ACADEMIA International Journal for Social Sciences
Volume 4, Issue 4, 2025 ISSN-L (Online): 3006-6638

Investigating the Adoption of Chatbot Services in Education Sector: The Moderating Role of Societal Resistance

Shazia Saleem
shzsaleem1@gmail.com
UE Business School, University of Education Lahore

Dr. Muhammad Shahbaz
shahbaz755@yahoo.com
Professor (Associate), UE Business School, University of Education, Lahore, Punjab, Pakistan

Amna Akram
amnaakram773@gmail.com
UE Business School, University of Education Lahore
Corresponding Author: * Dr. Muhammad Shahbaz shahbaz755@yahoo.com

Received: 03-11-2025 **Revised:** 23-11-2025 **Accepted:** 11-12-2025 **Published:** 25-12-2025

ABSTRACT

Artificial intelligence is increasingly being used to handle tasks that once depended on human intelligence. Among its many applications, chatbots have gained particular attention which communicate with users in natural language to provide information and support. It helps raise student involvement, learning results and educational efficiency. The present study focused on determining the adoption factors of chatbot system for use in the education sector, based on behavioral intention using dual factor theory. A questionnaire was used to collect 259 valid responses that were analyzed using PLS-SEM. The dual-factor perspective (enablers vs inhibitors) guided variable selection: Information Quality and Digital Literacy were included as facilitators, while Complexity and Technology Anxiety were treated as inhibitors. Behavioral intention has a positive effect on perceived education service quality. The interaction between societal resistance and behavioral intention was statistically significant. Implications for policymakers, educational managers, and system designers are provided.

Keywords: *Chatbot adoption intention, education service quality, digital literacy, complexity, technology anxiety, societal resistance*

INTRODUCTION

Artificial intelligence (AI) is reshaping how products and services are delivered by enabling automation, personalization, and large-scale decision support (Mohapatra et al., 2025). According to Perez et al. (2025), AI is the term used to describe computers that are capable of performing cognitive functions like learning and problem-solving generally associated with human cognition. As AI technology develops, it is transforming work environments, lifestyles, communication, and most importantly, education (X. Chen et al., 2020). With the rapid progress of large language models and conversational AI, systems can now understand and generate human-like text more effectively, making virtual assistants increasingly useful in everyday contexts (Schillaci et al., 2024). This change has generated a great deal of interest in comprehending and improving the use of AI in education.

As education keeps evolving, chatbots are starting to solve many of these challenges. Pérez et al. (2020) state that students can get help right away by having their questions answered, explanations presented, useful materials offered and guidance as teaching assistants. In education, these technologies offer opportunities for personalized feedback, round-the-clock academic support, and streamlined administrative processes. At the same time, they raise important concerns around accuracy, fairness, and governance (Rjab et al., 2023). Varying ways students learn and develop are major challenges in the traditional system, as well as their reluctance to keep up with technology. While some educators start using chatbots, others aren't as eager to add them to the education process (Shahid et al., 2024). Chatbots play a big role in improving instruction methods of teachers and in how students gain knowledge which urges the need to transform the education quality (Celik, 2023). Despite of this transformation, educators are still reluctant towards to use the chatbots in academics (Pérez et al., 2020). people are beginning to question chatbot systems because they may be biased, violate privacy and lead to too much trust in technology (Fakhimi et al., 2023). The use of chatbots in e-commerce and e-services has helped to improve service quality greatly (X. Cheng et al., 2022; S. Li et al., 2023). Yet, transferring such innovations to education is hurdling, therefore there is a dire need to study whether chatbots are an acceptable technological progress in education.

Researchers has used different approaches to examine how chatbots are used and accepted. The model is commonly applied to look at technology acceptance and was applied as a basis for studying the adoption and use of chatbots (Mohapatra et al., 2025). Such technology acceptance models have limited the understanding of employing chatbots to the technological perspective. Whereas users' psychological, competence and societal factors influence the technology adoption more than the technological factors (Choi & Kim, 2023; Shahid et al., 2024). Similarly previously researcher focused on the motivators of using chatbots (Celik, 2023; Mehmood et al., 2024), however the barriers in technology adoption has been neglected in prior literature. Although users can see both enablers and inhibitors, it is necessary to understand technology adoption by considering both the advantages and obstacles it brings (Balakrishnan et al., 2024). The paucity in the literature has impulses the need to study both enablers and inhibitors simultaneously to have the deep understanding of users' intention to use chatbots in education. To bridge this gap present study employed dual factor theory to capture the users' intention from a holistic view. The enablers make people form good opinions about technology and want to use it, whereas inhibitors discourage people from using technology (Raj et al., 2023). Still, the dual-factor approach maintains that factors that assist or hinder technology use are independent drivers of behavioral intention. Therefore, in present study Information Quality of chatbot and Digital Literacy of users are studied as facilitators while Complexity of chatbot and Technology Anxiety of users served as inhibitors.

Prior research has explored many technologies that influence educational outcomes (Celik, 2023; Shahzad et al., 2020; Zhang et al., 2024) but comparatively fewer studies have examined the specific drivers of chatbot adoption in education in a way that jointly considers positive enablers and negative inhibitors. This study addresses two related gaps and describes factors for acceptance of use of chatbot services in education sector particularly in developing countries like Pakistan. First, the dual-factor perspective is used to examine facilitators and inhibitors of chatbot adoption in higher education to deliver a more balanced view of acceptance determinants. Second, the role of societal resistance is examined as a context-level moderator that may change how behavioral intention translates into perceived education service quality. The remaining sections review recent literature, develop hypotheses, describe methods, present results, and discuss theoretical and practical implications.

HYPOTHESIS DEVELOPMENT BASED ON RESEARCH FRAMEWORK

In this section, we elaborate related prior work and theories in context of use of Chatbot services in Education System and how various factors impact user's intention to use chatbot. Based on our research framework which is presented in figure 1, we develop research hypothesis for analysis in this research study.

Information Quality

Information quality (IQ) is defined to the extent to which information is reliable, precise, updated, complete, relevant, and presented in a way that satisfy the needs of its users (Khoo & Ong, 2013). Present study defines it in terms of how well information matches user needs accuracy, validity, reliability, completeness, timeliness, transparency, and trust. When information exhibits these qualities, users tends to perceive it as meeting their expectations, which eventually influences satisfaction and their intention (Petter et al., 2008). Zhong & Chen (2023) emphasizing dimensions such as accuracy, consistency, completeness, relevance, timeliness, and transparency as central to evaluating the usefulness of information.

It has been shown in previous research that chatbots and the IQ that is required from them are connected (Kasinathan et al., 2020). Cheng & Jiang (2022) posit that AI-powered service agents, IQ was found to positively influence satisfaction, which then contributed to users' intention to continue using the chatbot. Similarly, Ahmad et al. (2023) insisted that information from a chatbot matches its purpose and the user's expectations is what makes IQ significant. Higher information quality leads to better decision making and solving problems as well as enhance the perception about quality of service (Chen et al., 2023).

More recent work within educational systems reinforces the importance of IQ. Rokhman et al. (2022) examining e-learning platforms found a strong direct relationship between information quality and student satisfaction by leveraging their intention. Another study revisiting the e-learning systems success model demonstrated that information quality remains a critical predictor of communication quality, user satisfaction, learning effectiveness, and intention (Zhang et al., 2024).

Previous research work indicates that IQ of chatbots positively impacts in customer services as well as online purchases and influence of IQ has an impact on usage behavior (Islam & Rahman, 2017). Therefore, based on above cited literature, we assume that information quality of chatbot will affect intention to use chatbots in education system:

H1: Information quality has a significant relationship with intention to use chatbot services.

