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AI-Powered Chatbots in the Telecommunications Industry in Jordan: Studying the Factors Impacting Consumer Adoption

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ABSTRACT

This study empirically investigates the factors influencing Jordanian customers' behavioral intention to adopt the Hala Chatbot in the telecommunications sector. Based on existing literature, the research identifies five key factors; perceived ease of use, perceived usefulness, perceived enjoyment, trust, and service quality that shape attitudes toward chatbot usage. The study also examines the mediating role of attitude and the moderating effect of user satisfaction. Data were collected through a questionnaire from a purposive sample of 307 Zain chatbot users. Statistical analyses were performed using Smart-PLS. The findings reveal that perceived usefulness, service quality, and trust significantly influence behavioral intention, with perceived usefulness and service quality having the strongest positive impact. Additionally, perceived ease of use, perceived usefulness, trust affect attitudes toward chatbots, with service quality demonstrating the most substantial influence. However, neither ease of use, perceived enjoyment nor user satisfaction affect the relationship between attitude and behavioral intention. These results offer valuable insights for improving chatbot adoption strategies in the telecommunications industry, highlighting the critical roles of perceived usefulness, service quality, and trust in shaping user behavior and attitudes.

1. INTRODUCTION

The modern business environment, shaped by artificial intelligence (AI) applications and heightened online engagement, has fundamentally altered how businesses approach firm-customer relationships in every sector (Kwangsawad and Jattamar, 2022). One of the most important AI related applications is "chatbots". Also known as Conversational Agents (CA), AI chatbot system "is a software program that interacts with users using natural language" (Ciechanowski et al., 2019, p. 540). There is a growing body of literature that recognizes the importance of adoption of AI chatbots by firms to optimize customer relationships, service effectiveness and customer experience improvement (e.g., Rahane et al., 2018; Sboui et al., 2024). Other benefits include cost savings and enhancement of the customer buying journey across various stages of the consumer decision making process (Sheehan et al., 2020; Sands et al., 2021). A recent survey conducted by the research and advisory firm Metrigy involving 697 businesses found that nearly half had already implemented AI applications in customer service, while a further 38% reported plans to adopt such technologies in 2024 (Schultz, 2025). However, a major problem with these applications is that customers do not always use or adopt chatbots in the way firms expect or intend. Despite the benefits of AI chatbots for firms, previous studies have shown that customers do not always like AI chatbots due to confusing answers, inadequate responses and failure to communicate like real human customer service agents (Elliott, 2018; Zhang et al., 2023). Similarly, other research findings have shown that many customers are skeptical with AI chatbots (Krogue, 2017, Jang et al., 2021), believing that these chatbots are designed to benefit firms in the form of eliminating jobs and cost cutting at the expense of their benefit (Castelo et al., 2023). These findings underscore the need to further understand how consumers use and adopt AI chatbots and the main factors that lead to this adoption Therefore, this study responds to calls for further research into the factors that contribute to use and adopt AI powered chatbots (Hmoud et al., 2023; Bouqlila et al., 2025).

The Technology Acceptance Model (TAM), rooted in the Theory of Reasoned Action (TRA), provides a robust framework for understanding technology adoption, positing that perceived ease of use (PEOU) and perceived usefulness (PU) shape user attitudes and behavioral intentions (Davis, 1989; Fishbein and Ajzen, 1975). While TAM is widely applied to AI tools (Beldad and Hegner, 2018), its use in studying chatbot adoption has not been explored sufficiently, with gaps in examining emotional and service-related factors like enjoyment, trust, and service quality, as well as the mediating role of attitude and moderating effect of user satisfaction (Aslam et al., 2022). To add more, the telecommunications sector is of particular importance due to its role in driving technological innovations and wide user diversity, making it ideal context to understand consumer adoption and use of AI chatbots. To stay competitive, telecom firms are enhancing customer service operations, leveraging information and communication technologies (ICTs) to provide 24/7 support (Kwangsawad and Jattamar, 2022; Pillai and Sivathanu, 2020). However, despite growing use of AI chatbots by firms, many users report frustrations with unsatisfactory chatbot interactions, highlighting barriers to widespread adoption (Følstad et al., 2018). Few studies have explored how users interact with these systems or the factors influencing their acceptance beyond basic demographics like age and gender (Aslam et al., 2022; Toader et al., 2019).

