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Exploring the adoption of Chatbots and AI for student queries handling using PLS-SEM techniques

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A B S T R A C T

In the dynamic realm of educational technology, the integration of Chatbots and artificial intelligence (AI) has become crucial in augmenting student support and engagement. The shift towards digital education platforms demands capable and prompt systems for addressing student inquiries. Chatbots and AI have seen widespread integration across educational settings, but their targeted application in handling student queries is a relatively unexplored area of educational support. There is a notable research void regarding the actual effectiveness of Chatbots in responding to student queries. Most existing studies focus broadly on AI's educational applications, often overlooking the specifics of student interactions and query resolution. This study addresses this gap by thoroughly assessing the impact of Chatbots and AI in managing student queries. Utilizing a quantitative approach, the research involved 572 university students in the UAE who have interacted with Chatbots for query resolution. The study employed the PLS-SEM model for analysis. Results indicated that information and system quality, along with perceived learning value and satisfaction, are significant factors influencing the acceptance of Chatbots. These findings are crucial for understanding the adoption and efficiency of AI tools in student query management. Some aspects of the model, however, did not show significant effects on Chatbots usage. Nonetheless, this research provides valuable insights for educational bodies and tech developers. The empirical evidence on Chatbots' effectiveness in handling student queries can guide future AI integrations in educational contexts. It also offers best practice guidelines for creating AI support systems that align with student needs. Furthermore, the study contributes to the development of policies on AI use in education, underscoring the need to match technological progress with educational objectives and student well-being.

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1. Introduction

In recent years, the landscape of educational technology has undergone significant transformation, with the integration of Chatbots and artificial intelligence (AI) emerging as a critical component in enhancing student support and engagement (Chen et al., 2022). The shift towards digital education platforms has underscored the need for efficient and responsive systems capable of managing student inquiries (Onyalo, 2022). While the use of Chatbots and AI has become increasingly prevalent in various educational contexts, their specific application in addressing student queries represents a novel and less-explored dimension of educational support (Mohd Rahim et al., 2022). This gap in research is particularly evident in the limited empirical studies focusing on the effectiveness of Chatbots in resolving student queries. Existing literature primarily examines the broader applications of AI in educational settings (Grassini, 2023; Akgun & Greenhow, 2021), frequently bypassing the detailed analysis of student interactions and the resolution process of their queries through these advanced technologies (Bahroun et al., 2023; Bala et al., 2017). Consequently, there is a pressing need to delve into this specific application of AI, understanding its implications, challenges, and benefits in the realm of student query handling.

The integration of Chatbots and AI in education represents more than just technological progress; it signifies a fundamental shift in pedagogical approaches. As the digital transformation becomes more entrenched in educational systems, it's crucial for educators and institutions to comprehend how these technologies aid in enhancing learning, increasing accessibility, and improving the overall student experience, as highlighted in reference (Studente & Ellis, 2020). This investigation is vital not only for the furtherance of educational technology but also for adapting teaching methodologies to the demands of the digital era. Fig. 1 provides a vivid conceptual representation of Chatbots and AI in action, specifically in the context of managing student queries during university admissions. The scene is a dynamic one, showcasing a diverse array of students interacting with digital kiosks and virtual assistants on their devices. This modern, technology-rich admissions environment exemplifies how AI can be harnessed to streamline and elevate the admissions process. The diversity observed among the student body, coupled with their engagement with advanced digital tools, illustrates the profound impact of AI in enhancing the efficiency of university admissions. Thus, this study embarks on an exploration into the role of Chatbots and AI in student query handling within educational contexts. Its aim is to bridge the existing gap in research and shed light on the practical effectiveness and utility of these technologies. Through this examination, the study not only contributes to the expanding corpus of knowledge in educational technology but also provides actionable insights for educators, administrators, and technology developers.

Fig. 1. The use of Chatbots and AI in student queries.

2. Literature Review

The advancement of Chatbots has leveraged the vast amount of textual data available on the internet, training these systems to produce text that closely resembles natural human language. Chatbots have been utilized for a range of processing tasks, including language translation, text summarization, dialogue systems, and providing practical feedback, which has enhanced their utility and influence in various domains (Openart AI, 2024). Despite their global proliferation and usage, some researchers have expressed concerns about Chatbots posing potential risks to the future of education. These apprehensions are primarily centered around the negative impacts on technical creators, educators, and professionals, leading to a cautious perception of Chatbot usage in academic settings due to ethical and creativity-related issues. There is a worry that reliance on Chatbots might diminish students' creativity, as these tools are capable of performing multiple tasks simultaneously, potentially reducing the need for independent problem-solving and creative thinking (McGee, 2023). The evolving role of Chatbots has garnered significant attention from researchers across various fields, with notable implications in healthcare. In the medical domain, the advanced capabilities of Chatbots have revolutionized access to medical information for both health professionals and patients (Seth et al., 2023; Khan et al., 2023). These sophisticated systems offer a wide spectrum of data, from theoretical knowledge to practical medical advice and consultations. At a medical level, Chatbots are distinguished from traditional information sources by their unique features, such as providing tailored feedback on patient-specific cases, personalized learning experiences, and realistic virtual simulations for medical training (McGee, 2023). In medical education, Chatbots play a pivotal role by automating tasks like grading student papers and essays based on sentence structure, vocabulary, grammar, and clarity. They also facilitate learning through quizzes and tests, act as virtual tutors to respond to students' queries and provide feedback, and generate case studies and scenarios to enhance medical students' diagnostic and treatment planning skills (Seth et al., 2023).

