Digital services to improve customer experience. An empirical analysis of the impact of chatbots on customer-brand relationships.

Francesca Magno
Department of Management, University of Bergamo (Italy)
Email francesca.magno@unibg.it

Giovanna Dossena
Department of Management, University of Bergamo (Italy)
Email giovanna.dossena@unibg.it

Abstract

Purpose of the paper: Many firms are investing in digital services in an attempt to improve customer experience. Virtual service agents or "e-service agents" such as chatbots are examples of these efforts. Chatbots are a type of virtual assistant software programs that are able to interact with users through voice or text. This paper aims to investigate whether perceived hedonic and utilitarian attributes of chatbots can influence customer satisfaction and as a consequence the relationship with the brands.

Methodology: 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 (PLS-SEM) to provide a prediction-oriented model assessment.

Main Findings: The first findings confirm the hypothesis that the perceived hedonic and utilitarian attributes of chatbots positively influence customer satisfaction and improve customer relationships with the brands.

Practical implications: This study suggests the importance for firms to invest (also) in the adoption of e-agents to strengthen the consumer–brand relationship.

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

Type of paper: Research paper

Keywords: chatbots, e-service agents, new technologies, customer satisfaction, consumer-brand interaction

1. Introduction

Technological advancements are changing the way through which firms can manage their interactions with customers and as a consequence the customer experience (Chung et al., 2020). In particular, among the emerging technologies, Artificial Intelligence (AI) is considered a disruptive technology that is able to radically change 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 analyse 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 the applications of AI (Martínez-López and Casillas, 2013). As a consequence, many firms are investing in digital services in an attempt to improve customer experience. Virtual service agents or "e-service agents" such as chatbots (one of the applications of AI) are examples of these efforts (Trivedi, 2019). A Chatbot is an instant chat service that is able to operate similarly to an offline service agent (Chung et al., 2020). Indeed, a chatbot interacts in a familiar way and its responses can consist in voice or text messages, images, and so on. Like an offline service agent, the role of chatbots is becoming central in determining customer satisfaction. Indeed, it represents the brand in the relationship with customers (Chung et al. 2020; Zarouali et al., 2018). The most popular chatbots include personal assistants like Alexa, Siri, Cortana. However, despite the increasing relevance of this topic, academic research about the role of chatbots in influencing customers satisfaction is still scarce (Hoyer et al., 2020). This study intends to contribute to filling this gap. In particular, this paper investigates whether perceived hedonic and utilitarian attributes of chatbots can influence customer satisfaction and as a consequence the relationships between customers and brands.

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

2. Theoretical background and hypotheses

As the competition has increased, providing quality customer service has become a strategic element for the success of a firm (Scheidt and Chung, 2019). As a consequence, service agents who personally interact with customers, represent the brand, and are central in solving customer problems, play a central role in determining customer satisfaction. Due to the advent of digital technologies, firms are increasingly shifting to digital services and the role of service agents is profoundly changing. Indeed, many firms are transforming their traditional customer service to digital customer service (Cheng and Jiang, 2021) E-service agents such as chatbot agents are new technology tools that try 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 through gags and trying to transmit emotions (Hoyer et al. 2020; Schmitt, 2019). Clients can interact with e-service agents 24 hours on 24 from anywhere (Cheng and Jiang, 2020). As a consequence of this digital revolution, not only people must increase their technology abilities but also technology itself is humanizing (Schmitt, 2019). Chatbots are becoming crucial in determining customer satisfaction and therefore, in enhancing the relationship with the brand. To analyse these effects, we follow the Consumer Acceptance of Technology (CAT) model (Kulviwat et al., 2007). Differently from traditional Technology acceptance model, such as Technology Acceptance Model (Davis, 1989) which considers only the cognitive elements, CAT model includes in addition also affective elements. This is coherent with what several researchers (Nasco et al., 2008; Fiore et al., 2005) have underlined, that is in the relationships with consumers the technology has to reach two goals: utilitarian goals and hedonic goals. Utilitarian goals are guided by cognitive elements and oriented to problem solving (Dhar and Wertenbroch, 2000). These components are strictly connected to the analytical characteristics of the technology. It represents the value derived from the elaboration of the information received by the chatbot (Hoyer et al., 2020). Hedonic goals are related to affective aesthetic, fun and enjoyment elements (Batra and Ahtola, 1991). They represent the value that consumers received from emotional stimulation (Hoyer et al., 2020). In particular in our model, we identified two utilitarian elements: information quality and system quality and one hedonic element related to the experience with chatbots.