Digital Literacy

Digital literacy means searching, checking and composing information, along with performing tasks online, during your normal activities at school and work (Torabi et al., 2023). Digital literacy changes society, helping people in education, banking, healthcare, trade, industry and services (Hill et al., 2008). Now, digital literacy in schools is essential to give students skills they need in the workforce and includes working with information online, teaming up with others for projects and understanding different computer tools. When digital literacy is taught in the curriculum, students improve their thinking and solve problems more easily and are better able to keep up with changes in technology. Songkram et al. (2023) noted that the use of generative AI tools greatly changes educational tasks like writing, learning and solving problems. Digital literacy makes the users more confident to use the technology and leads their intention (Torabi et al., 2023). Students that have skills, knowledge and confident to use chatbot for their educational purpose are more prone towards the adopting chatbot (Rokhman et al., 2022).

Prior studies is significant because they mainly included participants with strong internet skills (Li et al., 2023; Rahman et al., 2016; Shiau et al., 2020). Therefore, it is important to study areas such as Pakistan, with people having low digital literacy and how this influences people's desire to use chatbots. Hence it ca be hypothesized that:

H2: Digital Literacy has a significant relationship with intention to use chatbot services.

Complexity

Complexity is defined as a quality that leads to our ability to understand a system or object. It is easier to understand simple systems as compared with complex systems (Cheng et al., 2022). Complexity also refers to quantity when comparing two things and one thing being more complicated than other (Doğan et al., 2022). The level of complexity in a chatbot means that users of the chatbots finds it difficult to perform the certain task through chatbot (Cheng et al., 2022). Some of them are simple to understand, whereas others are built using deep learning and neural networks (Ahmad et al., 2023). Fatima et al. (2024) posits that the higher system complexity hinders the user's intent to adopt the innovation. The complexity of a chatbot depends on the job it must complete, the amount of data it manages and the expectations of its users. For example, these are things like chatbot language, how it communicates, its appearance and its use of visual clues (Reddy, 2024). Using chatbots in education means students can get personalized help, do their work, learn concepts, prepare for exams and team up with others (Pérez et al., 2020) which should be easy in use. Earlier literature tried to describe the building blocks of chatbots and suggested methods to adjust their parameters for quicker responses and higher quality service, depending on the industry that they would interact with (Moulaei et al., 2024). They covered technologies, users, expected environments for use, the algorithms behind the applications, tools and limiting aspects to make the system easier to use (Cheng et al., 2022). Even so, the effect of chatbot complexity on education use is not fully understood yet. For this reason, this study create the following hypothesis:

H3: Complexity has a significant relationship with intention to use chatbot services.

Technology Anxiety

Technology anxiety is a negative feeling people have toward technology. Whenever a person uses technology or technology equipment, they can feel technology anxiety which is an uneasy or negative state (Jeng et al., 2022). How much someone fears or feel hesitant to use technology generally impacts their use of new technological devices (Shahbaz et al., 2020). Computer or information technology anxiety as state anxiety refers to the unease or dread someone feels when using computers or when pondering doing so (Maduku et al., 2023). Experts now use the concept of computer anxiety while talking about AI-powered technology (Pillai et al., 2024). Because of this, we say chatbot anxiety is the general unease that prevents someone from having a conversation with chatbots. A stressful situation for users of chatbots often involves too much confusion and difficulties which can make them feel that nothing can be achieved (Jeng et al., 2022). Anxiety about AI has been shown to reduce people's positive opinion about it which hinders the adoption process by impacting the intentions of users in a negative way (Maduku et al., 2023). Shahbaz et al. (2020) found that negative emotions or resistance from users towards the technology restrict the firms to adopt new technology which in turn cost the firm's performance and efficiency. Similarly, technology anxiety from students to use the chatbots for their academic purpose might have drastic impact on their intention which has to be identified before the adoption. Furthermore, Pillai et al. (2024) posit that in adoption AI technology anxiety arises due to uncertain risks and lack of awareness in users which simultaneously deter the users intention towards technology. Yet, we do not have enough research to understand how technology anxiety affects using chatbots in schools and universities. Yet, with the implementation of technology anxiety in mind, we believe this will affect individuals' intention to use chatbots in education systems and we thus construct this hypothesis:

H4: Technology Anxiety has a significant relationship with intention to use chatbot services.

Behavioral Intention to use Chatbot

Behavioral intention is simply a person's willingness or plan to carry out a certain action, and it has long been considered an important concept in understanding why people adopt new technologies (Jeng et al., 2022). It helps to predict someone's actual use of technology. Al-Dokhny et al. (2021) examined that behavioral intention acted as an important connecting link between certain predictors and people's decision towards particular system. According to Shahbaz et al. (2020) self-reported intention to use leads directly to adoption of the technology.

Likewise, chatbots reflects how likely users are to start using and keep relying on them for activities such as learning, customer support, or decision-making (Hung et al., 2018). Research shows that this intention is shaped by practical factors like how useful and easy to use people find technology (Shahbaz et al., 2020), but also by deeper aspects such as trust and the emotional connection users feel when interacting with them (Ahmad et al., 2023). In educational settings, the behavioral intention to use chatbots has been linked to improved interaction, motivation, and personalized learning experiences (Hung et al., 2018). Similarly, in business and customer service domains, positive behavioral intention is associated with efficiency, satisfaction, and service personalization (Jeng et al., 2022; Patwary et al., 2023). Moreover, recent literature highlights that social presence and empathy embedded in chatbots can strengthen users' willingness to adopt such technologies (Cheng et al., 2022; Kim & Hur, 2023).

In the light of above literature, we construct our hypothesis as below:

H5: Behavioral Intention has significant relationship with perceived education service quality.

Societal Resistance

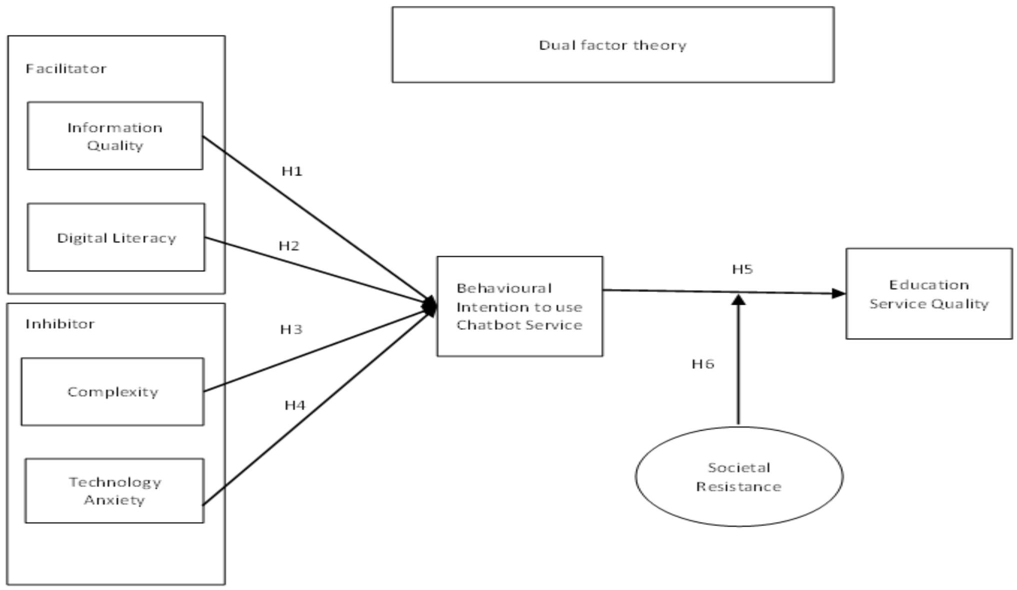
"Societal resistance is a social phenomenon in which disadvantaged, exploited, and dominated groups contest the dominating practices that nation-states, social institutions, social organizations, and traditional cultural practices have constructed" (Oliver, 1991). People in society usually show resistance to change their new and old way of thinking. (Khan et al., 2022) explains that resistance to change happens when people challenge new ways by maintaining their traditional systems. Experts have discovered that unwillingness to accept change leads to rejection of information and communication technology among individuals in society (Abbas Naqvi et al., 2020). Societal resistance might be spread by negative word of mouth which might deter the adoption process of innovation (Toor et al., 2019). Zhou (2011) found that influence from society or social circle impacts the people intention and their behavior which shapes their norms, similarly students might get influenced by their peers or from society towards the adoption of chatbots. Likewise, innovation resistance theory has been used to explain why some users hesitate to adopt these technologies. Concerns about security, limited functionality, or negative past experiences contribute to skepticism. Rese et al. (2020) found that customers were cautious about "Emma" chatbots, perceiving them as insecure and imperfect, which reduced their willingness to use them. Similarly, in education, students often hesitate to use chatbots if they seem difficult to adopt, if few classmates are using them, or if the tools are not yet widespread. This reluctance reflects resistance, as the change does not yet feel normal or fully trustworthy (Mehdaoui, 2024; Rese et al., 2020).