Conversely, in the context of engineering education, Chatbots are perceived as a potential disruptor that could challenge educational ethics. Their abilities to write and debug software pose a threat to the traditional roles of software engineers. This perception of Chatbots as both an impressive and disruptive tool in engineering underscores the need for a nuanced understanding of its impact. Engineering educators are urged to comprehend the implications of this technology comprehensively. It is essential to explore how engineering education can evolve to ensure that future engineers are equipped to leverage the benefits of Chatbots while mitigating any adverse effects. This approach aims to balance the innovative advantages of Chatbots with the ethical considerations and professional integrity within the engineering field (Safi et al., 2020).

3. The Theoretical Framework

The present model underscores the mediating roles of Task Technology Fit (TTF) and personal innovativeness in the dynamic between system and information quality and the endorsement of learning platforms. TTF acts as a bridging factor linking system and information quality with the acceptance of these platforms. Simultaneously, personal innovativeness facilitates the connection between perceived usefulness, learning value, and the adoption of learning platforms. Furthermore, the model delves into additional relationships to evaluate the efficacy of each platform, underlining the benefits associated with their usage.

3.1 The System Quality, Information Quality and Task Technology Fit

System quality is distinguished by key attributes such as reliability, usability, and functionality, each playing a crucial role in influencing users' acceptance and adoption of technology. Reliability reflects users' perception of the technology as dependable, fostering trust and confidence. If the technology is seen as unreliable, users may hesitate to depend on it for critical tasks or decision-making. Usability, another vital aspect, hinges on the system's ease of use. A user-friendly system with clear instructions can significantly heighten user engagement and interest. Lastly, functionality pertains to the user's ability to effectively comprehend and operate the technology (Frangoudes et al., 2021; Chen et al., 2023a). High system quality can bolster user confidence, and continuous monitoring, testing, and incorporation of user feedback are essential for ongoing improvements and relevance.

The quality of information in technology is intimately linked to perceptions of its accuracy, relevance, and reliability. It assesses the type and significance of the information provided. Information deemed current and substantial leads users to view it as precise, complete, and comprehensive. The perceived quality of this information is a major determinant in the technology's acceptance and usage (Frangoudes et al., 2021; Chen et al., 2023b). Various factors influence this quality, including the accuracy and completeness of the data, the reliability of its sources, and the timeliness of updates. Furthermore, the technology's usability and ease of navigation can impact the quality of information it provides. For instance, if technology is complex or unintuitive, users might find it challenging to locate needed information or enter data accurately, potentially leading to errors (Moldt et al., 2023; Shahsavar & Choudhury, 2023). This interconnectedness of system quality, information quality, and user interaction plays a pivotal role in the effective adoption and utilization of technology.

Task Technology Fit (TTF) is a concept assessing the extent to which a technology aligns with the specific needs and processes of its users, based on the synergy between the technology's capabilities and the tasks it is intended to facilitate. It implies that technology adoption is highly influenced by its relevance to the user's activities, indicating that tools and methods that enhance work efficiency are more likely to attract experienced users. Technologies failing to meet user needs and expectations are less likely to be adopted. The degree of compatibility between the technology and the tasks it supports is crucial; higher compatibility generally results in greater benefits and effective performance (Moldt et al., 2023; Shahsavar & Choudhury, 2023).

While numerous studies have explored Task Technology Fit, only a few have established its relationship with other critical factors like system and information quality. They often highlight the mediating role of perceived usefulness and ease of use in TTF (Moldt et al., 2023; Shahsavar & Choudhury, 2023). This study, therefore, emphasizes the intermediary role of TTF in bridging system and information quality with the acceptance of platforms like ChatGPT and Google in educational settings.

TTF and Information Quality are pivotal in determining the efficiency and efficacy of technology in task completion. A harmonious match between technology and task requirements, combined with the provision of high-quality information, can significantly boost productivity, streamline workflows, and improve overall outcomes. The interplay between TTF and Information Quality is reciprocal; effective technology-to-task alignment tends to yield higher quality information, which in turn, can further enhance the TTF by facilitating task completion (Kooli, 2023).

Ensuring optimal TTF and Information Quality necessitates a thorough understanding of both the tasks at hand and the technology's features and limitations. Similarly, exploring the relationship between TTF and System Quality is vital to augment the effectiveness of the technology, focusing on unique attributes that distinguish one technology from another. Consequently, the study proposes hypotheses to examine these interrelationships, aiming to deepen the understanding of how TTF, along with System and Information Quality, influences the acceptance and effectiveness of technological platforms in educational environments.

H_{1a}: *There is a significant relation between system quality and information quality with Chatbots acceptance in the admission process.*
H_{2a}: *There is a significant relation between information quality of Chatbots acceptance.*
H_{3a}: *There is a significant relation between the information quality of Chatbots acceptance, mediated by task technology fit.*
H_{4a}: *There is a significant relation between system quality of Chatbots, mediated by task technology fit.*
H_{5a}: *There is a significant relation between system quality of Chatbots acceptance.*
H_{6a}: *There is a significant relation between task technology fit of Chatbots acceptance.*

3.2 The Perceived Satisfaction, Perceived Learning Value and Personal Innovativeness

Perceived satisfaction is the extent to which users feel content with the tasks performed and services offered by a technology. Users who find a technology satisfying are more inclined to continue its use and recommend it to others. In contrast, dissatisfaction with a technology often leads users to discontinue its use or to explore alternatives (Safi et al., 2020; Frangoudes et al., 2021). Meanwhile, perceived learning value is the perceived benefits that students gain from using technology, encompassing aspects like improved access to information, time efficiency, and reduced effort. Students who perceive a high learning value in technology are more likely to persist in its usage. For educational institutions, providing technology that offers clear and tangible benefits is key to gaining a competitive edge. This strategy helps attract and retain students, thereby enhancing the institution's reputation and success (Openart AI, 2024; McGee, 2023).

