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The Impact of Chatbots on Customer Experience in e-commerce: Examining Responsiveness, Ease of Use, and Personalization

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Abstract. Modern technology tools play an important role in enhancing customer service and providing customers with prompt responses to their inquiries. Among these technologies, AI-based chatbots are becoming a key tool in improving customer experience. This study employed a quantitative approach to examine the impact of chatbots on customer service experience in e-commerce, focusing on three dimensions of the chatbot performance: responsiveness, perceived Ease of Use, and personalization. A total of 206 responses were collected from customers of Jordanian telecommunication companies engaged in e-commerce, and the data were analyzed using structural equation modeling, which revealed that all three antecedents positively predicted CX: responsiveness → CX ($\beta = 0.522$, $p < .001$; $f^2 = 0.366$, large), personalization → CX ($\beta = 0.214$, $p = .002$; $f^2 = 0.036$, small), and Ease of Use → CX ($\beta = 0.158$, $p = .008$; $f^2 = 0.027$, small). The model demonstrated substantial explanatory power and explained 63.6% of the variance in customer experience. Additional analysis highlighted the importance of demographic factors in shaping the chatbot interactions, as it revealed differences in perceptions of responsiveness between genders. The study provides practical implications for managers for enhancing AI-powered chatbots to improve service efficiency, thereby improving customer satisfaction and loyalty. It also advances the literature by presenting the central role of responsiveness in customer experience, and the importance of understanding the demographic differences.

Keywords: chatbots, Customer Experience, Responsiveness, Ease of Use, Personalization, Structural Equation modeling SEM, Jordan Telecommunications Sector.

1. Introduction

The use of digital tools is becoming visible in every aspect of today's business environment; these tools offer convenience and accessibility for customers with a personalized shopping experience (Verhoef et al., 2021). chatbots are among the most prevalent tools in e-commerce. They offer efficient, cost-effective, and instant customer service around the clock, providing customers with a conversational agent that enhances engagement and offers substantial benefits (Lu et al., 2019; Speicher et al., 2019; Toh & Tay, 2022).

Chatbots are computer programs that imitate human conversation to act as virtual assistants on e-commerce platforms (Fryer et al., 2019). They can provide customers with personalized and relevant responses and offer personalized recommendations and upsell opportunities that improve customers' online shopping journeys (Pantano & Pizzi, 2020; Prentice et al., 2020). It can generate instant responses 24/7 without the need for the customer to wait for a human agent to be available, and it can be programmed and designed to deal with a wide range of customer-service-related tasks, from product recommendation to tracking a shipment (Luo et al., 2019).

As the integration of chatbots in e-commerce customer service platforms can have significant effect on the customer-organization relationship. This can be achieved by providing a seamless and personalized interaction (Chung et al., 2020). However, designing and deploying chatbots are not straightforward. They must provide relevant information, understand customers' inquiries, and handle a variety of requests. Prior studies have discussed the challenges of designing AI-based chatbots (Svarajati & Tanaka, 2018; Vaddadi et al., 2023).

Despite the substantial benefits of chatbots in e-commerce, organizations face challenges integrating them into practice. Some customers still prefer to deal with a human agent, perceiving chatbots as lacking human touch and emotion (Følstad & Brandtzæg, 2017). Another challenge is that developing chatbots and other AI-based tools is complex, time-consuming, and costly (Jain et al., 2018).

As chatbots can provide a more efficient and convenient way for customers to interact with the organization, and as it offers numerous benefits for businesses too, there is still an ambiguity about the role that chatbots play in improving customer experience. This leaves managers and business practitioners in an uncertain position when formulating strategies for chatbot implementation. Most of the existing body of research has focused on general adoption of new technologies (Davis, 1989), customer satisfaction outcomes (Chung et al., 2020; Eren, 2021) or trust and acceptance (Araujo, 2018; Gefen & Straub, 2003). However, little attention has been given to the effects of responsiveness, Ease of Use, and personalization on enhancing customer experience. This research aims to study the impact of these factors on customer service experience in e-commerce to provide a holistic framework rather than addressing them in isolation.

Additionally, most of the empirical research has been conducted in East Asian or Western markets (Luo et al., 2019; Van Pinxteren et al., 2020). This leaves a gap in our understanding as the Middle East culture context is unique to the Western or East Asian contexts. Cultural context can strongly influence customer perception and behaviors in the digital services interactions (Megdadi, 2020; Qazi et al., 2022). Similarly, most of the existing literature examined the role of chatbots in retailing, hospitality, and banking services (Eren, 2021; Huang & Chueh, 2021; Prentice et al., 2020), little has been done in the telecommunications sector. telecommunications sector has its unique customer service challenges due to the service complexity a large customer bases. Customers in this sector often rely on chatbots for technical troubleshooting, billing inquiries, and service activation, which is substantially different from other sectors like retailing, hospitality, and banking.

