployed in educational contexts. When students think of chatbots as useful devices to enhance their learning experience, they tend to use these technologies to their best advantage.

The perceived ease of use significantly impacts AI chatbot capability (H2). This finding is associated with Boubker [17], users were more engaged with AI chatbots in educational settings when the interface was userfriendly and simple to operate. Nguyen et al. [78] assert that if a design is user-friendly, students will be willing to engage with AI-powered educational tools. Antonietti et al. [11] claimed that students were willing to use chatbots to learn because commands and navigations were easy to use. These studies show that through simplification of chatbot interactions, there is increased engagement as well as better improvement in the learning experience. On the other hand, some literature claims that PEU might not be adequate for continual acceptance. According to Wang et al. [125, 126], ease of use is crucial for initial acceptance; however, the adoption over the longer term is contingent on the chatbot's ability to provide personalized and contextual assistance, which is directly associated with one's PU. This emphasizes the relationship of PEU with other factors, particularly PU, and its impact on users' actions. Liu et al. [63] stated that the PEU significantly influenced the PU of the AI chatbots which enhanced the learning experience and satisfaction of the users. These studies highlight the fact that the ease of use saves the users from exerting too much cognitive effort and directs their attention toward the content or tasks. This result also aligns with the TAM, which posits perceived ease of use as a key factor influencing users' acceptance and utilization of technology [134]. According to Bancoro [16] and Zubir et al. [134], high ease of use results in higher adoption rates among students working with AI chatbots. In their opinion, using simple tasks increases technology's frequency of use and optimistically promotes its interactions. Tao et al. [119] argued that AI chatbots' operational threshold serves as an important filter in a medical student's confidence and propensity to use these tools for educational reasons. According to Pillai et al. [87] and Pillai et al. [88], perceived ease of use impacts not only the adoption of AI chatbots but further extends their operational scope by changing how users use them.

The results found that subjective norms do not significantly impact AI chatbot capability (H3). This is because users are more focused on the functional aspects, for instance, efficiency, speed, and resolution of issues than the desire to fit into social norms. The use of AI chatbots takes place to fulfill a set goal such as making inquiries or performing requests. Bhatnagr et al. [15] stated that subjective norms do not affect AI chatbots possibly due to the user-centric nature of AI chatbot interactions. Chandra et al. [20] contend that in such contexts of use, which mostly involve the individual's engagement with the tool such as interacting with AI chatbots, social socialization loses its relevance as the decision is taken by the user based on his interaction with the technology. Subjective norms are the mental images of social pressures that individuals feel within their social circles which encourage them to either undertake or refrain from doing certain activities [2]. In the use of educational technologies, users are influenced by their peers, instructors' recommendations, and even certain policies within the institution [78]. Nonetheless, the insignificant correlation obtained in this research may have contextual and theoretical explanations. To contextual factors, students in higher education are known to engage in self-directed learning where the choice made supersedes social expectations [125, 126]. In contrast to work settings where social norms may govern the use of technology, students tend to focus on their PU and PEU. Some students in higher education are classified as digital immigrants and users of many digital devices, including AI technologies [30]. This enables them to depend on their TC more than on the region's social factors when it comes to the adoption of AI chatbots for educational purposes.

With the theory context, some past studies suggested that SN weighs less when there are strong components within the model such as PU and TC [61]. Adoption intention may be based on one's evaluation of the utility and friendliness of the chatbot rather than any social endorsement. Unlike collaborative tools which necessitate group participation (e.g., discussion forums), AI chatbots tend to be used individually for self-directed learning. This pattern of use is likely to minimize the importance of social impact as a factor [81]. According to Lin and Yu [61], subject norms had an insignificant effect on students' adoption of self-service technologies such as AI chatbots with perceived ease of use and technology competence dominating self-service AI chatbots. Akpan et al. [12] stressed that self-paced learning technologies are based on an individual's self-concept rather than on the interpersonal peer group. Previous research has established that in extremely task-specific environments, subjective norms lose relevance because users become more concerned with the functional and actual use of the technology and less with external factors [29]. In contrast, Wang et al. [126] indicated that subjective norms influence students' attitudes toward the use of AI tools in education, as students would rather be selfcentered instead of being altruistic toward society and role models. Kushwah et al. [59] saw a weakening of such subjective norms when technology had an impression of being self-sufficient and when it was able to assist the user directly.

