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The impact of artificial intelligence chatbots' communication style on customer satisfaction in different service settings

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Abstract: This study investigates the relationship between the use of different communication styles on customer perceptions and satisfaction in online service chatbot encounters. To test these relations, an empirical approach through scenario-based experiments was arranged. Through the help of SPSS statistical software, the results showed that utilising a social-oriented communication style increases customer satisfaction, while perceptions of the chatbot's warmth mediate this impact, and perceptions of the chatbot's competence are not a mediator variable in this context; finally, the service outcome moderates this effect. These findings pave the way for more future research in the fields of human-computer interaction and anthropomorphism, and guide brand managers and technology developers to fully explore the value of different ways of interaction styles with customers, ensuring the long-term viability of this technology with proper implementation.

Keywords: communication style; customer satisfaction; chatbot; anthropomorphism.

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Biographical notes: Lei Kelly is an undergraduate student who was awarded the Chinese Government Scholarship by China Scholarship Council for pursuing her Master's degree of Technology Economics and Management at South China University of Technology in Guangzhou, China. In 2017, she received her Bachelor's degree in Industrial Engineering from Universidad del Norte in Barranquilla, Colombia. Her research interests include artificial intelligence, human-computer interaction, service robots, among others.

1 Introduction

In an era of growing digitalisation, service encounters are experiencing accelerated changes followed by the increasing use of artificial intelligence (AI) chatbots in marketing. Chatbots are software designed to interact with consumers in the same way as people do in a human-to-human chat interaction, but instead of a human chat agent

responding to customer queries, a computer program directs the conversation, handling a wide range of client demands, and gradually taking the place of human service representatives on online settings, reducing costs and employers' workloads (King, 2022). The market for chatbots is expected to approach 454.8 million US dollars in sales by 2027, up from 40.9 million dollars in 2018 (Statista, 2022). Even with the widespread use of chatbots, consumers remain hesitant to engage with them, as indicated by numerous claims of frustration (Shumanov and Johnson, 2021). However, because of the above-mentioned advantages, business interest in chatbot technology remains high (Thomaz et al., 2020). As a result, overcoming consumer reluctance is crucial, motivating firms to evaluate how artificial agents like chatbots should be developed to provide great customer support experiences. Hence, while service chatbots have the opportunity to increase business performance, the question of how effectively develop and use chatbots remains unresolved.

Moreover, given the nascence of this technology, the amount of research to educate how to best provide great consumer experiences with a chatbot is still scarce (Roy and Naidoo, 2021). Few findings propose to improve chatbots' humanness pointing to visual, identity, and conversational signals as effective strategies for giving human characteristics to artificial agents and thus, influence consumer attitudes and behaviours (Araujo, 2018; Shumanov and Johnson, 2021; Thomaz et al., 2020; van den Broeck et al., 2019). However, while certain strategies may be beneficial, little is known about the more fundamental characteristic of consumer-chatbot service encounters, the chatbot's communication style, which is a significant social cue that chatbots may employ to impact consumers' attitudes and behaviours (Feine et al., 2019). Calls have been made for more studies on chatbot discourse style (Bleier et al., 2019), but little research has addressed this gap in the commercial context. Moreover, prior works reported mixed results (Chattaraman et al., 2019; Guo et al., 2016; Lin et al., 2013; Veletsianos, 2012). Therefore, there is a need for more research on the characteristics of the interaction style that the conversational agent should have to be effective, and the present study aims to fill this critical research gap.

The main objective of this work is to explore the circumstances in which service chatbots have a more positive impact on customer service experiences and draws on two components of the service features that can shape the efficacy of the chatbot discourse for customer satisfaction: communication style and service outcome. Through a scenario-based approach, the findings show that a chatbot's social-oriented communication style enhances customer satisfaction, customers' warm impressions of the chatbot mediate this impact, and the service outcome moderates these effects, particularly this effect was stronger in successful settings. This work contributes to the human-computer interaction (HCI), and anthropomorphism in conversational agents' body literature, laying the foundations for a more humane pattern of conversation for people, and at the same time helping to guide brand managers and technology developers to fully explore the value of different ways of interaction styles with customers and to bring into play the role of communication itself ensuring the long-term viability of this kind of technology with proper implementation.

The rest of this paper is organised as follows: based on the theoretical foundations of the chatbot communication style effect, a model is built and hypotheses developed. Then through the design of the experiments and questionnaire, the hypotheses were tested. Finally, pertinent conclusions, limitations, and future research opportunities were discussed.

2 Conceptual background and hypotheses

2.1 Chatbots, communication style, and the role of social judgements

In the beginning, chatbots were developed to establish a simple conversation between a computer and a person, and then as the technology has become more sophisticated, the conversations have become even more human, even not distinguishing whether the conversational agent is a human or a bot (King, 2022). This is called 'anthropomorphism' which is the attribution of humanlike features, attributes, or mental states to non-human entities (Epley et al., 2007).

