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“FIND A FLIGHT FOR ME, OSCAR!” MOTIVATIONAL CUSTOMER EXPERIENCES WITH CHATBOTS

Purpose

Drawing on the self-determination theory, the assemblage theory, and customer experience literature, we aim to develop a framework to understand motivational customer experiences with chatbots.

Design/methodology/approach

We employ a multimethod approach to examine the interaction between individuals and airlines' chatbots. Three components of self-determined interaction with the chatbot (competence, autonomy, and relatedness) and five components of the customer–chatbot experience (sensory, intellectual, affective, behavioral, and social) are analyzed qualitatively and quantitatively.

Findings

The findings confirm the direct influence of self-determined interaction on customer experience and the direct effects of these two constructs on participants' attitudes toward and satisfaction with the chatbot. The model also supports the mediating roles of customer experience and attitude toward the chatbot.

Practical Implications

We offer managers a broad understanding of individuals' interactions with chatbots through three elements: motivation to use chatbots, experiential responses, and individuals' valuation of whether the interactions have amplified (or limited) the outcomes obtained from the experience.

Originality/value

We contribute to the hospitality and tourism literature with a hybrid approach that reflects on current theoretical developments regarding human- and interaction-centric interpretations of customer experience with chatbots.

Keywords Chatbot, Customer experience, Hybrid experiential model, Artificial intelligence.

1. Introduction

The use of smart technologies by hospitality and tourist companies is now a reality. Virtual assistants based on artificial intelligence (AI) are gradually taking part in customer–company relationships during all consumption phases (Pillai and Sivathanu, 2020). In this context, chatbots on social media and websites represent one of the most extended AI applications used by hospitality and tourism service providers. Companies such as Air New Zealand, Delta Air Lines, Expedia, among others, have considered the use of chatbot assistants for their customer services. In particular, the airline sector is a clear example of an early adopter of AI-based chatbot technology (Ghosh and Chakravarty, 2018).

Although chatbots have been available as simple language processing programs for decades, recent developments in their interactive capacity have attracted the attention of both service companies and academics (Belanche, *et al.*, 2020a, 2020b, 2020c; Belk, 2020; Cha, 2020; Luo *et al.*, 2019; Ratchford, 2020). AI-based chatbots can perform informational and conversational tasks typically undertaken by humans, such as responding to requests, learning from interactions, solving problems, and making decisions (Sands *et al.*, 2020). Service companies recognize the advantages of chatbots as new communication touchpoints. Recent studies have highlighted savings in personnel costs (Sands *et al*., 2020) and the ability to provide customer service outside working hours (Adam *et al.*, 2020). Additionally, the Global Market Insights (2019) agency recently estimated that the worldwide chatbot market could reach USD 1.34 billion by 2024.

To understand the main factors that facilitate the implementation of chatbots as communication channels for service companies, previous research has analyzed acceptance (Pillai and Sivathanu, 2020), the motivation for (Brandtzaeg and Folstad, 2018) and the benefits of using chatbots for customer support (Luo *et al.*, 2019). However, even though experiential interaction with chatbots is expected to directly impact customer–company relationships (Sands *et al.*, 2020), comprehension of the influence that customer experience with chatbots has on customers' attitudinal and behavioral responses is still limited (Hoyer *et al*., 2020). In addition, although customer experience has been investigated in relation to individuals' encounters with multiple company channels, researchers have highlighted the importance of generating knowledge about individuals' experiences with chatbots in the hospitality and tourism industries (Chiang, 2020; Pillai and Sivathanu, 2020).

The above discussion raises the question: How can chatbots produce satisfactory experiences for the customers of hospitality and tourism service companies? To solve this question, we aim to improve the understanding of customer experiences with chatbots in the hospitality and tourism contexts and their effect on individuals' attitudes and satisfaction. We first evaluate how customer experience has been interpreted in the marketing literature. Customer experience research based on a human-centric approach has recently been questioned for its passive view of individual interactions with companies' technological touchpoints (Hoffman and Novak, 2018). Recent studies, which adopt an interaction-centric approach, highlight the need to understand customers' motivations and active roles in their interactions with these technologies. In particular, emphasis has been placed on analyzing aspects such as the roles expressed by and the capacities of customer interactions with chatbots (Hoffman and Novak, 2018). Roles refer to an individual's ability to affect or be affected by the exchange. Capacities refer to what an individual can achieve during the interaction. Although customers' roles and capacities are inherent elements of individual–chatbot interactions, current multidimensional customer experience models do not offer evidence of their influence in the customer–company relationship (Novak and Hoffman, 2019). That is, the interactive use of AI technologies can establish new connections between individuals and hospitality and tourism organizations (Tuomi *et al.*, 2021). Hence, we contemplate new theoretical developments in customers' interactions with technology (such as the assemblage theory) to understand and observe individual customers' roles and capacities that can emerge during interactions with chatbots.