Personal innovativeness plays a mediating role, linking the perceived usefulness and learning value of technology to its acceptance in educational settings. It reflects users' propensity to embrace and utilize new technologies, particularly those offering innovative features not found in existing solutions. Personal innovativeness is a crucial determinant in technology acceptance, gauging the likelihood of users to explore and adopt new technologies (Openart AI, 2024). This characteristic is especially important in educational contexts, where the introduction of innovative technologies can significantly influence learning experiences and outcomes.

Individuals who exhibit high personal innovativeness often find greater joy and satisfaction in embracing and utilizing new technologies. This connection suggests that when technological innovations align with users' needs and expectations, they not only foster a sense of satisfaction but also enhance user acceptance. Therefore, the interplay between personal innovativeness and satisfaction is significant, where technologies crafted with high innovativeness tailored to user requirements are likely to be more readily accepted, leading to increased personal satisfaction and fulfillment among users (Openart AI, 2024; McGee, 2023). In a similar vein, the perceived value of learning from technology is intricately tied to its perceived innovativeness. Users who view a technology as offering substantial learning value are more inclined to explore and appreciate its innovative features (Moldt et al., 2023; Shahsavar & Choudhury, 2023). This observation underpins the formulation of the following hypotheses:

H_{1b}: *There is a significant relation between perceived satisfaction and perceived learning value with Chatbots acceptance in the admission process.*
H_{2b}: *There is a significant relation between the perceived value of Chatbots acceptance.*
H_{3b}: *There is a significant relation between the perceived value of Chatbots acceptance, mediated by personal innovativeness.*
H_{4b}: *There is a significant relation between perceived satisfactions of Chatbots acceptance, mediated by personal innovativeness.*
H_{5b}: *There is a significant relation between perceived satisfactions of Chatbots acceptance.*
H_{6b}: *There is a significant relation between personal innovativeness of Chatbots acceptance.*

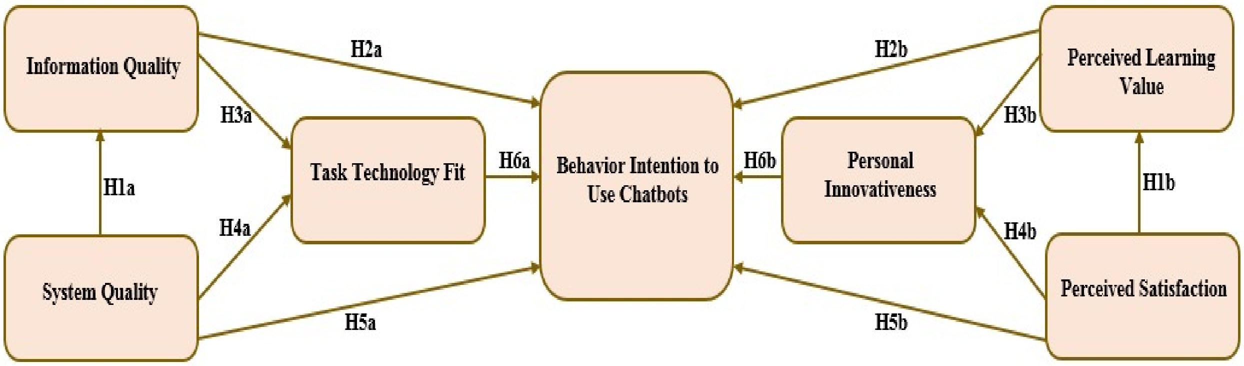

Fig. 2. Research Model

4. Research Methodology

4.1 Data collection

In this study, online questionnaires were distributed to students at various universities across the UAE. The data collection spanned from August 15, 2023, to October 15, 2023. Of the 600 questionnaires disseminated randomly by the study committee, a substantial 95.3% response rate was achieved, with participants completing 572 questionnaires. However, 28 questionnaires were excluded due to incomplete responses. The final tally of 572 fully completed questionnaires closely aligns with Krejcie and Morgan's (2010) recommendation for a sample size of 285 respondents from a population of 1100, thus validating the representativeness and adequacy of the sample. The sample size of 572, surpassing the minimum requirements, offers a robust basis for further analysis. Consequently, the study proceeded with structural equation modeling Krejcie and Morgan's (2010) to validate the research hypotheses using this sample. It is crucial to recognize that the hypotheses developed for this study are grounded in the extensive historical context of AI research. For the analytical process, the academic team employed Structural Equation Modeling (SEM) using SmartPLS Version 3.2.7. This approach was instrumental in assessing the measurement model. Additionally, the Final Path Model was utilized to execute complex analytical interventions, providing a comprehensive understanding of the relationships and dynamics within the study. This sophisticated methodology enhances the credibility and depth of the research findings.

4.2 Students' personal information / Demographic Data

Fig. 3 in the study provides a detailed breakdown of the demographic and personal characteristics of the participants. The gender distribution was notably skewed, with females comprising 79% of the participants, compared to 21% for males. Regarding age, a significant majority, 83%, were in the 18 to 29 age bracket, while the rest were 29 years or older. The educational background of the respondents varied. Specifically, 7% of the students held a diploma, 5% had an advanced diploma, a substantial 66% possessed a bachelor's degree, 18% had a master's degree, and 4% had attained a doctoral degree. The study utilized a "purposive sampling approach" as recommended by Salloum et al. (2019), particularly when participants expressed their willingness to volunteer. This approach ensured the inclusion of participants from a wide array of universities, representing diverse age groups and educational levels. To analyze this rich demographic data, the study employed IBM SPSS Statistics version 23. This tool facilitated a comprehensive and detailed analysis of the participants' demographic information, contributing to the study's robustness and depth.