Existing research demonstrates that introducing anthropomorphic cognition is associated with improved outcomes. Anthropomorphic interfaces can boost people's trust in technology by raising competence perception (Bickmore and Picard, 2005; Waytz et al., 2014) while making them more resilient to trust breakdowns (de Visser et al., 2016) and helping robots to recover from process failures (Choi et al., 2020). Nevertheless, other authors argued that anthropomorphism has a harmful influence on customer satisfaction, company evaluation, and purchase intentions if the firm does not take into account the emotional state of the customer (Crolic et al., 2022).

On the other hand, a relatively recent avenue has begun to focus on the anthropomorphic design of the speech pattern and conversational styles to improve chatbot human-like traits (Chattaraman et al., 2019; De Cicco et al., 2020; Gelbrich et al., 2021; Roy and Naidoo, 2021; Sheehan et al., 2020; Shumanov and Johnson, 2021). They argue that human-like language, message interactivity, conversation skills, emotional support, and conversational styles may all be useful. Thomas et al. (2018) highlight that due to communication styles being the most modifiable component in the development and design of chatbots, further research should be done to understand how conversational styles might inform chatbot anthropomorphisation.

There is two types of interaction style in the literature: task and social-oriented (Chattaraman et al., 2019; De Cicco et al., 2020). A task-oriented interaction style is characterised by formal language, goal-oriented and purposeful: emphasis on the efficiency at the lowest cost, effort, and time to meet functional goals whereas a social-oriented interaction style is typically informal, casual, and with a sense of humour, encouraging the sharing of socio-emotional and affective information. Both communication styles may meet the customer's utilitarian needs by giving product-related information and answering inquiries, but a social communication style may also satisfy certain customers' social needs but could take up extra time, in addition, to having differing effects on social, functional, and behavioural intent results.

Service personalisation is a major concern in person-to-person service delivery because of its importance in a customer's ultimate satisfaction with a specific service (Surprenant and Solomon, 1987), and for online settings, people can perceive it as an environment lacking in human warmth and friendliness (De Cicco et al., 2020), therefore figuring out how to increase engagement in online contexts using emerging technologies like chatbots is a difficult task.

The present study believes that the use of socially oriented communication can have a positive influence on customer satisfaction in human-chatbot interactions. Given that assigning human characteristics to chatbots encourages customers to see them as humans and have similar expectations to those they hold for people (Araujo, 2018; Gelbrich et al., 2021), consumers expect customised service when interacting with service human-like

chatbots. In particular, since the homogeneity of chatbot service delivery may lose emotional and social value, the personalisation of such service delivery is becoming increasingly vital to the customer service experience. A more social, friendly, and personalised dialogue from the service provider is one way to do this (Thomaz et al., 2020; Wilson-Nash et al., 2020). Consequently, when contrasted to utilising a task-oriented communication approach, expressing emotional and social traits are more meaningful and engaging and can boost customer satisfaction. Hence:

H1 Customers show a higher level of satisfaction when they are addressed by a chatbot that uses a social rather than a task-oriented communication style.

Following that, based on the social judgement theory, prior literature has used warmth and competence dimensions to define human-like traits in chat agent interactional style (Thomas et al., 2018). In other words, individuals largely assess others based on two fundamental aspects, namely, how much warmth and competence they perceive from others (Fiske et al., 2007). Warmth perception incorporates the perception of trustworthiness, helpfulness, and friendliness, while competence perception incorporated the perception of intelligence, skilfulness, and capability.

Given that customers associate higher warmth with anthropomorphic (rather than non-anthropomorphic) service robots (Choi et al., 2020), the current study proposes that consumers who interact with a chatbot that employs a social- (rather than a task-) oriented communication style would feel warmer. Instead, consumers would have a similar level of competence perception regardless of whether they are addressed by task- or social-orientated style. Hence:

H2 Customers show a higher level of warmth perception when they are addressed by a chatbot that uses a social rather than a task-oriented communication style.

H3 Customers show a similar level of competence perception regardless of whether they are addressed by a chatbot that uses a task or social-oriented communication style.

2.2 The role of service outcome

A service outcome refers to the result of the service transaction (Gronroos, 1988). Customers frequently encounter service delivery issues during the purchase process. Some of the inaccuracies may be due to the labour-intensive element and interpersonal communication (Fisk et al., 1993). Consequently, service failure and inadequate service recovery are two of the most common reasons for consumer discontent. A service failure is when the service delivery falls below the customer's expectation (Bell and Zemke, 1987), and a service recovery refers to the actions that firms take to correct the service failure perceived by the customer (Maxham, 2001). Understanding the previous concepts is critical for any service organisation's success.

Bot performance is high in all of the research described in the literature review, therefore reactions to chatbots' different communication styles in failure contexts remain yet to be examined. Making technology looks more human helps against trust breakdown caused by automation failures, both by decreasing early expectations and promoting less extreme reactions to reliability losses across the time (de Visser et al., 2016). Nonetheless, other studies affirm that these human traits can be counterproductive when the customer encounters a service failure. Crolic et al. (2022) found that when customers are angry, a visual anthropomorphic chatbot may have incited more negative outcomes.