Recent work also highlights resistance among teachers. Structural barriers such as large class sizes, limited resources, and low internet connectivity discourage them from integrating AI technologies, even when they recognize potential benefits (Celik, 2023). Studies in K–12 and higher education further reveal that some teachers and students are motivated to use chatbots, many remain skeptical due to unclear benefits or concerns about workload and pedagogical fit (Al-Amri & Al-Abdullatif, 2024).

Despite these findings, little is known about how societal resistance specifically affects the integration of chatbots in academia. Addressing this gap is important for designing strategies that reduce skepticism and encourage meaningful adoption in learning environments. Because of the listed findings, we formed the following hypothesis to address the gap in the research:

H6: Moderate relationship exists behavioral intention (BI) and the actual application of chatbot services.

Figure 1- Proposed Research Framework



Graphical presentation of variables and their relationship in the proposed research model

METHODOLOGY

This section describes the methodology followed by this study.

Development of measures

To ensure the validity of the constructs', previously validated measures were adapted that are relevant to the context. Items were presented on the Likert Scale in the manner of statements that could help evaluate situations under study. A 5-point Likert scale was used, assigning scores of 1 for strongly disagree, to 5 for strongly agree to each statement.

For information quality, we use the 6 items scale which was adapted by (Wang, 1996), and for digital literacy, 6 items the scale by (Compeau & Higgins, 1995) was adapted. 4 items scale for complexity is adapted from (Moore & Benbasat, 1991) and for technology anxiety, the 7 items scale by (Wilson et al., 2023) was adapted. 3 item behavioral intention to use was adapted from (Shahbaz et al., 2020). Finally, 3 item societal resistance scale was adapted from (Al-Somali et al., 2009) and 5 items of education service quality was adapted from (Rolo et al., 2023).

Sampling and data collection

To measure the proposed model, the empirical study used structured questionnaires as the survey method. Out of renowned universities and colleges, both public and private in Lahore, Faisalabad, Multan and Islamabad Pakistan, people interested in using chatbot systems volunteered to participate in the data collection exercise using a convenience sampling technique. An online survey was used to send the questionnaire to participants through social media platforms since this way helps keep the data collection consistent. In all, we sent 300 survey forms to the participants and 259 completed and valid forms were included in the analysis.

Demographics of Respondents

The participant's demographics are represented in Table 1 and describe that 55.2% of the participants are male and 44.8% are female. As far as age is concerned, 43.2% are between the ages of 25–35 years while 40.2% are between 35-45. Only 1.9% participants are High School/Diploma holder while most of them are highly educated; being 47.9% graduates, and 45.6% postgraduates and 4.6% having doctorate. Hence, majority of participants are young and highly educated.

Table 1- Demographic Variables

Category		**Frequency**	**Percentage**
Gender	Male	143	55.2
	Female	116	44.8
	Total	259	100.0
Age	18–25	30	11.6
	25-35	112	43.2
	35-45	104	40.2
	45 and above	13	5.0
	Total	259	100.0
Education	High School/Diploma	5	1.9
	Bachelor	124	47.9
	Master	118	45.6
	Doctoral	12	4.6
	Total	259	100.0

Common Method Bias (CMB)

the issue of Common method bias (CMB) arise when the data is gathered from one source at once for both predictor and dependent factors (Podsakoff et al., 2003). Harman's single factor and Inner variance inflation factor (VIF) tests has been used in this research to ensure that there was no CMB. The results divided the factors into seven, and the first factor explained 30.51% of the variance, which is below the threshold of 40% (P. M. Podsakoff, S. B. MacKenzie, 2012). The aforementioned findings demonstrated that CMB is not a problem in this research. The values of inner VIF must not exceed from 3.3 (Kock, 2015). The inner values of this study range from 1.008 to 1.326 which are under the criteria hence, there is no CMB concern in current investigation.

Table 2 – Inner VIF

	BI	**COML**	**DL**	**ESQ**	**IQ**	**SR**	**TA**	**SR x BI**
BI				1.008				
COML	1.326							
DL	1.142							
ESQ								
IQ	1.196							
SR				1.044				
TA	1.233							
SR x BI				1.050				

RESULTS

To evaluate the assumptions, Smart-PLS v4 was utilized to apply partial least squares-structural equation modeling (PLS-SEM). PLS-SEM is widely recognized for its effectiveness in evaluating path models with latent variables and their relationships (J. F. Hair et al., 2019).

Measurement model

The research was conducted using the methodology suggested by (J. F. Hair et al., 2014) to assess the discriminant, convergent, and content validity of the measurement model. Content validity was established through a review of relevant literature and a pilot testing of the instrument.

Table 3 - Results of factor loadings, Cronbach's alpha, CR, and AVE

Constructs	Items	Loadings	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	AVE
Behavioral Intention	BI1	0.930	0.905	0.912	0.941	0.841
	BI2	0.936				
	BI3	0.884				
Complexity	COML1	0.841	0.895	0.897	0.927	0.761
	COML2	0.905				
	COML3	0.902				
	COML4	0.839				
Digital Literacy	DL1	0.839	0.940	0.941	0.952	0.769
	DL2	0.919				
	DL3	0.868				
	DL4	0.843				
	DL5	0.920				
	DL6	0.870				
Education Service Quality	ESQ1	0.885	0.959	0.960	0.969	0.860
	ESQ2	0.949				
	ESQ3	0.930				
	ESQ4	0.946				
	ESQ5	0.928				
Information Quality	IQ1	0.888	0.934	0.937	0.948	0.755
	IQ2	0.922				
	IQ3	0.755				
	IQ4	0.897				
	IQ5	0.913				
	IQ6	0.826				
Societal Resistance	SR1	0.982	0.975	0.998	0.983	0.951
	SR2	0.961				
	SR3	0.983				
Technology Anxiety	TA1	0.884	0.961	0.962	0.967	0.809
	TA2	0.906				
	TA3	0.865				
	TA4	0.938				
	TA5	0.886				
	TA6	0.928				
	TA7	0.888				

Convergent validity was achieved by examining factor loading, Cronbach's alpha, composite reliability (CR), and the average variance extracted (AVE). Table 3 describes the results of factor overloading, Cronbach's Alpha and convergent validity. As all the values of required analysis are under the criteria therefore, convergent validity is not an issue in present study. All item loadings exceeded the recommended threshold of 0.70 (J. F. Hair et al., 2019), ranging from 0.755 (IQ3) to 0.983 (SR3). This shows that each observed item strongly represents its respective latent construct.