This study addresses these gaps by drawing on the technology acceptance model to examine how its variables affect consumers' decisions to use chatbots in Jordan's telecom sector. Jordan was selected because it represents a unique context; it is an Arab country where chatbot usage and adoption rates remain relatively immature compared to developed economies (Hmoud et al., 2023). Specifically, the study examines five factors PEOU, PU, perceived enjoyment (PE), trust, and service quality SQ as predictors of behavioral intention to use (BITU) chatbots, with attitude as a mediator and user satisfaction (US) as a moderator. By extending TAM to include context-specific constructs, the study offers a comprehensive model tailored for Jordan's context, contributing to both theory and practice in AI adoption.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

In today's digital age, consumers expect faster, seamless and personalized customer service. This has prompted firms to adopt advanced technologies to provide better customer service and enhance customer experience. Therefore, AI Chatbots have emerged to assist firms in offering faster and convenience customer service, thus transforming how businesses connect with consumers (Gümüş and Çark, 2021; Van den Broeck et al., 2019; Ngo et al., 2025). Increasing research has documented the benefits that chatbots can yield to both firms and customers. Through chatbots, customers can easily make purchases, receive personalized recommendations, and get instant support (Rahane et al., 2018; Sboui et al., 2024). By simulating real conversations, chatbots make online interactions feel more natural and engaging (Sun et al., 2023), while their accessibility on digital platforms ensures users can get help anytime, anywhere. However, despite the noted advantages of AI powered chatbots, Data from several studies suggest that that some customers still show reluctance towards using this technology. This lack of adoption can be due to multiple reasons such as perceived complexity, technological anxiety and consumer mistrust, the risk of personal hacking and the need for human interaction (Bouqlila et al., 2025). A recent study by Castelo et al. (2023), reports that some customers believe that these chatbots are designed to benefit firms in the form of eliminating jobs and cost cutting at the expense of their benefit, thus hindering chatbot acceptance and adoption. This study focuses on the Technology Acceptance Model (TAM) as its theoretical foundation. The proposed model tests five predictors of the behavioral intention to use (BITU), chatbots perceived ease of use (PEOU), perceived usefulness (PU), perceived enjoyment (PE), trust, and service quality (SQ) with attitude as a mediator and user satisfaction (US) as a moderator.

2.1. Perceived ease of use.

The degree to which a person thinks utilizing a technology would be effortless is known as perceived ease of use (Venkatesh et al., 2012). One significant factor influencing how technology or systems are used is perceived ease of use (Davis, 1989; Mathieson, 1991). Perceived ease of use is one of the most important factors in determining user intention to use AI (Pitardi and Marriott 2021; Belanche et al., 2019; Liang et al., 2020). Previous research has shown that sentiments about the adoption of AI are directly impacted by perceived simplicity (ease) of usage (Chatterjee et al., 2020; Belanche et al., 2019). Moreover, the study by (Wilson et al., 2021) found that perceived ease of use affects consumers' desire to repurchase. Also, Sadriwala and Sadriwala (2022) found that the adoption of AI is significantly influenced by its perceived ease of use. Based on the above-reviewed literature, H1a and H1b hypotheses can be proposed as:

H1a: Perceived ease of use has significant effect on Attitude.
H1b: Perceived ease of use has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude.

2.2. Perceived usefulness.

Perceived usefulness, according to Nagy and Hajdú (2021), is the degree to which a customer thinks that using artificial intelligence (AI) for online purchasing would increase the effectiveness of their purchases. It can also be described as the degree to which a person thinks that using a particular system will help them perform better at work (Davis, 1989). Customers' perceptions of chatbots are mostly influenced by their perceived usefulness. Therefore, a consumer's perception of a chatbot's usefulness determines how that customer feels about it. This demonstrates that an individual's likelihood of accepting a technology increases with its perceived usefulness (Rese et al., 2020). The intention to utilize is also influenced by the mindset that results from perceived usefulness (Hussein et al., 2016). it. This demonstrates that an individual's likelihood of accepting a technology increases with its perceived usefulness (Rese et al., 2020). Sadriwala and Sadriwala (2022) found that perceived usefulness has a significant effect on AI technology adoption. Many researchers, including Pitardi and Marriott (2021), Liang et al. (2020) and Ashfaq et al. (2020), have confirmed a positive relationship between perceived usefulness, perceived ease of use, and attitude toward intention to use. Ashfaq et al. (2020) concluded that perceived usefulness is a necessary precondition for satisfaction and continuance intention. Based on the above-reviewed literature, H2a and H2b hypotheses can be proposed as:

H2a: Perceived usefulness has significant effect on Attitude.
H2b: Perceived usefulness has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude.