1.1 Research problem

Although the integration of chatbots in e-commerce is growing, there is still a lack of clarity about the factors or chatbot performance dimension (responsiveness, Ease of Use, and personalization) that shape the customer experience. which leaves managers in an uncertain position when formulating strategies for chatbot implementation and designing them to achieve business goals. With better understanding and clearer perception of the role of each of these dimensions, managers can design a system that can predict better customer experience outcomes. Failing to do so might place organizations under the risk of failing to meet customer expectations, thereby weakening their digital services effectiveness.

1.2 Research questions

To address these gaps, the research is guided by the following questions:

- How do responsiveness, perceived Ease of Use, and personalization of chatbots influence customer experience in e-commerce?
- Which of these dimensions emerges as the strongest predictor of customer experience?
- Do demographic factors, such as gender, influence perceptions of chatbot performance?

By answering these questions, the study adds to the existing knowledge on chatbots and customer experience, and provides both practical and theoretical implications for managers and academics.

2. Literature Review

This study aims to integrate three chatbot dimensions that shape customer experience in an e-commerce platform. Each of these dimensions will be viewed through specific theoretical lenses: chatbot responsiveness through E-service quality theory, Ease of Use through technology acceptance model, and personalization through digital service encounter and social presence. Thus, creating a holistic paradigm that predicts service design stimuli that improve customer experience on e-commerce platforms.

2.1 Customer Experience

Customer experience became an essential concept in service marketing and a business priority (Gonçalves et al., 2020; Kranzbühler et al., 2018). It encompasses all of the interactions between the organization and the customer throughout the journey from discovering the product to the post purchase (Lemon & Verhoef, 2016). These responses can be characterized in many dimensions including but not limited to cognitive, social, emotional, and physical (Verhoef et al., 2009).

Early research in the context of customer experience identified several customer experience dimensions, including efficiency, fulfilment, system availability, and privacy (Parasuraman et al., 2005). But the rise of online platforms shifted the evaluation toward other dimensions such as convenience, personalization, and emotional connection (Verhoef et al., 2009). In order to effectively optimize customer experience, businesses focus on building their AI-based tools (specifically chatbots) with focusing on dimensions like responsiveness, perceived Ease of Use, and personalization (Araujo, 2018; Gefen & Straub, 2003).

The effects of these dimensions are not expected to be limited to how customers feel or behave during the interaction. It also shapes their future behavior such as loyalty and repeat purchase, and increases the propensity to do more business with existing customers (Al Kurdi et al., 2024; Chung et al., 2020; Jiang et al., 2022; Shahzad et al., 2024). It was also found that chatbots provide engaging and interactive service encounters (Eren, 2021). Recent research emphasized the dependence of customer experience on both functional quality and socio-emotional cues, social presence and anthropomorphism enhance engagement and continuance, thus highlighting the need to theorize a chatbot dimensions map and its contribution to customer experience outcomes (Nguyen et al., 2023).

2.2 chatbot Responsiveness and Customer Experience

Chatbot responsiveness refers to the readiness to help the client by offering accessible and instant handling of customers' inquiries, which means they are available to respond quickly when needed (Chung et al., 2020; Roy et al., 2018). Responsiveness plays a vital role in service quality and in forming the overall customer experience (Parasuraman et al., 1988), indeed, a quick and relevant responses to customers' inquiries lead to an engaging and seamless customer experience as it minimizes effort and alleviates the frustration (Luo et al., 2019). The responsiveness and the response time affects how customers feel comfortable and valued (Chung et al., 2020).

Chatbot responsiveness reflects helpful and timely response that reduces effort, hence contributing to higher service quality. Recent studies found that higher chatbot service quality in terms of timeliness, helpfulness, accuracy improves trust and experience quality, leading to a better customer experience (Shahzad et al., 2024).

Customers tend to use chatbots for tasks such as product inquiries and recommendations, order tracking, and resolving basic issue (Gnewuch et al., 2017; Luo et al., 2019). The core benefit of AI-based chatbots are the real-time support, customers appreciate instant responses when interacting with online customer service channels (Van Pinxteren et al., 2020). Therefore. It can be pivotal in assessing the quality and in the overall customer journey (Mende et al., 2019). Thus, we hypothesize the following:

H1: chatbot responsiveness positively influences the customer experience in e-commerce interactions.