Information quality represents the semantic success of the technology (Delone and Mclean, 1992). 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 has highlighted that poor quality of information provided is able to diminish the total performance of a firm by increasing costs (Swanson, 1997). The quality information provided by chatbots is crucial in influencing the customer satisfaction.

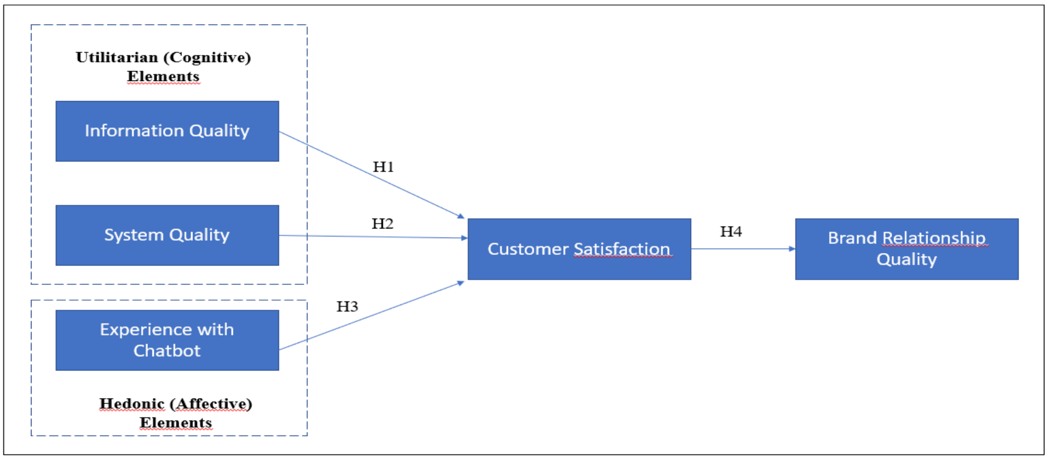
System quality is related to the technical aspects of a chatbot. In particular, the quality of a chatbot is determined by aspects such as being easy-to-use, timely, adaptable (Trivedi, 2019). In particular, if consumers perceive a chatbot as difficult to use this could negatively influence customer satisfaction. At the same time, consumers expect that the answer of a chatbot is given in a couple of seconds. If the time is too long this could negatively influence customer satisfaction (Chung et al., 2020, Trivedi, 2019; Zarouali et al., 2018).

Experience with chatbot is related to hedonic goal of using a technology, that is be engaged in an emotional experience. Emotional experience involves not only fun, enjoyment and entertainment elements but also the arousal to be involved in a mental stimulating conversation (Zarouali et al., 2018). Previous studies have highlighted that these aspects are able to determine whether consumers will respond in a positive way to e-service agents (Godey et al., 2016).

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 the interactions with a chatbot is able to enhance and empower the quality of relationship with a brand.

Following the CAT model in our research we consider the effects of cognitive elements on customer satisfaction (H1 and H2) and the effect of emotional elements on customer satisfaction (H3). Finally, we tested the effect of customer satisfaction on the overall brand relationship quality (H4).

Fig. 1 – The research model



3. Methods

To achieve our research goals, a questionnaire-based survey was conducted among a sample of Italian consumers.

The questionnaire included multiple-item measures for each construct developed from previous studies (Chung et al., 2020; Trivedi, 2019; Zarouali et al., 2018). All items were measured on five-point Likert scales, with extremes being 1=totally disagree and 5=totally agree. Constructs were modelled as reflective.