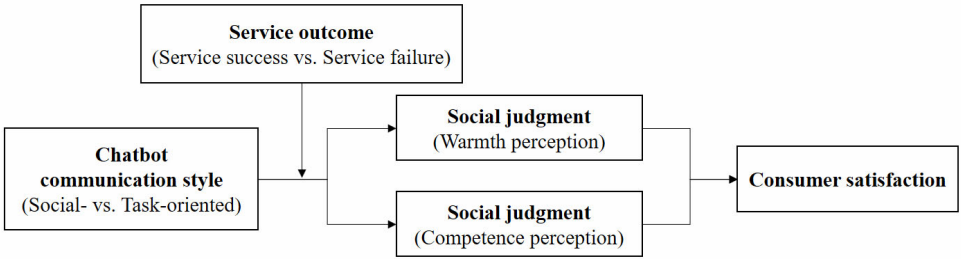
However, none of these studies have taken into account the chatbot's speech pattern. Consequently, companies need to know which communication style is the most appropriate to communicate with customers and to know whether or not the discourse influences customer satisfaction to a greater or lesser extent, especially in the context of service failure. Since service failures violate exchange norms (Wan et al., 2011), they might situationally increase the relevance of exchange norms (Li et al., 2019). Hence, this work believes that the existence of poor service would shift consumers' attention to examining the competence of service employees rather than their warmth and their anthropomorphic features, and the chatbot's use of a social-approach communication style will therefore lose its effectiveness in the customers' satisfaction. Instead, in the absence of service failures, this study argues that social-oriented style has a favourable influence on warmth perception, and thus customer satisfaction. Hence:

H4 Communication style has a more positive effect on customer satisfaction in success service than in failure service.

H5 Service outcome moderates the effect of a social-oriented (vs. task-oriented) communication style on customer satisfaction through the mediation of warmth perception. Specifically, this effect is weaker for a 'service failure' compared to its 'service success' counterpart.

The research model is shown in Figure 1.

Figure 1 Research model



3 Research methods

3.1 Sample

The questionnaire was shared through snowball and convenience sampling, selecting individuals over the age of 18. The sample sizes were determined a priori with the program G*Power (Faul et al., 2007). Using an expected effect size of f = 0.25 (Cohen, 1988), error probability $\alpha = 0.05$, power to $1 - \beta = 0.80$, numerator degrees of freedom df = 1, and number of groups = 4, a sample size of 128 people would be appropriate. A total of 151 valid surveys were collected, and among these research subjects, there were 64 men and 87 women, most of them are between 26 and 35 years old (61%), undergraduate (86.1%), purchased online a few times in a month (62.3%) and interacted with a chatbot a few times in a month (49.0%).

3.2 Questionnaire

The questionnaire is divided into three parts. The first part contains the stimuli scenario and the attention check questions ('according to the scenario, which of the following statements are NOT true?' and 'in the scenario, you interacted with'). The second part corresponds to the constructs related to the theoretical model (satisfaction, warmth, and competence), adapting the measurements from the existing literature to the context of this study on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree) (see Table 1). The third part aims to determine demographic information (e.g., age, gender, education background, prior experience, and shopping frequency).

Table 1 Measurement scales

Constructs	*Code*	*Measurement items*	*Source*
Warmth perception	W1	This chatbot is warm.	Cuddy et al. (2007)
	W2	This chatbot is kind.	
	W3	This chatbot is friendly.	
	W4	This chatbot is sincere.	
Competence perception	C1	This chatbot is competent.	Cuddy et al. (2007)
	C2	This chatbot is intelligent.	
	C3	This chatbot is capable.	
	C4	This chatbot is skillful.	
Customer satisfaction	S1	I am satisfied with the chatbot's provided handling service.	Evans et al. (2000) and Maxham and Netemeyer (2003)
	S2	I am not satisfied with this chatbot as a service assistant (R)	
	S3	Regarding this particular event, I am satisfied with the chatbot.	

Note: R – reverse coded.

3.3 Stimuli

The scenarios were built using Zeoob (2022). The company name 'Fashion Shop' and its logo, were used as a fictional brand to avoid potential biases related to effects on pre-existing perceptions of well-known brands (Coombs and Holladay, 2007). 'Bot', the name of the chatbot was made gender-neutral so that gender would not affect customer outcomes (Feine et al., 2020). The retail sector was chosen due to it was considered to be a suitable context to use customer service chatbots (Rese et al., 2020). For the conversation scripts, terms from real customer-chatbot interaction and the literature were taken to create it (Chattaraman et al., 2019; De Cicco et al., 2020). The social-oriented interaction style chatbot was configured to use informal language that included small talks, exclamatory messages, and emoticons. Instead, the task-oriented interaction-type chatbot is objective, straight to the point, with short answers, and formal. For the service outcome manipulation, in success service, the chatbot was able to manage the customer inquiries successfully, while in a failed service the chatbot was unable to manage it. Overall, the communication style and service outcome resulted in four different kinds of conversations. The completed conversation flow can be found in the Appendix.

