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The effects of chatbots' attributes on customer relationships with brands: PLS-SEM and importance–performance map analysis

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Received 28 February 2022
Revised 14 June 2022
Accepted 21 July 2022

Abstract

Purpose – Many firms are investing in digital services to improve customer experiences. Virtual service agents, or "e-service agents" ("e-agents") such as chatbots, are examples of these efforts. Chatbots are types of virtual-assistant software programs that interact with users through speech or text. This paper aims to investigate whether the perceived hedonic and utilitarian attributes of chatbots can influence customer satisfaction and, consequently, their relationships with brands.

Design/methodology/approach – Data were collected through a questionnaire-based survey among a sample of Italian consumers. A convenience sampling technique was used. Data were then analyzed through Partial Least Squares Structural Equation Modeling to provide a prediction-oriented model assessment. The findings were then complemented with an importance–performance map analysis (IPMA) to gain more detailed insights and actionable guidelines for managers.

Findings – The findings highlighted that the perceived hedonic and utilitarian attributes of chatbots positively influenced customer satisfaction and improved customer relationships with the brands. However, the IMPA highlighted that the performance levels of two most important attributes – system quality and experience with chatbot – could be improved resulting in additional improvements of customer satisfaction.

Practical implications – This study suggests the importance of firms' investments in and adoption of e-agents to strengthen consumer–brand relationships and of considering both the hedonic and utilitarian attributes of their e-agents.

Originality/value – This article attempts to enrich and consolidate the growing body of literature concerning the impacts of new technologies – and, specifically, chatbots – in service marketing.

Keywords Chatbots, e-service agents, New technologies, Customer satisfaction, Consumer–brand interaction

Paper type Research paper

1. Introduction

Technological advancements are changing the ways through which firms can manage their customer interactions and, consequently, the customer experience (Chung *et al.*, 2020). Among the emerging technologies, Artificial Intelligence (AI) is considered a particularly disruptive technology capable of radically changing firm–customer relationships in every sector (Campbell *et al.*, 2020). Kaplan and Haenlein (2019, p. 15) define AI as a "*system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation systems.*" The underlying idea of AI is that, thanks to the use of software and hardware, firms can analyze data and provide real-time interactions with customers, making technology-based interactions more human and customer-centric (Hoyer *et al.*, 2020; Libai *et al.*, 2020). Therefore, many marketing opportunities can derive from AI applications (Martínez-López and Casillas, 2013).

Consequently, many firms are investing in digital services to improve customers' experiences. Virtual service agents, or "e-service agents," such as chatbots (an AI application),

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The TQM Journal
Emerald Publishing Limited
1754-2731
DOI 10.1108/TQM-02-2022-0080

are examples of these efforts (Trivedi, 2019). A chatbot is an instant-chat service able to operate similarly to an offline service agent (Chung *et al.*, 2020). The most popular chatbots include personal assistants like Alexa, Siri and Cortana. Indeed, a chatbot interacts in a familiar way with consumers, and its responses can consist in voice or text messages, images and so on. Like those of offline service agents, the roles of chatbots are becoming central in determining customer satisfaction. Indeed, chatbots represent the brand in customer relationships (Chung *et al.*, 2020; Zarouali *et al.*, 2018).

However, despite the increasing relevance of this topic, academic research into the role of chatbots in influencing customer satisfaction still remains scant (Hoyer *et al.*, 2020). Specifically, there is a need to assess how chatbots should be designed to satisfy customers and improve their attitudes toward the brands represented. This study addresses this gap and investigates whether perceived hedonic and utilitarian attributes of chatbots can influence customer satisfaction and, consequently, the customer–brand relationship. For this purpose, a model comprising both the hedonic and utilitarian attributes of chatbots is developed and estimated. Moreover, to gain more detailed understanding and enrich the practical implications of the findings, the estimation of the model is complemented with importance–performance map analysis (IPMA).

The remainder of the paper is structured as follows. First, a review of previous studies on how chatbots affect customer satisfaction is provided. Next, the research model and hypotheses are presented, followed by a description of the methods and results. A discussion of the findings and conclusions completes the paper.