2.3. Perceived enjoyment.
The degree to which employing technology to do a task is thought to be enjoyable independent of the activity's effects is known as perceived enjoyment (Venkatesh et al., 2003; Davis et al., 1992). Davis et al., (1992) added the perceived enjoyment has frequently been included as an external variable in TAM. According to a study analyzing the antecedents of perceived enjoyment, the most crucial elements are focused attention, speed, content, and variation (Chung and Tan, 2004). The term perceived enjoyment describes how people feel about the "fun or pleasure derived from using a technology" (Venkatesh et al., 2012). Pitardi and Marriott (2021) found that the intention to use AI is significantly impacted by perceived enjoyment, since one is more likely to have a favorable experience while using something they enjoy (McLean and Osei-Frimpong, 2019). According to Ashfaq et al. (2020), customers are happier and more likely to use a chatbot again if they find it engaging. Based on the above-reviewed literature, H3a and H3b hypotheses can be proposed as:

H3a: Perceived Enjoyment has significant effect on Attitude.
H3b: Perceived Enjoyment has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude.

2.4. Trust.
According to Nagy and Hajdú (2021), trust is a subjective likelihood that people believe AI operates in their best interests. The concept of human trust is defined by Mayer et al. (1995) as a combination of people's faith in each other's competence, goodness, and morality. According to Wu et al., (2011), trust had a substantial positive influence on the main TAM constructs. New research keeps proving how important trust is to TAM. Song and Shin (2024), for instance, showed how trust can have a favorable impact on the ongoing usage of news recommendation systems, the results indicated that AI utility and ease of use are positively correlated with faith in the technology. Beldad and Hegner (2018) discovered that trust affected users' opinions of the app's utility rather than their intention to utilize a health-tracking app. Similarly, research has shown that trust increases usefulness and positive sentiments, which influence usage intention indirectly rather than directly. Based on the above-reviewed literature, H4a and H4b hypotheses can be proposed as:

H4a: Trust has significant effect on Attitude.
H4b: Trust has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude.

2.5. Service quality.
According to DeLone and McLean, (2003) and Eppler et al. (2015) information quality indicates information accuracy, relevance, sufficiency, and timeliness. Users' satisfaction is largely dependent on the users' ability to obtain sufficient, precise, accurate, current, and trustworthy information (Veeramootoo et al., 2018 and Lu and Hsiao, 2019). Earlier research has also shown that the quality of the information is a crucial element in encouraging users' trust (e.g., Filieri et al., 2015; Ponte et al., 2015 and Masri et al., 2020). Poor information quality will lead to a poor user experience: if the information provided by a chatbot is out-of-date, irrelevant, or inaccurate in any other way, users might have to go for alternative sources of information, which will involve more time and effort on their part (Eppler et al., 2015 and Gao et al., 2015). When it comes to chatbot e-services, users' satisfaction is positively impacted, which in turn influences their intention to use the chatbot continuously, if it offers current, trustworthy information (i.e., high information quality), quick responses, and personalized attention (i.e., high service quality) (Ashfaq et al., 2020). Based on the above-reviewed literature, H5a and H5b hypotheses can be proposed as:

H5a: Service Quality has significant effect on Attitude.
H5b: Service Quality has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude.

2.6. Attitude.
According to Eagly and Chaiken (1993), Attitude is a psychological propensity that manifests as a degree of favorable or unfavorable evaluation of a specific entity. It has been well established that attitude and intention are associated in TAM (Pitardi and Marriott, 2021; Nagy & Hajdë, 2021; Bou-Ghanem 2020; Lin and Xu 2022). Perceived ease of use and perceived usefulness affects attitude and behavioral intention to use, it in turn affects actual use (Nagy and Hajdë ,2020). Customers' intentions to make online purchases are significantly influenced by their attitude and perception of utility (Ha and Stoel, 2009). Furthermore, favorable opinions about technology have a beneficial impact on purchasing intentions (Liang et al., 2020). Recent studies on IT adoption (e.g: Dwivedi et al., 2021; Rana et al., 2017; Rana et al., 2016) have indicated that understanding behavioral intention requires taking into account an individual's attitude. Based on the above-reviewed literature, H6 hypothesis can be proposed as:

H6: Attitude has a significant mediating effect on behavioral intention to use Chabot's.