Cronbach's Alpha values ranged from 0.905 to 0.975, all being above 0.70. This indicates excellent internal consistency. Composite Reliability values were consistently higher than 0.90, further confirming scale reliability. The highest reliability was observed in Societal Resistance ($\alpha = 0.975$; CR = 0.983), while the lowest but still stronger values were observed in Behavioral Intention ($\alpha = 0.905$; CR = 0.941).

AVE values ranged from 0.755 to 0.951, all surpassing the threshold of 0.50 reflecting that more than 75% of the variance in items is explained by their underlying constructs. Societal Resistance (AVE = 0.951) had the strongest convergent validity, while Information Quality (AVE = 0.755) was relatively lower but still adequate.

Behavioral Intention and Complexity show strong measurement properties with loadings above 0.84 and AVEs > 0.76. Digital Literacy and Technology Anxiety demonstrate particularly robust reliability (CR > 0.95), suggesting highly stable measurement across items. Societal Resistance stands out as exceptionally strong, with extremely high loadings (≥ 0.96) and AVE exceeding 0.95, suggesting very high homogeneity among items. Education Service Quality is strongly measured, with loadings all above 0.92, reflecting strong construct validity.

Three methods were used to obtain discriminant validity, as recommended by (J. Hair et al., 2017). The first technique was correlations between factors and the square root of AVE as described by (Henseler et al., 2014) and considered as most effective technique for measuring discriminant validity. Table 3 demonstrates that the square root of AVE values is greater in comparison to the correlation coefficients between all variables. Second, there is no issue with discriminant validity due to the fact that all associated variables have larger item loadings and cross-loadings than other latent variables.

The HTMT ratio criterion was introduced to address the limitations of the cross-loadings and Fornell–Larcker techniques. In order for two elements to be certainly distinguished, the HTMT must not exceed one (Henseler et al., 2016). In table 4, values presented on the diagonal, are all greater than the corresponding inter-construct correlations in the rows and columns confirming that each factor is highly associated with its own indicators in comparison to other constructs. Hence discriminant validity is established. Specifically, the square roots of AVE values range from 0.869 (Information Quality) to 0.975 (Societal Resistance), all are above the recommended minimum criteria of 0.70. Behavioral Intention (0.917) is more strongly related to itself than to its highest correlation with Complexity (0.530). Similarly, Education Service Quality (0.928) demonstrates clear separation from related constructs, with its highest correlation being with Behavioral Intention (0.460).

It is also noteworthy that Societal Resistance shows weak correlations with other constructs, indicating that it represents a conceptually independent dimension within the model. Conversely, Behavioral Intention, Complexity, and Technology anxiety exhibit relatively stronger inter-construct correlations, suggesting conceptual linkages while still maintaining discriminant validity.

Table 4 - Inter-construct correlations and discriminant validity

	BI	COML	DL	ESQ	IQ	SR	TA
BI	**0.917**						
COML	0.530	**0.872**					
DL	0.287	0.216	**0.877**				
ESQ	0.460	0.383	0.039	**0.928**			
IQ	0.345	0.349	0.273	0.099	**0.869**		
SR	0.038	0.115	-0.036	0.151	0.003	**0.975**	
TA	0.494	0.397	0.256	0.365	0.149	0.079	**0.900**

In table 5, Behavioral Intention (BI) shows moderate correlations with Complexity (0.589), Education Service Quality (0.489), and Technology anxiety (0.528), suggesting that these constructs are conceptually related yet distinct. Digital Literacy (DL) exhibits relatively weak correlations with others. Similarly, Information Quality (IQ) demonstrates low-to-moderate correlations. Interestingly, Societal Resistance (SR) maintains very low correlations with most constructs (ranging from 0.035 to 0.154), confirming its independence and suggesting that resistance operates as a distinct social barrier not strongly linked to individual-level constructs such as BI or DL.

The interaction term SR × BI demonstrates small-to-moderate correlations with other constructs, the strongest being with Education Service Quality (0.279) and Technology anxiety (0.232). This implies that societal resistance, when moderating behavioral intention, could shape individuals' perceptions of education service quality and technology anxiety. Moreover, the moderate yet non-dominant correlations of the interaction term suggest that multi-collinearity is fine to proceed for the structural model.

The findings confirm that there were no concerns regarding content, convergent, or discriminant validity, thereby supporting the use of the data for structural model analysis.

Table 5 - HTMT ratio criterion

	BI	COML	DL	ESQ	IQ	SR	TA	SR x BI
BI								
COML	0.589							
DL	0.311	0.234						
ESQ	0.489	0.413	0.061					
IQ	0.372	0.377	0.291	0.110				
SR	0.046	0.125	0.035	0.154	0.056			
TA	0.528	0.425	0.269	0.377	0.154	0.077		
SR x BI	0.090	0.186	0.029	0.279	0.106	0.205	0.232	

Table 6 shows that all indicators load highest on their intended constructs compared to other constructs, thereby satisfying the discriminant validity requirement (Chin, 1998; Hair et al., 2019). For example, the items of Behavioral Intention (BI1–BI3) show loadings ranging from 0.884 to 0.936 on their construct, while their cross-loadings on other constructs remain significantly lower (≤0.516). Similarly, Complexity (COML1–COML4) items load strongly on their construct (0.839–0.905), with weaker associations with other latent variables.

Digital Literacy (DL1–DL6) items demonstrate consistently high loadings (0.839–0.920) Education

ACADEMIA International Journal for Social Sciences
Volume 4, Issue 4, 2025 ISSN-L (Online): 3006-6638

Service Quality (ESQ1–ESQ5) indicators load between 0.885 and 0.949, all higher than their correlations with non-target constructs. Information Quality (IQ1–IQ6) also meets the criterion, with loadings ranging from 0.755 to 0.922., while cross-loadings remain comparatively lower. Above all, Societal Resistance (SR1–SR3) displays exceptionally high loadings (0.961–0.983) on its construct, and negligible cross-loadings with others, indicating that societal resistance is conceptually distinct

Table 6 – Cross Loading

	BI	COML	DL	ESQ	IQ	SR	TA
BI1	**0.930**	0.516	0.271	0.460	0.334	0.057	0.468
BI2	**0.936**	0.462	0.269	0.471	0.332	-0.001	0.440
BI3	**0.884**	0.481	0.249	0.323	0.278	0.049	0.451
COML1	0.439	**0.841**	0.160	0.320	0.276	0.140	0.271
COML2	0.484	**0.905**	0.196	0.383	0.286	0.056	0.394
COML3	0.475	**0.902**	0.246	0.310	0.390	0.084	0.320
COML4	0.451	**0.839**	0.148	0.321	0.263	0.128	0.398
DL1	0.241	0.170	**0.839**	0.013	0.265	-0.042	0.163
DL2	0.263	0.232	**0.919**	0.033	0.297	-0.037	0.225
DL3	0.252	0.163	**0.868**	0.052	0.155	-0.016	0.285
DL4	0.243	0.174	**0.843**	0.026	0.270	-0.032	0.167
DL5	0.263	0.233	**0.920**	0.027	0.295	-0.043	0.218
DL6	0.249	0.161	**0.870**	0.051	0.154	-0.016	0.284
ESQ1	0.426	0.357	-0.047	**0.885**	0.043	0.109	0.314
ESQ2	0.447	0.356	0.054	**0.949**	0.062	0.125	0.350
ESQ3	0.416	0.355	0.064	**0.930**	0.149	0.171	0.333
ESQ4	0.446	0.353	0.043	**0.946**	0.064	0.132	0.355
ESQ5	0.397	0.355	0.063	**0.928**	0.146	0.164	0.338
IQ1	0.321	0.377	0.243	0.104	**0.888**	-0.075	0.152
IQ2	0.284	0.330	0.248	0.116	**0.922**	0.053	0.140
IQ3	0.297	0.161	0.224	0.035	**0.755**	0.044	0.096
IQ4	0.268	0.301	0.224	0.110	**0.897**	-0.038	0.131
IQ5	0.331	0.402	0.260	0.112	**0.913**	0.004	0.159
IQ6	0.284	0.225	0.220	0.036	**0.826**	0.035	0.088
SR1	0.012	0.110	-0.017	0.131	0.024	**0.982**	0.053
SR2	0.078	0.116	-0.051	0.170	-0.033	**0.961**	0.111
SR3	0.008	0.110	-0.032	0.133	0.029	**0.983**	0.056
TA1	0.436	0.338	0.242	0.321	0.116	0.043	**0.884**
TA2	0.437	0.354	0.169	0.312	0.152	0.096	**0.906**
TA3	0.450	0.384	0.255	0.370	0.154	0.092	**0.865**
TA4	0.443	0.339	0.262	0.297	0.106	0.038	**0.938**
TA5	0.492	0.425	0.185	0.433	0.177	0.109	**0.886**
TA6	0.440	0.331	0.261	0.289	0.097	0.021	**0.928**
TA7	0.399	0.315	0.240	0.254	0.126	0.093	**0.888**