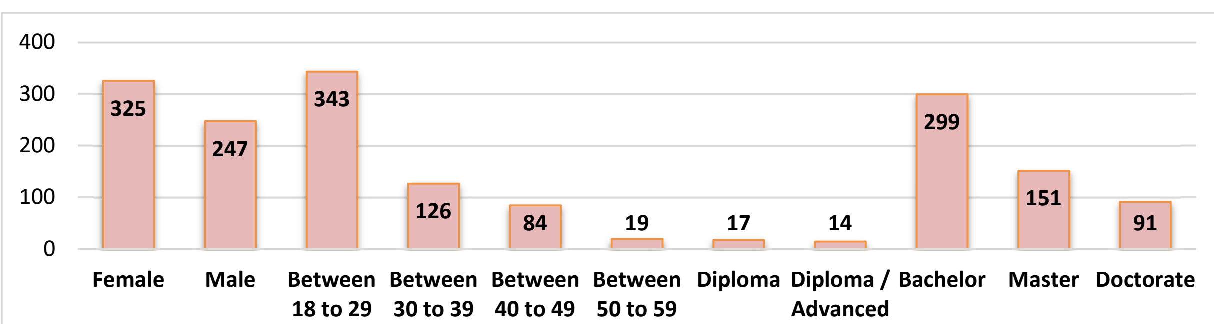

Fig. 3. Demographic data of the respondents (n=572).

4.3 Study Instrument

This study utilized a questionnaire to test the proposed hypothesis. A set of seven constructs, deemed as reliable indicators, was chosen, resulting in the addition of 22 items to the questionnaire. Table 1 outlines the basis of these constructs, with the intention of improving the applicability of the study's constructs and offering corroborative evidence from diverse prior research to solidify the existing framework. The survey questions were refined by the academic team, drawing on insights from past studies.

Table 1
Measurement Items

Constructs	Items	Definition	Instrument	Sources
Behavior Intention to Use Chatbots	BI1	Behavioral intention, within the context of Davis's Technology Acceptance Model (TAM), refers to the anticipated willingness or planned usage of a new technology by target users. It is a core component of the TAM framework, which seeks to predict and explain user behavior in the adoption of technological innovations. This concept emphasizes the role of user attitudes and perceptions in the decision to embrace and use new technology. Behavioral intention is often seen as a key predictor of actual technology usage, underpinning the idea that if users intend to use a technology, they are more likely to actually do so.	AI-powered chatbots present a significant opportunity for exploration in managing student inquiries during the admissions process	Chen et al. (2023a)
	BI2	Within Davis's Technology Acceptance Model (TAM), behavioral intention signifies the inclination or planned action of potential users to adopt a technology that is considered novel. This concept is a fundamental aspect of the TAM framework, which focuses on understanding and predicting the factors influencing users' readiness to embrace and use emerging technological solutions.	Utilizing chatbots in the admissions process represents a promising opportunity to explore.	Davis (1993)
System Quality	SQ1	System quality is intimately linked to the assessment of technology, highlighting key attributes like functionality, reliability, usability, efficiency, maintainability, and portability. These characteristics play a crucial role in evaluating the overall effectiveness and user-friendliness of a technological system.	The functionality of chatbots in handling student queries surpasses that of traditional systems.	Onyalo (2022)
	SQ2		The usability of chatbots for accomplishing admission process within a constrained timeframe is less compared to traditional systems.	
	SQ3		Chatbots demonstrate a higher level of efficiency in comparison to traditional systems.	
	SQ4		Chatbots exhibit a higher degree of reliability compared to traditional systems, which motivates their adoption.	
Information Quality	IQ1	Information quality is intricately connected to the evaluation of technology, focusing on vital characteristics like accuracy, timeliness, relevance, competence, and applicability. Essentially, it refers to the caliber of data delivered by information systems, emphasizing the importance of these attributes in determining the usefulness and reliability of the information provided.	Chatbots offer more precise and targeted information.	Mohd Rahim et al. (2022)
	IQ2		Chatbots deliver more extensive and comprehensive information.	
	IQ4		Chatbots effectively furnish the necessary information.	
Task Technology Fit	TTF1	The Task Technology Fit (TTF) model plays a pivotal role in enhancing student performance by ensuring that the technology in use is sufficiently capable of supporting the necessary tasks. TTF is utilized to gauge the extent to which a technology's capabilities align with the tasks it is intended to facilitate. Its significance lies in its focus on the variety and suitability of functions available to students, tailored to meet their specific learning needs. This model underscores the importance of matching technology features directly with the demands of student learning tasks.	The information provided by Chatbots is more current and up-to-date.	Bahroun et al., (2023)
	TTF2		The information received from Chatbots tends to be more relevant and detailed.	
	TTF3		The information acquired from Chatbots greatly exceeds the requirements for my admission process.	
The Perceived Satisfaction	PS1	Perceived satisfaction is a critical determinant in measuring the extent to which technology is adopted. The level of satisfaction experienced by users directly influences their likelihood of continued and repeated use of the technology in the future. High degrees of satisfaction typically correlate with increased usage, as users are more inclined to engage with technology that meets or exceeds their expectations. Conversely, if the technology falls short of meeting students' expectations and needs, this may result in infrequent use, reflecting lower levels of perceived satisfaction.	Chatbots possess more effective tools that streamline and facilitate the admission process.	Khan et al., (2023)
	PS2		Chatbots are equipped with innovative features that positively influence my level of satisfaction.	
	PS3		Chatbots adequately meet the needs of my admission process, encouraging their adoption.	
The Perceived Learning Value	PLV1	Perceived value relates to the benefits, such as information accessibility, time efficiency, and reduced effort that students gain from using technology. This perceived advantage encourages their ongoing engagement with the technology. It's a critical element for educational institutions, as it forms a basis for implementing an effective source of competitive advantage. By providing technology that aligns with these values, educational institutions can enhance the learning experience and maintain a competitive edge in the educational sector.	Chatbots provide substantial advantages in my admission process.	Shahsavar & Choudhury (2023)
	PLV2		Chatbots hold a unique value in various admission processes.	
	PLV3		Chatbots possess a distinctive value that motivates me to adopt this technology.	
Personal Innovativeness	PI1	Personal innovativeness is a significant factor influencing technology adoption within educational settings. It reflects a student's openness and willingness to experiment with new technologies. This inclination towards innovation can significantly increase the likelihood of students utilizing technology in various learning activities. A student's personal innovativeness often correlates with their readiness to embrace and integrate emerging technological tools into their learning processes, thereby shaping their overall educational experience.	Chatbots feature modern, up-to-date technology that meets my needs.	Kooli (2023)
	PI2		Chatbots boast innovative features that enhance the overall value of the technology.	
	PI3		Chatbots offer a superior level of unique experience, motivating me to adopt them.	

