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Int J Educ Technol High Educ (2024) 21:20
https://doi.org/10.1186/s41239-024-00451-8

International Journal of Educational Technology in Higher Education

RESEARCH ARTICLE Open Access

Exploring intention of undergraduate students to embrace chatbots: from the vantage point of Lesotho

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Abstract

The increasing prevalence of Fourth Industrial Revolution (4IR) technologies has led to a surge in the popularity of AI application tools, particularly chatbots, in various fields, including education. This research explores the factors influencing undergraduate students' inclination to embrace AI application tools, specifically chatbots, for educational purposes. Using an expanded diffusion theory of innovation framework, the study investigates the relationship between relative advantages, compatibility, trialability, perceived trust, perceived usefulness, perceived ease of use, and behavioral intention. Using a 7-point scale, a questionnaire was given to 842 undergraduate students to collect data. The analysis, conducted using SmartPLS 4.0.9.2 software with a covariance-based structural equation model, produced significant findings. The study confirms hypotheses related to the relative advantages, compatibility, trialability, perceived usefulness, and perceived trust associated with chatbots. Notably, students who perceive the benefits of chatbots show a strong intention to use them for academic purposes. The perception of compatibility between students and chatbots positively influences adoption intention, highlighting the importance of compatibility. Additionally, students who have the opportunity to trial chatbots are more likely to use them, emphasizing the significance of trialability. Interestingly, the study did not establish direct relationships between perceived usefulness, perceived ease of use, and behavioral intention. This suggests the presence of other influential factors or dynamics in the adoption of chatbots for educational purposes. These findings offer practical insights for students and contribute to the theoretical understanding of the diffusion theory of innovation. Future research can further explore these insights to unravel the complexities of chatbot adoption and facilitate the broader adoption of AI tools in educational settings.

Keywords: Artificial intelligence, Chatbots, Diffusion theory of innovation, Undergraduate students

Introduction

Researchers and stakeholders have acknowledged the significance of integrating Industry 4.0 technologies into higher education, leading to initiatives aimed at their promotion within higher education institutions (HEIs) (Ayanwale et al., 2022; Ayanwale, 2024).

Early exposure to these emerging technologies is deemed crucial for fostering students' competencies and establishing a solid foundation for future learning and career development (Touretzky & Gardner-McCune, 2022; Kim et al., 2023). Coined to describe the fourth industrial revolution (4IR), Industry 4.0 involves the integration of digital technologies into global industrial processes and economies (Ayanwale, 2023a; Mamadou & Ernesto, 2020). This encompasses the Internet of Things (IoT), artificial intelligence (AI), cloud computing, virtual and augmented reality, big data, and robotics. Within higher education (HE), the adoption of Industry 4.0 technologies is propelled by various factors, including preparing students for the contemporary workplace, enhancing the quality of teaching and learning, and ensuring competitiveness in a globalized environment (Almela, 2023). This study specifically focuses on a pivotal technology within Industry 4.0—artificial intelligence (AI), increasingly employed in HEIs to support students in their academic pursuits. AI refers to machines demonstrating human-like intelligence, capable of executing tasks and undergoing self-improvement through the collection and storage of data (Yau et al., 2022). AI application tools, including ChatGPT, Bing Chat, paperpal, paperdigest, Elicit, Humata, Copilot, trinkin.ai, Paper Brain, and ExperAI, are actively used to streamline student assignments, research, and term papers, facilitating and expediting these processes. Comprehending how AI operates and the problems it can address is crucial for students to effectively curate the tools they use in their lives (Ayanwale, 2023; Ma et al., 2023). Ongoing efforts aim to develop curriculum frameworks, guidelines, and standards to effectively introduce AI application tools and concepts to students in HE. The integration of these technologies into the HE curriculum is anticipated to enhance learning outcomes, elevate student engagement and motivation, and foster the development of digital skills increasingly sought after in the job market (Mamadou & Ernesto, 2020; Oladele et al., 2022, 2023).

The exploration of emerging technologies, particularly the adoption of AI application tools such as chatbots, is a crucial subject of discourse among higher education (HE) students. Understanding the psychological factors that shape students' decisions to embrace these technologies is vital for devising effective strategies to support their adoption. However, existing studies predominantly focused on students' adoption of chatbots in HE outside the African context, employing frameworks like the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), or Theory of Planned Behaviour (TPB) (Roy et al., 2022; Pillai et al., 2023; Garcia de Blanes et al., 2022; Alboqami, 2023; Malik et al., 2021; Mohd Rahim, et al., 2022). The generalizability of these findings to other regions is questionable. Moreover, a prior study by Ragheb et al. (2022) exclusively focused on students from private universities in Egypt, limiting its applicability to other regions. In light of these gaps, the present study aims to extend Ragheb et al.'s (2022) research by examining the behavioral intentions of public undergraduate students in a Southern African country regarding the adoption of AI application tools (chatbots) for academic purposes. To achieve this, we leverage the Innovation Diffusion Theory (IDT) proposed by Rogers (1995, 2003), a widely recognized theory utilized to comprehend the acceptance and adoption of new technologies. IDT has found application in various studies exploring the adoption of AI application tools (Aizstrauta et al., 2014; Al-Rahmi et al., 2019; Pinho et al., 2021). Furthermore, perceived trust in using chatbots emerges as a significant factor influencing students' behavioral intention to engage with them in the context of higher education (Al-Sharafi et al., 2016; Laumer et al., 2019; Mohd Rahim, et al., 2022; Ragheb et al., 2022).

In summary, existing research on chatbots adoption in higher education in Northern Africa, particularly at a private university in Egypt (Ragheb et al., 2022), is confined to specific contexts. Given Africa's diverse nature and distinct needs for embracing AI tools, it becomes imperative to explore the viewpoints of undergraduate students in other regions, such as Southern Africa. Considering the unique social context of each region is essential for devising strategies to introduce and support the adoption of AI application tools among students in higher education. Therefore, this study aims to contribute to the expanding literature on how undergraduate students perceive the adoption of AI tools in higher education. It particularly focuses on public higher education undergraduate students across various disciplines, including Science, Technology, Education, Humanities, Health Sciences, Social Sciences, Agriculture, and Law. Examining their behavioral intentions to use AI tools provides valuable insights for supporting adoption in higher education and enhancing student learning outcomes.

In this research paper, we present the findings of a quantitative study involving 842 undergraduate students from different faculties at the National University of Lesotho, investigating their behavioral intentions to use chatbots for academic purposes. The study explores various psychological factors such as relative advantages, observability, trialability, perceived usefulness, perceived ease of use, perceived trust, and behavioral intention to use AI applications. The primary research question addressed is, "How do the seven psychological factors relate to the intention to use AI applications by higher education students?" The paper's structure includes an introduction and rationale, a literature review providing context and emphasizing the importance of AI tool adoption among higher education students in Lesotho, a section detailing the research methodology, and sections presenting and interpreting the study's results. The paper concludes by identifying study limitations and proposing directions for future research.

Literature review and hypotheses development

The incorporation of emerging technologies, such as AI, has significantly improved the landscape of teaching, learning, and research at universities. While AI adoption in higher education (HE) is on the rise in Lesotho and Africa as a whole, it lags behind more developed regions, particularly in the global north. Numerous studies have explored the adoption and usage of AI application tools, particularly chatbots, in various contexts. These contexts range from customer service chatbots (Sheehan, 2018) to Siri chatbot implementation in tourism (Ivanov et al., 2019), and enterprise chatbots (Brachten et al., 2021). In the realm of education, research has delved into AI-based T-bot adoption in higher education (Pillai et al., 2023), chatbots in higher education (Ragheb, et al., 2022), AI-based applications in higher education (Wang & Tu, 2021), social chatbots supporting students for studies (Al-Ghadhban & Al-Twairesh, 2020), the role of chatbots in education (Molnar & Szuts, 2018), chatbots for learning (Malik et al., 2021), chatbots for e-learning (Colace et al., 2018), and Nabhiha—the role of chatbots in education (Molnar & Szuts, 2018). These studies collectively demonstrate the potential of chatbots to enhance teaching, learning, and research in the field of education.