Data collection took place in April 2021. The questionnaire was distributed online through the personal network of the authors, relying on a convenience sampling technique. Overall, we received 275 questionnaires but 19 were excluded from the analysis because they had no experience with chatbots. Data were analysed 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).

Table 1 summarizes some of the main characteristics of the sample.

Table 1. Descriptive Statistics of the sample

Variables	Frequency (%) Total sample
Gender	
Female	165 (60%)
Male	110 (40%)
Age	
<20	4 (1.5%)
20–29	68 (24.7%)
30–39	104 (37.8%)
40–49	88 (32%)
>59	11 (4%)
Education	
Middle school level	6 (2.2%)
High school level	103 (37.5%)
Bachelor and/or master's degree	148 (53.8%)
Doctoral and other postgraduate degrees	18 (6.5%)
Occupation	
Student	45 (16.5%)
Employee	148 (53.8%)
Self-employed	36 (13%)
Unemployed	5 (1.8%)
Other	41 (14.9%)
Have you ever interacted with a chatbot in an online relationship with a brand?	
Yes	256 (93.1%)
No	19 (6.9%)
Why did you interact with a chatbot?	
Asking information	89 (34.6%)
Buying a product/service	41 (16%)
Asking for assistance	91 (35.6%)
Making complaints	35 (13.8%)
To what sector belong the chatbot more frequently used?	
Fashion	21 (8.4%)
Personal Care	16 (6.2%)
Technology	72 (28%)
Telecommunications	75 (29.4%)
Travels and entertainment	34 (13.1%)
Financial and Insurance Services	38 (14.9%)

Respondents were mainly female (60%) and 64% were under to 39 years old. The vast majority of the total respondents has interacted with a chatbot (93.1%). Technology and telecommunications are the sectors mainly involved (57.4%).

4. Results

4.1 Measurement model assessment

All constructs were reflective measured. Therefore, the measurement model was evaluated based on indicator loadings, internal consistency reliability, convergent validity and discriminant validity (Hair et al., 2020). All indicator loadings were above the recommended value and they were able to explain more than 50 percent of the variance (Table 2). Therefore, they offer acceptable reliability. Then, we assessed the convergent validity of each construct through the average variance extracted. Each construct presented a value higher than the minimum acceptable level of 0.50, therefore, indicating that the construct explained more than 50 percent of the variance of the items that composed the construct. We then evaluated internal consistency using Cronbach's alpha and composite reliability. For all constructs, the values were above 0.70 indicating that internal consistency and reliability were met. As regards discriminant validity, the heterotrait-monotrait ratios of the correlations (HTMT) were below 0.85 and significantly different from 1 (Hair et al., 2019).

Table 2 – Measurement model assessment

Construct	Item	Indicator Reliabilities – Outer loadings	Convergent Validity – Average Variance Extracted (AVE)	Internal consistency reliability – Cronbach's Alpha and Composite Reliability	
Information Quality	IQ1	0.97	0.84	Cronbach's Alpha:	0.94
	IQ2	0.91			
	IQ3	0.91		Composite Reliability	0.96
	IQ4	0.88			
System Quality	SQ1	0.83	0.70	Cronbach's Alpha:	0.87
	SQ2	0.87			
	SQ3	0.73		Composite Reliability:	0.90
	SQ4	0.86			
	SQ5	0.75			
Experience with Chatbot	EWC1	0.86	0.75	Cronbach's Alpha:	0.83
	EWC2	0.90			
	EWC3	0.83		Composite Reliability:	0.90
Customer Satisfaction	CS1	0.92	0.83	Cronbach's Alpha:	0.94
	CS2	0.91			
	CS3	0.88		Composite Reliability:	0.95
	CS4	0.94			
Brand Relationship Quality	BRQ1	0.69	0.63	Cronbach's Alpha:	0.72
	BRQ2	0.87			
	BRQ3	0.82		Composite Reliability:	0.84

4.2 Structural model Assessment

Since the measurement models were satisfactory, the structural model was then evaluated. The were no collinearity issues, all the VIF values are lower than 3. After that, we examined the R^2 values of the endogenous constructs which is a measure of the model's explanatory power (Shmueli and Koppius, 2011) and it also represents the in-sample predictive power (Rigdon, 2012). R^2 values were greater than 0.50 indicating a strong explanatory power. The out-of-sample predictive power was judged on the basis of the Q^2 values using the blindfolding procedure. All Q^2 values were largely above 0, confirming that the model had good out-of-sample predictive power.