Structural model

The relationship between constructs based on standardized pathways was tested using the structural model Smart PLS4. Results are shown in Table 7, showing the path coefficients, t-statistics, and significance levels. Several hypothesized relationships were supported.

Information Quality (IQ → BI) was found to have a positive and significant effect on Behavioral Intention ($\beta = 0.157$, $t = 2.771$, $p = 0.006$), indicating that higher-quality information strengthens individuals' intention to use system; leading to acceptance of H1. Digital Literacy (DL → BI) exhibited a positive relationship with Behavioral Intention ($\beta = 0.192$, $t = 1.704$, $p = 0.043$) and study accepted H2.

Interestingly, both Complexity (COML → BI) and Technology Anxiety (TA → BI) demonstrated significant negative effects on Behavioral Intention ($\beta = –0.330$, $t = 5.245$, $p < 0.001$; $\beta = –0.316$, $t = 4.931$, $p < 0.001$). This suggests that higher perceived complexity and technology anxiety reduces individuals' willingness to adopt and we accepted both H3 and H4. In addition, Behavioral Intention (BI → ESQ) strongly and positively predicted Education Service Quality ($\beta = 0.438$, $t = 6.402$, $p < 0.001$). This highlights the central role of behavioral intention in shaping perceptions of service outcomes. The moderating effect of Societal Resistance (SR × BI → ESQ) was also significant ($\beta = 0.186$, $t = 2.931$, $p = 0.003$), indicating that societal-level barriers influence the extent to which behavioral intentions translate into perceived education service quality.

Table 7 – SEM Hypothesis results

	Original sample (O)	**T statistics (|O/STDEV|)**	**P values**
IQ -> BI	0.157	2.771	0.006
DL -> BI	0.192	1.704	0.043
COML -> BI	-0.330	5.245	0.000
TA -> BI	-0.316	4.931	0.000
BI -> ESQ	0.438	6.402	0.000
SR x BI -> ESQ	0.186	2.931	0.003

Finally, table 8 shows that model explains a substantial proportion of variance in the endogenous constructs. For Behavioral Intention (BI), the R-square value is 0.412 indicating that approximately 41% of the variance in BI is explained by its predictors. This highlights the meaningful contribution of factors such as information quality, digital literacy, complexity, and technology anxiety.

For Education Service Quality (ESQ), the R-square value is 0.275 suggesting that around 27% of the variance in ESQ is explained by behavioral intention and the moderating effect of societal resistance. While this represents a weaker explanatory power compared to BI, it is still considered acceptable.

Table 8 – R square

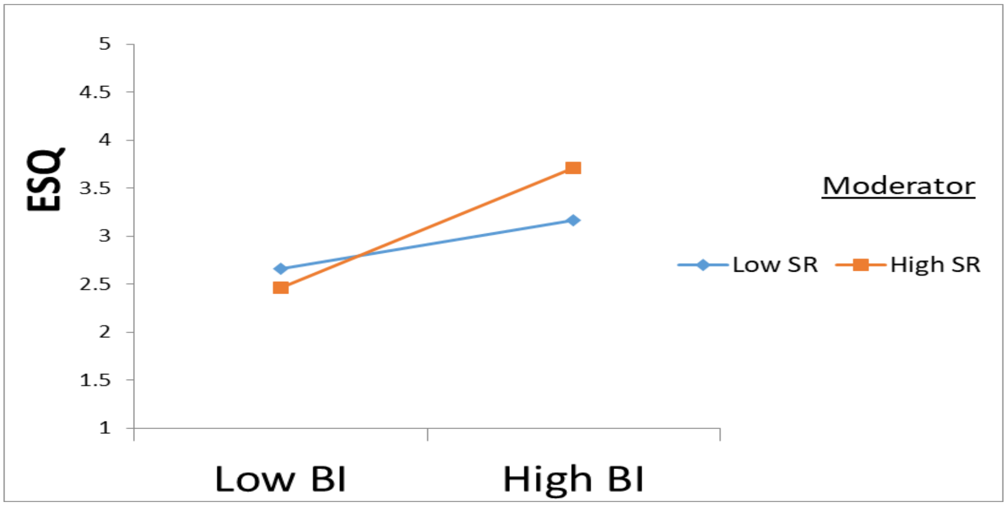
	R-square	**R-square adjusted**
BI	0.412	0.403
ESQ	0.275	0.266

In summary, overall findings indicate that information quality and digital literacy enhance behavioral intention, whereas complexity and technology anxiety negatively affect it. Furthermore, behavioral intention serves as a major determinant of education service quality.

Moderation effect of Societal Resistance

Figure 2 suggests that Education Service Quality increases with higher BI under both low and high levels of SR. However, the slope of the relationship is markedly stronger when SR is high compared to when SR is low. Under low BI, Education Service Quality values remain similar across low and high SR conditions, showing only marginal differences. However, under high BI, ESQ rises more steeply when SR is high, reaching its maximum effect. This suggests that the positive impact of behavioral intention on education service quality is hinders in the presence of higher societal resistance.

Figure 2 – Relationship between ESQ and BI



DISCUSSION

The present study investigated the adoption of Chatbot systems within Pakistan's education sector, applying the Dual Factor Theory to study both facilitators (Information Quality and Digital Literacy) and inhibitors (complexity and technology anxiety), whereas societal resistance served as a moderator. The findings revealed several important insights into how these variables interact to influence behavioral intention (BI) and subsequently education service quality.

The analysis shows that Information quality has a significant positive connection with behavioral intention ($\beta = 0.157$, $p = 0.006$). This indicates that if Chatbot system provide a good quality information to students, teachers and researchers, they are more likely to use these systems. These findings are consistent with prior study as well Kwangsawad & Jattamart (2022).

Similarly, Digital Literacy also positively affects BI ($\beta = 0.192$, $p = 0.043$). If users of education sector are assured in their capability to use digital tools and algorithms, they are more willing to use Chatbot system. This aligns with Torabi et al. (2023) which ensures that users' digital literacy is crucial in making their intentions towards the technology. Digital literacy makes the person feel self-efficient and confident that they have knowledge about using the technology, hence makes the adoption easier.