While existing research provides valuable insights into the factors influencing chatbot adoption and use in education, there is a gap in understanding the specific factors affecting chatbot adoption and use in HE, particularly in developing countries like Lesotho. This study seeks to address this gap by exploring the factors that influence university students' behavioral intention to adopt AI application tools, specifically chatbots, in higher education. Identifying these factors is crucial for Lesotho and other developing countries to devise strategic initiatives that effectively promote the integration of AI in teaching, learning, and research. By understanding the influences on students' behavioral intentions to adopt chatbots for academic purposes, developing countries can establish a more comprehensive framework for comprehending the adoption and diffusion of technological innovations in higher education.

Diffusion theory of innovation

The theory of innovation diffusion asserts that the spread of novel ideas, products, or technologies within social systems involves the active participation of individuals and groups. In the context of Lesotho, deeply rooted in its traditions and customs, the cultural foundation profoundly shapes the acceptance of AI. Utilizing Rogers' innovation theory of diffusion, which outlines the stages of technology adoption, provides a relevant framework to scrutinize this process. Lesotho's cultural values, centered on community and tradition, play a pivotal role in shaping attitudes toward AI. The prevalent communal spirit facilitates a collective decision-making process in adopting new technologies, with seamless acceptance more likely when aligned with cultural values. Unique communication channels, rooted in oral traditions, hold significant influence, with word-of-mouth communication and community leaders playing pivotal roles in disseminating information about AI. The social structure of Lesotho, characterized by close-knit communities, emerges as a key determinant in AI adoption, where social networks and interpersonal relationships serve as conduits for the diffusion of AI-related information. Lesotho's education and literacy levels wield influence over how individuals and communities engage with AI. Initiatives to enhance education and digital literacy can expedite the adoption process by demystifying AI and highlighting its potential benefits to a population eager for progress. Government policies play a pivotal role, exerting a significant force in swaying the diffusion of AI in Lesotho by encouraging innovation, providing infrastructure support, and addressing ethical concerns.

Building upon Rogers' (2003) framework, the adoption of new technology is influenced by five key factors: relative advantage, compatibility, complexity, trialability, and observability. The rate and extent of new technology adoption vary based on these factors, with relative advantage and compatibility highlighted as particularly significant by various studies (Agag & El-Masry, 2016; Chiang, 2013; Kim et al., 2019). Rogers (1995) identified these two factors as having the most substantial influence and effective predictability regarding an individual's technology adoption among the five characteristics. Sahin (2006) also established a high correlation between trialability and adoption. This study delves into the factors influencing higher education (HE) students' intention to use chatbots for academic purposes, focusing on relative advantage, compatibility, and trialability. Additionally, the study introduces supplementary variables, including perceived ease of use, usefulness, trust, and behavioral intention to use chatbots, expanding upon the model (see Fig. 1). These variables share a common premise: innovation adopters evaluate innovations based on perceived attributes and characteristics. As indicated by prior studies (Davis et al., 1989; Rogers, 1995, 2003), innovations with favorable features are more likely to be adopted. The primary objective of this study is to explore how these additional variables may impact students' intentions to adopt chatbots, supplementing the three main factors identified by Rogers (1995) and Sahin (2006).

Relative advantage (RA)

The theory of innovation diffusion posits that, the acceptance of new technologies is influenced by several factors, one of which is the relative advantage of the technology. Relative advantage refers to the perceived extent to which the new technology is considered superior to existing ones (Al-Jabri & Sohail, 2012; Chang & Yang, 2013; Shin et al., 2022). In the context of this study's focus on chatbots' AI application, relative advantage entails the perceived benefits of using chatbots in comparison to traditional methods of learning or communication. These benefits may include faster response times, increased accessibility, and personalized learning experiences. According to this theory, if students perceive chatbot technology as offering greater advantages compared to existing methods, they are more likely to adopt it. Lin (2011) discovered that customers are more inclined to adopt innovations in mobile banking when they perceive significant benefits. Additionally, Nguyen and Nguyen (2020) found modest support for the predictive validity of innovation characteristics, particularly the role of the relative advantage of chatbots in predicting adoption intentions. In light of these findings, the study posits the hypothesis:

H1: Relative advantage will significantly predict Lesotho higher education students' behavioral intention to use chatbots.

Compatibility (CO)

Compatibility refers to the extent to which a new technology aligns with an individual's existing beliefs, values, and experiences (Karahanna et al., 1999; Rogers, 1983, 1995; Tornatzky & Klein, 1982). It signifies the degree to which students' expectations regarding

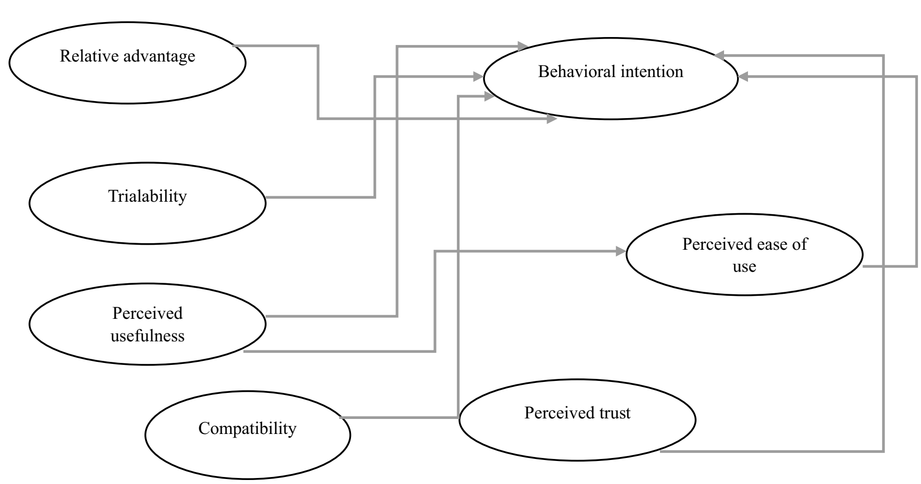

Fig. 1 Research conceptual framework

interaction with educational resources and tools are fulfilled by the technology under consideration in this study. Research suggests that individuals are more inclined to adopt and utilize technology when they perceive it to be in harmony with their beliefs and values. Consequently, their intention to use the technology is heightened as they find it useful and pertinent (Chang & Yang, 2013; Chen, 2015; Olasina, 2019; Shin et al., 2022; Svendsen et al., 2011; Wang et al., 2020a, 2020b). Harrington and Ruppel (1999) also observed that compatibility diminishes the risk of failure when employing innovative technologies. Therefore, the hypothesis posits:

H2: Compatibility will significantly predict Lesotho higher education students' behavioral intention to use chatbots.

Trialability (TR)

Trialability, as a concept, pertains to the degree to which individuals are inclined to experiment with an innovation before committing to its adoption (Al-Jabri & Sohail, 2012; Al-Rahmi et al., 2019). In the context of this study, trialability relates to students' perceptions of how the integration of chatbot AI applications into their learning process influences their learning performance. Therefore, designers of chatbots should offer users opportunities to test the chatbot before making a commitment. This approach is likely to result in higher adoption rates and greater success for the chatbot. Strategies to enhance trialability include providing a free trial or demo version, offering incentives such as discounts or rewards for testing the chatbot, delivering clear instructions during the trial period, soliciting feedback for improvement, and extending the trial period for users to fully explore the chatbot's capabilities. Empirical studies support the notion that trialability significantly influences users' willingness to adopt new technologies. In Pinho et al.'s (2021) study, trialability was associated with users' intentions to use chatbots for e-learning, with those who used the chatbot during the trial period being more likely to use it again in the future. Almeida (2023) found trialability to be a significant predictor of students' intention to use a chatbot for academic advice, indicating that students who had the chance to try the chatbot were more likely to use it again. Additionally, the use of innovative technology is positively impacted by trialability (Lee, 2007; Yang, 2007), and Sahin (2006) suggests a positive correlation between trialability and adoption rates. Consequently, innovation developers can expedite the adoption process by providing potential users with a trial of the product or service. Given these arguments, the research hypothesis is proposed as follows:

H3: Trialability will significantly predict Lesotho higher education students' behavioral intention to use chatbots.