Finally, we test a motivational customer experience model that includes multidimensional measures of the experience and the customer-expressed roles and capacities in the interaction with a tourism company's chatbot. In contrast to prior customer experience models, we reflect on the self-determination theory (SDT) to observe how customers' expressed roles and capacities can be measured as motivational factors while using chatbots. Based on the SDT, individuals' motivations are structured across three basic psychological needs while interacting with technology (i.e., the need for competence, autonomy, and relatedness). Overall, we contend that the fulfillment of basic psychological needs during episodic chatbot interactions can affect different outcomes, such as customer experience, attitudes, and satisfaction with the chatbot.

Our study responds to recent calls for research on customer–chatbot interactions in the hospitality and tourism context by developing a model that integrates the human- and interaction-centric approach of customer experience with chatbots. Additionally, we overcome the limitations of prior hospitality and tourism studies by exploring the potential of AI to influence customer experiences (Chiang, 2020), extending comprehension of the customer–chatbot interaction with individuals from developed countries (Pillai and Sivthanu, 2020), and particularly exploring individuals' comprehension of interactions with airlines' chatbots (Buhalis and Cheng, 2019).

2. Theoretical background

2.1 Chatbots in hospitality and tourism

Research on customer interactions with AI-based chatbots in the hospitality and tourism industries is recent and limited. Existing studies has focused on examining elements that influence its adoption and use intentions. For instance, Pillai and Sivathanu (2020) found that ease of use, usefulness, trust, intelligence, and anthropomorphism drive consumer desires to adopt chatbots, and Lv *et al.* (2021) showed that chatbots' cuteness design positively affects customer tolerance of service failure. Additionally, customer characteristics have been identified as drivers of attitudes toward a service company's chatbot. In particular, Martin *et al.* (2020) demonstrated that the customer tendency to impute human-like characteristics to nonhuman agents enhances engagement and enjoyment of cognitive endeavors that will drive positive customer attitudes toward the nonhuman agents. Yet, the influence of customer motivation in the customer–chatbot interaction, the dimensionality of the customer experience with chatbots, and their potential impact on attitude toward and satisfaction with the chatbot remain unclear.

2.2 Customer experience with chatbots

Pioneering research into customer experience has examined different models that measure individuals' internal and subjective responses in their encounters with companies' marketing channels, such as retail stores, online stores, among others (Bleier *et al.,* 2019; Brakus *et al*., 2009). Prior customer experience models demonstrate that experience is a multidimensional construct that can influence individuals' attitudes and satisfaction. Among the dimensions of customer experience analyzed in these studies, experiential components interpreted as individual responses to company or brand stimuli recur: sensory (i.e., the degree to which a brand or organization's stimuli influence the senses), intellectual (i.e., customer thinking and problem-solving while in contact with the brand or organization's stimuli), affective (i.e., emotions emerging in contact with the brand or organization's stimuli), behavioral (i.e., behaviors evoked by a brand or organization's stimuli), and social (i.e., sociability and feeling of human contact conferred by the brand or organization's stimuli).

Recent conceptual research in the marketing literature supports that customer experiences with new technology may involve customers' responses to stimuli generated by chatbots (Hoyer *et al*., 2020). Given this assertion, we propose that it is possible to measure customer experience derived from an online conversation with a tourism service company's chatbot through a multidimensional construct. However, current marketing literature indicates that the customer experience derived from being in contact with a smart assistant should be framed within the interactional scenario represented by the conversation between consumers and technology. This means that traditional multidimensional constructs of customer experience inherently situate individuals as mere receptors and processors of stimuli produced by intelligent assistants (i.e., a human-centric approach). Hoffman and Novak (2018), drawing on assemblage theory, suggest that individuals and smart assistants can participate in the interaction, augmenting or limiting the outcomes obtained from the interactive experience (i.e., an interaction-centric approach). This last experiential perspective indicates the importance of analyzing the roles and capacities of individuals and technology assistants that emerge from the interactive experience between them.

