Exploring the predictors of chatbot service quality

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Abstract. The ever-growing applications of AI-enabled agents in customer relationship management require a comprehensive understanding of customers' perception of the services provided by chatbots, which is an underexplored research area so far. To fill this gap, this study draws on the literature on human-chatbot interaction to identify and test the main determinants of customers' perception of the quality of chatbot services. To test our research model, data was collected from 529 respondents who had interacted with chatbots as part of their shopping experience and analysed using partial least squares-structural equation modelling. The analysis confirmed that a positive evaluation of service quality is predicted by service convenience, competence and functional congruity. Our study contributes to the literature on customer-chatbot interactions by providing insights into service quality perception by customers in the context of chatbot services.

Keywords: artificial intelligence; chatbot; service quality; automation

1 Introduction

Artificial intelligence (AI) is continuing to change the nature of customers' service experiences and their relationships with service providers, and it is doing so at a rapid pace (Hollebeek, Sprott, & Brady, 2021; Van Doorn et al., 2017). AI has enabled the automation of the customer journey, whereby services that were undertaken by human agents are now executed by machines, such as chatbots. Chatbots represent disembodied conversational agents that do not have a physical presence, but mimic the conversational characteristics of human–human interaction (Jurafsky & Martin, 2008). By combining AI with natural language processing, chatbots are capable of understanding the context of what the customer is saying, offering more than just responses to specific commands. They learn from experience, becoming smarter with each conversation (Schlicht, 2016). Due to advanced communication and intelligent functionality, chatbots can be used in a manner that is complementary to human service providers or even replace humans completely (Van Doorn et al., 2017). The evolving capabilities of chatbots have led to predictions of growth in the chatbot market (Bozic & Wotawa, 2018). The total value of eCommerce transactions facilitated by chatbots is projected to amount to $112 billion by 2023 (Jupiter Research, 2020). The ever-growing integration of AI-enabled agents in the service sector requires a more comprehensive understanding of customers' perception of the services provided by chatbots.

Within the emerging body of research on human-chatbot interaction, researchers have been exploring chatbot communicative, problem-solving and interactive competencies (Chung, Ko, Joung, & Kim, 2020; M.-H. Huang & Rust, 2018; Lee & Choi, 2017; Zarouali, Van den Broeck, Walrave, & Poels, 2018). The studies explored the fit of those competencies to users' needs (Araújo & Casais, 2020; Van den Broeck, Zarouali, & Poels, 2019; Zarouali et al., 2018) and operational aspects of service delivery (Ameen, Tarhini, Reppel, & Anand, 2021; Hari, Iyer, & Sampat, 2021; Mostafa & Kasamani, 2021). Although chatbot benefits and capabilities are the enablers of customer-chatbot interaction, their role in service quality evaluation has not been explored. Hence, in this study, we aim to address a gap in the literature by examining the factors that impact the evaluation of chatbot service quality.

2 Literature review

Chatbots are defined as "*system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organisation's customers*" (Wirtz et al., 2018). The integration of chatbots in service management to efficiently process queries, interact and customise communication has been reshaping consumption and brand engagement experiences, influencing customer pre-purchase and post-purchase decision-making (Chung et al., 2020; Wirtz et al., 2018; Youn & Jin, 2021). The factors shaping customers' perception mainly concern chatbots' competencies, functional utility for service delivery and operational aspects of interaction (Chung et al., 2020; Croes & Antheunis, 2021; Hari et al., 2021; Lee & Choi, 2017).

Competencies refer to expertise in processing routine and non-routine inquiries, solving problems, and demonstrating empathy and friendliness, manifested in communication through verbal cues (Chung et al., 2020; Croes & Antheunis, 2021; M.-H. Huang & Rust, 2018; Lee & Choi, 2017; Van den Broeck et al., 2019; Zarouali et al., 2018). AI agents' competences in terms of helpfulness, interactive capabilities and response accuracy, drive service satisfaction (Chung et al., 2020; Go & Sundar, 2019; Grimes, Schuetzler, & Giboney, 2021; Lee & Choi, 2017; Zarouali et al., 2018). Also, error-free communication can significantly contribute to the intention to use chatbots (Sheehan, Jin, & Gottlieb, 2020). Individuals tend to positively respond to competent conversational agents, because chatbots enhance the perception of their human-likeness (anthropomorphism). They have the ability to project themselves as humans in communication, thus creating a feeling of social presence (Sheehan et al., 2020; Tsai, Liu, & Chuan, 2021; Youn & Jin, 2021) and decreasing users' psychological reactance (response to the threat to personal freedom) (Pizzi, Scarpi, & Pantano, 2021).