2.7. User satisfaction.
In the business sector, the idea of satisfaction has been widely used to gauge how well goods and services meet customers' expectations (Chung et al., 2018). According to the expectance-confirmation paradigm, clients may become satisfied if the good or service performs up

to or better than their expectations (Oliver, 1980). User satisfaction is a critical metric for measuring user experience in communication research. Satisfaction is defined as an overall sense of well-being that arises from routine media use; it encompasses expectations for the average long-term outcome (LaRose, 2015). According to Gogan et al.'s (2018) research, user satisfaction and utilitarian, hedonistic, and social gratifications are positively correlated. Based on the above-reviewed literature, H7 haypothesis can be proposed as:

H7: User Satisfaction has a significant moderating effect on the relationship between Attitude on behavioral intention to use Chabot’s.

2.8. Behavioral intention to use.

The probability that a person will use chatbots is known as behavioral intention. There is a relationship between behavioral intention and attitudes toward chatbots. We can forecast a customer's intention to utilize chatbots based on how they will feel about them. Consumers are more likely to intend to use chatbots in a favorable way if they think there is enough infrastructure and resources available. In other words, consumers are more likely to utilize chatbots if they think that technical methods (Internet infrastructure and the interoperability of the data, systems, and technology needed for online access) are effective (Wong et al., 2015). It was found that perceived usefulness is more significant than perceived ease of use as the other important factor in attitudes and behavioral intention (Nagy and Hajdú, 2021). According to Huang and Chueh (2021), users' satisfaction with the veterinary consultation chatbot was influenced by their perceptions of its completeness, accuracy, and ease of use. The results also indicate that users' behavioral intention to use a chatbot for veterinary consultations was increased by their perceptions of its convenience and satisfaction.

2.9. Conceptual model.

Figure (1) presents the conceptual model used in this study to test PEOU, PU, PE, trust, and SQ as predictors of BITU chatbots, with attitude as a mediator and US as a moderator (Figure 1, Conceptual Model). The model draws on previously developed frameworks (e.g., Silva et al., 2023; Gümüş and Çark, 2021; Nguyen and Nguyen, 2023; Wang et al., 2020; Huang and Chueh, 2021; Masa’deh et al., 2022 and Faqih, 2011).