3.4 Pre-test

Respondents were required to interact with one of the four scenarios of a 2 (chatbot social-oriented communication style vs. chatbot task-oriented communication style) × 2 (service success vs. service failure) between-subject design and were directed to answer the pretest questions (see Table 2). A total of 151 valid responses were collected (57.6% female; M_{age} = 26–30). Using the statistical tool SPSS, the results showed that the chatbot was assessed to have a substantially more engaging personality when the interaction style was social-oriented (M_{social} = 5.816, SD_{social} = 0.715) than task-oriented (M_{task} = 4.651, SD_{task} = 0.985, t(149) = –8.326, p < 0.001) (α = 0.870). For the service outcome check, respondents in the unsuccessful condition perceive the service outcome significantly more as a failure ($M_{failure}$ = 3.041, $SD_{failure}$ = 3.041) than the respondents in the successful condition ($M_{success}$ = 5.667, $SD_{success}$ = 0.921, t(149) = 13.010, p < 0.001). The scenarios were perceived as realistic ($M_{realism}$ = 5.427, $SD_{realism}$ = 0.893). In sum, the manipulations were successful.

Table 2 Measurements for the manipulation check

Constructs	*Code*	*Measurement items*	*Source*
Communication style	P1	The chatbot was expressive.	Chattaraman et al. (2019)
	P2	The chatbot was enthusiastic.	
	P3	The chatbot was entertaining.	
	P4	The chatbot was motivating.	
	P5	The chatbot was friendly.	
Service outcome	O1	Ranging from 'service failure' (1) to 'service success' (7)	Belanche et al. (2020)
Realism	R1	The situation as described is realistic	Dabholkar (1996)
	R2	It was not difficult to imagine myself in the situation	

4 Empirical analysis

4.1 Reliability and validity test

After the data was collected, all scales were tested for reliability and validity using the software SPSS. Cronbach's alpha (α) was used to assess the reliability (Cortina, 1993). The warmth perception's α could be considered good (α > 0.80), while competence perception and customer satisfaction's α were excellent (α > 0.90). Overall, the α in this study indicates the high reliability of the scales used (see Table 3).

Confirmatory factor analysis (CFA) was used to verify the degree of precision that the instrument can measure (Collier, 2020). The CFA showed the acceptable threshold levels are consistent with the parameters: chi-square test (CMIN/DF) = 1.370 were lower than 3; comparative fit index (CFI) = 0.989, normed fit index (NFI) = 0.961, and goodness-of-fit index (GFI) = 0.937 were higher than 0.90; and root mean square error of approximation (RMSEA) = 0.050 and standardised root mean square residual (SRMR) = 0.038 were lower than 0.10. The average variance extracted (AVE) is ranged

from 0.676 to 0.855, greater than 0.50, denoting that the indicators have convergent validity on the construct; and composite reliability (CR) is ranged from 0.893 to 0.946, more than 0.60, supporting the discriminant validity of the constructs in the model (Fornell and Larcker, 1981). Overall, every item represents the underlying construct and provides evidence for construct validity (see Table 4).

Table 3 Reliability of measurement scale through Cronbach's alpha (α)

Constructs	*Items*	*Cronbach's alpha if the item is deleted*	*Cronbach's alpha*
Warmth perception	W1	0.849	0.891
	W2	0.847	
	W3	0.868	
	W4	0.873	
Competence perception	C1	0.880	0.912
	C2	0.897	
	C3	0.872	
	C4	0.892	
Customer satisfaction	S1	0.907	
	S2	0.940	0.946
	S3	0.917	

Table 4 Reliability and validity analysis of measurement scale

Construct	*Standardised factor loading*	*Standard error*	*t-value*	R^2	*AVE*	*CR*
Warmth perception					0.676	0.893
W1 (parameter weight)	0.853	-	-	0.727		
W2	0.861	0.085	12.777	0.742		
W3	0.786	0.078	11.227	0.618		
W4	0.786	0.091	11.222	0.618		
Competence perception					0.727	0.914
C1 (parameter weight)	0.875	-	-	0.766		
C2	0.815	0.071	12.781	0.664		
C3	0.873	0.079	14.487	0.763		
C4	0.846	0.082	13.679	0.716		
Customer satisfaction					0.855	0.946
S1 (parameter weight)	0.957	-	-	0.916		
S2	0.886	0.048	19.204	0.786		
S3	0.928	0.044	22.449	0.862		
Model fit statistics (CMIN/df = 1.370; P = 0.480; CFI = 0.989, NFI = 0.961, GFI = 0.937, RMSEA = 0.050, SRMR = 0.038).						

Note: R2 – shared variance between constructs; AVE – average variance extracted;
CR – Composite reliability.