Among inhibitors, Complexity and Technology Anxiety exhibit strong negative effects on BI. These findings suggest that when Chatbot systems appear overly complicated and difficult to understand, user's intention to use them declines. Moreover, when users feel anxious, they may doubt their ability to interact effectively with the chatbot, worry about making errors, or become frustrated with the automated responses, ultimately their confidence level reduces. These results echo the concerns in earlier literature.

Chatbot language, how it communicates, its appearance and its use of visual clues (Kwangsawad & Jattamart, 2022; Pillai & Sivathanu, 2020; Sheehan et al., 2020) are various reasons for a user's adoption to use chatbot. As far as technology anxiety is concerned, a stressful situation for users of chatbots often involves too much confusion and difficulties which can make them feel that nothing can be achieved (Kwangsawad & Jattamart, 2022; Mehdaoui, 2024).

The present study results depict the strong correlation of behavioral intention to use chatbot system (BI) with education service quality (ESQ). A moderate predictive performance is indicated by the model's ability to explain 41.2% of the variance in BI and 27.5% in EQS. Societal Resistance (SR) considerably exerts adverse impact on behavioral intention to use chatbot systems, as indicated by the interaction term (SR x BI). These results provide validity to the idea that with societal resistance; even if individuals recognize potential benefits of chatbot system, the pressure from societal norms and collective attitudes can discourage them from adopting chatbots. This negative impact underscores the role of social influence in technology adoption. Moreover, the interaction plot indicates that the impact of BI on ESQ is greater among those with lower societal resistance.

CONCLUSION

This research supports researchers, students, teachers, academic coordinators to use chatbot systems in education sector of our country. Present study underpins the pivotal influencing factors for adoption of chatbots in educational services. The findings confirm that information quality and digital literacy serve as strong enablers of behavioral intention, as users become more prone towards the chatbot adoption when they perceive the information to be reliable and when they possess the necessary digital skills. In contrast, complexity and technology anxiety emerge as significant barriers, discouraging individuals from embracing chatbot technology due to perceptions of difficulty and discomfort with digital interaction. Furthermore, societal resistance exerts a negative influence on behavioral intention, underscoring the role of social and cultural dynamics in shaping technology acceptance.

Importantly, the results demonstrate that behavioral intention directly enhances education service quality, signifying that user willingness to engage with chatbots translates into improved learning experiences and service delivery. Another difference with previous research is how this study points out the huge advantage of the Using dual Factor theory to understand intentions to use chatbot service in education. Dual factor theory gives better results when compared to the TAM and the UTAUT. We collected date for our research in Pakistan, which it is a developing country. People's lack of digital literacy as well as their anxiety towards new technology are the main reasons why innovative systems are not embraced in developing countries like ours.

Theoretical Implication

The findings of the study make multiple important theoretical implications to the literature on technology adoption and educational service delivery. To our knowledge, this research offers the first Dual Factor theory-based model for understanding behavioral intentions to use chatbot system. To our knowledge, this perspective on Dual Factor theory is a new and enrich the literature on chatbot adoption. According to our dual factor theory, the positive impact of information quality and digital literacy on intention reinforces the relevance of cognitive and skill-based factors within previously established technology adoption frameworks. Further, the negative influence of complexity and technology anxiety extends prior research by demonstrating that not only functional barriers but also psychological barriers must be considered in understanding resistance to chatbot use. The results emphasize the importance of incorporating emotional and perceptual factors more thoroughly into adoption theories, especially in the context of emerging educational technologies.

The adverse role of societal resistance provides a novel contribution by showing how cultural and social pressures can shape individual behavioral intention. This emphasizes the importance of considering contextual and societal factors within adoption models. This finding theoretically advances the discourse by linking adoption behavior directly to educational outcomes.

Practical Implication

The outcome of this study brings several practical implications for educators, technology developers, and officials. Positive influence of information quality and digital literacy highlights the need for institutions to provide reliable, accurate, and user-friendly chatbot systems as well as investing in digital literacy training for students and teachers. Such measures would build trust in chatbot usage and elevate their value in the learning environment. Negative impact of complexity and technology anxiety indicates that chatbot solutions should be designed with simplicity and user-centered design principles. Developers must focus on intuitive interfaces, step-by-step guidance, and help features to minimize user frustration. Additionally, training sessions, awareness campaigns, and hands-on practice can help reduce anxiety and build trust in the technology.

To cope up with societal resistance, broader awareness and cultural acceptance campaigns are necessary. Educational leaders should work to address uncertainty by demonstrating the tangible benefits of chatbots, integrating success stories, and aligning chatbot use with cultural values to reduce resistance from parents, teachers, and communities.

Finally, institutions should prioritize strategies that encourage user adoption to use chatbot systems. This means creating supportive environments, offering incentives for early adopters, and ensuring that chatbots are seamlessly integrated into the educational ecosystem to improve learning support, administrative efficiency, and overall service quality.

LIMITATIONS AND FUTURE DIRECTIONS

Despite offering valuable insights, this study has several limitations that should be acknowledged. For example, the data were collected within a specific educational context and in a developing country, which might restraint the acceptability of these outcome to other regions, cultures, or educational systems. Future investigations could extend this work to different environments to validate the consistency of the outcomes. Further, study relied on self-reported survey data, which may cause the biased responses or social desirability effects. Employing longitudinal designs, behavioral data, or experimental methods in further investigation could deliver a more nuanced comprehension of chatbot adoption. Another limitation is that our model included key factors such as information quality, digital literacy, complexity, technology anxiety and societal resistance. We suggest to examine the impact of some more potentially influential variable like trust, perceived enjoyment, personalization, or institutional support in future research.

Declaration of interest statement

The corresponding author on behalf of all authors declared that manuscript has not been published previously, that it is not under consideration for publication elsewhere, that its publication is approved by all authors. The authors declare that they have no competing interests.

Funding

No funding is related to this study.

Competing Interest

The authors have no relevant financial or non-financial interests to disclose.

Consent for publication.

Not applicable

Consent to participate

Not applicable

Compliance with ethical standards

We acknowledge that this research does not involve Human Participants and/or Animals. All the authors are aware of this submission.

Author Contributions:

S.S: write the original draft, collect the data, prepare the analysis. **M.S**: contributed to conceptualizing the idea, prepare the literature, design research framework, analysis, and draft the manuscript. Reviewed and edited the manuscript, supervised and guide throughout the process, and results writing. **A.A** collect the data, build theory, reach the respondents. All authors read and approved the final manuscript.

REFERENCES

Abbas Naqvi, M. H., Jiang, Y., Miao, M., & Naqvi, M. H. (2020). The effect of social influence, trust, and entertainment value on social media use: Evidence from Pakistan. *Cogent Business and Management*, *7*(1). https://doi.org/10.1080/23311975.2020.1723825

Ahmad, N., Du, S., Ahmed, F., ul Amin, N., & Yi, X. (2023). Healthcare professionals satisfaction and AI-based clinical decision support system in public sector hospitals during health crises: a cross-sectional study. *Information Technology and Management*. https://doi.org/10.1007/s10799-023-00407-w

Al-Amri, N. A., & Al-Abdullatif, A. M. (2024). Drivers of Chatbot Adoption among K–12 Teachers in Saudi Arabia. *Education Sciences*, *14*(9). https://doi.org/10.3390/educsci14091034

Al-Dokhny, A., Drwish, A., Alyoussef, I., & Al-Abdullatif, A. (2021). Students' intentions to use distance education platforms: An investigation into expanding the technology acceptance model through social cognitive theory. *Electronics (Switzerland)*, *10*(23). https://doi.org/10.3390/electronics10232992

Al-Somali, S. A., Gholami, R., & Clegg, B. (2009). An investigation into the acceptance of online banking in Saudi Arabia. *Technovation*, *29*(2), 130–141. https://doi.org/10.1016/j.technovation.2008.07.004