Tech competency has a significant relationship with attitudes (H4) because students more adept with technology tend to have more positive attitudes about the adoption of online learning. This finding is related to Ait Baha et al. [7] who found that, among users who understood the technology well, the likelihood of willingly applying efficient AI technologies such as chatbots was a common disposition, and they could extend such sophistication more effectively than others. In line with Nguyen et al. [79], users with a specific technical competence do not see problems in mastering the interface and functionality of the chatbots which enables them to efficiently utilize the potential of the chatbot in a short period. Sahin et al. [111] pointed out that users with better technical skills usually develop a more positive attitude toward the adoption of new educational technologies because it is easy for them to use digital tools. On the other hand, earlier studies demonstrate that the absence of technical skills can be a barrier to adoption. According to Antonietti et al. [11], students with lower levels of technological skill often feel frustrated in their interactions with chatbots, and this affects their perceived value and ease of use. This emphasizes the necessity for instructional design which increases users' technological skills. Ponsree and Naruetharadhol [92] found that well-devised training programs greatly enhanced the users' perceptions of chatbot technology. More tech-savvy students are more than likely going to have a favorable attitude toward online learning tools like AI chatbots as they can integrate them easily and provide valuable assistance [97]. Mohebbi [75] mentioned how students with better technological skills were keen on using AI tools as they understood the advantages. Guan et al. [39] stated that students who were more familiar with the technology faced no issues with AI-based education tools.

AI chatbot capability has a significant relationship with adopting AI chatbots for online learning effectiveness (H5). As recent studies showed [127], students seem to have a greater willingness to use AI-supported systems in learning

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when these smart systems provide personalized and contextual support. In addition, AI chatbots positively impact educational performance as users believe in their strengths and seek to employ these tools to enhance their results. According to Kuhail et al. [58] and Stohr et al. [114], students trust chatbots that they perceive as performing at high levels (e.g., reliable and quick response), and therefore are more willing to use such chatbots for online education. Similarly, according to Chang et al. [22], students' efficiency in learning is accomplished when chatbots that have competent problem-solving and resolving functions are used. According to Chen et al. [23], students have a greater chance of regarding AI as a necessary aid in increasing students' learning outcomes if real-time assistance is efficiently offered. Mejeh and Rehm [71] recommend modern chatbots that apply advanced natural language processing with adaptive learning features in online education because these chatbots motivate learners and enhance their experience with online courses. Alowais et al. [5] explained how the performance of AI chatbots was pivotal for their employment in medical education since performance and contextual accuracy are vital for such a sensitive field.

AI chatbot capability mediates the effect of perceived usefulness, perceived ease of use, and tech competency on the adoption of AI chatbots for online learning effectiveness (H6). According to Akpan et al. [12], the high adoption rates of AI chatbots in educational settings are only achieved when users find the AI chatbots skillful enough for smooth interaction and problem-solving. Akpan et al. [12] observed that advanced elements like individualized messages and on-demand support greatly boost the functional worth of chatbots in education. In contrast to previous studies which only focused on PU and PEU as direct factors [111], this study emphasizes the capability of the AI chatbot to operate as a crucial variable. This study fills the gap in understanding how user attitudes and competencies on technology are mediated through AI chatbot capabilities toward its adoption in online teaching and learning settings. Perceived usefulness and ease of use as major predictors of technology adoption were recognized by the TAM model. Davis et al. [28] stated that technology will be adopted when the prospective users perceive that it will be beneficial, and simple to use in their learning processes. AI chatbot users are more likely to adopt the AI system if they feel it is effective in helping to complete tasks and when it aids in learning more efficiently [23]. Chatbots have a higher potential to improve efficiency and demonstrate their ability to enhance educational outcomes by being responsive, personalized, and accurate [7]. Haugeland et al. [43] asserted that the technical design of chatbots is a factor that contributes to the interaction between the ease of use of the chatbots and the use of these chatbots by the users. Bahaddad [14] stated that AI tools can help users who have high-tech abilities by linking their performance.