2.3 Perceived Ease of Use and Customer Experience

The perceived Ease of Use refers to the extent of a person’s belief that using the online system doesn’t require a lot of effort. It is crucial for organizations in understanding how customers see and perceive their interaction with the brand (Davis, 1989). Chatbots are supposed to be easy to use. They are supposed to be simple and easy to navigate (Van den Broeck et al., 2019), when customers find chatbot easy to use and interact with. It makes their experience more enjoyable and less exhausting (Chung et al., 2020). The chatbot Ease of Use increases the users' satisfaction about the system (Huang & Chueh, 2021).

According to the Technology acceptance model (TAM), the customers perceived Ease of Use is considered one of the key aspects to predict the willingness of customers to accept new technologies and to adopt the usage of AI-based tools such as chatbots (Davis, 1989), if the design of chatbot interface does not provide easy and smooth interaction. It might negatively impact the customer experience. Studies show that low-effort interactions enhance the micro-journey touchpoints that constitute the larger service experience (Elkhatibi et al., 2024; Lemon & Verhoef, 2016; Retkutė & Davidavičienė, 2021). This effort reduction leads to reduce expectancy violations, which translates into a better customer experience, even in simple tasks (Cai et al., 2024; Toh & Tay, 2022).

H2: The perceived Ease of Use of chatbots has a significant positive effect on the customer experience in e-commerce.

2.4 chatbot Personalization and Customer Experience

Personalization is considered one of the fundamental drivers for a positive customer experience in online business (Verhoef et al., 2009), we can refer to a personalization system as a system that allows users to find information that meet their needs and interests between vast amounts of information in an accurate and quick manner (Kim et al., 2020). There are many methods of personalization including the leading agent method, the collaborative filtering method, and the rule-based filtering method (Kim et al., 2020). The main goal of personalization is to analyse the user’s search and text to improve the search performance of the tool, and eventually providing the user with a more accurate and relevant results that suits the user's interests and preferences (Kim, 2012).

Chatbots use customers' data to provide tailored and personalized responses, and providing customers with relevant information regarding their inquiries and recommendations (Ameen et al., 2021), which makes the interaction of the customer with the organization more meaningful and fruitful, and eventually enhancing the overall experience of the customer, and contributes to a more engaging experience (Følstad et al., 2018). Customers will perceive the interaction to be more valuable if they feel The chatbot understand their needs and preferences (Lemon & Verhoef, 2016). AI-driven predictive analytics can anticipate unarticulated customer needs and generate more relevant responses, strengthening chatbot personalization (Alshaketheep et al., 2024). Personalization enhances engagement and continuance with The chatbot, as it increases the relevance and provides customers with human-like responses, amplifying social presence (Cai et al., 2024). Social presence refers to the degree a technology like a genuine agent (Gefen & Straub, 2003), a considerable body of literature considered social presence as a predictor of trust, engagement, and chatbot use continuity (Chung et al., 2020).

H3: chatbot personalization enhances the customer experience in e-commerce.

A synthetic review of relevant literature (2022–2024) shows that chatbot service quality strengthens customer trust, loyalty, and the quality of interaction; Ease of Use smooths e-commerce interactions; and personalization improves the relational dimensions of customer experience. However, studying these dimensions of chatbot service quality as a holistic coordinated model is not notable, and evidence from the Middle East context is still scarce. The present study is designed to address these gaps and to create a holistic customer experience antecedents model (Cai et al., 2024; Jin & Youn, 2023; Nguyen et al., 2023; Ranieri et al., 2024; Shahzad et al., 2024).

3. Research Methodology

The methodology describes how data were gathered and analyzed. This study employed a quantitative approach to examine the relationships between different chatbot dimensions (responsiveness, perceived Ease of Use, and personalization) and customer experience. This study used an online survey to collect data from a convenience sample of e-commerce customers who have interacted with chatbots in the telecommunication industry in Jordan. These customers are supposed to have a past experience in interacting with a chatbot so they can provide insights on their experience regarding the research variables. The use of convenience sampling technique is needed due to the lack of a comprehensive sampling frame in the Jordanian telecommunication market. Customer experience should recur similarly in similar e-services context (Lynch, 1999); thus we treat our results as analytically generalizable to other similar sectors or markets.