Balakrishnan, J., Dwivedi, Y. K., Hughes, L., & Boy, F. (2024). Enablers and Inhibitors of AI-Powered Voice Assistants: A Dual-Factor Approach by Integrating the Status Quo Bias and Technology Acceptance Model. *Information Systems Frontiers*, *26*(3), 921–942. https://doi.org/10.1007/s10796-021-10203-y

Celik, I. (2023). Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in Human Behavior*, *138*(May 2022), 107468. https://doi.org/10.1016/j.chb.2022.107468

Chen, Q., Lu, Y., Gong, Y., & Xiong, J. (2023). Can AI chatbots help retain customers? Impact of AI service quality on customer loyalty. *Internet Research*, *33*(6), 2205–2243. https://doi.org/10.1108/INTR-09-2021-0686

Chen, X., Xie, H., & Hwang, G. J. (2020). A multi-perspective study on Artificial Intelligence in Education: grants, conferences, journals, software tools, institutions, and researchers. *Computers and Education: Artificial Intelligence*, *1*(October), 100005. https://doi.org/10.1016/j.caeai.2020.100005

Cheng, X., Bao, Y., Zarifis, A., Gong, W., & Mou, J. (2022). Exploring consumers' response to text-based chatbots in e-commerce: the moderating role of task complexity and chatbot disclosure. *Internet Research*, *32*(2), 496–517. https://doi.org/10.1108/INTR-08-2020-0460

Cheng, Y., & Jiang, H. (2022). Customer–brand relationship in the era of artificial intelligence: understanding the role of chatbot marketing efforts. *Journal of Product and Brand Management*, *31*(2), 252–264. https://doi.org/10.1108/JPBM-05-2020-2907

Choi, I., & Kim, W. C. (2023). Enhancing financial literacy in South Korea: Integrating AI and data visualization to understand financial instruments' interdependencies. *Societal Impacts*, *1*(1–2), 100024. https://doi.org/10.1016/j.socimp.2023.100024

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly: Management Information Systems*, *19*(2), 189–210. https://doi.org/10.2307/249688

Doğan, B., Ghosh, S., Hoang, D. P., & Chu, L. K. (2022). Are economic complexity and eco-innovation mutually exclusive to control energy demand and environmental quality in E7 and G7 countries? *Technology in Society*, *68*. https://doi.org/10.1016/j.techsoc.2022.101867

Fakhimi, A., Garry, T., & Biggemann, S. (2023). The Effects of Anthropomorphised Virtual Conversational Assistants on Consumer Engagement and Trust During Service Encounters. *Australasian Marketing Journal*, *31*(4), 314–324. https://doi.org/10.1177/14413582231181140

Fatima, N., Abrar, M., & Shahbaz, M. (2024). Untangling the Influencing Factors of Intention to Adopt Green Supply Chain Management Practices: An Integration of Toe Framework and Self-Determination Theory. *Operations and Supply Chain Management: An International Journal*, *17*(1), 104–122. https://doi.org/10.31387/oscm0560417

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1, pp. 2–24). https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. In *European Business Review* (Vol. 26, Issue 2, pp. 106–121). https://doi.org/10.1108/EBR-10-2013-0128

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management and Data Systems*, *117*(3), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems*, *116*(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hill, R., Beynon-Davies, P., & Williams, M. D. (2008). Older people and internet engagement: Acknowledging social moderators of internet adoption, access and use. *Information Technology and People*, *21*(3), 244–266. https://doi.org/10.1108/09593840810896019

Hung, W. H., Hsieh, P. H., & Huang, Y. De. (2018). Critical factors of the adoption of e-textbooks: A comparison between experienced and inexperienced users. *International Review of Research in Open and Distance Learning*, *19*(4), 171–190. https://doi.org/10.19173/irrodl.v19i4.3854

Islam, J., & Rahman, Z. (2017). The impact of online brand community characteristics on customer engagement: An application of Stimulus-Organism-Response paradigm. *Telematics and Informatics*, *34*(4), 96–109. https://doi.org/10.1016/j.tele.2017.01.004

Jeng, M. Y., Pai, F. Y., & Yeh, T. M. (2022). Antecedents for Older Adults’ Intention to Use Smart Health Wearable Devices-Technology Anxiety as a Moderator. *Behavioral Sciences*, *12*(4). https://doi.org/10.3390/bs12040114

Kasinathan, V., Wahab, M. H. A., Idrus, S. Z. S., Mustapha, A., & Yuen, K. Z. (2020). AIRA Chatbot for Travel: Case Study of AirAsia. *Journal of Physics: Conference Series*, *1529*(2). https://doi.org/10.1088/1742-6596/1529/2/022101

Khan, M. A. S., Du, J., Malik, H. A., Anuar, M. M., Pradana, M., & Yaacob, M. R. Bin. (2022). Green innovation practices and consumer resistance to green innovation products: Moderating role of environmental knowledge and pro-environmental behavior. *Journal of Innovation and Knowledge*, *7*(4). https://doi.org/10.1016/j.jik.2022.100280

Khoo, H. L., & Ong, G. P. (2013). Evaluating perceived quality of traffic information system using structural equation modeling. *KSCE Journal of Civil Engineering*, *17*(4), 837–849. https://doi.org/10.1007/s12205-013-0248-6

Kim, W. Bin, & Hur, H. J. (2023). What Makes People Feel Empathy for AI Chatbots? Assessing the Role of Competence and Warmth. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2023.2219961

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration*, *11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kwangsawad, A., & Jattamart, A. (2022). Overcoming customer innovation resistance to the sustainable adoption of chatbot services: A community-enterprise perspective in Thailand. *Journal of Innovation and Knowledge*, *7*(3). https://doi.org/10.1016/j.jik.2022.100211

Li, S., Peluso, A. M., & Duan, J. (2023). Why do we prefer humans to artificial intelligence in telemarketing? A mind perception explanation. *Journal of Retailing and Consumer Services*, *70*. https://doi.org/10.1016/j.jretconser.2022.103139

Li, Z., Zuo, T., Wei, X., & Ding, N. (2023). ICT Self-efficacy scale: the correlations with the age of first access to the internet, the age at first ownership of a personal computer (PC), and a smartphone. *Medical Education Online*, *28*(1). https://doi.org/10.1080/10872981.2022.2151068

Maduku, D. K., Mpinganjira, M., Rana, N. P., Thusi, P., Ledikwe, A., & Mkhize, N. H. boy. (2023). Assessing customer passion, commitment, and word-of-mouth intentions in digital assistant usage: The moderating role of technology anxiety. *Journal of Retailing and Consumer Services*, *71*. https://doi.org/10.1016/j.jretconser.2022.103208

Mehdaoui, A. (2024). Unveiling Barriers and Challenges of AI Technology Integration in Education:

Assessing Teachers' Perceptions, Readiness and Anticipated Resistance. *Futurity Education*, *4*(4), 95–108. https://doi.org/10.57125/fed.2024.12.25.06

Mehmood, K., Kautish, P., & Shah, T. R. (2024). Embracing digital companions: Unveiling customer engagement with anthropomorphic AI service robots in cross-cultural context. *Journal of Retailing and Consumer Services*, *79*. https://doi.org/10.1016/j.jretconser.2024.103825

Mohapatra, N., Shekhar, S., Singh, R., Khan, S., Santos, G., & Carvalho, S. (2025). Unveiling the Nexus Between Use of AI-Enabled Robo-Advisors, Behavioural Intention and Sustainable Investment Decisions Using PLS-SEM. *Sustainability (Switzerland)*, *17*(9). https://doi.org/10.3390/su17093897

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Moulaei, K., Yadegari, A., Baharestani, M., Farzanbakhsh, S., Sabet, B., & Reza Afrash, M. (2024). Generative artificial intelligence in healthcare: A scoping review on benefits, challenges and applications. *International Journal of Medical Informatics*, *188*. https://doi.org/10.1016/j.ijmedinf.2024.105474

Oliver, C. (1991). STRATEGIC RESPONSES TO INSTITUTIONAL PROCESSES. *Academy of Management Review*, *16*(1), 145–179. https://doi.org/10.5465/amr.1991.4279002

P. M. Podsakoff, S. B. MacKenzie, and N. P. P. (2012). Sources of method bias in social science research and recommendations on how to control it,. *Annual Review of Psychology*, *63*(1), 539–569.