The results revealed that facilitating conditions moderate the effect of perceived usefulness, and tech competency on the adoption of AI chatbot capability for online learning effectiveness (H7). Sahin et al. [111] stated that perceived usefulness highly influences technology adoption in settings with favorable facilitating conditions because students can gain the benefits of chatbots when they face fewer technological hurdles. These results confirm that barriers to the adoption of AI chatbots are lowered in instances where facilitating conditions are sufficient. Also, within the boundaries of tech competency, the findings agree with Antonietti et al. [11] who stated that users with high technical competence need a great deal of institutional support to take full advantage of the more sophisticated AI. Even students with a high degree of tech competence are handicapped in the presence of lacking technical and organizational resources. Institutions can use such an approach to increase the positive effects of technological skill levels on the adoption of chatbots for teaching and learning by providing adequate resources. When students are well-equipped, technically supported, and possess the required resources, it appears that their perceptions of the usefulness of AI technology and their tech competencies are greater in their adoption of AI chatbots. This is in line with prior studies that assert that the adoption of technology in education is greatly determined by external support [44, 98, 122]. Users' perception of usefulness and competency in technology may be supplemented or neutralized by facilitating conditions regarding the AI chatbots. Liesa-Orus et al. [65] determined that facilitating conditions such as institutional support may increase the impact of perceived usefulness on technology adoption. Faced with these facilitating conditions, students are more likely to accept the AI chatbot as an effective instrument to enhance the quality of their learning experience and incorporate it into their online learning activities. On the other hand, robust technical support and appropriate training materials together with the compatibility of chatbots with other educational systems mitigate negative perceptions toward the adoption of the tools [14]. Michalak and Ellixson [74] explain that technological aids usage by educators and students can be improved by external factors or by integrating constructive aids like smooth connectivity and suitable help desks that assist the AI tools to perform better.

Theoretical contribution

Several motivating factors underpin the integration of AI chatbots among students. AI chatbot capability can be beneficial in the learning process and the students integrate well in the 21st-century setting. The utility of instructional materials and their perceived usefulness and perceived ease of use allow the students to be constructive to the learning process. This research adds a new dimension to the existing literature on the AI chatbot capability in online learning environments while expanding the scope of the TAM by illustrating its key constructs in the context of AI-driven learning technologies. The findings support the core assumptions of TAM and highlight the role of perceived usefulness and perceived ease of use concerning the adoption of AI chatbots. The study presents facilitating conditions and AI chatbot capability as important moderating and mediating variables that contribute to our theoretical understanding of the external and internal resource influences between AI chatbot capabilities and learning outcomes. Integration of these variables provides a more informed understanding of AI chatbot adoption in general particularly in education. The findings show that social norms do not have much effect on the use of AI chatbots, which is contrary to most of the earlier models of technology acceptance that provide much weight to social influences. In this case, the study implies that users are more concerned with the functionality and usability of the AI chatbots instead of conforming to any social expectations. As such, it provokes debates concerning the sources of this change in emphasis and the contexts and conditions in which social norms do not play a role in the adoption of technology, especially in teaching and learning. These dynamics may apply in any number of such cases where existing theories are to be developed or enhanced for a greater understanding of user engagement with AI technologies.

Practical contribution

The results depict multiple recommendations that can be adopted by universities, educators, and policymakers to proficiently use AI chatbots for learning purposes. Universities must invest in a proper technological infrastructure such as stable high-speed internet and dependable service IT support. The incorporation of AI learning spaces in libraries, classrooms, and other learning hubs can enhance the ease of adoption as well as educational outcomes derived from the use of chatbots. AI chatbots are only effective if their performance and impact at educational institutions are evaluated. The level of AI engagement, academic achievement, performance, and satisfaction can significantly improve the effectiveness of AI chatbots. Educational institutions must partner with technology companies to create AI chatbots with the capability to interact on an intuitive level and provide relevant assistance. The chatbots should offer real-time dialogue feedback and guidance to students through learning hurdles. A user-centered design approach will foster engagement and prolonged usage. The policymakers must articulate policies around the moral implications of AI chatbots in education, including privacy of information, algorithmic bias, and responsibility for action. All these issues require that an institution plans compliance with user privacy and ethical AI practices.

In addition, the perceived usefulness and ease of use aspects of AI chatbots suggest that academicians and developers need to raise the standards for creating chatbots that are simple and serve real purposes to the students. Chatbots providing instant feedback and assistance, along with user-friendly design, are more likely to be accepted. The ability of students to technology is important in AI chatbots for learning outcomes.