Apart from the demographic data section, the study consisted of four parts, one part for each of the research variables; the first part was designed to measure the responsiveness of The chatbot. It consisted of four items on a seven-point scale anchored by (strongly agree, strongly disagree) adapted from (Chen et al., 2021). The second part measured the customers' perceived Ease of Use, the scale consisted of 6 items on a 7-point scale anchored by (strongly agree, strongly disagree) adapted from (Hess et al., 2014). The third part measured The chatbot personalization, the scale consisted of items on a 7-point scale anchored by (strongly agree, strongly disagree) adapted from (Liang et al., 2009). The last part of the questionnaire was designed to measure the customer experience and was adapted from (Kumar & Anjaly, 2017). It consisted of items on a 7-point scale anchored by (strongly agree, strongly disagree).

Table 1. Latent constructs and Survey Items

Construct	Survey Item
Personalization	This online brand understands my needs
	This online brand knows what I want
	This online brand takes my needs as its own preferences

Experience	My online retailer has a very easily navigated site
	I value social impact created by purchase with my online retailer
	My online retailer's brand reputation encourages me to buy
	Experience with other retailers encourages me to value my online retailer
	I value the aesthetics of the site of my online retailer
	Shopping with my online retailer gives a social image of being tech-savvy
Responsiveness	The chatbot replies quickly
	Getting in contact with the chatbot is easy
	The chatbot is always available when I need it
	The chatbot provides credible advice
Ease of use	Learning to operate Chatbot is easy for me.
	I find it easy to get Chatbot to do what I want it to do.
	My interaction with the Chatbot is clear and understandable.
	The Chatbot is flexible to interact with.
	It would be easy for me to become skillful at using the Chatbot
	Overall, I find the Chatbot easy to use.

The causality direction of the model flows from the construct to the indicators, thus, all latent variables were modelled as reflective (Coltman et al., 2008). Accordingly, we assessed reliability, convergent validity, and discriminant validity using reflective-model criteria (CR, AVE, HTMT with bootstrapped CIs).

The collected data from the questionnaire was then analyzed using SmartPLS software. Following Henseler et al. (2015), we re-estimated the measurement model, and we removed the overlapping item (customer experience 4) from the construct. we recalculated the Heterotrait–Monotrait ratio of correlations (HTMT) as well as the adjusted HTMT2 values with 5,000 bootstrap resamples to derive 95% confidence intervals. Results indicated that HTMT and MTMT2 values were below 0.90 and the upper bound of the bootstrapped confidence intervals did not include 1.00.

4. Data analysis and results

The survey was designed in Arabic to ensure proper comprehension of the respondents, although English is widely understood in Jordan, Arabic is the official language and it will be more suitable and convenient for respondents to handle a survey in Arabic, the researchers translated the survey into Arabic and back translated to English to ensure accuracy, few linguistic modifications were made to ensure proper understanding of the items and to ensure they measure what is supposed to be measured. the survey was distributed to 250 respondents in the Jordanian market, 206 survey responses were returned and valid for analysis. Participation was voluntary as the customers were selected in few selected branches of the telecommunication companies (Umniah, Zain, Orange) in the main cities in Jordan (Amman, Irbid, Zarqa).

We drew on established guidelines to justify our sample size. For multiple regression with three predictors, the minimum required sample size is below our achieved sample size (e.g. Cohen's power primer indicates ≈ 77 cases to detect a medium effect ($f^2 = .15$, while Green's rules of thumb suggest $N \geq 50 + 8m = 74$ for testing the overall multiple correlation) (Cohen, 2016; Green, 1991). And for a PLS-SEM context, the sample size required to reliably detect modest paths is about 80 responses (Kock & Hadaya, 2018). Our sample exceeds these benchmarks.

The response rate was around 82.4% which is considered relatively high (DeMaio, 1980). Around sixty percent of the sample were females (123 respondents), and most of the sample members were under 25, while almost half of the study sample used the e-commerce platforms for less than 5 years as shown in Table 2. The skewness toward younger adults may limit the generalizability of the results, but reflects the high adoption rates of digital self-service among youth adults (Lim et al., 2025).