4.2 Assumptions checking

According to Hair (2009), before running a parametric test there are several assumptions to consider:

- *Independence of observations:* this assumption was achieved through the random distribution of the surveys of the current study via online and offline channels, making sure that the subjects are not related to each other and do not participate in more than one scenario, or repeat the experiment.
- *Normality:* normality was verified using Shapiro-Wilk statistics (sample sizes $n < 50$) (Mishra et al., 2019). From the results in Table 5, for warmth perception, the null hypothesis cannot be rejected ($p > 0.05$) for groups 1 and 3; for competence perception, groups 1 and 4; and for customer satisfaction, groups 1 and 2. This means that the data of these groups are normally distributed. However, the null hypothesis can be rejected for the rest of the groups. However, a breach of the normalcy assumption should not cause serious issues due to the central limit theorem (Ghasemi and Zahediasl, 2012), which says that when a sample is large enough ($n > 30$), then whatever the distribution of the sample mean is, it will approximately follow a normal distribution. Hence, this study assumes the normal distribution for the groups.
- *Homogeneity of variance:* the Levene test was used to confirm homoscedasticity. For warmth perception ($F(3,147) = 4.991$, $p = 0.003$), competence perception ($F(3,147) = 3.592$, $p = 0.015$), and customer satisfaction, ($F(3,147) = 10.582$, $p = 0.000$) indicated that the assumption for homogeneity of variance was not met.

Table 5 Normality test

Construct	*Group*	*Shapiro-Wilk*		
		Statistic	*df*	*Sig.*
Warmth perception	1	0.951	41	0.077
	2	0.891	37	0.002
	3	0.961	35	0.249
	4	0.916	38	0.007
Competence perception	1	0.957	41	0.124
	2	0.933	37	0.028
	3	0.934	35	0.037
	4	0.962	38	0.226
Customer satisfaction	1	0.949	41	0.065
	2	0.951	37	0.108
	3	0.924	35	0.019
	4	0.931	38	0.021

Note: df – degrees of freedom; Sig. – significance; 1 – chatbot with social-oriented communication style in success condition; 2 – chatbot with task-oriented communication style in success condition; 3 – chatbot with social-oriented communication style in failure condition; 4 – chatbot with task-oriented communication style in failure condition.

4.3 Hypothesis testing

4.3.1 Main effects of communication style

This study conducted a non-parametric Kruskal-Wallis H test with SPSS (see Table 6) because, while the data can be assumed normality (due to the central limit theorem), the assumption of variance homogeneity was violated for all variables. Then, to determine the significant difference among the groups, the post hoc analyses carried out with the Games Howell statistician were used.

- *Customer satisfaction:* the results of the Kruskal-Wallis test identified a significant effect of communication style on customer satisfaction $H(3) = 102.400$, $p < 0.001$. The post hoc analyses carried out with the Games Howell statistician, showed that the chatbot with a social-oriented communication style under conditions of service success had a higher score in customer satisfaction (Mdn = 6.000) than the chatbot with a task-oriented communication style (Mdn = 5.333, $p < 0.001$) CI 95% [0.419, 1.186]. In contrast, the groups under failures conditions do not differ in their customer satisfaction scores, the chatbot with a task-oriented communication style (Mdn = 2.667) has the same score as the chatbot with a social-oriented communication style (Mdn = 3.000, $p = 0.730$) CI 95% [–1.079, 0.472]. These results support partially H1 and H4 (see Figure 3).
- *Warmth perception:* there is a significant effect of communication style on warmth perception $H(3) = 64.649$, $p < 0.001$. The chatbot with a social-oriented communication style under conditions of service success had a higher score in warmth perception (Mdn = 6.250) than the chatbot with a task-oriented communication style (Mdn = 5.000, $p < 0.001$) CI 95% [0.920, 1.706]. However, the groups under failure conditions do not differ in their warmth perception scores, a chatbot with a social-oriented communication style (Mdn = 5.000) has the same score as the chatbot with a task-oriented communication style (Mdn = 4.750, $p = 0.064$) CI 95% [–0.024, 1.224]. These results support partially H2 (see Figure 4).
- *Competence perception:* there were no significant group differences in competence perception under success conditions, a chatbot with a task-oriented communication style (Mdn = 5.000) has the same score as the chatbot with a social-oriented communication style (Mdn = 5.000, $p = 0.902$) CI 95% [–0.650, 0.381]. In the same way, the groups under failures conditions do not differ in their competence perception scores, the chatbot with a task-oriented communication style (Mdn = 3.125) has the same score as the chatbot with a social-oriented communication style (Mdn = 3.500, $p = 0.412$) CI 95% [–1.173, 0.303]. These results support H3 (see Figure 5).

4.3.2 Moderated mediation analysis

To formally test H6, a moderated mediation analysis was conducted using the bootstrapping approach (PROCESS Model 8, bootstrapping samples = 5,000; Hayes, 2017) (Hayes, 2017), with communication style as the independent variable, service outcome as the moderator, perceived warmth as a mediator, and customer satisfaction as the dependent variable.

Table 6 Kruskal-Wallis test

	1	*2*	*3*	*4*	*H*	*P*
	Mdn (rank)	*Mdn (rank)*	*Mdn (rank)*	*Mdn (rank)*		
Warmth perception	6.250 (2.250)	5.000 (3.250)	5.000 (3.000)	4.750 (4.500)	64.649	<0.001
Competence perception	5.000 (3.750)	5.000 (3.750)	3.500 (4.500)	3.125 (4.750)	65.667	<0.001
Customer satisfaction	6.000 (2.667)	5.333 (3.000)	3.000 (4.333)	2.667 (4.667)	102.400	<0.001

Note: 1 – chatbot with social-oriented communication style in success condition;
2 – chatbot with task-oriented communication style in success condition;
3 – chatbot with social-oriented communication style in failure condition;
4 – chatbot with task-oriented communication style in failure condition;
Mdn – Median.