Perceived trust (PT)

Trust is a concept denoting the perception or belief in the credibility, trustworthiness, and reliability of individuals, organizations, or technologies (Liden & Nilros, 2020; Winkler & Soellner, 2018). It involves a subjective evaluation of an individual's trust in a given entity or system. The trust users place in technology is crucial for its adoption and continued usage. Users are more inclined to adopt and regularly use technology when they perceive it as trustworthy, relying on their confidence in its reliability and dependability (Gallimore et al., 2019; Pillai et al., 2023; Smith, 2019). In the context of this study, trust pertains to students' belief in the reliability of daily interaction and communication with the chatbot, as well as their willingness to share personal data with it. The adoption of chatbots by higher education students is contingent on their trust in the technology, and such trust is more likely to develop when users intend to use the chatbot. To establish trust, chatbot designers must ensure its accurate, reliable, and secure functioning, coupled with an easy and enjoyable user experience. Strategies for gaining trust from chatbot users include providing clear and concise responses, incorporating natural language processing for more human-like interactions, thorough testing for accuracy and reliability before deployment, and ensuring overall security.

Previous studies underscore the significance of trust in the adoption of robots and chatbots (Aoki, 2020; Tarhini et al., 2017). Trust, as perceived by individuals, plays a role in fostering commitment to specific activities (Al-Sharafi et al., 2016; Laumer et al., 2019). Students' trust in technology enhances their likelihood of adoption and learning (Hamidi & Chavoshi, 2018; Panigrahi et al., 2018), especially when it involves sharing student data with a T-bot and receiving personalized outcomes. Extending the acceptance of technology model with the trust construct, which considers users' beliefs about using new technologies, further supports the importance of trust (Baby & Kannammal, 2020). In light of this argument, the hypothesis is formulated as follows:

H4: Perceived trust will significantly predict Lesotho higher education students' behavioral intention to use chatbots.

Perceived usefulness (PU)

As per Davis et al. (1989), perceived usefulness refers to the belief that technology enhances work efficiency. This study assesses the perceived usefulness of a chatbot designed to accurately address students' queries. The examination focuses on how students' perception of the chatbot's utility influences their willingness to use it. Prior studies (Almahri et al., 2020; Almaiah et al., 2019) have established a close relationship between students' satisfaction with obtaining precise answers via chatbots and their perceived usefulness. Researchers, such as Artem (2017) and Almahri et al. (2020), utilizing the UTAUT2 model, have explored students' intentions to use chatbot technology in customer relationship management in higher education, finding that perceived usefulness significantly predicts students' behavior toward using chatbots. Similarly, Malik et al. (2021) conducted a study on the utilization of chatbots for educational purposes among university students, revealing that the perceived usefulness of chatbots is a significant predictor of the intention to use them. In essence, when students perceive chatbots as valuable and beneficial for their educational needs, they are more inclined to express an intention to utilize them. These findings underscore the importance of perceiving chatbots as effective tools that enhance the learning experience. When students recognize the usefulness of chatbots in supporting their educational goals, such as providing instant access to information, personalized assistance, or facilitating interactive learning experiences, they are more likely to develop a positive attitude toward using them. This positive attitude, in turn, translates into a stronger intention to engage with chatbots for educational purposes. Moreover, research indicates that perceived usefulness directly influences students' perceptions of the ease of use of intelligent tutoring systems and their intention to continue using them (Cao et al., 2021; Huang et al., 2021; Wang et al., 2020a, 2020b). In light of these considerations, the hypotheses are formulated as follows:

H5: Perceived usefulness will significantly Lesotho predict higher education students' behavioral intention to use chatbots.

H6: Perceived usefulness will significantly Lesotho predict higher education students' perceived ease of use of chatbots.

Perceived ease of use (PEU)

Perceived ease of use refers to the belief that utilizing a specific technology will require minimal effort on the part of an individual, as outlined by Davis et al. (1989). Individuals are more inclined to use technology if they perceive it to be easy to use. In the context of this study, perceived ease of use pertains to a student's intention to effortlessly use a chatbot or the ease with which a chatbot can be utilized. Numerous studies have demonstrated that perceived ease of use, among other factors, serves as a predictor of an individual's willingness to adopt new technology (Albanna et al., 2022; Hussein, 2017; Tan et al., 2017; Tselios et al., 2011). A study conducted by Almahri et al. (2020) found that university students perceive chatbots as user-friendly, enhancing the likelihood of future adoption. Consequently, students who perceive chatbots as easy to use are more likely to hold a positive attitude toward them and are inclined to use them in the future. Therefore, the hypothesis is formulated as follows:

H7: Perceived ease of use will significantly predict Lesotho higher education students' behavioral intention to use chatbots.

Behavioral intention (BI)

In Ajzen's theory of planned behavior, behavioral intention is considered a measure of how human actions are guided. Behavior is influenced by factors that impact motivation and the level of effort and determination an individual is willing to exert for a specific task. When the intention is strong, the behavior is more likely to occur, provided it is intentional. This study specifically delves into understanding the intentions of undergraduate students regarding the use of chatbots to support their academic activities. The majority of students in this study have participated in a comprehensive two-day workshop focused on the opportunities and challenges associated with using chatbots for academic purposes. The study posits that various factors influence the intention to use AI applications, particularly chatbots. These factors encompass the relative advantages or benefits of employing chatbots compared to other alternatives, the compatibility of chatbots with students' specific needs and preferences, the opportunity for students to experiment with and explore chatbot functionality (trialability), the perception of the ease of use of chatbots, the perceived usefulness of chatbots in aiding academic tasks, and the level of trust students place in chatbot systems. In summary, the study concludes that the strength of an individual's behavioral intention plays a pivotal role in determining their actual usage of AI application tools, such as chatbots, for academic purposes.

Methodology

Research context

In the small nation of Lesotho, the National University of Lesotho (NUL) is a respected public research institution. Founded in 1945, it is one of the oldest universities in the region. As a prominent educational institution in Lesotho, the University of Lesotho offers a wide range of programs in science, technology, agriculture, health, education, humanities, law, and social sciences. Despite its esteemed reputation and significant contributions to human capital development in Lesotho, the National University of Lesotho faces various challenges, including insufficient funding, limited resources, outdated curricula, and aging infrastructure. In response, NUL has actively embraced emerging technologies, particularly AI, to enhance its teaching, learning, and research endeavors. This proactive approach reflects the university's commitment to maintaining a position of leadership in educational innovation, even with limited resources. To fully understand the context of Lesotho, it is important to explore the cultural, social, and educational aspects that make Lesotho unique. The cultural fabric of Lesotho is deeply rooted in traditions and customs, which significantly influence students' perceptions and interactions with technology. On the educational front, the challenges faced by NUL, such as limited resources and outdated curricula, mirror broader issues within Lesotho's education system. Addressing these challenges requires a nuanced understanding of the local context, where innovative solutions, including the integration of AI, can have transformative effects.

Training procedure and participants

In collaboration with the Center for Teaching and Learning at NUL, we developed a two-day training program for undergraduate students on using AI application tools, specifically chatbots, for academic purposes. The first day covered theoretical aspects, introducing chatbot concepts and benefits, lasting two hours. The second day demonstrated different chatbot types, applications, and practical usage for academic tasks, spanning three hours. The program equipped students with knowledge, skills, and ethical considerations for effective chatbot utilization in their academic work. Also, employing a quantitative cross-sectional design, the study surveyed undergraduate students in Lesotho to explore their usage of chatbots, considering factors like compatibility, relative advantage, trialability, ease of use, perceived usefulness, perceived trust, and behavioral intentions. A total of 842 participants were involved in the research. Table 1 provides an overview of the participants' demographic characteristics. Notably, 63.6% of the sample comprised female participants, while 36.6% were male. The majority fell within the 21–24 age group (50.6%), with 45.4% being under 20 years old. Participants aged 25–28 constituted 4.0% of the sample. Regarding academic classification, 47.9% were third-year students, 24.5% were first-year students, 15.1% were fourth-year students, and 12.5% were second-year students. Across faculties, 28.4% were from the faculty of education, 25.5% from science and technology, 17.2% from social sciences, 11.0% from humanities, 7.4% from law, 5.9% from agriculture, and 5.6% from health sciences. Notably, over 91% of participants attended the AI application tools training program, while 8.8% did not participate.