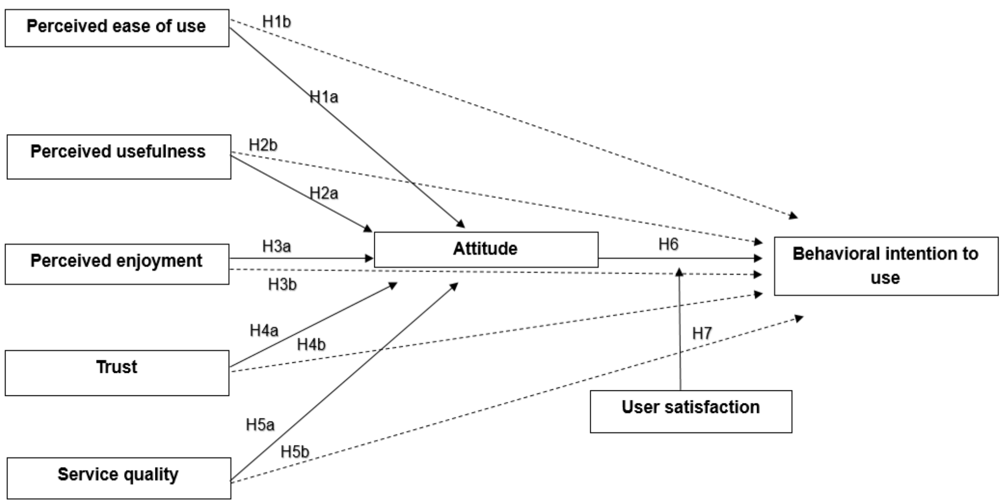

Figure 1: Proposed Conceptual Model informed by earlier research

3. METHODOLOGY

3.1. Population and data collection.

In order to examine the factors that affect consumers’ attitudes toward using and adopting AI-powered chatbots in the telecommunications sector in Jordan, a quantitative research approach was designed to test the proposed model, focusing on Zain Company’s Hala chatbot. Jordan’s telecommunications sector is characterized by high mobile penetration and a tech-savvy population which has driven continuous shifts in consumer behavior, compelling businesses to adapt their digital marketing strategies to meet evolving demands (Araújo and Casais, 2020 and Hmoud et al., 2023). Indeed, Jordanian telecom firms deploy chatbots for tasks like account balance checks, bill payments, and troubleshooting, delivering fast, individualized support to redu ce wait times and improve satisfaction (Zain Company Annual Report, 2022). Zain company is one of the leading telecom firms in Jordan and was selected due to its market leadership and advanced chatbot implementation, making it an ideal case for examining adoption dynamics (Zain Company Annual Report, 2022). Data were collected from 307 Zain customers in Jordan between January and March 2024, using purposive sampling, a non-probability technique suitable for targeting specific populations relevant to the study’s objectives (Palinkas et al., 2015). Participants were selected based on their current or potential use of Zain’s Hala chatbot, ensuring insights into user perceptions and behaviors. This method was chosen for its efficiency in accessing a pre-identified group, commonly used in technology adoption research to capture context-specific data (Palinkas et al., 2015).

The survey approach facilitates robust data collection to investigate the relationships among perceived ease of use (PEOU), perceived usefulness (PU), perceived enjoyment (PE), trust, service quality (SQ), attitude, user satisfaction (US), and behavioral intention to use (BITU). The survey was distributed online via email and Zain's social media platforms, leveraging the company's customer database to reach active users. To ensure data quality, participants were informed of the study's purpose, and only fully completed questionnaires were included. The 307 valid responses provide a sufficient sample size for structural equation modeling (SEM) analysis of complex models with multiple constructs (Hair et al., 2019). The sample comprised a diverse mix of current and potential chatbot users, reflecting Jordan's tech-savvy telecommunications market.

3.2. Measures.

The questionnaire was developed by adapting validated scales from prior research, tailored to the context of Zain's Hala chatbot. Scales were sourced from established studies on technology adoption and chatbot use, with input from industry experts to ensure relevance to Jordan's telecommunications sector. A pre-test with 25 Zain customers was conducted to verify question clarity, cultural appropriateness, and scale reliability, resulting in minor wording adjustments to enhance comprehension. The questionnaire included eight constructs, each measured with 3–6 items on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) to ensure consistency and respondent ease. The specific items, adapted from their original sources, are detailed below as seen in table 1.

Table 1. The survey constructs and items.

Constructs	Measurement Details
Perceived Ease of Use (PEOU)	4 items, adapted from Ashfaq et al., (2020)
Perceived Usefulness (PU)	4 items, adapted from Ashfaq et al., (2020)
Perceived Enjoyment (PE)	4 items, adapted from Pitardi Marriott, (2021)
Trust	4 items, adapted from Pitardi & Marriott, (2021)
Service Quality (SQ)	6 items, adapted from Ashfaq et al., (2020)
Attitude	3 items, adapted from Pitardi & Marriott, (2021)
User Satisfaction (US)	3 items, adapted from Huang & Chueh, (2021)
Behavioral Intention to Use (BITU)	3 items, adapted from Huang & Chueh, (2021)

The number of items per construct (3–6) was designed to balance comprehensive measurement with respondent fatigue, following survey design best practices (Hair et al., 2019). Items originally referring to "voice-based assistant" or "veterinary consultation" were rephrased to focus on Zain's Hala chatbot, ensuring contextual alignment with Jordan's telecommunications sector. Moreover, a pilot study was conducted to evaluate the questionnaire's reliability and validity before the full survey. This preliminary step ensured the instrument's clarity and effectiveness, allowing refinements to enhance data quality. The pilot involved 25 Zain Hala chatbot users who completed the questionnaire and provided feedback on question clarity and readability. Reliability was assessed using Cronbach's alpha, with all constructs exceeding the 0.8 threshold, confirming strong internal consistency (Hertzog, 2008). Based on participant feedback and reliability results, minor wording adjustments were made to improve the questionnaire's clarity and validity for the main data collection.

3.3. Model Validation.

Prior to hypothesis testing, the research model was validated. Model fit was confirmed with a standardized root mean square residual (SRMR) of 0.051 (< 0.08) and a Normed Fit Index (NFI) of 0.854 (> 0.8), indicating good fit (Hair and Alamer, 2022), Confirmatory factor analysis (CFA) assessed reliability and validity, with composite reliability (CR > 0.7), and average variance extracted (AVE > 0.5) meeting thresholds for all constructs (Baharum et al., 2023) as seen in Table 2.

Table 2. Constructs' reliability, Validity and Factors Loadings.