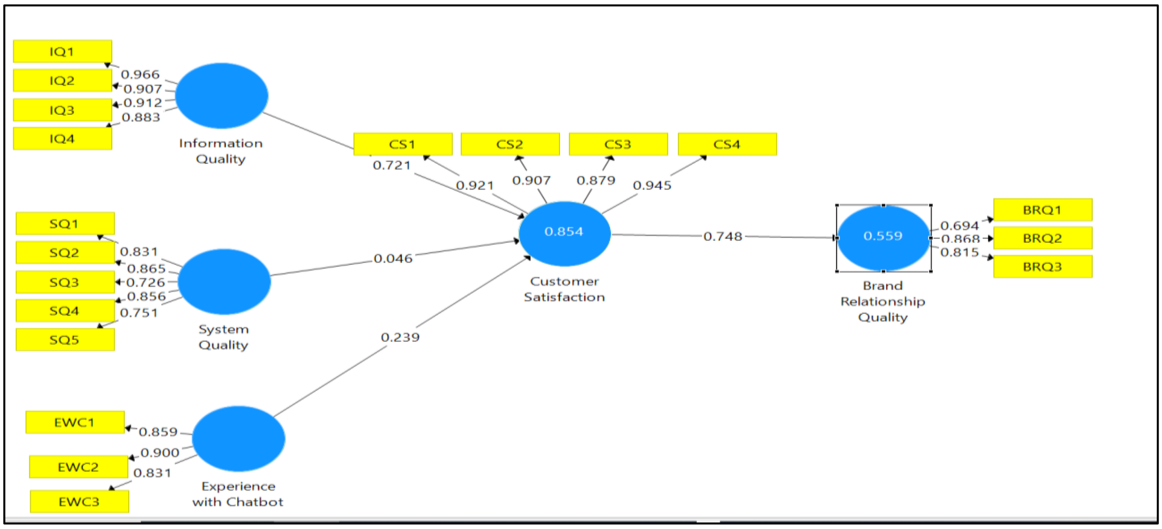
The assessment of the structural model was based on the bootstrapping routine (5,000 subsamples, bias-corrected and accelerated bootstrap, two-tailed test). Table 3 provides the detailed results of the estimations of the effects based on the bootstrapping routine and Figure 2 summarizes the model estimations.

Table 3 – Bootstrapping results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Customer Satisfaction_ -> Brand Relationship Quality	0.748	0.751	0.044	16.964	0.000
Experience with Chatbot -> Customer Satisfaction_	0.239	0.242	0.049	4.839	0.000
Information Quality_ -> Customer Satisfaction_	0.721	0.717	0.064	11.320	0.000
System Quality_ -> Customer Satisfaction_	0.046	0.048	0.073	0.627	0.531

The analysis supports the hypothesized effects of information quality on customer satisfaction (H1) and experience with the chatbot on customer satisfaction (H3). On the contrary, the hypotheses about the effect of system quality on customer satisfaction is rejected. Finally, the result confirms the effect of customer satisfaction on the relationship with the brand (H4).