2. Theoretical background and hypotheses

Technology has assumed a key role in enabling companies to achieve competitive advantage (Chaiprasit and Swierczek, 2011). At the same time, in today's highly globalized competitive environment, companies are paying extreme attention to total quality management (TQM) methods, tools and techniques. Continuous improvement, innovation and standardization through TQM play a key role in increasing competitiveness (Tasleem *et al.*, 2019).

Following this perspective, from the management point of view, it therefore becomes essential to integrate elements of technology management (TM) and TQM. The first is related to dimensions such as product technology, process technology and information technology and more recently industry 4.0 and Industrial Internet of things. The second is both a philosophy and a strategy oriented toward continuous change (de Souza *et al.*, 2021).

Although there is still no agreement on the factors that constitute TQM, many researchers have attempted to overcome this lack of consensus through the use of a multidisciplinary approach. This work has led to the identification of the following six factors as the elements that make up TQM: leadership, strategic planning, customer focus, workforce focus, process management, and information and knowledge management (Agarwal, 2017). Hence, again, technology plays a fundamental role for quality management and improvement. Moreover, these factors represent the components of one of the world's major awards for excellence namely the Malcolm Baldrige National Quality Award, established by the U.S. Congress in 1987. The award aims to promote a culture of quality, raise awareness of the importance of quality management and give recognition to organizations that have implemented a successful quality management system (Tasleem *et al.*, 2019). TQM and technology are thus becoming two key elements of successful organizations that complement and influence each other (Brah and Lim, 2006; Chiarini, 2020; Prajogo and Sohal, 2006).

Among the multiple technologies which have the potential to contribute to quality improvements, chatbots are exponentially gaining popularity in many sectors, such as education and health (Laranjo *et al.*, 2018; Pérez *et al.*, 2020). However, it is in the area of firms' customer services that chatbots have the greatest application. In this context, as the competition has increased, providing quality customer service has become a strategic element for a firm's success (Scheidt and Chung, 2019). Thus, service agents who personally interact with customers in representing the brand are central in solving customer problems and play fundamental roles in determining customer satisfaction. Due to the advent of digital technologies, firms increasingly are shifting to digital services, and the roles of service agents are changing profoundly. Indeed, many firms are transforming their traditional customer-service approaches to digital methods (Cheng and Jiang, 2022). E-service agents, such as chatbots, are new technology tools that attempt to satisfy customers in a similar way as offline service agents (Chung *et al.*, 2020). Indeed, chatbots are virtual assistants that simulate human conversations, not only by providing information but also by interacting, using a familiar language and attempting to transmit emotions (Hoyer *et al.*, 2020; Schmitt, 2019). Clients can interact with e-service agents from any location on a 24-h basis (Cheng and Jiang, 2022). As a result of this digital revolution, people must increase their technological ability, while the technology itself must become humanized (Schmitt, 2019). Chatbots are crucial in determining customer satisfaction and, therefore, in enhancing the brand relationship.

To analyze these effects, we follow the Consumer Acceptance of Technology (CAT) model (Kulviwat *et al.*, 2007). Unlike the traditional Technology Acceptance Model (Davis, 1989), which considers only cognitive elements, the CAT model also includes affective elements. This aligns with the work of several researchers (Fiore *et al.*, 2005; Nasco *et al.*, 2008), who suggest that in consumer relationships, technology must reach two types of goals: utilitarian and hedonic. Utilitarian goals are guided by cognitive elements and oriented to problem-solving (Dhar and Wertenbroch, 2000). These components are connected strictly to the technology's analytical characteristics. They represent the value derived from elaborating on the information received by the chatbot (Hoyer *et al.*, 2020). Hedonic goals are related to affective aesthetics – fun and enjoyable elements (Batra and Ahtola, 1991). They represent the value that consumers receive from emotional stimulation (Hoyer *et al.*, 2020). In our model, we identified two utilitarian elements in particular – information quality and system quality – and one hedonic element related to the chatbot experience.