4.4 Pilot study of the questionnaire

This study included a pilot test to establish the reliability of its survey questions. Initially, a random selection process was employed, choosing 60 students from the targeted demographic to participate in the pilot. The total number of participants in the study was 600, with the pilot comprising 10% of this group. The internal consistency of the survey items was evaluated using IBM SPSS Statistics version 23, applying Cronbach's alpha as the measure of reliability. This process enabled a thorough examination of the pilot results, ensuring the dependability of the survey's measurement items. In the field of social sciences, a Cronbach's alpha value of 0.70 is generally accepted as indicating satisfactory reliability (Kooli, 2023). The calculated Cronbach's alpha values for each of the five measurement scales used in the study are detailed in Table 2.

Table 2
Cronbach's Alpha values for the pilot study (Cronbach's Alpha ≥ 0.70)

Construct	Cronbach's Alpha
BI	0.872
IQ	0.793
PI	0.805
PLV	0.799
PS	0.863
SQ	0.872
TTF	0.739

5. Findings and Discussion

5.1 Data Analysis

In this study, we applied the Partial Least Squares-Structural Equation Modeling (PLS-SEM) technique using the SmartPLS V 3.2.7 software (Ringle et al., 2015) for an in-depth analysis of the data. The methodology encompassed a dual-phase evaluation process, incorporating both the measurement and structural models as per established guidelines (Hair et al., 2017). The selection of PLS-SEM as our analytical tool was influenced by multiple considerations discussed in the research paper. Primarily, the use of PLS-SEM was integral for examining our proposed theoretical framework Ringle et al. (2015). Additionally, it proved instrumental in adeptly managing and interpreting the exploratory data gathered in alignment with our conceptual models Hair et al.(2017). A distinctive feature of our approach was the holistic analysis of the entire model through PLS-SEM, avoiding segmentation into discrete components (Urbach & Ahlemann, 2010). Moreover, we conducted simultaneous assessments of both the structural and measurement models utilizing the capabilities of PLS-SEM. The efficacy of PLS-SEM in this context is particularly notable for its precision in generating reliable measurements and insights (Urbach & Ahlemann, 2010).

5.2 Convergent validity

The assessment of the Measurement Model Hair et al. (2006) in our study was methodically structured around the principles of construct validity, encompassing aspects of both discriminant and convergent validity, alongside construct reliability, which includes measures like Cronbach's Alpha (CA) and Composite Reliability (CR). As evidenced in Table 3, the values for Cronbach's Alpha, a marker of construct reliability, spanned from 0.795 to 0.893. These figures, interestingly, are above the commonly accepted threshold of 0.7 Hair et al. (2016), indicating robust reliability. Additionally, the Composite Reliability (CR) scores, as reported in Table 3, ranged from 0.801 to 0.875, clearly exceeding the established benchmark Hair et al. (2016), further affirming the reliability of the constructs. For evaluating convergent validity, it was pivotal to scrutinize the mean-variance extracted (AVE) along with the factor loadings Hair et al. (2016). Notably, with the exception of a few outliers, all factor loading values in Table 3 surpassed the standard criterion of 0.7. Moreover, the AVE values, as detailed in the same table, ranged from 0.594 to 0.724, all comfortably above the minimum threshold of 0.5. These results, barring the earlier exceptions, suggest a strong likelihood of achieving convergent validity, as they align well with the set parameters. This comprehensive analysis underlines the robustness and validity of the constructs used in our study.

5.3 Discriminant validity

In our study, to thoroughly evaluate discriminant validity, we employed two distinct methods: the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larker criterion (1981). The outcomes of this analysis, as detailed in Table 4, affirm the validity of the Fornell-Larker criterion. This confirmation comes from the observation that for each construct, the square root of the Average Variance Extracted (AVE) demonstrated a stronger association with its respective construct than with others Hair et al. (2016), indicating clear discriminant validity.

Furthermore, the results pertaining to the HTMT ratio are presented in Table 5. Here, it is noteworthy that each construct's HTMT ratio is comfortably below the specified threshold of '0.85' Barclay et al. (1995). This outcome confirms that the HTMT ratio successfully meets the set criterion, thereby reinforcing the discriminant validity of our study. The comprehensive analysis of these results leads to the conclusion that the validity and reliability of the Measurement Model in our study are well-established. Therefore, the data that has been collected and scrutinized under this model is deemed reliable and suitable for further analysis, particularly in the assessment of the structural model. This robust validation of the Measurement Model enhances the overall integrity and credibility of the study's findings.

Table 3

Convergent validity results which assures acceptable values (Factor loading, Cronbach's Alpha, composite reliability, & AVE > 0.5).