Fig. 2 – Model estimations



5. Discussion and conclusions

The results of this study enhance available knowledge about the effects of e-service agents (chatbot) on customer satisfaction and on customer relationship with the brand. As regards the utilitarian (cognitive) elements, our study confirms the importance of the quality of the information provided by chatbots. At the same time, differently from other studies (Trivedi, 2019), in our work, the technical element is not important in determining customer satisfaction. As regards the hedonic (affective) elements, our study confirms the role of emotional experience in determining customer satisfaction. Information quality and the emotional experience with chatbots are crucial in determining customer satisfaction and finally to enhance the relationship with the brand. Therefore, while e-service agents are typically the result of technological advancements, firms must not forget what the consumers really search for from service agents, that is the quality of information and an emotional experience. Consumers do not search for technical perfection but, overall, consumers appear interested in the quality of the information received and in the motions derived by the relationship with chatbots. The results confirm the trend to humanize the technology. 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 if the role of chatbots changes in relation to the sector (for example, technological advanced versus traditional sectors). In the future, it will be useful also to repeat the survey in different countries to capture possible differences.

References

Batra, R., & Ahtola, O. T. (1991). Measuring the hedonic and utilitarian sources of consumer attitudes. *Marketing letters*, 2(2), 159-170.

Campbell, C., Sands, S., Ferraro, C., Tsao, H. Y. J., & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business Horizons*, 63(2), 227-243.

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, 117, 587-595.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information systems research*, 3(1), 60-95.

Dhar, R., & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. *Journal of marketing research*, 37(1), 60-71.

Fiore, A. M., Jin, H. J., & Kim, J. (2005). For fun and profit: Hedonic value from image interactivity and responses toward an online store. *Psychology & Marketing*, 22(8), 669-694.

Godey, B., Manthiou, A., Pederzoli, D., Rokka, J., Aiello, G., Donvito, R., & Singh, R. (2016). Social media marketing efforts of luxury brands: Influence on brand equity and consumer behavior. *Journal of business research*, 69(12), 5833-5841.

Hair, J. F., Hult, T. M., Ringle, C., Sarstedt, M., Magno, F., Cassia, F. and Scafarto, F. (2020), *Le equazioni strutturali Partial Least Squares. Introduzione alla PLS-SEM*, FrancoAngeli, Milano.

Hair, J. F., Risher, J. J., Sarstedt, M. and Ringle, C. M. (2019), "When to use and how to report the results of PLS-SEM", *European Business Review*, Vol. 31 No. 2, pp. 2-24.

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of Interactive Marketing*, 51, 57-71.

Kulviwat, S., Bruner II, G. C., Kumar, A., Nasco, S. A., & Clark, T. (2007). Toward a unified theory of consumer acceptance technology. *Psychology & Marketing*, 24(12), 1059-1084.

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). Brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing*, 51, 44-56.

Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management*, 42(4), 489-495.

Nasco, S. A., Kulviwat, S., Kumar, A., & Bruner Ii, G. C. (2008). The CAT model: Extensions and moderators of dominance in technology acceptance. *Psychology & marketing*, 25(10), 987-1005.

Ringle, C., Da Silva, D., & Bido, D. (2015). Structural equation modeling with the SmartPLS. Bido, D., da Silva, D., & Ringle, C.(2014). Structural Equation Modeling with the Smartpls. *Brazilian Journal Of Marketing*, 13(2).

Rigdon, E. E. (2012). Rethinking partial least squares path modeling: In praise of simple methods. *Long range planning*, 45(5-6), 341-358.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S. and Ringle, C. M. (2019), "Predictive model assessment in PLS-SEM: guidelines for using PLSpredict", *European Journal of Marketing*, Vol. 53 No. 11, pp. 2322-2347.

Swanson, E. B. (1997). Maintaining IS quality. *Information and Software Technology*, 39(12), 845-850.

Trivedi, J. (2019). Examining the customer experience of using banking chatbots and its impact on brand love: the moderating role of perceived risk. *Journal of internet Commerce*, 18(1), 91-111.

Wiedmann, K. P., Hennigs, N., & Siebels, A. (2009). Value-based segmentation of luxury consumption behavior. Psychology & Marketing, 26(7), 625-651.

Zarouali, B., Van den Broeck, E., Walrave, M., & Poels, K. (2018). Predicting consumer responses to a chatbot on Facebook. *Cyberpsychology, Behavior, and Social Networking*, 21(8), 491-497.