Table 2. Descriptive Statistics

Profile	Description	Frequency	Percentage
Gender	Male	83	40.3
	Female	123	59.7
Age	Below 25	177	85.9
	25 - 45	25	12.1
	More than 45	4	1.9
How long have you been using E-commerce platforms	Less than 5 years	112	54.4
	5-10 years	65	31.6
	More than 10 years	29	14.1

The collected data from the questionnaire was then analyzed using SmartPLS software. constructs reliability and validity were analyzed using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). The Cronbach's alpha is used to assess the internal consistency reliability of the scales, table 3 shows high coefficient values for all constructs in the model as the minimum accepted or threshold is 0.70, Similarly, the Composite Reliability (CR) were all above the 0.7 standard values, ranging from 0.861 to 0.883. This indicated that the model constructs have a good reliability and consistency (Hair et al., 2021; Nunnally, 1978). We then calculated the constructs convergent validity (AVE) to which explains the items variance, all AVE values were above the 0.5 minimum threshold (Fornell & Larcker, 1981), and ranged between 0.578 and 0.683, thus showing convergent validity. Additionally, we tested the discriminant validity using the Heterotrait-Monotrait ratio (Henseler et al., 2015). As shown in table 4, HTMT ratios were between 0.626 to 0.870. Most construct pairs were below the conservative threshold of 0.85, except Experience–Responsiveness (0.870) which slightly exceeded the conservative threshold but remained within the acceptable lenient threshold of 0.90, showing adequate discriminant validity.

Table 3. Construct's reliability

Scale	Cronbach's Alpha	Composite reliability (CR)	Average variance extracted (AVE)	Number of items
Customer Experience	0.816	0.872	0.578	5
Responsiveness	0.784	0.861	0.608	4
Ease of Use	0.842	0.883	0.558	6
Personalization	0.767	0.866	0.683	3

Table 4. The Heterotrait-monotrait ratio (HTMT) – Matrix

	Ease of use	experience	personalization
Ease of use			
experience	0.693		

personalization	0.751	0.631	
responsiveness	0.771	0.870	0.626

The main statistical analysis in this research is Structural Equation modeling using SmartPLS software. We used PLS-SEM because our study emphasizes prediction and explanation of Customer Experience and the relative importance of its drivers over the reproduction of a covariance matrix (Henseler et al., 2016; Hair et al., 2021), Likert-type indicators typically show non-normal distributions; PLS-SEM is robust to such departures and supports out-of-sample predictive assessment (Q^2; PLSpredict), which we report. The structural model was assessed using path coefficients (β), t-values, and p-values. Results from bootstrapping as shown in table 5 confirmed all three hypotheses significant at the level 0.01 level, with responsiveness as the most influential driver of customer experience in this model ($\beta = 0.522$, $t = 9.153$, $p < 0.001$).

Table 5. Results of structural equation modeling analysis

	Path coefficient (β)	Standard deviation (Stdev)	t values	p values
Ease of use -> experience	0.158	0.059	2.874	0.008
personalization -> experience	0.214	0.067	3.169	0.002
responsiveness -> experience	0.522	0.057	9.153	<0.001

Thus, all hypotheses were confirmed. It was also found that chatbot variables (responsiveness, Ease of Use, and personalization) explained a significant portion of the variance in the customer experience (R^2=0.636). This indicates a strong explanatory power of the model (Chin, 1998). The R-squared (R^2) value of 0.636 (63.6%) indicated high explainability of the variance in the dependent variable by the independent variables (Personalization, Responsiveness, and Ease of Use). This suggests a strong relationship between the outcome and predictor, the p-value ($P < 0.001$) indicates that the model is statistically significant. This model provides a strong predictive capability for understanding how personalization, responsiveness, and ease contribute to customer experience.

The F squared values were evaluated to assess the individual contribution of each exogenous construct to the variance in customer experience. Results showed large effect of responsiveness (f^2 = 0.366) on customer experience, and small effects of both Ease of Use (f^2 = 0.027) and personalization (f^2 = 0.063). These results highlights responsiveness as the most influential driver of customer experience, which indicates the importance of prioritizing chatbots responsiveness over design simplicity or personalization when organizations have limited resources. This also confirms the earlier path coefficients where responsiveness had the largest effect on customer experience.

Table 6. F-squared value

	experience
Ease of use	0.027
personalization	0.063
responsiveness	0.366

To assess multicollinearity, we calculated the Variance Inflation Factor (VIF) values of the predictor constructs. Table 7 shows that all VIFs were below the maximum threshold of 3.3 as suggested by (Hair et al., 2021), VIF values were between 1.978 to 2.530. meaning that there is no collinearity concerns in this model and that the predictor constructs provide unique contributions to the variance explained in Customer Experience. Our VIFs values also indicates no serious common method bias as suggested by (Kock, 2015) as all of the VIFs are below 3.3.