Constructs	Items	Factor Loading	Composite reliability	Average variance extracted (AVE)
Attitude	Attitude1	0.935	0.952	0.867
	Attitude2	0.932		
	Attitude3	0.927		
Bl Intention to Use	Bl Intention to Use1	0.901	0.938	0.834
	Bl Intention to Use2	0.930		
	Bl Intention to Use3	0.908		
P Enjoyment	P Enjoyment1	0.909	0.950	0.825
	P Enjoyment2	0.883		
	P Enjoyment3	0.915		
	P Enjoyment4	0.927		
PEU	PEU1	0.786	0.877	0.641
	PEU2	0.804		
	PEU3	0.767		
	PEU4	0.843		
P Usefulness	PUsefulness1	0.880	0.941	0.800
	PUsefulness2	0.908		

	PUsefulness3	0.883		
	PUsefulness4	0.906		
Service Quality	Service Quality1	0.816	0.919	0.655
	Service Quality2	0.828		
	Service Quality3	0.784		
	Service Quality4	0.723		
	Service Quality5	0.835		
	Service Quality6	0.861		
Trust	Trust1	0.868	0.939	0.793
	Trust2	0.886		
	Trust3	0.908		
	Trust4	0.899		
User Satisfaction	User Satisfaction1	0.897	0.917	0.787
	User Satisfaction2	0.881		
	User Satisfaction3	0.884		

Discriminant validity was established utilizing Heterotrait-monotrait ratio (HTMT), as the square root of AVE exceeded inter-construct correlations. These results ensure the model's robustness for hypothesis testing as seen in Table 3.

Table 3. Discriminant validity.

Constructs	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8
Attitude								
Bl Intention to Use	0.817							
P Enjoyment	0.731	0.727						
PEU	0.764	0.674	0.662					
P Usefulness	0.824	0.800	0.835	0.776				
Service Quality	0.831	0.765	0.757	0.820	0.814			
Trust	0.756	0.734	0.642	0.660	0.731	0.762		
User Satisfaction	0.852	0.869	0.747	0.725	0.814	0.879	0.764	
User Satisfaction x Attitude	0.229	0.175	0.234	0.259	0.256	0.272	0.153	0.209

4. ANALYSIS AND RESULTS

To determine factors that contribute to consumers adoption to AI powered chatbots in the telecom sector in Jordan, structure equation modeling (SEM) was used to examining the effects of perceived ease of use (PEOU), perceived usefulness (PU), perceived enjoyment (PE), trust, and service quality (SQ) on attitude (ATT) and behavioral intention to use (BITU) the Hala chatbot, with attitude as a mediator and user satisfaction (US) as a moderator. PLS-SEM was used to test the proposed model (Figure 4.1), as its suitable for complex models with mediation and moderation (Hair et al., 2011). Also, the sample was predominantly young (67.8% aged 25–40, 15% under 25, 12.1% aged 41–50, 5.2% over 50, reflecting Jordan's tech-savvy telecommunications market. Females comprised 57% of respondents, and males 43%. Education levels were high, with 66.8% holding a bachelor's degree and 13.4% a master's degree. Income distribution showed 31.9% earning 500–1000 JOD monthly and 24.8% less than 500 JOD. Most respondents (73.9%) had used the Hala chatbot, with 72.6% using it 1–3 times. These demographics, validated by the pilot study's testing (Cronbach's alpha > 0.8; Hertzog, 2008), providing a robust basis for analyzing chatbot adoption.bThereafter, the PLS-SEM results provided by SmartPLS 4 were used to assess the measurement model. Moreover, bootstrapping procedure was employed to test hypothesized effects (Hair et al.,2019). Addetionly, SEM-PLS Path analysis as seen in Table 4 revealed that PU ($\beta = 0.171$, $p = 0.001$, and trust ($\beta = 0.12$, $p < 0.05$) significantly predicted BITU. PE, PEOU and SQ had non-significant effects on BITU. For attitude, PEOU ($\beta = 0.124$, $p < 0.05$), PU ($\beta = 0.27$, $p < 0.001$), trust ($\beta = 0.202$, $p < 0.001$), and SQ ($\beta = 0.269$, $p < 0.001$) were significant predictors, with PUsefulness and SQ exerting the strongest effect, confirming the role of accurate information. PE had no significant effect on attitude ($p > 0.05$). Attitude significantly predicted BITU ($\beta = 0.218$, $p < 0.001$), supporting its role in adoption.

Table 4. Path effects.