Service outcome was found to moderate the effect of communication style and customer satisfaction, and the interaction between communication style and service outcome has a negative impact on warmth perception (B = -0.713, SE = 0.277, t = -2.573, p = 0.011). While, the perception of warmth has a positive impact on the satisfaction of the customer, greater warmer perception was associated with greater customer satisfaction (B = 0.323, SE = 0.092, t = 3.502, p < 0.001). The overall moderated mediation model was supported with the index of moderated mediation = -0.231 95% CI [-0.467, -0.044]. As zero is not within the CI this indicates a significant moderating effect of service outcome on communication style on the indirect effect via warmth perception (Hayes, 2017). The conditional indirect effect was strongest in service success condition (indirect effect = 0.424, SE = 0.133, 95% CI [0.165, 0.690]) and weakest in service failure (indirect effect = 0.194, SE = 0.104, 95% CI [0.287, 0.437]). These results support H5.

Figure 2 Mean values for customer satisfaction (see online version for colours)

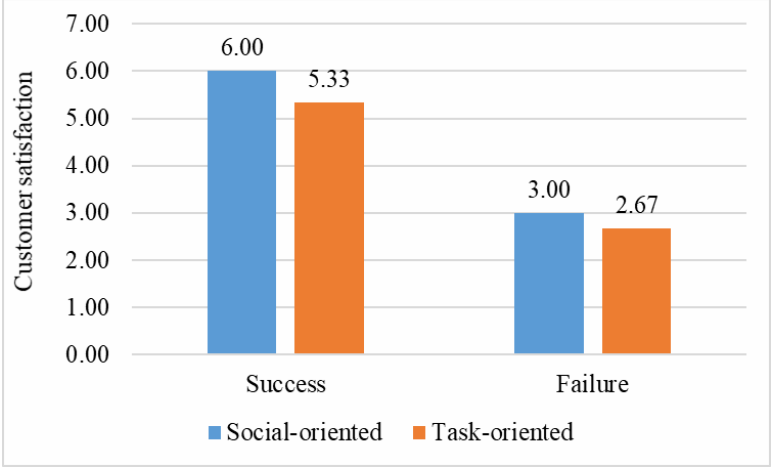


Figure 3 Mean values for warmth perception (see online version for colours)

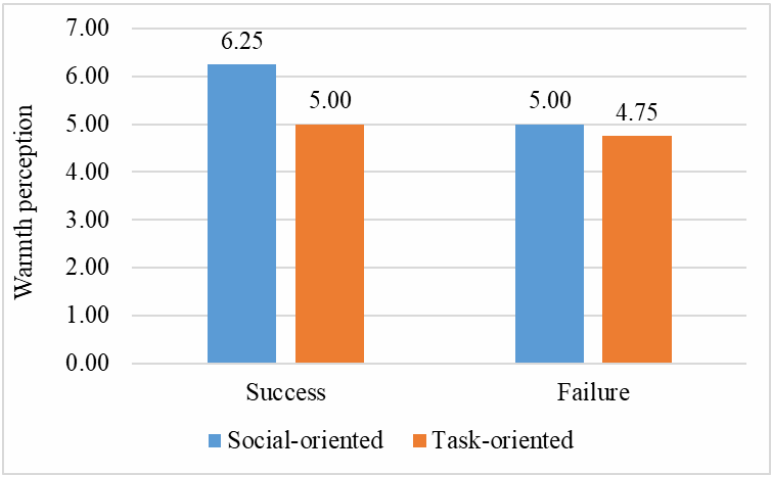
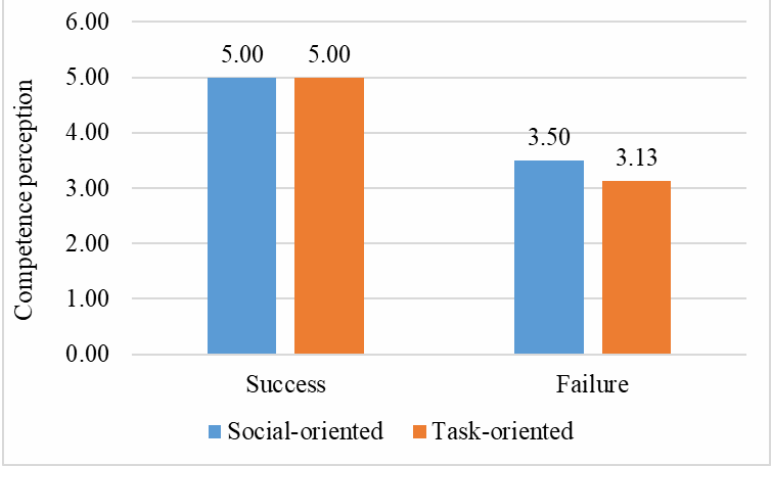


Figure 4 Mean values for competence perception (see online version for colours)



5 Discussion

5.1 Summary of findings

The findings show that there is a significant positive relation between social-oriented communication style on warmth perceptions and customer satisfaction. Using a social communication style for chatbots encourages consumers to perceive them as humans (Araujo, 2018; Gelbrich et al., 2021) and engage in a psychological process similar to interpersonal judgement, which influences customer service experiences. However, this conclusion is valid only when the chatbot ends in a context of successful service, but this tactic is not effective when the chatbot was in the context of handling service failures,

causing Hypotheses H1 and H2 to be partially supported, and confirming the importance of the role of the service outcome.