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Behavior Intention to Use Chatbots	BI1	0.769	0.893	0.824	0.724
	BI2	0.799			
Information Quality	IQ1	0.771	0.836	0.843	0.628
	IQ2	0.866			
	IQ3	0.808			
	IQ4	0.888			
Personal Innovativeness	PI1	0.901	0.851	0.853	0.662
	PI2	0.852			
	PI3	0.802			
Perceived Learning Value	PLV1	0.832	0.888	0.875	0.668
	PLV2	0.810			
	PLV3	0.782			
Perceived Satisfaction	PS1	0.819	0.795	0.801	0.622
	PS2	0.825			
	PS3	0.807			
System Quality	SQ1	0.850	0.834	0.831	0.646
	SQ2	0.795			
	SQ3	0.769			
	SQ4	0.799			
Task Technology Fit	TTF1	0.771	0.798	0.802	0.594
	TTF2	0.866			
	TTF3	0.808			

Table 4

Fornell-Larcker Scale

	BI	IQ	PI	PLV	PS	SQ	TTF
BI	**0.840**						
IQ	0.031	**0.813**					
PI	0.442	0.616	**0.842**				
PLV	0.018	0.288	0.629	**0.912**			
PS	0.288	0.327	0.261	0.108	**0.888**		
SQ	0.369	0.429	0.183	0.464	0.669	**0.829**	
TTF	0.459	0.402	0.581	0.554	0.459	0.402	**0.881**

Table 5

Heterotrait-Monotrait Ratio (HTMT)

	BI	IQ	PI	PLV	PS	SQ	TTF
BI							
IQ	0.632						
PI	0.610	0.698					
PLV	0.287	0.559	0.511				
PS	0.018	0.611	0.212	0.327			
SQ	0.286	0.515	0.567	0.765	0.541		
TTF	0.434	0.747	0.503	0.765	0.490	0.434	

5.4 Hypotheses testing using PLS-SEM

In this research, the structural equation model was constructed using Smart PLS, which employs maximum likelihood estimation for analyzing the interrelationships among the various theoretical constructs in the structural model (Nunnally & Bernstein, 1978, 1994). By adopting this methodological approach, the study rigorously examined the proposed hypotheses. The findings, as detailed in Table 6 and illustrated in Fig. 4, reveal that the model possesses a moderate level of predictive power Urbach & Ahlemann (2010). Notably, the "Behavior Intention to Use Chatbots" variable explains about 64.2% of the variance, underscoring its significance in the model. Further analytical insights are provided in Table 7, which outlines the beta (β) values, t-values, and p-values for each hypothesis, derived using the PLS-SEM technique. The empirical data analysis substantiated several of the study's hypotheses, specifically supporting H1a, H2a, H3a, H4a, H1b, H3b, H4b, H5b, and H6b. Conversely, certain hypotheses, namely H5a, H6a, and H2b, did not find empirical backing and were consequently rejected. This delineation of supported and unsupported hypotheses offers a nuanced understanding of the model's strengths and limitations, contributing valuable insights to the field.

Table 6
R^2 of the endogenous latent variables

Construct	R^2	Results
BI	0.642	Moderate
IQ	0.651	Moderate
PI	0.593	Moderate
PLV	0.585	Moderate
TTF	0.521	Moderate

Table 7
Hypotheses-testing of the research model (significant at p** < = 0.01, p* < 0.05)

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1a	SQ → IQ	0.588	2.439	0.011	Positive	Supported*
H2a	IQ → BI	0.725	9.573	0.000	Positive	Supported**
H3a	IQ → TTF	0.560	5.561	0.001	Positive	Supported**
H4a	SQ → TTF	0.763	16.404	0.000	Positive	Supported**
H5a	SQ → BI	0.221	0.238	0.512	Positive	Not supported
H6a	TTF → BI	0.449	0.153	0.840	Positive	Not supported
H1b	PS → PLV	0.259	10.509	0.000	Positive	Supported**
H2b	PLV → BI	0.691	0.044	0.967	Positive	Not supported
H3b	PLV → PI	0.485	5.412	0.000	Positive	Supported**
H4b	PS → PI	0.364	2.118	0.044	Positive	Supported*
H5b	PS → BI	0.699	4.952	0.001	Positive	Supported**
H6b	PI → BI	0.233	9.942	0.000	Positive	Supported**

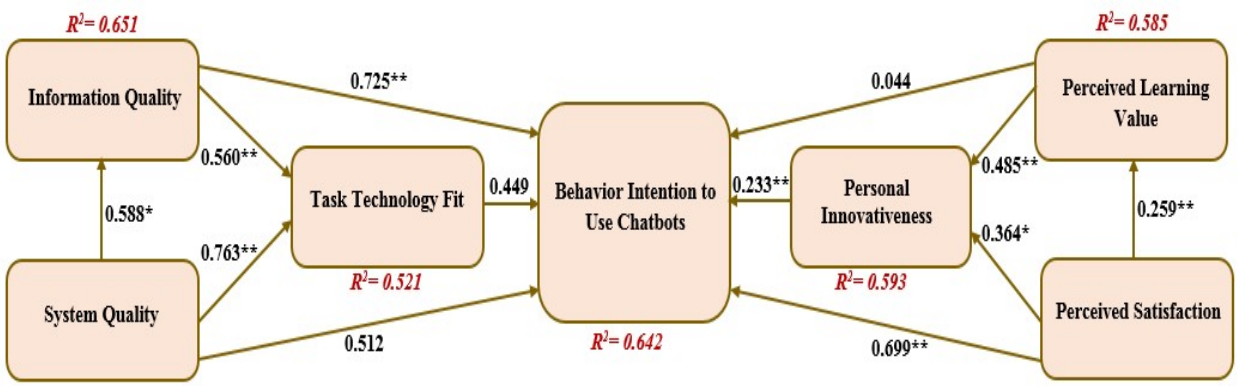

Fig. 4. Path coefficient of the model (significant at p** < = 0.01, p* < 0.05)