Information quality represents the semantic success of the technology (DeLone and McLean, 1992). In general, the concept encompasses both the intrinsic and extrinsic elements of information quality. Specifically, the term "intrinsic elements" refers to objective elements, such as the provision of correct, credible and congruent information. These are important aspects that cannot, however, be separated from extrinsic considerations relating to the context in which they are applied (Lee *et al.*, 2002) and representational aspects (Wang and Strong, 1996). Contextual elements involve the completeness and currency of information. From this point of view, one must evaluate the quality of the information to the users and whether the information provided by the technology is capable of helping them complete an activity – for example, making a decision (Nelson *et al.*, 2005). The representational component involves the way in which the presentation of the information (the format) allows the receiver to better understand and interpret the information itself. In conclusion, information quality encompasses the accuracy, currency, completeness and format of the information, shaping perceptions of quality in the context of use. Following this reasoning, the information provided by a chatbot should be relevant, correct, accurate, credible, and, of course, useful (Chung *et al.*, 2020; Zarouali *et al.*, 2018). The literature also highlighted that poor information quality can diminish the total performance of a firm by increasing costs (Swanson, 1997). Thus, the role of the communicator – even if it is computer-mediated – becomes fundamental. In any case, consumers must have the perception that the chatbot is able exactly to understand their problems and provide appropriate answers. Chatbots must therefore be credible, experienced and competent (Chung *et al.*, 2020). According to Trivedi (2019), the quality of information offered by chatbots is critical in determining the customer experience. If the information is not correct, accurate or up-to-date, it can lead to a negative perception of the entire business and in particular to the belief that the company's offerings (of products/services) are of limited quality (Gao *et al.*, 2015). Based on these arguments, we hypothesize the following:

H1. The quality of the information provided by chatbots has a positive impact on customer satisfaction.

System quality is related to the technical aspects of a chatbot. In particular, the quality of a chatbot is determined by aspects such as usability, reliability, availability, adaptability and timeliness (Trivedi, 2019). "Usability" refers to the ease of use of a chatbot. In particular, if consumers perceive a chatbot as difficult to use, it can negatively influence customer satisfaction. Reliability involves the ability to interact with the chatbot continuously, at any time and in any place. "Adaptability" refers to the capacity to keep up with changing developments. Simultaneously, consumers expect that a chatbot's answer is given in a couple of seconds. If the time is too long, this can negatively influence customer satisfaction (Chung *et al.*, 2020; Trivedi, 2019; Zarouali *et al.*, 2018). Therefore, we hypothesize the following:

H2. System quality has a positive impact on customer satisfaction.

In general, customer experience has become a key factor for the success of a business. In the digital age, when enterprises must be continuously available 24 h a day, optimizing and improving online experiences are critical today more than in the past (Lemon and Verhoef, 2016). Indeed, consistent with offline occurrences, Rose *et al.* (2012) highlight how important emotions are, even in the online context. In this context, online communication becomes essential in enhancing the customer experience. Experiences with chatbots are related to the hedonic goal of using a technology – that is, to be engaged in an emotional experience. An emotional experience involves the enjoyable aspects of interaction: pleasure, arousal and dominance. "Pleasure" refers to the pleasantness or enjoyment of a chatbot conversation, but emotional experience involves not only enjoyment but also the arousal of being involved in a mentally stimulating conversation (Zarouali *et al.*, 2018). "Domain" ("dominance") refers to the fact that consumers, when interacting with a chatbot, feel that they can act freely and are in absolute control of their actions (Coyle *et al.*, 2012). Previous studies have highlighted that these aspects can determine whether consumers will respond positively to e-service agents (Godey *et al.*, 2016). Therefore, we hypothesize the following:

H3. Experience with a chatbot has a positive impact on customer satisfaction.

Finally, we know that when a product or a service meets customers' expectations, the customers are satisfied (Wiedmann *et al.*, 2009). Therefore, customer satisfaction derived from interactions with a chatbot can enhance and empower the quality of the overall brand relationship. Hence, we suggest the following:

H4. Customer satisfaction has a positive impact on brand-relationship quality.