Table 1 Demographic characteristics of the participants

Variable	Category	Frequency	Percent
Gender	Male	308	36.6
	Female	534	63.4
Age group	Less than 20	382	45.4
	21–24	426	50.6
	25–28	34	4
Academic year	Year One	206	24.5
	Year Two	105	12.5
	Year Three	404	48
	Year Four	127	15.1
Faculty	Science & Technology	206	24.5
	Education	239	28.4
	Humanities	93	11
	Social Science	145	17.2
	Agriculture	50	5.9
	Health Science	47	5.6
	Law	62	7.4
Attendance at AI application tools training	Yes	842	100

Measures

This study employed an instrument adapted from previous research (e.g., Rahim et al., 2022; Al-Rahim et al., 2019; Rogers, 1995; Moore & Benbasat, 1991), encompassing seven factors: relative advantage, compatibility, trialability, perceived ease of use, perceived usefulness, perceived trust, and behavioral intention to use chatbots. Participants provided ratings on a Likert scale ranging from 1 to 7, where 1 signified strong disagreement and 7 indicated strong agreement. While the items were drawn from established theories like diffusion innovation theory and studies on students' intention to adopt E-learning systems, the researcher utilized a validated instrument (Rahim et al., 2022; Al-Rahmi et al., 2019; Moore & Benbasat, 1991) to gather perspectives on undergraduate students' behavioral intention to use AI application tools (chatbots) in the Lesotho context. The survey was conducted using straightforward and easily understandable English to eliminate any potential ambiguity which comprised two sections: a demographic section capturing gender, age, academic level, faculty affiliations, and enrollment in the training program, and a closed-ended section probing students about their intent to use chatbots for academic purposes. Participants expressed their agreement with the statements on each of the seven factors using a seven-point scale. The specific items employed to gather data from the closed-ended section of the survey are highlighted as follows.

Relative advantage with reliability of 0.882
Chatbots would be more time-saving than other methods of searching for information for my academics-RA1
For my academics, chatbots would provide more precise results than other search tools-RA2
For my academics, chatbots would provide a more efficient way of accessing information-RA3
A chatbot would be a more convenient tool for personalizing learning than other tools-RA4

Compatibility with reliability of 0.829	
	Chatbots for academic purposes meet my expectations for academic support-CO1
	My approach to academic tasks and assignments usually aligns with using a chatbot-CO2
	Using a chatbot for academic purposes is consistent with how I prefer to interact with technology-CO3
	My preferred learning style fits chatbots for academic purposes-CO4
Trialability with reliability of 0.790	
	Before I decide to use chatbots regularly for my studies, I could easily try them out-TR1
	If chatbots are useful for my needs, I would be willing to test them out-TR2
	Using a chatbot for academic purposes might help me better understand its potential advantages and disadvantages-TR3
	Using a chatbot for academic purposes would enhance my learning experience-TR4
Perceived ease of use with reliability of 0.886	
	Using chatbots for my academic work would require little effort from me-PEU1
	A chatbot makes it easy for me to find information for my academics-PEU2
	To solve my academic problem, the instructions and communication with the chatbot are clear and easy to understand-PEU3
	It's easy to learn how to use chatbots for my academics-PEU4
Perceived usefulness with reliability of 0.870	
	Chatbots can be a valuable resource for getting personalized academic support and guidance-PU1
	My academic performance would be enhanced if I used a chatbot-PU2
	My understanding of difficult concepts and course materials would be improved with the aid of a chatbot-PU3
	I would benefit from a chatbot for accessing relevant information and resources for academic purposes-PU4
Perceived trust with reliability of 0.904	
	I trust that a chatbot will protect my academic privacy and data-PT1
	It is my trust that the chatbot will provide me with accurate and relevant information for my queries-PT2
	I trust chatbots to operate ethically and transparently-PT3
	I trust that my academic needs and queries can be handled by a chatbot-PT4
Behavioral intention to use chatbot with reliability of 0.895	
	I trust that my academic needs and queries can be handled by a chatbot-BI1
	To ask questions about my coursework, I would use the chatbot-BI2
	Chatbots would be useful for quick answers to assignment questions-BI3
	My overall experience at the university would be improved if I used a chatbot-BI4
	Using the chatbot for academic purposes is something I plan to do often-BI5

Data collection procedure

This research gathered data from students at the National University of Lesotho (NUL) using a self-administered questionnaire designed to measure the variables under investigation. Respondents used a 7-point Likert scale to express their agreement or disagreement, with 1 representing "strongly disagree" and 7 representing "strongly agree." To enhance convenience and sample size, a Google Forms survey was created and distributed via platforms such as WhatsApp, Telegram, and other student channels. The survey link was available for access between March and April 2023, with closure at the designated period's end marking the conclusion of data collection. A total of 861 responses were received, but after careful review, 19 were deemed invalid due to participants providing the responses who did not participate in the training. The analysis proceeded with 842 valid responses.

Common method bias

To assess the potential existence of common method bias (CMB) in the data, we utilized the Harman single-factor test through SPSS software version 26.0. This widely employed method helps determine if respondents' responses are affected by bias. According to Mukherjee et al. (2022) and Podsakoff et al. (2003), the presence of CMB is suggested if one factor accounts for more than 50% of the total variance extracted. Our study conducted the Harman single-factor test, and upon analysis, it revealed that there were no concerns regarding CMB in the dataset. The total variance extracted by one factor was 47.336%. Since this value is below the recommended threshold of 50%, as advised by Mukherjee et al. (2022) and Podsakoff et al. (2003), it can be concluded that there was no significant common method bias present in the study. This result enhances the validity and reliability of the obtained results, indicating that respondents' responses were not significantly influenced by a single underlying bias. Consequently, researchers can express increased confidence in both the data and the subsequent analyses conducted in the study.

Method of data analysis

In this study, covariance-based structural equation modeling (SEM) using SmartPLS software version 4.9.0.2 (Ringle et al., 2022) was employed for data analysis. Initially, descriptive statistics were conducted to assess the skewness and kurtosis of the values, aiming to determine the univariate normality of the data. The critical values used for assessing skewness and kurtosis were 3.0 and 10.0, respectively, as recommended by Kline (2010). Additionally, the multivariate normality of the data was tested using Mardia's normalized multivariate kurtosis (Mardia, 1970). After normality assessment, confirmatory factor analysis (CFA) was performed to evaluate the structural validity of the questionnaire. During this stage, the consistency of the outer loading, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted were examined to ensure that the measurement items adequately represented the latent constructs they were intended to measure. Finally, a path model was verified to examine the hypothesized relationships among the measurement variables under investigation and undergraduate students' intention to adopt or use AI application tools, specifically chatbots, for their academic purposes. The path model analysis allowed for the assessment of the direct effects of the variables, providing insights into the factors influencing students' behavioral intentions.

Results

Assessment of CB-SEM assumptions

To ensure the credibility of the research results, Hair et al. (2010) highlight the importance of upholding certain assumptions. In this study, normality assumptions were assessed using skewness and kurtosis values. Skewness measures asymmetry in data distributions, while kurtosis indicates flatness or peaking. The skewness and kurtosis values in Table 2 range from − 2.128 to 0.261 and − 1.490 to 5.479, respectively. According to Kline (2010), skewness and kurtosis values should not exceed 3.0 and 10.0, respectively. Therefore, the results suggest that this study did not violate the normality assumption. Additionally, Pearson correlation coefficients were employed to test linearity

Table 2 Normality assessment

Manifest variables	Mean	Std dev	Kurtosis	Skewness
CO1	4.043	1.977	− 1.403	− 0.260
CO2	3.677	1.877	− 1.332	0.067
CO3	3.451	1.837	− 1.210	0.261
CO4	3.735	2.011	− 1.490	0.040
TR1	5.457	1.345	3.511	− 1.868
TR2	5.387	1.338	3.178	− 1.730
TR3	4.735	1.685	− 0.638	− 0.601
TR4	5.523	1.188	5.458	− 2.092
PEU1	5.325	1.340	2.126	− 1.497
PEU2	5.303	1.292	2.755	− 1.576
PEU3	5.458	1.193	4.665	− 1.911
PEU4	5.450	1.209	4.804	− 2.019
PT1	5.423	1.229	5.045	− 2.128
PT2	5.493	1.080	5.479	− 1.981
PT3	5.378	1.261	3.326	− 1.730
PT4	5.340	1.239	2.871	− 1.574
BI1	5.405	1.163	3.452	− 1.611
BI2	5.400	1.266	3.821	− 1.790
BI3	5.271	1.316	2.473	− 1.501
BI4	5.430	1.230	4.352	− 1.954
BI5	5.493	1.171	5.275	− 2.055
RA1	5.418	1.192	4.070	− 1.827
RA2	5.146	1.278	2.178	− 1.356
RA3	5.493	1.189	4.420	− 1.924
RA4	5.452	1.192	4.954	− 2.078
PU1	5.521	1.170	2.670	− 1.405
PU2	5.258	1.388	1.396	− 1.222
PU3	5.449	1.195	3.728	− 1.621
PU4	5.394	1.315	1.177	− 1.143

assumptions, measuring the strength and direction of linear relationships between variables. The results in Fig. 2 confirmed the linearity assumption by demonstrating significant linear relationships among all variables.