On the other hand, customers show a similar level of competence perception regardless of whether they are addressed by a chatbot that uses a task or social-oriented communication style, making Hypothesis H3 to be supported. Chatbots with different dialogue patterns do not differ in competence perception due to they had the same capabilities and were be able to handle the same customer's queries, in other words, chatbots that had the same outcome of the service, people's perception of chatbot's competence were perceived at the same level (Bleier et al., 2019; Huang et al., 2020). Additionally, people give more importance to warmth in many service settings, hence they highlight warmth traits more so than competence in their perceptions (Choi et al., 2020).

The chatbot communication style can influence customer satisfaction in successful service settings and most specifically the social-communication approach has a positive effect on customer satisfaction, but this effect cannot be found in service failure settings. Therefore, these results support partially H4.

Following that, the current study found that service outcome positively moderated the influence of communication style on warmth perception, thus affecting customer satisfaction and this effect is stronger in success service context than under service failure. Thus, supporting H5. To explain why the effect of communication style is not as strong in service failure contexts, the approach of relationship norm orientation could be used (Aggarwal, 2004). Aggarwal (2004) made a distinction between relationships that are largely based on economic reasons and those that are primarily based on social reasons: exchange and communal relationships. In exchange relationships, the reason for providing a benefit to the partner is to receive something in return. In communal relationships, individuals provide benefits to others to show care and respond to their needs. This study suggests that due to services failure violating exchange norms (Wan et al., 2011) (because the client requests a service and the company does not meet what the customer should get from the service), it might situationally increase the relevance of exchange norms. In other words, in the context of unsatisfactory services (regardless of the type of discourse that the conversational agent use), the customer-service interaction is more likely to be guided by exchange norms. In consequence, this study state that the existence of poor service would shift consumers' attention to examining the competence of service employees rather than their warmth, explaining the reason of why the moderating effect is stronger in contexts where there are no service failures.

The test results enrich and are helpful to clarify the effect of different types of communication on social perceptions and customer satisfaction from the perspective of this empirical research.

5.2 Managerial implications

The recent study has substantial marketing implications. By identifying the communication style that affects the customer's social perception and satisfaction, this work provides a valuable strategy for improving the customer service experience. The main goal of this research is to assist developers, brand managers, and the general public interested in chatbots in determining if variables such as conversational style impact customer satisfaction.

The decision to 'humanise' a chatbot is a deliberate and tactical choice made by the service provider. For brand managers, employing social-oriented communication for chatbots may make customers feel more warmth and increase their satisfaction. However, a social-oriented style can help improve service satisfaction when the service outcome is satisfactory, but it can backfire when service failures are present. Therefore, it is suggested to use this strategy with caution, as it might be disadvantageous in certain situations.

Crolic et al. (2022) suggest that it is important to understand the emotional context in which chatbots are employed, principally in customer service encounters that involve resolving problems or handling complaints. Field personnel should keep in mind that when a client is searching for answers and solutions, details such as conversational style tend to be ignored, and the effectiveness and efficiency in handling the problem take priority. As a first step, it is essential to assess whether clients are upset in the beginning. As Crolic et al. (2022) propose, this could be done using keywords or real-time natural language processing (NLP). If the customer is not angry, can use a social-oriented approach. If the customer is angry, focus on service recovery strategies or promptly divert angry customers to a human agent who can be more empathetic and has more agency and flexibility to solve a problem. Another solution would be to assign social-oriented approach agents in a more neutral or promotion-oriented environment (such as product information searches) due to their earlier documented positive effects and focus more on service recovery strategies in customer service roles that typically involve angry customers (such as customer complaint centres).

Here, the current study shows that the indiscriminate implementation of human-like chatbots has a detrimental impact on marketing outcomes. However, with proper implementation, that takes into account the customer's emotional state (such as rage), organisations may reap the benefits of this new technology.

5.3 Limitations and prospects for future research

The present study is not free of limitations that point to potential future research directions. First, the experiments relied on a scenario-based approach, images of dialogue were exposed to the respondents. Future research should allow people to communicate with a chatbot directly to increase external validity. Second, the experiments concentrated on retail environments. Upcoming investigation expanding to other service settings would be beneficial in determining the generalisability of this research. Third, this study only focuses on one type of service failure. Future research should look into the effects of chatbot communication in settings with varying failure types or severities. Fourth, this study manipulates the communication style as a binary variable but it is also worthwhile to investigate operationalising the social-oriented communication style as a continuous variable. Five, other moderators of the observed effects should be investigated. Future studies should explore other individual differences, such as relationship norm orientation.