Path	β	T statistics	P values
P Enjoyment -> Attitude	0.090	1.470	0.142
P Enjoyment -> Bl Intention to Use	0.101	1.676	0.094
PEU -> Attitude	0.124	1.999	0.046
PEU -> Bl Intention to Use	-0.004	0.067	0.947
PUsefulness -> Attitude	0.270	3.829	0.000
PUsefulness -> Bl Intention to Use	0.171	2.557	0.011
Service Quality -> Attitude	0.269	4.298	0.000
Service Quality -> Bl Intention to Use	-0.018	0.256	0.798
Trust -> Attitude	0.202	3.861	0.000
Trust -> Bl Intention to Use	0.120	2.184	0.029

The Mediation analysis as seen in Table 5, assessed attitude's role in mediating the effects of PEOU, PU, PE, trust, and SQ on BITU. Significant indirect effects were found for PU ($\beta = 0.059$, $p < 0.05$), trust ($\beta = 0.044$, $p < 0.05$), and SQ ($\beta = 0.059$, $p < 0.05$), confirming attitude's mediating role. PEU, and PE's indirect effect was non-significant ($p > 0.05$), indicating absent mediation of attitude on these variables. For Moderation analysis, it tested US's effect on the attitude-BITU relationship. The interaction term (US x ATT) was non-significant ($\beta = 0.024$, $p = 0.396$), indicating US does not moderate the relationship, despite US's direct effect on BITU ($\beta = 0.351$, $p < 0.001$) as seen in Table 5.

Table 5. Mediation and Moderation Analysis.

Path	β	T statistics	P values
PEU -> Bl Intention to Use	0.027	1.661	0.097
PUsefulness -> Bl Intention to Use	0.059	2.109	0.035
Service Quality -> Bl Intention to Use	0.059	2.210	0.027
Trust -> Bl Intention to Use	0.044	2.169	0.030
User Satisfaction x Attitude -> Bl Intention to Use	0.024	0.849	0.396
P Enjoyment -> Bl Intention to Use	0.020	1.187	0.235

The results of the analysis for all hypotheses are shown in Table 6 below:

Table 6. Results of Hypotheses Testing.

Hypotheses	Results
H1a: Perceived ease of use has significant effect on Attitude	Accept
H1b: Perceived ease of use has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude.	Reject
H2a: Perceived usefulness has significant effect on Attitude.	Accept
H2b: Perceived usefulness has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude.	Accept
H3a: Perceived Enjoyment has significant effect on Attitude.	Reject
H3b: Perceived Enjoyment has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude	Reject
H4a: Trust has significant effect on Attitude.	Accept
H4b: Trust has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude	Accept
H5a: Service Quality has significant effect on Attitude.	Accept
H5b: Service Quality has significant effect on behavioral intention to use Chabot's through the mediating role of Attitude	Accept
H6: Attitude has a significant mediating effect on behavioral intention to use Chabot's.	Accept
H7: User Satisfaction has a significant moderating effect on the relationship between Attitude on behavioral intention to use Chabot's.	Reject

Finally, The R^2 values indicate strong explanatory power: BITU ($R^2 = 0.646$) suggesting 64.6% of its variance is explained by attitude and predictors, while ATT ($R^2 = 0.693$) indicates 69.3% is explained by PEOU, PU, PE, trust, and SQ (Hair et al., 2011, 2013). These values reflect robust model fit for a complex adoption model.