There is a need for training programs related to the incorporation of AI chatbots for educational applications. Students need to know what AI chatbots are capable of and what they cannot do. Improving their educational technological competencies will enhance their self-efficacy and self-competency in the use of AI chatbots in their learning contexts. Students who have effectively utilized AI chatbots are also able to relay how AI chatbots can be utilized for educational purposes to their friends. Students may evaluate how effective AI chatbots are in an educational environment and educate managers and other relevant participants about the conducted research. This will build confidence on the part of the top management, students, and teachers, regarding the use of AI chatbots for educational purposes. The adoption of AI chatbots is also aided by favorable circumstances, like dependable technical systems and institutional support. It is the responsibility of educational institutions to make provisions for students to have access to requisite services like stable internet and constant technological support to ease their learning processes. Enhancing the adoption of technology in the campus, library, and classroom is a great strategy to boost student participation and performance. Institutions of higher learning must formulate explicit institution-wide policies and regulations that address ethical issues and compliance with legal standards and ethical concerns of AI chatbot use in education.

Limitations and future research direction This research explores the students' views regarding the incorporation of AI chatbots. There are several limitations of this study. First, the population sample was 429, which was derived from three universities in Malaysia only, which may not be representative of the views and experiences of students belonging to diverse cultures, institutions, or educational systems. Thus, it is necessary to use thoughtfulness in generalizing these findings to other student populations from other institutions. Second, the study fills a knowledge gap about students' adoption of AI chatbots for online learning effectiveness. The participants of the study were surveyed and provided their motivation which influenced them to adopt AI chatbots. The motivating and inhibiting factors such as perceived usefulness, perceived ease of use, tech competency, and facilitating conditions can serve as a foundation for future researchers. The academicians can investigate how these factors work together in various educational settings, verify their effects on different groups of students, and examine other aspects that could be responsible for AI chatbot adoption for educational purposes. This can help formulate wider models of technology acceptance in education and provide insights into effective policies for implementation.

Conclusion

The objectives of this study are to investigate the factors that determine the use of AI chatbots for the effectiveness of online learning in higher education institutions. The results were in line with the objectives of the study and provided an interesting conclusion. There was a highly statistically significant influence of perceived AI chatbot capability on perceived usefulness and perceived ease of use which influence the key predictors of technology adoption. This is supported by previous studies which have pointed out their contribution to improving user engagement and learning effectiveness. The presence of AI chatbots did not appear to cause subjective norms to play a role, which means functional considerations were more important in their adoption. On the other hand, tech competency emerged as a key variable, which positively affected AI chatbot adoption. The capability of AI chatbots showed a statistically significant relationship with adopting AI chatbots for online learning, which explains customized systems to the overall improvement of educational performance. In addition, AI chatbot capability also played a mediator role in the effects of TPB components such as perceived usefulness, perceived ease of use, and tech competency on adoption as predicted in the TAM model. Lastly, facilitating conditions were found to moderate the effects of perceived usefulness and tech competency, demonstrating the importance of external assistance in technology acquisition. These results contribute to the knowledge of the factors that affect the adoption of AI chatbots in online learning environments and provide concrete recommendations for practitioners and organizations to enhance the effectiveness of such technologies.

Abbreviations

AI	Artificial intelligence
PLS	P artial least square
PU	Perceived usefulness
PEU	P erceived ease of use
TC	T ech competency
SN	Subjective norm
ACC	AI chatbot capability
AAC	A doption of AI chatbot
IT	I nformation technology
TAM	T echnology acceptance model
UTAUT	Unified theory of acceptance and use of technology
ICT	I nformation communication technology
ML	Machine learning
NLP	N atural language processing

VIF	V ariance inflation factor
CMB	Common method bias
SEM	S tructural equation modeling
SPSS	Statistical Package for the Social Sciences
CR	Composite reliability
AVE	A verage variance extracted
FL	F actor loading
CA	Cronbach's alpha
HTMT	Heterotrait-monotrait
HP	H ypothesis
β	B eta value
SD	S tandard deviation
IPMA	Importance-performance matrix analysis

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Author contributions

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Availability of data and materials

Due to privacy concerns, the datasets used in this study are not publicly accessible; however, the data supporting this study's findings are available from the corresponding author upon reasonable request. **Declarations**

Ethics approval and consent to participate

This study follows the ethical principles of the Declaration of Helsinki and received approval from the research management and innovation center research ethics committee (reference: rmic/umkrec-507). All survey participants provided written consent after reading an ethical statement at the top of the survey questionnaire. This statement explained that participation was voluntary, involved no risks or compensation, and that participants could choose to withdraw at any time. Additionally, no data was collected from individuals under 18.

Consent for publication

We confirm that the content of this manuscript, or any major part of it, has not been published in a peer-reviewed journal and is not under consideration for publication elsewhere.

Competing interests

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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