Furthermore, we conducted an evaluation of multicollinearity by calculating the variance inflation factor (VIF) and tolerance values (T). VIF measures how much the variance of a predictor variable is inflated due to multicollinearity, while tolerance values indicate the proportion of variance in a predictor variable that is not shared with other predictors. Following the recommendations of Ayanwale et al. (2024), Awodiji and Ayanwale (2023a, 2023b), Bagozzi et al. (1991), Hair et al. (2010), low multicollinearity is characterized by T values greater than 0.1 and VIF values less than 10. In this study, VIF values ranged from 1.334 to 3.942, and tolerance values ranged from 0.254 to 0.749 for all variables. These results suggest the absence of multicollinearity among the variables considered. Thus, based on the assessment of normality, linearity, and multicollinearity assumptions, the data in this study fulfill these criteria. This enhances the credibility of the subsequent analysis and contributes to a more comprehensive understanding of the results.

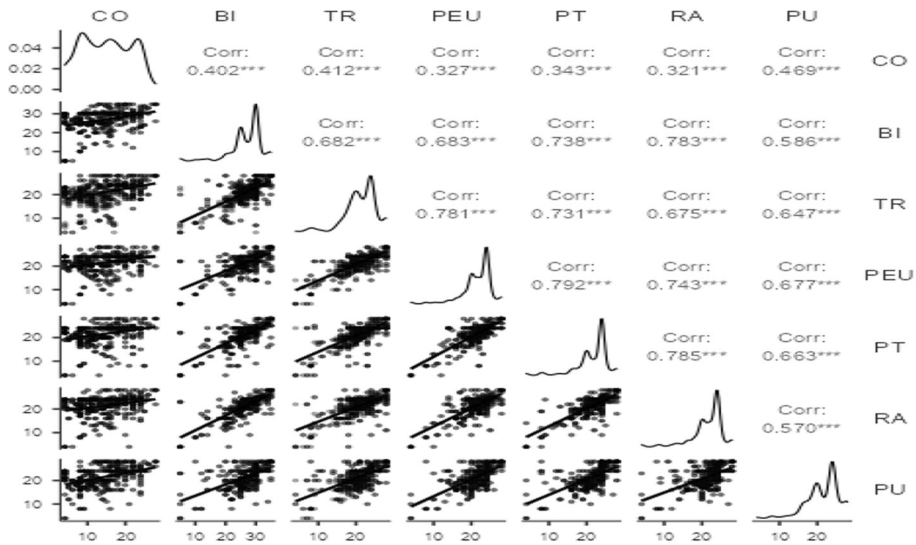

Fig. 2 Pearson correlation heatmap (linearity)

Assessment of measurement model

The Confirmatory Factor Analysis (CFA) was employed to assess the measurement model in this study, evaluating its fit to the data. The assessment involved identifying and eliminating measurement errors exceeding 0.25 and factor loadings below 0.50, following recommendations by Ayanwale et al. (2023a), Molefi and Ayanwale (2023a, 2023b), Adelana et al. (2023) and Hair et al. (2022). Various criteria, including uni-dimensionality, reliability, convergent validity, and discriminant validity, were considered to evaluate the measurement model. Figure 2 illustrates the results of these assessments, incorporating goodness-of-fit indices such as the Tucker-Lewis index (TLI), goodness of fit index (GFI), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residuals (SRMR). Ayanwale, 2023b, Byrne (2016), Hair et al. (2012), Kline (2023), and Oladipo-Abodunwa et al. (2019) emphasized the significance of these indices in evaluating model fit. The recommended values for the fit indices were considered, and the measurement model demonstrated satisfactory fit with an X2 value of 1263.520, 425 degrees of freedom, X2/df ratio of 2.97, p-value of 0.00, CFI of 0.988, GFI of 0.979, TLI of 0.961, NFI of 0.974, RMSEA of 0.013, and SRMR of 0.027. These results affirm that the measurement model effectively captures the constructs of interest, ensuring the validity and reliability of the measurement model.

Furthermore, the measurement model underwent an assessment to ensure convergent validity, discriminant validity, and internal consistency of the constructs. Various criteria were scrutinized, encompassing standardized factor loadings (SL) indicating the reliability of measurement items, composite reliability (CR), Cronbach's Alpha (CA), and average variance extracted (AVE). The standardized factor loadings, detailed in Table 3, ranged from 0.505 to 0.931, surpassing the recommended threshold of 0.50 by Gefen et al. (2000) and Hair et al. (2016), affirming the good reliability of the measurement items. The CR values, evaluating the internal consistency of latent constructs, ranged from 0.790 to 0.904, exceeding the 0.70 threshold suggested by Hair et al. (2022) and Heinzl et al. (2011), indicating satisfactory internal consistency. Likewise, the CA values

Table 3 Confirmatory factor analysis result

Manifest variable	SL	CA	CR	AVE
Compatibility		0.744	0.829	0.552
CO1	0.667			
CO2	0.884			
CO3	0.795			
CO4	0.931			
Perceived ease of use		0.734	0.886	0.665
PEU1	0.505			
PEU2	0.648			
PEU3	0.844			
PEU4	0.762			
Perceived trust		0.783	0.904	0.702
PT1	0.790			
PT2	0.884			
PT3	0.850			
PT4	0.807			
Perceived usefulness		0.790	0.872	0.634
PU1	0.790			
PU2	0.826			
PU3	0.653			
PU4	0.788			
Relative advantage		0.740	0.882	0.652
RA1	0.766			
RA2	0.700			
RA3	0.830			
RA4	0.832			
Trialability		0.706	0.790	0.485
TR1	0.770			
TR2	0.743			
TR3	0.547			
TR4	0.857			
Behavioural intention				
BI1	0.831	0.782	0.895	0.630
BI2	0.746			
BI3	0.731			
BI4	0.744			
BI5	0.788			

ranged from 0.706 to 0.790, surpassing the 0.70 cut-off specified by Kline (2015), further supporting the internal consistency and reliability of the latent constructs. AVE values, gauging the proportion of variation explained by the latent variable relative to measurement error, ranged from 0.485 to 0.702, exceeding the 0.50 lower limit proposed by Fornell and Larcker (1981) and Kock (2014), indicating robust convergent validity. It's noteworthy that the AVE value for trialability was below the 0.50 threshold, but its substantiality was supported by the CR value exceeding 0.70, as emphasized by Hair et al. (2017), and Oladele and Ayanwale (2021).