Patwary, A. K., Aziz, R. C., & Hashim, N. A. A. N. (2023). Investigating tourists' intention toward green hotels in Malaysia: a direction on tourist sustainable consumption. *Environmental Science and Pollution Research*, *30*(13), 38500–38511. https://doi.org/10.1007/s11356-022-24946-x

Pérez, J. Q., Daradoumis, T., & Puig, J. M. M. (2020). Rediscovering the use of chatbots in education: A systematic literature review. In *Computer Applications in Engineering Education* (Vol. 28, Issue 6, pp. 1549–1565). https://doi.org/10.1002/cae.22326

Perez, K., Wisniewski, D., Ari, A., Lee, K., & Lieneck, C. (2025). Investigation into Application of AI and Telemedicine in Rural Communities : A Systematic Literature Review. *Healthcare*, 1–54.

Petter, S., DeLone, W., & McLean, E. (2008). Measuring information systems success: Models, dimensions, measures, and interrelationships. *European Journal of Information Systems*, *17*(3), 236–263. https://doi.org/10.1057/ejis.2008.15

Pillai, R., Ghanghorkar, Y., Sivathanu, B., Algharabat, R., & Rana, N. P. (2024). Adoption of artificial intelligence (AI) based employee experience (EEX) chatbots. *Information Technology and People*, *37*(1), 449–478. https://doi.org/10.1108/ITP-04-2022-0287

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, *32*(10), 3199–3226. https://doi.org/10.1108/IJCHM-04-2020-0259

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. In *Journal of Applied Psychology* (Vol. 88, Issue 5, pp. 879–903). https://doi.org/10.1037/0021-9010.88.5.879

Rahman, M. S., Ko, M., Warren, J., & Carpenter, D. (2016). Healthcare Technology Self-Efficacy

(HTSE) and its influence on individual attitude: An empirical study. *Computers in Human Behavior*, *58*, 12–24. https://doi.org/10.1016/j.chb.2015.12.016

Raj, S., Singh, A., & Lascu, D. N. (2023). Green smartphone purchase intentions: A conceptual framework and empirical investigation of Indian consumers. *Journal of Cleaner Production*, *403*(March), 136658. https://doi.org/10.1016/j.jclepro.2023.136658

Reddy, S. (2024). Generative AI in healthcare: an implementation science informed translational path on application, integration and governance. *Implementation Science*, *19*(1), 1–15. https://doi.org/10.1186/s13012-024-01357-9

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services*, *56*. https://doi.org/10.1016/j.jretconser.2020.102176

Rjab, A. Ben, Mellouli, S., & Corbett, J. (2023). Barriers to artificial intelligence adoption in smart cities: A systematic literature review and research agenda. *Government Information Quarterly*, *40*(3), 101814. https://doi.org/10.1016/j.giq.2023.101814

Rokhman, F., Mukhibad, H., Bagas Hapsoro, B., & Nurkhin, A. (2022). E-learning evaluation during the COVID-19 pandemic era based on the updated of Delone and McLean information systems success model. *Cogent Education*, *9*(1). https://doi.org/10.1080/2331186X.2022.2093490

Rolo, A., Alves, R., Saraiva, M., & Leandro, G. (2023). The SERVQUAL instrument to measure service quality in higher education – A case study. *SHS Web of Conferences*, *160*, 01011. https://doi.org/10.1051/shsconf/202316001011

Schillaci, C. E., de Cosmo, L. M., Piper, L., Nicotra, M., & Guido, G. (2024). Anthropomorphic chatbots' for future healthcare services: Effects of personality, gender, and roles on source credibility, user satisfaction, and intention to use. *Technological Forecasting and Social Change*, *199*. https://doi.org/10.1016/j.techfore.2023.123025

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Arshad, M. R. (2020). Moderating Effects of Gender and Resistance to Change on the Adoption of Big Data Analytics in Healthcare. *Complexity*, *2020*, 1–13. https://doi.org/10.1155/2020/2173765

Shahid, M. K., Zia, T., Bangfan, L., Iqbal, Z., & Ahmad, F. (2024). Exploring the relationship of psychological factors and adoption readiness in determining university teachers' attitude on AI-based assessment systems. *International Journal of Management Education*, *22*(2), 100967. https://doi.org/10.1016/j.ijme.2024.100967

Shahzad, F., Xiu, G. Y., Khan, I., Shahbaz, M., Riaz, M. U., & Abbas, A. (2020). The moderating role of intrinsic motivation in cloud computing adoption in online education in a developing country: a structural equation model. *Asia Pacific Education Review*, *21*(1), 121–141. https://doi.org/10.1007/s12564-019-09611-2

Sheehan, B., Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research*, *115*, 14–24. https://doi.org/10.1016/j.jbusres.2020.04.030

Shiau, W. L., Yuan, Y., Pu, X., Ray, S., & Chen, C. C. (2020). Understanding fintech continuance: perspectives from self-efficacy and ECT-IS theories. *Industrial Management and Data Systems*, *120*(9), 1659–1689. https://doi.org/10.1108/IMDS-02-2020-0069

Songkram, N., Chootongchai, S., Osuwan, H., Chuppunnarat, Y., & Songkram, N. (2023). Students' adoption towards behavioral intention of digital learning platform. *Education and Information Technologies*, *28*(9), 11655–11677. https://doi.org/10.1007/s10639-023-11637-4

Toor, A., Husnain, M., & Hussain, T. (2019). The impact of e-payment service quality on consumer action in Pakistan: Intentions as a mediator. *Asian Journal of Business and Accounting*, *10*(1), 167–199.

Torabi, Z. A., Rezvani, M. R., Hall, C. M., & Allam, Z. (2023). On the post-pandemic travel boom: How capacity building and smart tourism technologies in rural areas can help - evidence from Iran. *Technological Forecasting and Social Change*, *193*. https://doi.org/10.1016/j.techfore.2023.122633

Wang, R. Y. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, *12*(4), 5–34. https://doi.org/10.1080/07421222.1996.11518099

Wilson, M. L., Huggins-Manley, A. C., Ritzhaupt, A. D., & Ruggles, K. (2023). Development of the Abbreviated Technology Anxiety Scale (ATAS). *Behavior Research Methods*, *55*(1), 185–199. https://doi.org/10.3758/s13428-022-01820-9

Zhang, W., Cai, M., Lee, H. J., Evans, R., Zhu, C., & Ming, C. (2024). AI in Medical Education: Global situation, effects and challenges. *Education and Information Technologies*, *29*(4), 4611–4633. https://doi.org/10.1007/s10639-023-12009-8

Zhong, J., & Chen, T. (2023). Antecedents of mobile payment loyalty: An extended perspective of perceived value and information system success model. *Journal of Retailing and Consumer Services*, *72*. https://doi.org/10.1016/j.jretconser.2023.103267

Zhou, T. (2011). Understanding online community user participation: A social influence perspective. *Internet Research*, *21*(1), 67–81. https://doi.org/10.1108/10662241111104884