Table 7. VIF values

	VIF
Ease of use -> experience	2.530
personalization -> experience	1.978
responsiveness -> experience	2.042

Fit indices indicated acceptable global model fit. The standardized root mean square residual (SRMR) was 0.091 for both the saturated and estimated models. This value falls below the recommended cut-off of 0.10, which indicates acceptable fit, although it is slightly above the stricter 0.08 benchmark sometimes suggested in the SEM literature. The SRMR result supports an adequate overall fit, and the strong explanatory and predictive values reported earlier provide additional evidence that the structural model is appropriate for testing the hypothesized relationships. Furthermore, predictive relevance was assessed via the blindfolding approach, Q^2 for Customer Experience was 0.92, which is well above the conventional thresholds (0.02 small, 0.15 medium, 0.35 large), indicating strong predictive relevance of the model for the endogenous construct.

Results of the independent T-test are presented below in Table 8. These results showed that there is a statistically significant difference between the two genders in their assessment of responsiveness at ($p < 0.001$) meaning that males and females perceive responsiveness differently, while no differences were found for gender in the assessment of Customer Experience, Ease of Use, and personalization at ($p = 0.392$, $p=0.077$, $p=0.089$ respectively). This finding may indicate the difference between the two genders in their expectancy of immediacy. This highlights the importance of understanding the users' demographics when designing a chatbot, as the customers' perceptions on different dimensions of chatbots service quality are not uniform across different customer groups.

Table 8. Independent T-Test Results for Gender Effect

	T value	P value
Customer Experience	-0.858	0.392
Responsiveness	-4.421	<0.001
Ease of use	-1.776	0.077
Personalization	-1.710	0.089

Results from bootstrapping are shown in Figure 1 below. It presents structural model results of the effects of Ease of Use, personalization, and responsiveness on customer experience, along with their respective path coefficients and significance levels.