In assessing discriminant validity, the study employed the Heterotrait-Monotrait ratio (HTMT) to measure the correlation between pairs of latent variables. The coefficients

Table 4 Divergent validity-HTMT

Construct	Mean	Std. Dev	BI	CO	PEU	PT	PU	RA	TR
BI	27.000	5.165							
CO	14.910	6.501	0.457						
PEU	21.540	3.925	0.816	0.398					
PT	21.630	4.211	0.824	0.39	0.745				
PU	21.620	4.199	0.674	0.549	0.832	0.762			
RA	21.510	4.084	0.802	0.372	0.704	0.831	0.668		
TR	21.100	4.438	0.806	0.495	0.786	0.742	0.787	0.812	

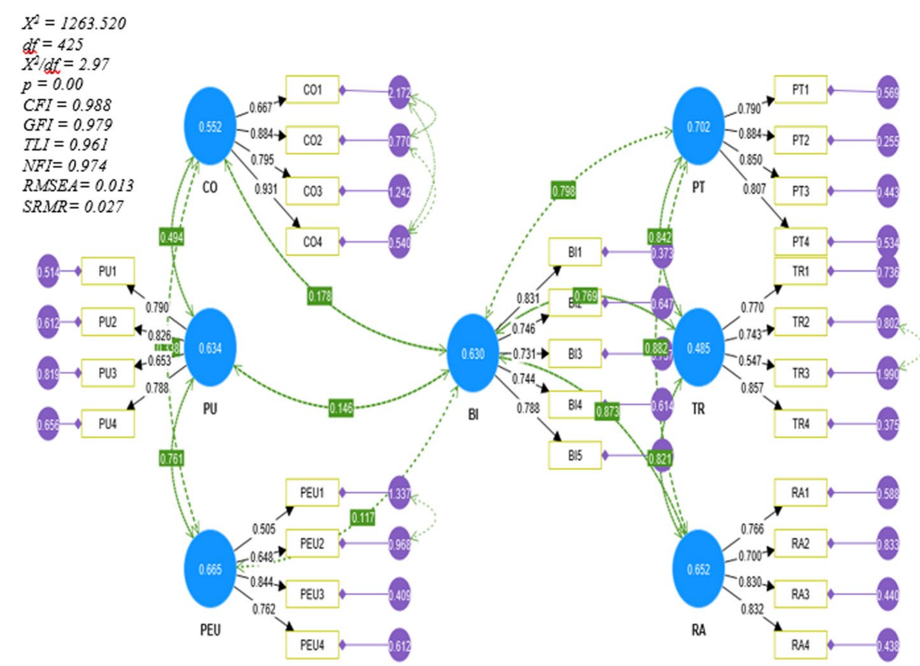

Fig. 3 Measurement model

obtained from this analysis, presented in Table 4, all remained below the 0.85 threshold, aligning with the criteria set by Amusa and Ayanwale (2021), Ayanwale et al., (2023b), and Henseler et al. (2015). This affirmation indicates that the latent variables under consideration in the study maintain distinctiveness, avoiding excessive correlation and providing robust evidence of discriminant validity. To summarize, the evaluation of the measurement model not only demonstrated the reliability and convergent validity of the latent constructs but also validated their internal consistency. Furthermore, the analysis confirmed discriminant validity by revealing that the measured items effectively captured the intended constructs without significant overlap or interrelation with other variables in the study model (Fig. 3).

Structural model assessment

In this research, we employed path modeling analysis to explore the impact of extended factors, rooted in the innovation diffusion theory, on the behavioral intention of

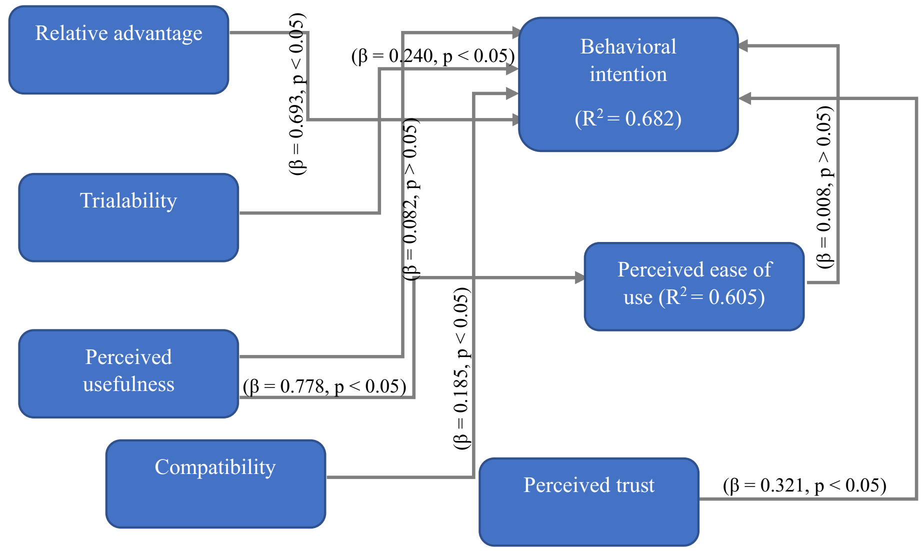

Fig. 4 Structural model assessment

Table 5 Hypotheses testing of the structural model

Hypothesis	Paths	β	Std dev	T statistics	Bias	5%	95%	p-values	Remarks
H1	RA—> BI	0.693	0.078	8.898	-0.014	0.556	0.807	0.000	Supported
H2	CO—> BI	0.185	0.041	4.560	-0.003	0.119	0.250	0.000	Supported
H3	TR—> BI	0.240	0.081	2.979	-0.003	0.100	0.380	0.002	Supported
H4	PT—> BI	0.321	0.076	4.242	-0.005	0.189	0.433	0.000	Supported
H5	PU—> BI	0.082	0.089	0.914	0.004	-0.068	0.233	0.181	Not supported
H6	PU—> PEU	0.778	0.038	20.577	-0.001	0.708	0.834	0.000	Supported
H7	PEU—> BI	0.008	0.142	0.058	0.007	-0.216	0.241	0.477	Not supported
		R^2							
	BI	0.682							
	PEU	0.605							

undergraduate students to adopt AI application tools for their academic endeavors. The factors scrutinized encompassed relative advantage, compatibility, trialability, perceived ease of use, perceived usefulness, and perceived trust. The structural model was employed to present and compare the outcomes obtained through hypothesis testing. The second phase of the study involved conducting confirmatory factor analysis (CFA) within the structural equation modeling framework to further validate the proposed hypotheses, as illustrated in Fig. 4. This visual representation delineates the relationships among the variables under investigation. Out of the seven hypotheses examined, five found support in the results, while two did not receive confirmation.

The standardized coefficients derived from the structural model, as presented in Table 5, indicated the standardized values associated with each hypothesis. The goodness-of-fit indices, which assessed the model's fit to the data, yielded the following results: $X^2 = 2066.508$, $df = 573$, $X^2/df = 3.61$, $p = 0.00$, $CFI = 0.916$, $GFI = 0.965$, $TLI = 0.961$, $NFI = 0.978$, $RMSEA = 0.025$, $SRMR = 0.049$. These indices fell within the acceptable range according to the thresholds proposed by Byrne (2016), signifying that the model adequately fits the data. Additionally, Table 5 presented the R^2 values, indicating the proportion of variance explained by the endogenous latent variables in the structural model. Higher R^2 values suggested effective accounting for and prediction of the constructs of interest by the latent variables. Cohen (1988) provided benchmarks for interpreting R^2 values: 0.26 (substantial), 0.13 (moderate), and 0.02 (weak). This study's R^2 value for behavioral intention (BI) was 0.682, signifying a substantial amount of explained variance. The R2 value for perceived ease of use (PEU) was 0.605, indicating a substantial level of explained variance. These values offered insight into the extent to which the latent variables in the structural model elucidated the constructs of interest.

As depicted in Fig. 4 and summarized in Table 5, the results reveal significant findings pertaining to the associations between various factors and individuals' intentions to use chatbots. The first hypothesis (H1), positing a positive and significant relationship between the relative advantages of chatbots and behavioral intention, is supported by the data ($\beta = 0.693$, $t = 8.898$, $p < 0.05$). This suggests that all students recognize the benefits of employing AI tools and express a readiness to use them for educational purposes. Similarly, the second hypothesis (H2) suggesting a direct and significant impact of compatibility between individuals and chatbots on behavioral intention is confirmed by the results ($\beta = 0.185$, $t = 4.560$, $p < 0.05$). This implies that students perceive a sense of compatibility with AI tools, influencing their intention to utilize them for academic activities. In line with the third hypothesis (H3), which proposes a positive and significant relationship between perceived trialability of the chatbot and behavioral intention, the findings support this hypothesis ($\beta = 0.240$, $t = 2.979$, $p < 0.05$). Consequently, it can be concluded that students perceive the opportunity to experiment with AI tools, leading to their intention to incorporate them into their learning. Likewise, the fourth hypothesis (H4), asserting that perceived trust has a direct and significant effect on behavioral intention, is validated by the data ($\beta = 0.321$, $t = 4.242$, $p < 0.05$). This indicates that the level of trust students have in AI tools influences their intention to use chatbots for academic pursuits. Moving on to the sixth hypothesis (H6), which examines the relationship between perceived usefulness and perceived ease of use, the results show a positive and significant association ($\beta = 0.778$, $t = 20.577$, $p < 0.05$), signifying that students perceive AI tools as useful and find them easy to use for their learning needs. However, the fifth hypothesis (H5) suggesting a direct effect of perceived usefulness on behavioral intention, and the seventh hypothesis (H7) proposing a direct effect of perceived ease of use on behavioral intention, are not supported by the findings. The data indicate no significant connection between perceived usefulness, perceived ease of use, and students' intention to use chatbots ($\beta = 0.082$, $t = 0.914$, $p > 0.05$) and ($\beta = 0.008$, $t = 0.058$, $p > 0.05$), respectively.