In sum, as shown in Figure 1, following the CAT model in our research, we evaluate the effects of cognitive elements on customer satisfaction (H1 and H2) and the effects of emotional elements on customer satisfaction (H3). Finally, we test the effects of customer satisfaction on quality (H4).

3. Methods

To achieve our research goals, we conducted a questionnaire-based survey among a sample of Italian consumers. Data collection took place in April 2021. The questionnaire was distributed online through the personal networks of the authors, relying on a convenience sampling technique. Overall, we received 275 questionnaires; however, 19 were excluded from the analysis because respondents had no experience with chatbots. Hence, the final sample was composed of 256 participants. Table 1 summarizes the main characteristics of the

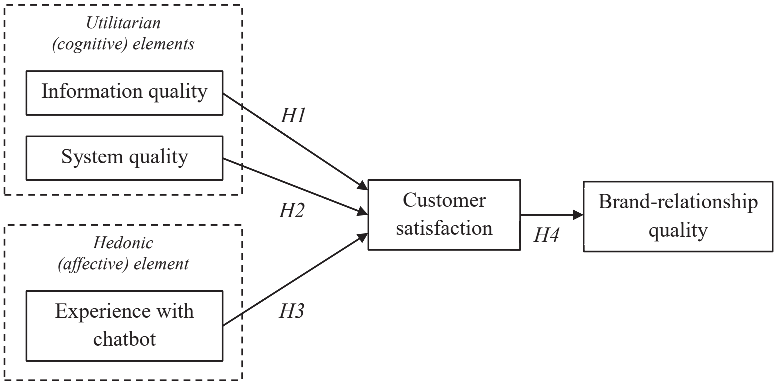

Figure 1.
The research model

Variables	Frequencies (n = 256)
Gender	
Women	152 (59.4%)
Men	104 (40.6%)
Age	
<20 years	4 (1.6%)
20–29 years	63 (24.6%)
30–39 years	96 (37.5%)
40–49 years	82 (32.0%)
50+ years	11 (4.3%)
Education	
Middle school degree	4 (1.6%)
High school degree	97 (37.9%)
Bachelor/Master's degree	138 (53.9%)
Doctoral and other postgraduate degrees	17 (6.6%)
Occupation	
Student	45 (17.6%)
Employee	137 (53.5%)
Self-employed	31 (12.1%)
Unemployed	5 (2.0%)
Other	38 (14.8%)
Why did you interact with a chatbot?	
Asking information	89 (34.6%)
Buying products/services	41 (16.0%)
Asking for assistance	91 (35.6%)
Making complaints	35 (13.8%)
To what sector do your most frequent chatbots belong?	
Fashion	21 (8.4%)
Personal (health)care	16 (6.2%)
Technology	72 (28.0%)
Telecommunications	75 (29.4%)
Travel and entertainment	34 (13.1%)
Financial and insurance services	38 (14.9%)

Table 1.
Sample description

sample. Participants reported using chatbots mostly to ask information or ask for assistance. Chatbots that were mostly used by participants belonged to telecommunications and technology, while chatbots from industries such as personal (health)care and fashion were rarely mentioned. While these data reflect the respondents' actual experience, they also suggest that the results of our analysis cannot be directly generalized to all industries.

The questionnaire included multiple-item measures for each construct developed from previous studies. Specifically, information quality, system quality and customer experience with the chatbot were measured, using four, five and three items, respectively, from the study by Trivedi (2019). Customer satisfaction was determined on the basis of four items from Chung *et al.* (2020). Finally, three items from Algesheimer *et al.* (2005) were used to measure brand relationship quality. Respondents were asked to refer to their latest experience with a chatbot and then give their ratings. All items were measured on five-point Likert scales, with extremes being 1 = totally disagree and 5 = totally agree. Consistently with the original scales, constructs were modeled as reflective. Table 2 shows the complete list of items.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair *et al.*, 2020). The analysis was conducted using the software SmartPLS 3 (Ringle *et al.*, 2015). PLS-SEM is a nonparametric method and, unlike covariance-based structural equation modeling, makes no distributional assumptions (Hair *et al.*, 2017). This method is suitable when the purpose is the assessment of a model's predictive power, the main focus of this study (Hair *et al.*, 2019).