2.3 Roles and capacities in customer–chatbot interaction: the assemblage theory approach

Assemblage theory suggests that communicating parties (i.e., individuals and chatbots) can affect and be affected by each other when the consumer seeks a particular piece of information in a consumption context (DeLanda, 2016). Based on this theory, Hoffman and Novak (2018) analyzed the roles and capacities expressed by individuals in their interactions with smart objects. For example, in analyzing the properties of the customer experience, one can measure how an individual is affected by a smart technology and the behavioral properties of how, in return, the individual affects the smart technology.

Thus, from the assemblage theory perspective, consumers and smart objects are characterized by their agentic and communal roles (see Table I). The *agentic role* involves customers proactively asking questions, requesting information, and complementing the feedback received with their own ideas and comments. The *communal role* involves customers, as a result of the interaction, developing cooperative capacities in their search for service company-related information or entertainment (Novak and Hoffman, 2019). Both roles can also have negative connotations. A low agentic role could involve a limitation in proactive capacity and a low communal role a limitation in cooperative capacity, both causing an inability to get the desired information from a service company's chatbot.

[Insert Table I about here]

3. Motivational customer experience with chatbots: hypotheses development

Expressing a specific role in interactions with chatbots could be interpreted as a materialization of the individual's intrinsic motivations with respect to chatbot use. Individuals' motivations in the phenomenological context of the experience have been examined in the psychological literature under SDT postulates (Ryan and Deci, 2020). The SDT maintains that individuals, by nature, have intrinsic motivations that are manifested in behaviors based on curiosity, exploration, and the search for challenges and new experiences. This means that individuals continually seek challenges in their environments to develop new capacities and satisfy the basic psychological needs that are essential for their well-being (Gilal *et al.*, 2019). The basic psychological needs that individuals seek to satisfy throughout multiple contexts have been described as the needs for competence, autonomy, and relatedness.

While interacting with chatbots, the *need for competence* relates to individuals' feelings of security and self-confidence. In these circumstances, individuals may identify opportunities in which they can express and demonstrate their capabilities to know about something or solve a particular task (Gilal *et al.*, 2019). The *need for autonomy* relates to individuals' behaviors with the chatbot as guided by their interests and values: when individuals feel that they can behave autonomously, they may perceive their behavior as self-expression (Deci and Ryan, 2002). Finally, the *need for relatedness* refers to the individuals' need to connect with others, to care, and to be cared for (Baumeister and Leary, 1995). Researchers examining interactions between humans and new technology have concluded that it is appropriate to measure the intrinsic motivations generated by technologies through a construct termed self-determined interaction, which is formed in three dimensions: competence, autonomy, and relatedness (Gilal *et al.*, 2019).

Following the SDT, to the extent that episodic interactions with chatbots contribute to satisfying customers' basic psychological needs, customers could develop a high degree of self-determination that positively affects their contextual interactions with a chatbot and their overall satisfaction (Gilal *et al.*, 2019). A positive interaction with a chatbot, based upon a sense of self-determination, enables an immersive experience (Gillet *et al.*, 2013), which positively affects learning enhancement (Baloglu *et al.*, 2019), emotions, and well-being. Therefore, it seems plausible that well-implemented and -managed chatbots that permit customers to feel competent, in control, and understood may enhance positive experiential responses at the sensory, intellectual, affective, behavioral, and social levels.

For example, a highly responsive chatbot used as a company's touchpoint may produce a sense of being agile, smart, and sophisticated while shopping or searching for information (Fitzsimons *et al.*, 2008). The overall perception regarding the chatbot's capacity to solve customers' queries may facilitate experiential responses, such as thoughts about how it is possible to obtain maximum value from the company's service (i.e., cognitive experience) but also to have positive feelings (i.e., affective experience) and sensations (i.e., sensory experience) derived from being well understood and attended by the chatbot. This logic is in line with theoretical propositions that consider that, as brand-related stimuli, chatbots implemented by companies can evoke different experience dimensions and create experiential value (Hoyer *et al.*, 2020).

Building on these arguments, we contend that there is a perceptual mechanism that interplays between customers' self-determination and experiential responses while interacting with a chatbot (i.e., the motivational customer experience). Thus, our research suggests that, to the extent that the resulting self-determined interaction is positive, it will enhance the customer experience with the chatbot. Therefore, we propose our first hypothesis:

H1: Self-determined interaction positively affects customer experience with the chatbot.