6 Conclusions

Chatbots are one of the most frequent and early applications of AI, and their conversations have gotten more humanlike as technology has advanced. This capability has been extremely beneficial in customer service settings, but the literature about the

chatbot communication style is still scarce. The objective of this work was to explore the circumstances in which service chatbots have a more positive impact on customer service experiences, responding to the calls for additional studies on anthropomorphic design signals to improve chatbot humanness in artificial intelligence literature, and therefore to contribute to the HCI literature. Through a scenario-based approach and using snowball and convenient sampling, this study explored the effect of different communication styles on customer satisfaction, using perceived warmth as a mediator and service outcome as a moderator variable. The empirical results show that the results support our theoretical theory by demonstrating that a social-oriented dialogue approach increases customer satisfaction and that the warmth perception of the chatbot mediates this relation, but this effect is significant in the service success context. The competence perception is similar to the different communication styles. The service outcome moderates the effect of a social-oriented (vs. task-oriented) communication style on customer satisfaction through the mediation of warmth perception, and this effect was strongest in successful services and weakest in a service failure context.

A friendlier approach can help improve service satisfaction when the service result is satisfactory but can fail when there are service failures, so having recovery strategies such as acknowledging customer emotional states, transferring customer queries to a human employer, designing a specific communication style for specific service environments, apologising, giving financial compensation, discounts, gifts, among others, is necessary to be used in case of service failures. Because such failure scenarios can highlight exchange norms, leading customers to conclude that the chatbot lacks competence and rendering the communication style strategy ineffective and not sufficient to mitigate the dissatisfaction generated by the service failure. The results of this study pave the way for more future research in the fields of HCI and anthropomorphism in conversational agents, laying the foundations for a more humane pattern of conversation for people, and at the same time help to guide brand managers and chatbot developers to fully explore the value of different ways of interaction styles with customers and to bring into play the role of communication itself and ensuring the long-term viability of this technology with proper implementation.

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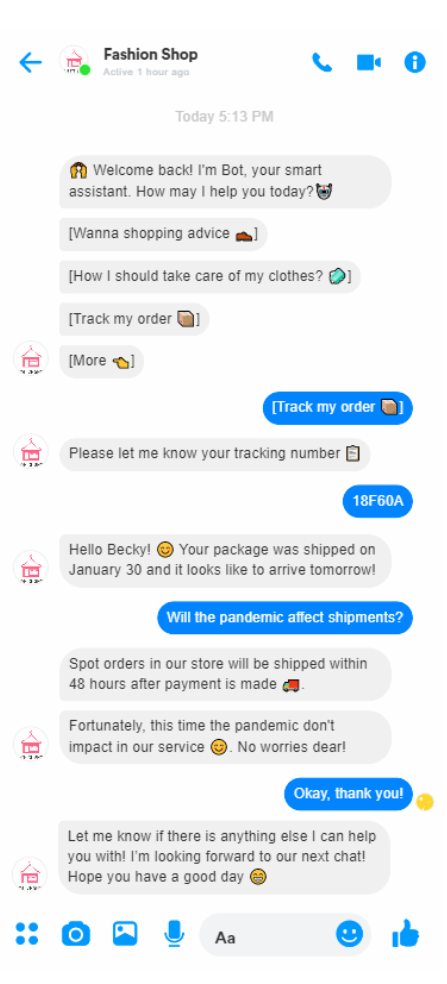
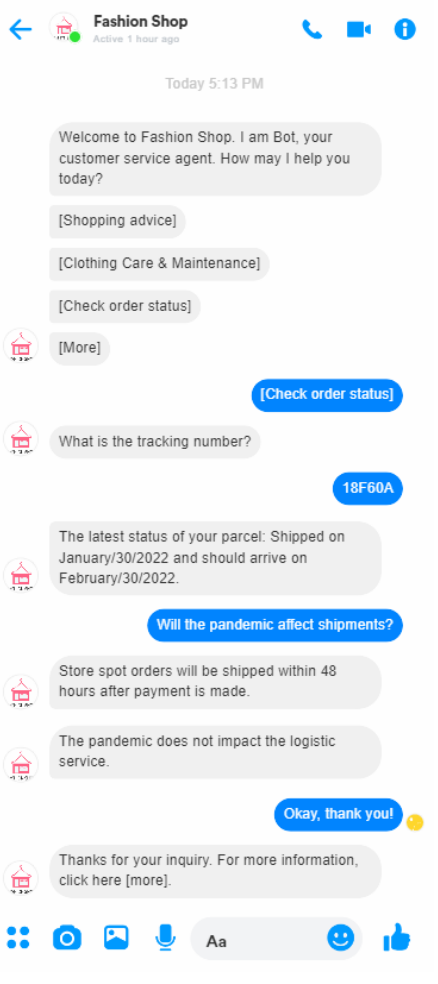
Appendix

Scenarios 1 and 2: chatbot with social-oriented (left) and task-oriented (right) communication style in successful service





Scenario 3 and 4: chatbot with social-oriented (left) and task-oriented (right) communication style in service failure