The first hypothesis of the study delved into the relationship between System Quality (SQ) and Information Quality (IQ), yielding a beta (β) value of 0.588 and a significance level below 0.01. The results underscore a substantial positive impact of SQ on IQ, thereby validating hypothesis H1a. Further analysis revealed that Task Technology Fit (TTF) is notably influenced by both Information Quality (IQ) and System Quality (SQ), with β values of 0.560 and 0.763 respectively, both achieving significance levels below 0.001. This finding lends credence to hypotheses H3a and H4a, confirming the significant roles of IQ and SQ in affecting TTF. The study also shed light on various relationships impacting Behavior Intention to Use Chatbots (BI). Notably, BI was positively associated with Information Quality (IQ) (β = 0.725, P < 0.001), Perceived Satisfaction (PS) (β = 0.699, P < 0.001), and Personal Innovativeness (PI) (β = 0.913, P < 0.001), substantiating hypotheses H2a, H5b, and H6b, respectively. Conversely, the influence of System Quality (SQ), Task Technology Fit (TTF), and The Perceived Learning Value (PLV) on BI was not statistically significant, leading to the rejection of hypotheses H5a, H6a, H2b, and H5b.

Additionally, the study demonstrated that Perceived Satisfaction (PS) is significantly affected by The Perceived Learning Value (PLV) ($\beta = 0.259$, $P < 0.001$) and Personal Innovativeness (PI) ($\beta = 0.364$, $P < 0.05$), thus supporting hypotheses H1b and H4b. These results highlight the importance of PLV and PI in influencing PS. Moreover, the relationship between The Perceived Learning Value (PLV) and Personal Innovativeness (PI) was also explored, revealing a significant positive effect of PLV on PI ($\beta = 0.485$, $P < 0.001$), thereby validating hypothesis H3b. These findings collectively provide a comprehensive understanding of the various factors influencing the adoption and satisfaction of learning platforms, emphasizing the critical roles of system and information quality, task-technology fit, and personal innovativeness.

6. Discussion

The discussion in this study is methodically divided into two distinct phases, each addressing separate but integral aspects of the research. In the first phase, the focus is primarily on analyzing and interpreting the results concerning the dependent variables of the conceptual model. This involves a detailed examination of how these variables interact within the framework, their impact on the study's outcomes, and the implications of these findings. The exploration of these dependent variables is crucial for understanding the core dynamics and effectiveness of the conceptual model in practice. The second phase shifts the spotlight to the moderators present in the study. Here, the discussion delves into how these moderators influence the relationships between the variables within the conceptual model. This phase is vital for comprehending the nuanced roles that these moderators play, how they potentially alter or define the dynamics within the model, and their overall contribution to the validity and applicability of the research findings. By splitting the discussion into these two phases, the study ensures a comprehensive and thorough exploration of both the direct outcomes and the underlying mechanisms at play within the research framework.

6.1 Discussion of the Dependent Variable Results

Recent advancements in artificial intelligence tools have garnered significant interest from researchers' worldwide, motivating students to adopt these innovative technologies. This shift marks a departure from traditional platforms, highlighting the advanced capabilities inherent in AI-driven solutions. Numerous studies have delved into the factors influencing student adoption of Chatbots, aiming to enhance the educational experience (Chen et al., 2023b). In line with the goals of this research, the interactions among various variables, such as system quality, information quality, perceived value, and perceived satisfaction, are scrutinized. Additionally, the study investigates the substantial influence of these factors in relation to two moderators, assessing their impact on the efficacy of the learning environment. Consequently, this study seeks to evaluate the proposed hypotheses, with a focus on the critical role of moderators within the conceptual model. The analysis of the results reveals mixed support for the proposed hypotheses. It's evident that system quality and information quality offer significant insights, positively influencing Chatbot acceptance, which aligns with prior research findings. These elements are noted for their distinct impact in Chatbots, especially when compared to platforms like Google. The influence of system quality on acceptance is mediated through factors like ease of use and perceived usefulness. Contrarily, other studies have identified system quality and related aspects as key determinants of learners' intentions to use various educational technologies (Moldt et al., 2023; Shahsavar & Choudhury, 2023). In this study, the positive impact of perceived value on Chatbot adoption is clearly demonstrated. Chatbot users recognize these tools as valuable due to their effective and comprehensive outputs. This finding aligns with earlier research, which has identified perceived value as a mediating factor in the adoption of other technologies, such as IoT (Moldt et al., 2023; Shahsavar & Choudhury, 2023). Similarly, the results support the notion of perceived satisfaction, consistent with previous studies. The consensus among researchers is that perceived satisfaction significantly shapes users' perspectives, particularly in educational contexts (Moldt et al., 2023; Shahsavar & Choudhury, 2023).

The Discussion of the Moderation Results

The moderating role of Chatbots users in this study is pivotal, as it elucidates the dynamic interplay among the proposed dependent variables, namely system quality, information quality, perceived satisfaction, and user satisfaction. Drawing from prior research focusing on moderation effects, a notable interaction between perceived satisfaction and other variables has been observed in technology utilization contexts. It's been discerned that moderators like task-technology fit wield an indirect but significant influence on technology adoption. Incorporating task-technology fit as a moderator within the model notably enhances the explanation of variance in the dependent variables. This inclusion underscores the relevance of the application's alignment with current student usage patterns, highlighting its contemporaneity and appropriateness. Evidently, integrating task-technology fit as a moderator not only augments the practicality of chatbots but also aligns with existing research underscoring the amplifying impact of technology fit on technology usage. Jeyaraj (2022), for instance, has indicated that technology fit can positively sway technology acceptance, especially when backed by governmental support.