The functional utility of conversational agents is evaluated in relation to particular use contexts. The utility of agents can be assessed in terms of their relevance to interaction scenarios, such as providing updates, processing claims, purchases or bookings (Van den Broeck et al., 2019; Zarouali et al., 2018). The functional utility factors (i.e. service usefulness, relevance and compatibility with customers' needs) were found to improve customers' attitude towards a product or brand. In addition, these factors can impact the likelihood and willingness to buy and recommend a brand's offerings (Araújo & Casais, 2020; Van den Broeck et al., 2019; Zarouali et al., 2018).

Finally, the operational aspect of interaction refers to the ease with which humans interact with chatbots and the ability to obtain information at a time convenient for customers. Ease of use and time convenience are important for customers' perception of services (Hari et al., 2021; Mostafa & Kasamani, 2021). Such factors contribute to the formation of trust in chatbots, and, in turn, increase chatbot usage intention and engagement (Mostafa & Kasamani, 2021). Given the above, the next section discusses the role of the identified three groups of factors in service quality perception.

3 Hypothesis development

In the context of customer-chatbot interaction, a chatbot's competence refers to its expertise and the knowledge that underpins the outcomes of interaction with customers in terms of addressing their concerns, ensuring efficient communication, providing reliable information and solutions to inquiries (Chung et al., 2020; Yen & Chiang, 2020). Competence is dependent on the intelligent capabilities of chatbots that enable them to learn and adapt their responses based on users' prior interaction, process routine and non-routine tasks, and complex inquiries (Godey et al., 2016; M.-H. Huang & Rust, 2018; Moussawi, Koufaris, & Benbunan-Fich, 2020). Chatbot competencies can drive service acceptance (Chung et al., 2020; Pillai & Sivathanu, 2020; Pizzi et al., 2021; Wirtz et al., 2018). They can also contribute to the development of positive beliefs about the chatbot (Moussawi et al., 2020). For example, the perception of the intelligence of conversational agents and expertise strengthens trust in the technology (Moussawi et al., 2020). The trustworthiness of an agent is, in turn, important to encourage purchasing behaviour (Liew & Tan, 2018; Yen & Chiang, 2020). Given the role of competence in the perception of conversational agents, we propose that:

H1. Perceived chatbot competence is positively related to the perceived service quality of chatbots.

The literature on conversational agents suggests that the use of technology in managing customer inquiries offers greater convenience than services involving human interaction (Hagberg, Sundstrom, & Egels-Zandén, 2016). While customers' communication with human agents often results in long queues and delays in service delivery due to human inability to deal with a big workload (Demoulin & Djelassi, 2013; Kumar, Kalwani, & Dada, 1997), chatbots can enhance the experience by providing real-time interaction (Hagberg et al., 2016). As a result, the convenience of chatbot services increases the intention to continue using brand offerings (D.-H. Huang & Chueh, 2021). In addition, in line with findings from the service marketing literature, convenience predicts a positive evaluation of service performance and post-performance behaviour (Chen, Hsu, & Lee, 2020; Roy, Shekhar, Lassar, & Chen, 2018; Su & Teng, 2018). Hence, we hypothesise that:

H2. Perceived service convenience is positively related to the perceived service quality of chatbots.

Functional congruity is a measure of how useful the functions of a product or service are to an individual for implementing the required tasks (Sirgy, Johar, Samli, & Claiborne, 1991; Sop & Kozak, 2019). Chatbot functionality refers to responding to inquiries, facilitating communication with brands and resolving issues related to brand products and services (Chung et al., 2020; Van den Broeck et al., 2019; Zarouali et al., 2018). Therefore, it can be assumed that consumers will evaluate them high on the functional congruity scale. In addition, prior research confirmed the effect of the usefulness of chatbots and service-task fit on service quality and patronage intention (Dedeke, 2016; Zarouali et al., 2018). Given the above, we hypothesise the following:

H3. Perceived functional congruity is positively related to the perceived service quality of chatbots.