In addition, a multi-group structural equation model (SEM) analysis was conducted to identify the relationships exhibiting significant differences between male and female students. This approach helps to identify whether the structural paths hypothesized within the model differ significantly between sex groups. The aim of the analysis was to identify specific relationships or paths that may be differently influenced by the gender, providing

Table 6 Multiple group analysis results with gender as moderator

Paths	Female	Male	Difference (female -male)
RA—> BI	2.538	4.103	− 1.565
CO—> BI	1.266	4.122	− 2.856
TR—> BI	1.676	1.434	0.242
PT—> BI	2.665	3.195	− 0.530
PU—> BI	2.681	1.973	0.708
PU—> PEU	1.486	1.068	0.418
PEU—> BI	1.511	1.859	− 0.348

insights into potential gender-specific patterns in the aim of introducing chatbots among Lesotho students (see Table 6).

The results of the multiple group analysis, presented in Table 6, provide insights into the nuanced variations in the paths from different factors to behavioral intention (BI) regarding the adoption of chatbots among female and male undergraduate students in Lesotho. Male students demonstrate a significantly stronger positive association between relative advantage and behavioral intention than their female counterparts, suggesting that perceived benefits of chatbots may play a more decisive role in shaping adoption intention for male students. Male students also exhibit a notably stronger positive relationship between compatibility and behavioral intention than female students, indicating that the alignment of chatbots with existing practices and expectations is a more influential factor for males in their adoption intention. Both female and male students consider trialability important in shaping their adoption intention, with a slight difference between genders. The opportunity to try out chatbots seems to impact behavioral intention similarly for both groups. Male students show a slightly stronger positive association between perceived trust and behavioral intention than females, highlighting the significance of trust in shaping adoption intention for both genders, but slightly more so for males. On the other hand, female students demonstrate a higher positive relationship between perceived usefulness and behavioral intention than male students. The perceived usefulness of chatbots may be more decisive for females in shaping their adoption intention. Additionally, female students exhibit a stronger positive relationship between perceived usefulness and ease of use than males. The perception of chatbots as applicable contributes more to the ease of use for females. Moreover, female students demonstrate a slightly stronger positive association between perceived ease of use and behavioral intention than males. Ease of use plays a slightly more significant role in influencing adoption intention for females. These findings have implications for recognizing gender-specific differences, which is crucial for tailoring effective strategies and interventions to encourage chatbot adoption among female and male students. Strategies emphasizing relative advantage and compatibility may be effective for males, while focusing on the perceived usefulness of chatbots may resonate more with females. Building and maintaining trust in chatbot technology is pivotal for both genders and should be a priority in interventions. Interventions should also address factors contributing to ease of use, ensuring a user-friendly experience, particularly for female students.

Discussion and implications

This study focused on the expanded diffusion innovation theory and its application to the adoption of AI chatbot tools for academic purposes among undergraduate students from a public university in Lesotho. We examined factors such as perceived ease of use, perceived usefulness, and perceived trust in relation to students' behavioral intention to use chatbots. We also explored individual factors like relative advantage, perceived compatibility, and perceived trialability and how they influenced students' willingness to adopt AI technology. The study found significant results indicating the relationships between these factors and students' intention to use chatbots. These findings contribute to our understanding of the factors that influence the adoption of AI tools, specifically chatbots, in educational settings in the Southern part of Africa. The study revealed that there is a positive and significant relationship between the perceived relative advantages of chatbots and students' behavioral intention to use them. This suggests that students recognize the benefits of using AI tools and are willing to incorporate them into their academic activities. This finding aligns with the innovation diffusion theory, which suggests that individuals are more likely to adopt an innovation if they perceive it as advantageous (Nguyen & Nguyen, 2020; Rogers, 2003). The relative advantages of chatbots, such as personalized assistance and timely responses, contribute to their perceived value for students in their academic pursuits. Furthermore, the study found that compatibility between individuals and chatbots has a direct and significant effect on behavioral intention. Students who perceive a sense of compatibility with AI tools are more likely to embrace them as useful tools for learning. This finding is consistent with the expanded innovation diffusion theory, which emphasizes the importance of compatibility in the adoption process of new technology (Rogers, 2003). When students perceive chatbots as compatible with their existing learning practices and preferences, they are more inclined to use them. This study also confirms the findings by Shin et al. (2020) and Olasina (2019) that individuals perceived greater compatibility with AI tools, which led them to interact and engage with the chatbot more frequently. As a result, users are more likely to engage in desired behaviors, such as continued usage or adoption of the chatbot, if they have a positive user experience and a sense of alignment with its capabilities, personality, and communication style.

The study also examined the relationship between the perceived trialability of chatbots and behavioral intention. The findings supported this hypothesis, indicating that students who perceive the opportunity to try out AI tools are more likely to have the intention to use chatbots for learning purposes. This aligns with previous research that highlights the significance of trialability as a means to reduce uncertainty and encourage adoption (Almeida, 2023, Pinho et al., 2021; Rogers, 1983, 2003). The perceived trialability of chatbots allows students to experiment with the tool and experience its potential benefits, thus increasing their intention to use it. The presence of other factors, however, could raise doubts about this relationship. Several studies have shown that perceived usefulness and ease of use are key factors determining users' behavior toward technology (Davis et al., 1989; Laumer et al., 2019). Potentially, these factors might overwhelm perceived trialability's influence on behavioral intentions. Other factors, such as perceived usefulness or ease of use, may reduce or mediate a preference for trialability's significance. Moreover, the level of trust that students have in AI tools was found to play a role in shaping their intention to use chatbots for academic purposes. Trust is a critical factor in the adoption of new technologies, as individuals are more likely to adopt innovations they perceive as trustworthy (Aoki, 2020; Venkatesh et al., 2012). In the context of AI application tools, students' trust in the tool's ability to provide accurate information and support their learning needs influences their intention to use it (Tarhini et al., 2017).

Additionally, a positive and significant correlation exists between perceived usefulness and perceived ease of use, suggesting students find AI tools useful and easy to use. In the adoption process of emerging technologies, perceived usefulness and ease of use play an important role, as noted by Malik et al. (2021) and Cao et al. (2021). Student adoption of and integration of chatbots into their learning activities is enhanced when they perceive chatbots as useful and easy to use. The study also examined the relationships between perceived usefulness, perceived ease of use, and students' behavioral intention to use chatbots. However, the findings did not support the hypotheses proposing direct effects of perceived usefulness and perceived ease of use on behavioral intention. These results are somewhat surprising, as previous research has consistently shown that perceived usefulness and ease of use are strong predictors of intention to use technology (Albanna et al., 2022; Davis et al., 1989; Huang et al., 2021; Tselios et al., 2011). It is important to consider the study's specific context and the sample population's characteristics when interpreting these results. Firstly, the study's unique context, which involved undergraduate students in Lesotho, may introduce cultural, educational, or technological differences that can influence how students perceive the relationships between PU, PEU, and BI. These specific contextual factors might shape perceptions differently compared to the contexts examined in previous research. The nature of academic tasks could also play a role in shaping students' perceptions. Depending on task complexity or personalization requirements, students might prioritize factors like trialability or compatibility over PU and PEU when it comes to influencing their behavioral intentions. Additionally, the study population's limited familiarity with chatbots may impact how they perceive such technology's usefulness and ease of use. Students might rely more on factors like trust or compatibility due to a lack of firsthand experience with chatbots. The interaction effect between PU and PEU could contribute to the unexpected results. Instead of their individual effects, the combined influence of these two factors might shape students' behavioral intentions. The study did not explicitly explore interaction effects, so there is room for further investigation. Lastly, sample characteristics, including technological literacy, prior exposure to AI technologies, and individual preferences, may influence the observed relationships. If the sample exhibits specific characteristics that differ from other populations in the literature, this could contribute to the lack of support for the hypotheses. Further, the results of the multiple group analysis reveal gender-specific variations in the factors influencing the behavioral intention to adopt chatbots among undergraduate students in Lesotho. Male students show a stronger positive association between relative advantage and behavioral intention, emphasizing the importance of perceived benefits for males. Additionally, compatibility has a more influential role for males in their adoption intention. Both genders consider trialability important, with slight differences. Trust is crucial for both, slightly more so for males, while perceived usefulness plays a more decisive role for females. Female students also show a stronger relationship between perceived usefulness and ease of use, suggesting its significance in shaping adoption intention for females. Overall, recognizing these gender-specific differences is vital for tailoring effective strategies and interventions for encouraging chatbot adoption among students.