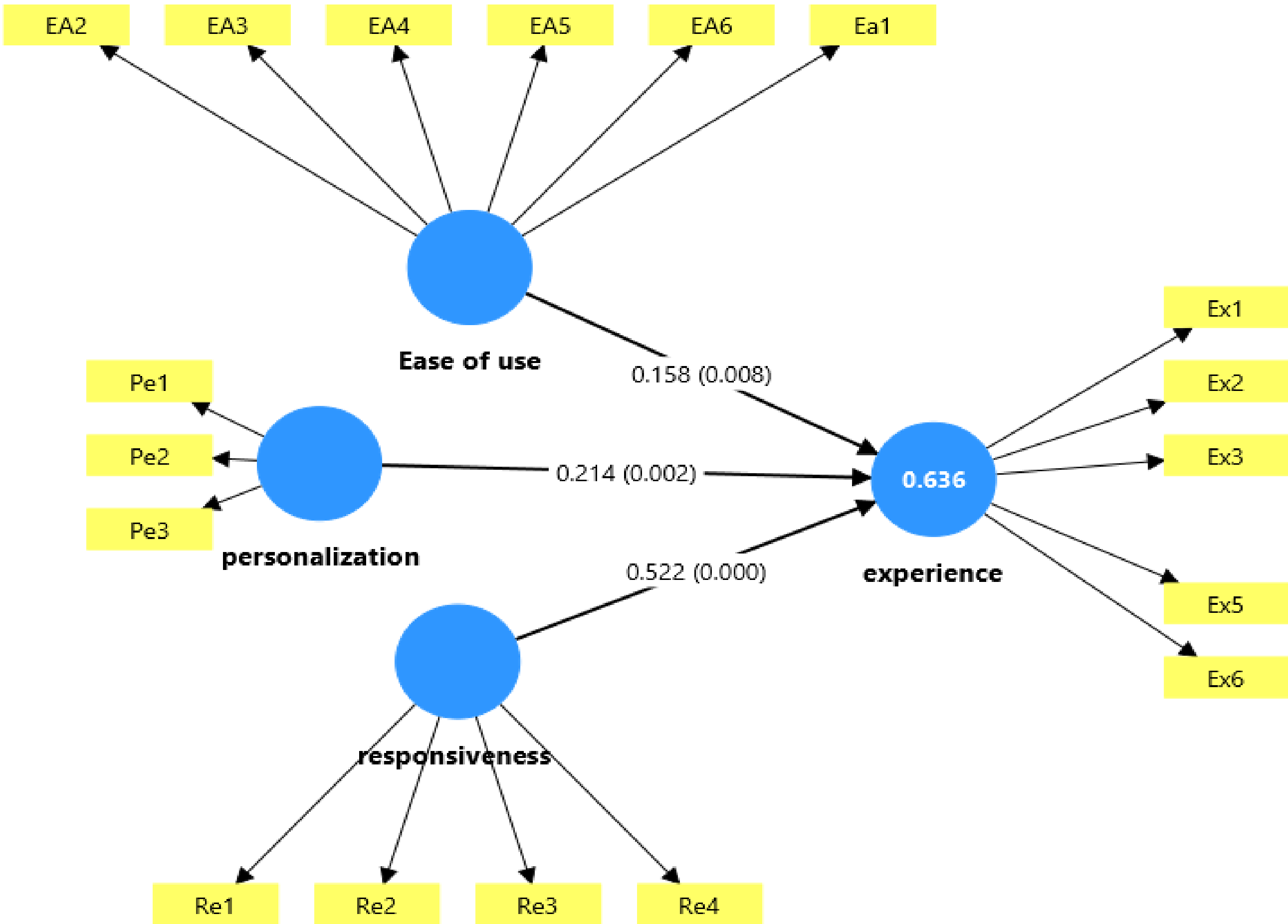

Fig.1: SmartPLS bootstrapping results

5. Discussion and Recommendations

These findings highlight the importance of the use of chatbots on the customer experience in e-commerce, our analysis for the data confirmed the three hypotheses, and showed that the three key variables (responsiveness, Ease of Use, and personalization) positively contribute to the customer experience. The high coefficient of responsiveness indicates that chatbot responsiveness is a crucial factor in enhancing the customer experience and in customer service. It leads to an engaging and seamless customer experience as it minimizes effort and alleviates the frustration (Luo et al., 2019). Our results aligned with previous studies that confirmed the essential role of responsiveness in improving customer service in e-commerce (Chen et al., 2021; Mende et al., 2019; Van Pinxteren et al., 2020). The setting of the telecommunications sector where support encounters and customer service are often time sensitive rationalize our findings. In this context, customers evaluate service through signals, and any delay is often interpreted as incompetency. chatbot responsiveness and latency are often associated with satisfaction and humanness, and as a factor that reduces risk under time pressure (Kim et al., 2025; Rese & Witthohn, 2025). Several studies indicated that the effects of timely and quick responses are conditional on task complexity and human support expectation; a customer is usually satisfied with the quick and timely response in the case of simple routine tasks, but when complexity arises, the need for human intervention (Casadei et al., 2022; Huang & Dootson, 2022). Therefore, we interpret the strong effect of responsiveness as partially detecting complexity in the early stages and minimizing the time to resolve customers' inquiries.

Our findings also found that Perceived ease of use significantly affects customer experience, customers appreciate the seamless interaction with the system and the easy interaction with it. This reduces the effort and increases the satisfaction (Chung et al., 2020; Huang & Chueh, 2021; Meyer & Schwager, 2007), these findings are consistent with previous studies (Bilgihan et al., 2016; Nissinen et al., 2024), our finding also aligned with the Technology Acceptance Model (TAM) framework by (Davis et al., 1989), which emphasizes the critical role of Ease of Use as one of the main determinants of technology acceptance. Ease of Use showed smaller effect than chatbot responsiveness to overall customer experience. This pattern is consistent with TAM where Ease of Use matters most in early adoption than late stages of it (Schepers & Wetzels, 2007).

Chatbot personalization plays an important role in shaping the customer experience and enhancing the online customer service. It helps in providing customers with relevant and accurate results that suit the customers'' preferences and interests (Ameen et al., 2021; Kim, 2012), our findings confirmed this positive effect and were aligned with previous studies on the effect of chatbots personalization on customer experience (Brandtzaeg & Følstad, 2017; Følstad & Brandtzæg, 2017). In the telecommunication context, customers prioritize accuracy and speed over tailor and personalized response. Furthermore, the role of personalization and its algorithms is unclear, although it helps in routing issues or providing more relevant content; it can raise privacy issues that might harm their overall experience (Moravec et al., 2025).

To enhance customer experience, organizations of e-commerce should ensure that they are providing their customers with real-time responses that are capable of handling customers' inquiries efficiently. Organizations should enhance the responsiveness of chatbots by continuous updates and integration with their systems, one of the key aspects of this issue is employing machine learning techniques in their systems to ensure the accuracy and relevance of the responses provided to their customers. Practically, managers can ensure the following: Monitoring the first-response and defection without delays rules; developing a proactive escalation when solution is not resolved below the threshold time; recovery protocols and remedy procedures. With a proper application of these procedures, managers can ensure an effective and efficient application of chatbot responsiveness (Rese & Witthohn, 2025).