4 Methods

4.1 Data collection and measurements

We designed a cross-sectional survey, consisting of questions measuring the constructs in the research model and the socio-demographic profile of the respondents. To answer the questions, respondents were requested to refer to their most recent encounter with a chatbot service. Prior to collecting the data, a pilot test using 15 responses was conducted to ensure the clarity of the questions and the structure of the survey. The final version of the survey was distributed to the participants, who were recruited via a consumer panel based in the United Kingdom, using a purposive sampling technique. Our sample consisted of 529 respondents who have used chatbots as part of their shopping experience. 64.3% of the respondents were female, 29.5% had a graduate degree, 37.4% were aged 20-29 years, 48.2% had an annual income of £24,999 or lower and 28.4% of them had their first interaction with a chatbot less than one year ago.

Measurement items and the scales were adopted from previous studies (Table 1). The constructs were measured using a 7-point Likert scale, ranging between “1 = strongly disagree” and “7 = strongly agree”, with the mid-point being “4 = neither agree nor disagree”.

Table 1. Measurement items

Items	Factor Loading

Chatbot competence	
(R. Huang & Ha, 2020)	
CC1	
CC2	0.940
CC3	0.940
CC4	0.963
CC5	0.880
Service quality	
(Wolfinbarger & Gilly, 2003)	
SQ1	
SQ2	0.917
SQ3	0.924
SQ4	0.745
Convenience	
(Collier & Sherrell, 2010)	
C1	0.875
C2	0.906
C3	0.906
C4	0.897
Functional congruity	
(Sop & Kozak, 2019)	
FC1	0.949
FC2	0.947
FC3	0.956
FC4	0.916

4.2 Data analysis

For the empirical analysis of the data, we adopted partial least squares-structural equation modelling (PLS-SEM), which offers a higher level of flexibility than covariance-based structural equation modelling (CB-SEM) (Joe F Hair Jr, Howard, & Nitzl, 2020). The statistical analysis was performed in two steps: first, the measurement model analysis; and second, the structural model analysis after the validation of the measurement model. The hypothesised model was estimated using SmartPLS3 with a bootstrap re-sampling procedure using 5000 sub-samples, which were randomly generated in the analysis process (Joe F Hair Jr et al., 2020).

5 Results

The first stage of assessing the measurement model was to check the reliability and validity of the factors and their measurement items (Table 2). In terms of the reliability, the Cronbach's alpha and composite reliability values (C.R.) for all factors were above the threshold value of 0.7 (Joseph F Hair Jr, Hult, Ringle, & Sarstedt, 2021). In terms of convergent validity, the average variance extracted (AVE) values were all above the threshold value of 0.5. All factor loadings were above the threshold value of 0.7 (Joseph F Hair Jr et al., 2021). We assessed the measurement model in terms of discriminant validity using the cross-loadings, Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio (HTMT) (Tables 2 and 3). The Fornell-Larcker Criterion was examined by comparing the square root of the average variance extracted for each construct with correlations among the latent variables (Fornell & Larcker, 1981). For HTMT, the values are lower than the recommended value (Henseler, Ringle, & Sarstedt, 2015). Finally, we assessed collinearity in the data and the analysis showed that the values were lower than the threshold value of 3.3 (Petter, Straub, & Rai, 2007).

Table 2. Reliability, Validity, Fornell-Larcker Criterion

	α	rho_A	C.R.	AVE	1	2	3	4
1. Chatbot competence	0.949	0.949	0.963	0.867	0.931			
2. Convenience	0.917	0.921	0.942	0.803	0.489	0.896		
3. Functional congruity	0.957	0.958	0.969	0.887	0.395	0.385	0.942	
4. Service quality	0.833	0.892	0.898	0.748	0.344	0.223	0.216	0.865

Table 3. Heterotrait-Monotrait Ratio (HTMT)

	1	2	3	4
1. Chatbot competence				
2. Convenience	0.735			
3. Functional congruity	0.639	0.728		
4. Service quality	0.723	0.819	0.840	

The results of the structural model showed that all of the hypothesised direct relationships were significant (Table 4). As such H1, H2 and H3 were all supported.