Further, the study reveals that task-technology fit exerts a more pronounced influence on student populations, primarily impacting perceptual rather than behavioral variables. This suggests that task-technology fit is more adept at gauging perceptions, particularly in relation to specific technologies and user groups. Roth et al. (2023) support this view, suggesting that task-technology fit analysis can significantly contribute to understanding blockchain adoption in the public sector, enhancing the theory in contexts that are federally structured and cross-organizational. Similarly, personal innovativeness has emerged as a crucial moderator, affirming the relationship between system quality, system information, and the intention to use technology. This relationship has been positively received by users, indicating a strong effect of innovativeness as a moderator in elevating Chatbot usage. These findings corroborate the proposed hypotheses and align with prior studies, which have shown personal innovativeness to be an effective moderator in gauging technology acceptance (Moldt et al., 2023; Shahsavar & Choudhury, 2023). Additionally, other research highlights the indirect role of innovativeness in fostering technology adoption, potentially bolstering future technology use. Thus, this study not only confirms these hypotheses but also contributes to the broader discourse on technology adoption and user engagement.

6.2 Theoretical and Practical Implications

This study offers profound theoretical implications for universities and application administrators, emphasizing the critical role of application utility in enhancing the admissions process and making significant educational contributions across various sectors. To optimize the effectiveness of Chatbots in educational settings, it is crucial to align these applications with the constructs outlined in our conceptual framework. Our conceptual model enriches the discourse on Chatbots adoption by focusing on key moderators such as technology-task fit and innovativeness. Theoretically, this study highlights the importance of user perspectives in recognizing how Chatbots can positively impact behavior and social perceptions in educational contexts. By proposing constructs like system quality, perceived value, and user satisfaction, we aim to provide a comprehensive assessment of this model's effectiveness. A notable theoretical strength of our model is its exploration of the relationship between perceived value and satisfaction and personal innovativeness as a moderator, as well as the interplay between system quality, information quality, and the technology-task fit moderator. From a practical standpoint, the findings underscore the relevance of our conceptual model for government-level implementation. The insights gained from this study reinforce the potential of Chatbots in public university settings and their applicability to other government sectors. Furthermore, the conceptual framework established by this study serves as a benchmark for qualitative research approaches, offering a more nuanced understanding of the significance and applications of Chatbots in the broader public sector. This comprehensive analysis positions the study as a pivotal contribution to both theoretical and practical domains in the field of Chatbots technology and its applications.

6.3 Managerial Implications

This research offers valuable perspectives on the strategic utilization of Chatbots to streamline the admissions process for students. Educational institutions in the UAE can leverage these findings to enhance their operations in several ways. Firstly, Chatbots applications must be tailored to meet student requirements, thereby enhancing the educational experience. Integrating Chatbots within academic courses as an informational resource can simplify and enrich the admission process by providing diverse and accessible information. Secondly, there is potential for governmental bodies to utilize chatbots in developing cooperative and regulatory frameworks. These policies could facilitate the broader deployment of Chatbots across various government sectors, emphasizing the importance of including similar technologies and open-access functionalities. This approach would ensure that Chatbots become a universally accessible information resource. Lastly, this study serves as a catalyst for policymakers responsible for chatbot deployment. It underscores the need for developing policies that safeguard user rights while enhancing their perceived value and willingness to engage with Chatbots technologies. Through such policy developments, the study aids in understanding the key factors that encourage the adoption and effective use of Chatbots applications.

6.4 Limitations of the Study and Future Studies

This study, while comprehensive, is constrained by certain limitations in its scope and perspective. The data collection was specifically focused on a select sample from the United Arab Emirates (UAE), predominantly comprising students enrolled in various universities. These individuals primarily use the applications in question for educational purposes, which may not fully represent the broader range of potential users. Looking forward, it would be beneficial for future research to expand the participant base to include samples from other sectors, particularly from different government institutions. Such a diverse sample could provide deeper insights into how these applications could be optimized for broader and more effective usage.

Additionally, the conceptual framework of this study is somewhat narrow, concentrating primarily on factors like system quality, user satisfaction, perceived value, and innovativeness. These elements are evaluated with specific moderators aimed at measuring the impact of tools like ChatGPT. However, future research could significantly benefit from incorporating a wider array of variables and exploring alternative moderators. This expansion would allow for a more holistic understanding of other critical factors that influence the usage and effectiveness of such applications. By broadening the scope in this manner, subsequent studies could offer a more rounded and comprehensive analysis, contributing to a richer understanding and potentially leading to more impactful applications of these technologies.

7. Conclusion

In the context of managing student queries during university admissions, this study offers compelling insights into the prominence of Chatbots and AI. The findings firmly establish that chatbots exhibit heightened levels of interest and confer significant advantages compared to alternative applications. Rather than merely serving as a technical tool, Chatbots emerge as fully integrated platforms capable of consolidating multifaceted concerns spanning diverse subject matter, practical theories, and technological considerations. This study unequivocally affirms the effectiveness of chatbots, surpassing the capabilities of traditional platforms in numerous aspects. Chatbots stand out as well-designed tools characterized by a high degree of sufficiency, further reinforcing their significance in the educational landscape. Consequently, a comprehensive exploration of Chatbots' impact becomes imperative. The research divulges that chatbots wield substantial influence over user acceptance, mediated by factors such as information and system quality, as well as perceived learning value and satisfaction. However, it is worth noting that certain facets explored in the study did not garner sufficient support and, consequently, do not exert a significant predictive influence on Chatbots adoption. This underscores the necessity for continued development efforts aimed at optimizing Chatbots' performance and augmenting their overall contributions to the educational sphere.

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