5. DISCUSSION

This study enhances the understanding of AI-powered Chabot adoption in Jordan's telecommunications sector, focusing on Zain Company's Hala chatbot, by extending the Technology Acceptance Model (TAM) with perceived enjoyment (PE), trust, and service quality (SQ). The results show that perceived usefulness (PU), and trust significantly predict behavioral intention to use (BITU), consistent with prior research on AI adoption (Sun and Zhang, 2006; Nagy and Hajdú, 2021; Glikson and Woolley, 2020; Choung et al., 2023). PU's strong influence aligns with studies highlighting its role in driving efficient task resolution in telecommunications (Davis, 1989; Rese et al., 2020). In contrast, perceived ease of use (PEOU) and SQ did not significantly affect BITU, supporting findings that ease of use may be less critical in familiar technology contexts (Kilani and Rajaobelina, 2024; Ashfaq et al., 2020). The lack of SQ's direct impact, despite its emphasis on accuracy and timeliness (DeLone and McLean, 2003), suggests users prioritize functional outcomes over interface quality. However, PEOU, PU, trust, and SQ significantly shaped attitudes toward chatbots, with SQ having the strongest effect. This supports research by (Shanmugam et al., 2014). Pitardi and Marriott (2021), and Liang et al. (2020), which links reliable, high-quality information to positive user perceptions. PE's insignificant effect on attitude diverges from studies emphasizing emotional engagement (Venkatesh et al., 2003; Pitardi and Marriott, 2021), indicating that enjoyment may be less relevant in Jordan's service-oriented market. Addetionally, mediation analysis confirms attitude's role in translating PEOU, PU, trust, and SQ into BITU, aligning with research on attitude's mediating function in technology adoption (Eagly and Chaiken, 1993; Zarouali et al., 2018; Verma and Sinha, 2017). However, PE's non-significant indirect effect suggests emotional factors may not mediate adoption in utilitarian contexts, consistent with boundary conditions noted by Sun and Zhang (2006) and (Shanmugam et al., 2014). Also, Moderation analysis using a product-indicator test (Kenny and Judd, 1984), found that user satisfaction (US) did not significantly moderate the attitude-BITU relationship, despite 70% of respondents reporting high satisfaction. This contrast with studies suggesting US enhances adoption when expectations are met (Oliver, 1980; Chung et al., 2018; Ashfaq et al., 2020). This indicates that US may play a limited role in Jordan's high-service-expectation telecommunications market.

6. RESEARCH IMPLICATIONS AND LIMITATIONS

This study offers several theoretical contributions to the existing literature on chatbot adoption and technology acceptance. First, it extends the Technology Acceptance Model (TAM) by confirming the significant influence of perceived usefulness, trust, and service quality on user attitudes and behavioral intentions in the context of AI-driven chatbots. While previous studies only focused on functional aspects such as ease of use and usefulness, this research highlights the central role of service quality and trust, particularly in shaping attitudes toward chatbots. Second, the study provides empirical support for the mediating role of attitude in the adoption process, reinforcing the importance of attitude formation as a pathway linking key predictors (perceived ease of use, perceived usefulness, trust, and service quality) to behavioral intention. This mediation finding adds depth to TAM-based frameworks by illustrating that positive attitudes toward chatbots can partially explain why these predictors lead to adoption. Third, the research contributes to the understanding of chatbot adoption in the specific cultural and service context of Jordan's telecommunications sector, which has been underexplored in prior literature. This contextual focus offers new insights into consumer behavior in emerging markets. Finally, while user satisfaction was tested as a moderator, its lack of significant effect challenges assumptions in related studies that satisfaction always strengthens the link between attitudes and behavioral intention. This suggests that other psychological or contextual factors may play a more critical role in influencing chatbot adoption. For the managerial implications, service quality emerged as the most significant drivers of behavioral intention followed by perceived usefulness, indicating that managers should focus on ensuring the chatbot delivers practical value to users. This can be achieved by enhancing the chatbot's ability to provide accurate information, resolve customer issues efficiently, and streamline service processes. Second, service quality demonstrated the strongest influence on customer attitudes toward chatbot usage. It is therefore essential to continuously improve the chatbot's response speed, reliability, and conversational quality. Investing in advanced natural language processing (NLP) capabilities and regular system updates can help maintain high service standards and foster positive user perceptions. Interestingly, user satisfaction did not significantly moderate the relationship between attitude and behavioral intention, suggesting that simply satisfying users may not be sufficient to influence their intention to continue using the chatbot. Instead, sustained focus should be placed on delivering usefulness, quality, and trust throughout the user journey. By focusing on these key drivers, businesses can create innovative products and services that are not only functional but also engage consumers effectively, helping them stay ahead of competitors in the market.

While this study offers valuable findings, several limitations should be acknowledged. One limitation is the restricted scope of the five factors examined, which included PEU, PU, PE, trust, and SQ. Future research could expand this model by incorporating additional factors such as Perceived Credibility, and irritation that could affect consumers' attitudes to use artificial intelligence (AI). Another limitation is the demographic distribution of the sample, which was predominantly composed of participants aged 25 to 40. To enhance the generalizability of findings, future research should aim for a more balanced demographic representation, including both older and younger populations. Additionally, the study was limited to Zain Company in Jordan, which may impact the generalizability of the results to other sectors. Therefore, future research should consider expanding the sample to include other telecommunications companies in Jordan and internationally to validate the findings. By addressing these limitations and expanding the scope of future research, scholars can build on the findings of this study and provide deeper insights into the factors that influence the adoption of AI technologies, helping businesses and organizations enhance their customer engagement and service delivery strategy.

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