The "standard" PLS-SEM estimations was then complemented with an IPMA. This is a well-established method of analysis to assess customer acceptance of specific features of the offering and is based on the assumption that "consumer satisfaction is a function of both expectations related to certain important attributes and judgments of attribute performance" (Martilla and James, 1977, p. 77). Available studies particularly emphasize how IPMA can provide managerially relevant insights, helping organizations to prioritize important attributes to work on (Phadermrod *et al.*, 2019). Specifically IPMA has been extensively applied to quality improvement (Roy *et al.*, 2020) and to technology design, such as in the case

Table 2.
Measurement scales

Construct	Items	Outer loadings
Information quality	IQ1: (Brand) chatbot provided me with the necessary information	0.966
	IQ2: (Brand) chatbot provided responses to queries as I expected	0.907
	IQ3: (Brand) chatbot provided sufficient information	0.912
	IQ4: The information provided by (brand) chatbot was helpful regarding my questions or problems	0.883
System quality	SQ1: I found it easy to become skillful at using (brand) chatbot	0.831
	SQ2: I believe that (brand) chatbot is easy to use	0.865
	SQ3: Using (brand) chatbot required minimal mental effort	0.726
	SQ4: (Brand) chatbot was quick in response	0.856
	SQ5: Chatbots from (brand) are reliable	0.751
Experience with the chatbot	EWC1: I enjoyed using (brand) chatbot	0.859
	EWC2: The experience of using (brand) chatbot was interesting	0.831
	EWC3: I am happy with the experience of using (brand) chatbots	0.900
Customer satisfaction	CS1: I am satisfied with the chatbot	0.921
	CS2: The chatbot did a good job	0.907
	CS3: The chatbot did what I expected	0.879
	CS4: I am happy with the chatbot	0.945
Brand-relationship quality	BRQ1: This brand says a lot about the kind of person I am	0.694
	BRQ2: This brand's image and my self-image are similar in many respects	0.868
	BrQ3: This brand plays an important role in my life	0.815

of mobile applications' features (Chen *et al.*, 2016). Prior applications of IMPA have shown that direct measures of attributes' importance – i.e. measures obtained from participants' ratings using Likert scales – can provide biased findings (Oh, 2001). Thus, indirect measures of importance such as those derived for example from correlation or multiple regression analysis have been recommended (Azzopardi and Nash, 2013). Therefore, in this work, we used an indirect measure of importance, which is equal to the total effects on the target construct, provided by the PLS-SEM analysis.

IPMA has been recently applied in the context of PLS-SEM to enable researchers to gain richer and more precise insights from their findings because it simultaneously considers both the path coefficients estimates and the average values of the latent variable scores (Ringle and Sarstedt, 2016). In our study, the "standard" PLS-SEM analysis allowed to understand the magnitude of the effects of the three independent variables information quality, system quality and experience with chatbot on customer satisfaction. However, this analysis did not evaluate the average values of these three independent variables. In other words, it did not consider whether, according to participants' ratings, chatbots performed well or not in terms of information quality, system quality and experience. The joint evaluation of these constructs' importance (i.e. of their effects of customer satisfaction) and performance (i.e. of their average values) enabled us to completement "standard" PLS-SEM results with relevant insights to guide managerial action (Hair *et al.*, 2018).

The final output of the IPMA is a map in which the x-axis shows the importance and the y-axis the performance of each attribute. In particular, the performance latent results from the rescaling of each attribute's average scores on a scale from 0 to 100 (where 0 and 100 indicate the lowest and highest levels of performance, respectively). The map can further be divided into four areas through the addition of a vertical line representing the mean importance value and a horizontal line depicting the mean performance value. As a result, each attribute will be placed within one specific area characterized by a certain level of importance (low or high) and a certain level of performance (low or high) (Hair *et al.*, 2018).