Table 4. Structural model

Hypothesis	Relationship	Original sample	Sample mean	Standard deviation	*t* statistics/ significance
H1	Chatbot competence -> service quality	0.480	0.481	0.055	8.792***

H2	Convenience -> service quality	0.240	0.238	0.035	6.797***
H3	Functional congruity -> service quality	0.222	0.224	0.053	4.189***

6 Discussion

The analysis of the determinants of chatbot service quality shows that customers evaluate service quality based on the benefits they receive from interaction in terms of convenience, competence and functional congruity. These factors refer to the process and outcome quality dimensions of chatbot services. As demonstrated by its moderate effect size, the strongest of all predictors is perceived chatbot competence. The relationship between competence and service quality means that individuals appreciate chatbots' capabilities to keep up communication, provide credible and reliable information and address inquiries. It is not surprising that competence is critical for customers, given the ample evidence in the literature about the intelligent capabilities of AI-enabled conversational agents (Godey et al., 2016; M.-H. Huang & Rust, 2018; Moussawi et al., 2020), and their role in driving technology acceptance (Pillai & Sivathanu, 2020; Pizzi et al., 2021; Wirtz et al., 2018). Secondly, service convenience was also found to be related to service quality. Interaction with chatbots should be both convenient in terms of access to service and efficient in terms of the time and effort spent at any stage of the customer journey. The result of path analysis is in line with the evidence from the service marketing literature, suggesting that convenience is important for a positive evaluation of service performance (Chen et al., 2020; Roy et al., 2018; Su & Teng, 2018). Also, this research complements existing evidence related to AI-enabled conversational agents, postulating that digital assistance provides a superior experience for customers in managing their inquiries compared to interaction with human agents, as it helps avoid long queues and feedback delays (Hagberg et al., 2016). Finally, the confirmed positive relationship between perceived functional congruity and service quality means that the evaluation of chatbot services is contingent on the degree to which these services meet customers' expectations. This finding is consistent with research exploring the functional congruity of services in other contexts (Sirgy et al., 1991; Sop & Kozak, 2019) and confirms the dependence of service quality on service-task fit (Dedeke, 2016). The significant role of functional congruity was expected, as chatbots were designed to respond to inquiries, facilitate communication with brands and resolve problems that customers face in different scenarios (Chung et al., 2020; Van den Broeck et al., 2019; Zarouali et al., 2018).

7 Conclusion

7.1 Theoretical contributions and managerial implications

Our findings contribute to the existing literature by exploring service quality in the context of chatbot services. Further to the prior research that encouraged the investigation of factors affecting customers' perceptions of their interactions with chatbots (Kull, Romero, & Monahan, 2021; Tsai et al., 2021; Youn & Jin, 2021), this study confirms that service quality assessment is predicted by the interactional aspects of chatbots, namely service convenience, chatbot competence and functional congruity. These findings have important implications for companies using chatbots for automating their services or planning to use chatbots in the future. It is important for such brands to focus first on technical attributes (i.e. the convenience, benefits and functionality of chatbots) to improve the perception of service performance. On the one hand, brands should focus on increasing the scope of embedded chatbots and improving their functionality for ensuring a positive customer experience. On the other hand, firms should communicate to their target audience how useful automating services with chatbots is for ensuring service convenience (i.e. being able to use a chatbot to communicate with the brand any time and anywhere) and providing effective, timely and accurate responses to customers' inquiries.

7.2 Future research suggestions

The study is not without limitations, which could be addressed in future research. First, our research focused on consumer interactions with chatbots. Future studies could focus on examining brand-related factors in customers' interaction, which would explain the effect of variables on service perception that are not related to chatbots. Second, future research could focus on other types of AI-based products, such as voice assistants and robots. Such an approach could help explain the impact of audio and visual cues on the individual's perception of machine competence, which could be rooted in the perceived agent's anthropomorphism. Third, future research could explore the moderation role of the factors drawing on consumer psychology, such as ideological views (luddites vs technopians), which could potentially explain the individual difference in service perceptions. Finally, future studies could focus on generational marketing and chatbot interactions, for example, by comparing how Generation Z and millennial consumers interact with and assess chatbots.

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