The practical implications of this study's findings are relevant for undergraduate students in higher education, specifically in Lesotho. By understanding the implications, students can make informed decisions about the use of chatbot technology and effectively integrate it into their learning processes. Incorporating chatbot technology into higher education has the potential to enhance students' learning experiences and support their academic success. However, students should approach the adoption of chatbot technology thoughtfully, considering the benefits, compatibility, trial opportunities, trustworthiness, usefulness, and ease of use. The theoretical implications of this study's results within the framework of innovation diffusion theory are twofold. First, they confirm the role of perceived trialability in shaping behavioral intention, aligning with the theory's propositions. Second, the findings provide insights into the influence of other factors, such as perceived usefulness, ease of use, and trust, highlighting the need for a more comprehensive understanding of technology adoption. The study also raises questions about the mediating or moderating role of contextual factors, suggesting avenues for further investigation in the field of innovation diffusion theory.

Conclusion

This study focused on examining the factors that influence undergraduate students' intention to use chatbots for educational purposes within the framework of innovation diffusion theory. By analyzing these factors and their relationships with behavioral intention, the study offers valuable insights while also highlighting areas that require further investigation. One of the key findings of the study is the confirmation of several aspects of innovation diffusion theory. For instance, the study validated the significance of perceived relative advantages. It revealed that students who recognized the benefits of using chatbots for academic purposes expressed a strong intention to adopt them. Similarly, the research supported the role of compatibility, indicating that students who perceived a sense of compatibility with chatbot technology were more likely to adopt it. Additionally, the study confirmed the importance of trialability, as students who had the opportunity to try out chatbots were more inclined to use them. Lastly, the research validated the association between perceived usefulness and perceived ease of use and impact of perceived trust, showing that students with a higher level of trust in chatbot technology demonstrated a greater intention to adopt it. However, the study also provided insights that deviated from traditional expectations within an expanded innovation diffusion theory. The findings did not support the direct relationships between perceived usefulness, perceived ease of use, and behavioral intention. This suggests that in the context of chatbot adoption, these factors may not have as significant an influence as initially hypothesized. It implies that there may be additional factors or dynamics at play that require further exploration. The implications of this study hold practical significance for undergraduate students in higher education. The findings highlight the importance of creating awareness among students about the benefits of using chatbots and how they can be compatible with their learning practices. It is crucial to provide students with opportunities to trial and explore chatbot technology, allowing them to experience its potential benefits firsthand. Building trust in chatbot technology is also essential, as it positively influences students' intention to adopt it for academic purposes. In conclusion, this study enhances our understanding of the factors influencing undergraduate students' intention to use chatbots in higher education. The findings provide practical implications for students, emphasizing the importance of awareness, trialability, and trust. Additionally, the study contributes to the theoretical understanding of innovation diffusion theory. Future research can build upon these findings to gain deeper insights into the complexities of chatbot adoption and further enhance the integration of AI tools in educational settings.

Contributions of the study

This study makes substantial contributions to the existing literature in several key areas. Firstly, it uniquely focuses on the adoption of AI chatbots within an African context, specifically within the educational landscape of Lesotho. This emphasis adds a distinctive layer to the literature, offering insights into how cultural and contextual factors influence students' perceptions and intentions regarding the use of chatbots in higher education. Secondly, the study enriches the theoretical framework by incorporating cultural dimensions relevant to the African/Lesotho context. This enhancement enables a more nuanced exploration of the factors that shape students' attitudes and behaviors concerning AI technology. By integrating cultural factors, values, and beliefs into the theoretical framework, the study contributes to a deeper understanding of the intricate interplay between cultural context and technology adoption. Moreover, the research provides a comprehensive understanding of chatbot acceptance in African higher education, surpassing generic models. The study delves into specific cultural and contextual factors that influence the acceptance patterns of AI chatbots among students in Lesotho, offering valuable insights for researchers, practitioners, and policymakers. Additionally, the study fills a noteworthy research gap by specifically addressing AI adoption in Lesotho, contributing to the limited body of literature on technology adoption within African higher education institutions. This geographical focus provides a distinct contribution, shedding light on the unique challenges and opportunities associated with AI integration in the African educational landscape.

Limitations and future directions

This study acknowledges several limitations that need to be addressed. Firstly, the findings are based on a specific sample of undergraduate students from a particular institution, so caution should be exercised when generalizing the results to other student populations or educational contexts. To ensure broader applicability, future research should include a more diverse range of participants. This means involving students from different universities, different academic programs, and diverse cultural backgrounds. By doing so, we can gain a better understanding of how these factors may influence chatbot adoption in various educational settings. Secondly, the cross-sectional design used in this study makes it challenging to establish causal relationships between variables. Since the data were collected at a single point in time, it is difficult to determine whether the factors examined actually influence students' intention to use chatbots or if there are other underlying factors at play. To overcome this limitation, future research should employ longitudinal studies that track students' intentions and actual usage of chatbots over an extended period. By observing changes in intentions and usage patterns over time, we can better understand the causal relationships and how they may evolve. Another limitation is the reliance on self-report measures, which may be subject to response biases and may not accurately capture students' true behaviors and intentions. To enhance the validity of the findings, future studies could consider incorporating objective measures or behavioral observations alongside self-report data. For example, researchers could collect data on the actual usage of chatbots by tracking students' interactions with the technology or analyzing system logs. This would provide more reliable and objective data on students' behaviors and intentions. Moreover, the study solely relied on survey data for data collection, which may limit the depth of understanding of students' experiences and perceptions. To gain a more comprehensive understanding of the factors influencing chatbot adoption, future studies could incorporate qualitative interviews or observations in addition to surveys. Qualitative research methods can delve deeper into students' experiences, attitudes, and perceptions regarding chatbot adoption. By conducting interviews or observations, researchers can explore specific challenges, concerns, and motivations that influence students' decision-making processes and shed light on the underlying reasons behind their intentions. Furthermore, experimental designs can be utilized to examine the causal relationships between the identified factors and students' intention to use chatbots. By manipulating variables in controlled settings, researchers can establish a cause-and-effect relationship and provide stronger evidence of the factors' impact on adoption. Finally, investigating the influence of contextual factors, such as educational disciplines or specific learning tasks, on chatbot adoption would provide a nuanced understanding of the technology's applicability and effectiveness in different academic contexts. By examining how these factors interact with students' intentions and behaviors, researchers can identify potential barriers or facilitators to chatbot adoption and tailor the implementation strategies accordingly.

Acknowledgements

We sincerely thank the undergraduate students for their valuable participation in this study, as their insights and contributions were essential for our research on chatbot adoption among undergraduate students. We are also grateful to the educational institution for their support in granting us access to participants and facilitating the data collection process. Their cooperation was crucial to the successful completion of this research.

Author contributions

MAA Conceptualization, Writing- Original draft preparation, Methodology, Data Curation, Validation, Formal analysis, Writing—Review & Editing, Visualization, Supervision. RRM Writing- Original draft preparation, Writing Review, Formatting, Investigation. References alignment, Editing.

Funding

The study did not receive any external funding, and the authors conducted the research independently.

Data availability

The data collected and analyzed during the current study are indeed available on request. Researchers interested in accessing the data for legitimate research purposes can contact the corresponding author to discuss the possibility of data sharing while ensuring the protection of participants' confidentiality and adherence to ethical guidelines.

Declarations

Competing interests
The authors state that they have no competing interests to disclose.

Received: 18 September 2023 Accepted: 2 March 2024
Published online: 22 March 2024

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