Finally, we extended IPMA on the indicator level, meaning that we examined the importance and performance of each of the items used to measure the three independent variables (Table 2). This additional level of analysis made it possible to identify more specific areas of intervention (Hair *et al.*, 2022; Ringle and Sarstedt, 2016).

4. Results

4.1 Measurement model assessment

All constructs' measurement models were specified as reflective. Hence, they were evaluated based on outer loadings, internal consistency reliability, convergent validity and discriminant validity (Hair *et al.*, 2020). As shown in Table 2, outer loadings were above the recommended value of 0.707, with only one exception, which was nonetheless very close to that value (BRQ1, 0.694). Hence, the underlying factor explains more than 50% of each indictor's variance. Next, the internal-consistency reliability was assessed (Table 3). For all latent variables, the values of Cronbach's alpha, exact reliability, ρ_A and composite reliability were greater than 0.70, showing that the internal-consistency reliability was met (Dijkstra and Henseler, 2015; Hair *et al.*, 2017). Moreover, convergent validity was assessed because, for all constructs, the values of the average variance extracted (AVE) were greater than 0.50 (Hair *et al.*, 2019). Finally, discriminant validity was met as well because the square root of each construct's AVE was greater than its highest correlation with any other construct, as requested by the Fornell–Larcker criterion (Fornell and Larcker, 1981) (Table 4).

4.2 Structural model assessment

After we successfully assessed the measurement models of the five constructs, we evaluated the structural model. First, we checked the absence of collinearity issues by inspecting the values of the inner variance inflation factor. All the Variance Inflation Factor (VIF) values are well below 5 (the highest being 2.28), highlighting that collinearity was not an issue (Hair *et al.*, 2019). We then assessed the relevance and significance of the structural-model relationships based on the bootstrapping routine (5,000 subsamples, bias-corrected and accelerated bootstrap, two-tailed test). Table 5 and Figure 2 provide the detailed results of the estimations.

The analysis showed that information quality ($\beta = 0.721, p < 0.01$) and experience with the chatbot ($\beta = 0.239, p < 0.01$) had positive effects on customer satisfaction with the chatbot. Therefore, both H1 and H3 were supported. However, system quality had no significant effect on customer satisfaction with the chatbot ($\beta = 0.046, p > 0.10$) and was thus rejected. Finally, the findings supported H4, indicating a positive effect of customer satisfaction on brand-relationship quality ($\beta = 0.748, p < 0.01$).

The results of the IPMA allowed to enrich the understanding and interpretation of these findings (which highlighted the importance of each construct) by considering also the performance of the constructs. As shown in Figure 3, system quality is the attribute registering the lowest importance and the higher performance. Hence, investing on system quality improvements should not be the top priority for chatbots' designers. The high level of performance reported by system quality may to a certain extent explain its nonsignificant effect on customer satisfaction. In fact, good system quality may have been taken for granted by chatbots' users, thus causing a sort of ceiling effects (i.e. when the independent variable is above certain levels, it has no more effects on the dependent variable). On the contrary, the

Latent variable	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Information quality	0.937	0.940	0.955	0.842
System quality	0.870	0.920	0.903	0.652
Experience with the Chatbot	0.830	0.832	0.898	0.747
Customer satisfaction	0.933	0.935	0.953	0.834
Brand-relationship quality	0.715	0.768	0.837	0.634

Table 3.
Reliability and validity statistics

	Brand-relationship quality	Customer satisfaction	Experience with the chatbot	Information quality	System quality
Brand-relationship quality	0.796				
Customer satisfaction	0.748	0.913			
Experience with the Chatbot	0.709	0.716	0.864		
Information quality	0.694	0.902	0.623	0.918	
System quality	0.682	0.704	0.612	0.711	0.808

Note(s): Correlations among constructs are shown below the diagonal; the square roots of the AVEs shown on the diagonal