Businesses should also invest in developing a user-friendly, easy to use interfaces of the chatbots, and to rectify any possible barriers or difficulties customers might have during their interaction with the interface of The chatbot, as these systems are supposed to be easy and intuitive to use. Personalization plays a pivotal role in enhancing the customer experience and improving the customer service, thus it is crucial for organizations to enhance the ability of their systems to deliver personalized recommendations and responses, integrating machine learning techniques into their systems is vitally important to improve the ability of the system to predict and understand the customers' needs and preferences. Pairing The chatbot system with privacy controls could alleviate the customer concerns and enhance the performance of The chatbot (Moravec et al., 2025). Continuous improvement and monitoring the chatbot interactions assist organizations to better serve customers with evolving needs and preferences. This gives organizations the opportunity to identify areas of improvement and be adaptive to changing customer expectations. These recommendations help organizations to foster better customer relationships. Future research could be conducted with an expanded model that might include other variables such as empathy, security, privacy, and interface aesthetic. This could provide more insightful results and deeper understanding.

Our findings revealed that gender plays a significant role in the assessment of responsiveness, meaning that males and females perceive responsiveness differently. These results are consistent with the existing literature that suggest that females prioritize interpersonal communication in a digital interaction, while males focus more on functional aspects of the interaction (Qazi et al., 2022). Although businesses are adopting a universal design that meet the needs for different demographics (Klaus et al., 2024). They still need to have a robust understanding of the gender dynamics in the digital environment interactions, our research findings are significant in creating this understanding and providing insightful thoughts about role of gender and other demographics in creating a better customer experience. Further research is needed to not only validate this research findings, but to contribute to a more comprehensive understanding of the gender dynamics in digital environment, contributing to guiding organizations to create a more favourable and satisfying user experience.

The study is not without limitations, which provides direction for future research. This research focused on the telecommunications sector in Jordan, which limits the generalizability of the findings. Finding from our research can be interpreted as analytically generalizable to the same sector of the study, however, we encourage cross-sector or cross-national replication in future work, across cultural contexts would enrich understanding of sector-specific and cultural variations in chatbot performance. Similarly, more research need to be done on different demographic groups (age, gender) to validate the results and increase the generalizability of the paradigm.

The present study provides strong evidence of the direct effects of the model. However, it did not test possible mediation or moderation effects. Future research should address these pathways and offer better understanding of how and under what conditions chatbots can shape customer experience. Future research should examine whether constructs such as trust, empathy, or service failure recovery mediate the relationship between chatbot responsiveness and customer experience. Furthermore, robustness checks such as alternative model specifications or predictive validity tests could be applied to confirm the stability of the findings.

6. Conclusions

The findings of this research confirmed the significant proposed role of AI-powered chatbots in improving the customer service. AI chatbots enhances customer experience by providing personalized and relevant responses to customers, thus improving their satisfaction level and ultimately their loyalty by tailoring responses and recommendations that align with their needs and preferences (Shahzad et al., 2024). Predictive analysis allows chatbots to understand customers better and anticipate their needs, enabling a more empathetic and proactive interaction. Ease of Use also plays a significant role, a friendly and easy to deal with chatbot provides smooth interaction with customers (Chung et al., 2020). Additionally, the responsiveness of The chatbot was found to be essential, emphasizing the importance of real-time support that enhance the customers' satisfaction and minimize their efforts and frustration (Luo et al., 2019). Furthermore, our findings showed that gender plays an important role in customers' perceptions of The chatbot responsiveness, while no statistically significant differences the two genders for Ease of Use and personalization. This emphasizes the importance of customers' demographics in designing chatbots interfaces to create more favourable way.

The age distribution of the study sample was highly skewed; the majority of the respondents were below 25 years of age, which could limit the generalizability of the findings. Likewise, a single-industry focus limits the external validity. Building on these limitations, we propose a forward-looking research agenda. Future research could explore other moderating variables to create an enhanced understanding of the interrelatedness of the model's elements. Comparative research across industries and cultural contexts is needed to test the robustness of chatbot effects under varying service environments. Moreover, future research should explore the integration of emerging technologies such as AI-based chatbots, VR, metaverse-based service encounters, to better understand how these technologies shape the customer experience in the digital world.

These findings provide strong evidence to enhance our understanding on integrating AI-powered chatbots technologies as a strategic tool in customer service and customer interactions.

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