Table 4.
Discriminant validity: Fornell-Larcker criterion

HP number	Effect	Path coefficients	*t* values	95% confidence intervals
1	Information Quality → Customer Satisfaction	0.721	12.241*	[0.599, 0.831]
2	System Quality → Customer Satisfaction	0.046	0.655	[−0.105, 0.168]
3	Experience with Chatbot → Customer Satisfaction	0.239	4.882*	[0.157, 0.352]
4	Customer Satisfaction → Brand-Relationship Quality	0.748	18.176*	[0.639, 0.811]

Note(s): $^{*}p < 0.01$

Table 5.
Model estimates

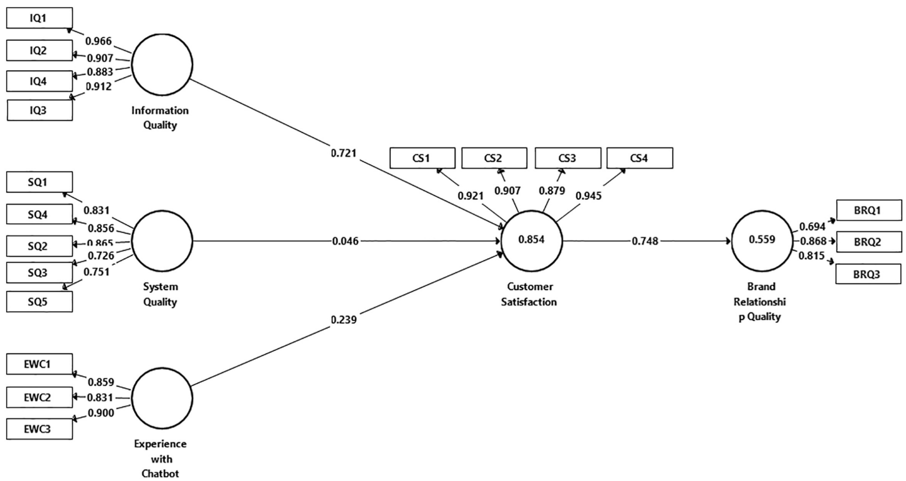

Figure 2.
Model estimates

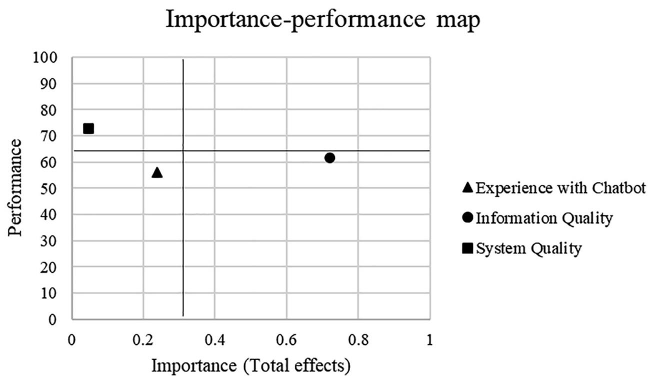

Figure 3.
The results of IMPA (construct level)

performance of the two most important attributes (information quality and experience with chatbot) is below the average value of performance, indicating that there is room for improvement. Specifically, a one-unit increase in information quality's performance (from the current level of 61.65–62.65) would increase customer satisfaction by 0.72 points (from the current level of 58.94–59.66). A one-unit increase in customer experience's performance would increase customer satisfaction by 0.23 points. Therefore, chatbot designers should prioritize actions to increase information quality.

Finally, Table 6 shows the results of the IPMA on the indicator level. These data highlight the specific aspects to improve. Among the items that measure information quality, IQ3 shows a high level of importance and a relatively low level of performance, suggesting that designers could focus on the improvement of the quantity of information provided by the chatbot. On the contrary all system quality's items have high levels of performance and low levels of importance. These findings indicate that currently there is no urgency to enhance these aspects.

To complete the PLS-SEM analysis we evaluated the model explanatory power. The coefficients of determination R^2 of the endogenous constructs were high. Specifically, for customer satisfaction, R^2 was 0.854, and for brand-relationship quality, R^2 was 0.559. Hence, we concluded that the model had high explanatory power. Finally, we assessed the model's predictive power using the PLSpredict routine instead of the blindfolding procedure, as suggest by recent methodological works (Sarstedt *et al.*, 2022a, b). We ran PLSpredict with 10 folds and 10 repetitions. The findings showed that, for all items except one (BRQ1), the PLS-SEM estimation generated a lower prediction error (root mean squared error) compared with the linear-model benchmark. In addition, all the items measuring brand relationship quality had a value of Q^2_{predict} higher than 0. This analysis confirmed that the model had suitable predictive power (Shmueli *et al.*, 2019).

5. Discussion and conclusions

The results of this study enhance the available knowledge concerning the effects of e-service agents (chatbots) on customer satisfaction and on customer–brand relationships. In particular, while previous studies have approached the topic from the perspective of technology acceptance (Meyer-Waarden *et al.*, 2020; Murtarelli *et al.*, 2022), the present study represents one of the first concrete attempts to assess the impact of chatbots on a brand relationship. Therefore, the results of the study allow us to obtain significant information related to the effects after actual use of this technology in customer services.

Regarding the utilitarian (cognitive) elements, our study confirms the importance of the information quality provided by chatbots. At the same time, unlike other studies (Trivedi, 2019), in our work, the technical element is not important in determining customer

Indicator	Importance (0.00–1.00)	Performance (0–100)
IQ1: (Brand) chatbot provided me with the necessary information	0.210	64.440
IQ2: (Brand) chatbot provided responses to queries as I expected	0.199	63.362
IQ3: (Brand) chatbot provided sufficient information	0.192	57.974
IQ4: The information provided by (brand) chatbot was helpful regarding my questions or problems	0.184	60.129
EWC3: I am happy with the experience of using (brand) chatbots	0.096	57.543
EWC1: I enjoyed using (brand) chatbot	0.091	53.879
EWC2: The experience of using (brand) chatbot was interesting	0.090	55.819
SQ1: I found it easy to become skillful at using (brand) chatbot	0.017	60.129
SQ4: (Brand) chatbot was quick in response	0.013	77.371
SQ2: I believe that (brand) chatbot is easy to use	0.011	76.940
SQ5: Chatbots from (brand) are reliable	0.009	76.724
SQ3: Using (brand) chatbot required minimal mental effort	0.007	80.172

Note(s): *The items are ordered according to their levels of importance

Table 6.
The results of the IPMA (indicator level)*

satisfaction. However, as noted in our analysis, this unexpected finding may be related to a sort of ceiling effect. Regarding the hedonic (affective) elements, our study confirms the role of the emotional experience in determining customer satisfaction. Information quality and emotional experiences with chatbots are crucial in determining customer satisfaction and, finally, enhancing the brand relationship. Therefore, while e-service agents are typically the results of technological advancements, firms must not forget what consumers truly require from service agents: the quality of information and an emotional experience. Consumers do not expect technical perfection, but, overall, consumers appear interested in the quality of the information received and in the emotions derived by their relationships with chatbots. The results confirm the trend to humanize the technology. Therefore, firms are encouraged to consider both the utilitarian and hedonic aspects of the consumer experience carefully when designing their chatbots. In addition, from the managerial point of view, the results also confirm the need to integrate elements of TQM with elements related to TM. Thus, it becomes essential in the perspective of continuous improvement of customer services to take into account the growing importance of the impacts of these new technologies.

Of course, this study presents several limitations. More data should be collected to corroborate the results. In the future, it will be useful to deepen the analysis by comparing the estimations in different sectors to identify whether the roles of chatbots change in relation to the sector (e.g., the advanced technological versus the traditional sectors). Customer perceived importance of chatbots' attributes may also vary depending on the industry. For example, system quality may register higher importance in the health-care industry (May and Denecke, 2022). It also will be useful also to repeat the survey in the future in different countries to capture potential differences.

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