To the extent that customer experiences with organizations' technological touchpoints (such as chatbots) produce attractive, positive, and memorable results, it is plausible that customers' attitudes toward and satisfaction with the chatbot will be favorable (Bleier *et al*., 2019). In this sense, the experiential responses derived from the interaction with chatbots are expected to directly impact customer–brand relationships in terms of customer attitudes and satisfaction (Sands *et al.*, 2020). Hence, when users have favorable customer experiences in their interactions with chatbots, these experiences may predict positive attitudes toward and satisfaction with chatbots. More formally, we present the following hypothesis:

H2: Favorable customer experience with the chatbot positively influences attitude (a) toward and satisfaction (b) with the chatbot.

Drawing on the SDT, we contend that in customer–chatbot interactions, there is a perceptual mechanism through which individuals' attitudes toward AI-based assistants may depend on how technology contributes to meeting their basic psychological needs.

Individuals may perceive that new technologies constitute a challenge through which they might satisfy their intrinsic motivations and self-determination to interact (Peters *et al.*, 2018; Ryan and Deci, 2020). To the extent that chatbots develop customers' capabilities and potential, fulfilling their basic psychological needs, it seems reasonable that customers' attitudes toward and satisfaction with chatbots will be enhanced. Consequently, the following hypotheses are proposed:

H3: Self-determined interaction with the chatbot positively affects customers' attitude (a) toward and satisfaction (b) with the chatbot.
H4: Attitude toward the chatbot positively influences customer satisfaction with the chatbot.

4. Research overview

Due to the empirical complexity that represents the customer experience, motivations, and expressed roles in the interaction with chatbots, we designed a sequential multimethod program to establish a holistic understanding of our research goal. First, we inductively examined individuals' opinions, beliefs, and thoughts about our focal constructs when describing an elicited scenario that reproduced fluid (Study 1) and problematic (Study 2) conversations with a fictitious airline chatbot. Second, we deductively tested our hypotheses (see Figure I) after evaluating the relationships between individuals' self-determined interaction, experience, attitude, and satisfaction after a real interaction with an airline chatbot (Study 3).

[Insert Figure I about here]

4.1. Study 1

In Study 1, we analyzed how customers understood and processed a fluid simulated interaction with a service company's chatbot. To do so, we explored two elements of the customer–chatbot interaction: (1) the roles and capacities expressed by individuals while interacting with a chatbot; and (2) individuals' experiential responses. In Study 1, participants were shown an intentionally fluid and coherent conversation (developed by the authors) between a consumer and a fictitious airline's chatbot (Figure II). The present study used a metaphorical projective technique based on online storyboarding elicitation, which uses a narrative sequence of consumption in vignettes. This technique facilitates participants' immersion in and understanding of the research topic under study (Hart, 1998).

First, to present the research context to the participants, they were told to imagine a situation in which they searched for information about a flight using an airline chatbot. Then, they were shown a simulated conversation in which a consumer asks an airline chatbot about its offer and the availability of flights between New York and Paris. After the experiment, we asked participants three open-ended questions: (1) *After looking at this scenario, which questions/information would you add to the conversation with the chatbot?* (2) *What do you think about the idea of communicating with a chatbot to search for information and/or book* *a flight?* and (3) *Which aspects are essential in a conversation with a chatbot about booking a flight?* A total of 58 US residents were recruited (paid US $1.05; 50% female; mean age 31 years; 28% with university degrees) from the online panel, Amazon Mechanical Turk (MTurk). However, only 22 participants' narratives were included in the analysis of Study 1, because we observed saturation of themes in the data gathered with the 22nd participant.

[Insert Figure II about here]

4.1.1. Data analysis

The participants' responses were analyzed using the grounded theory approach. Grounded theory is a data analysis technique in which an inductive systematic process informs and develops a theory about a specific phenomenon (Strauss and Corbin, 1990). In line with Strauss and Corbin (1990), we conducted three steps in our qualitative data analysis: first, we revised the narratives to form a broad understanding of the participants' opinions, beliefs, and interpretations of the scenarios proposed. Second, we performed manual, open, axial, and selective coding. In the open coding, the participants' quotes were extracted line by line according to the potential elements included: (1) the roles and capacities expressed by the consumers in their interactions with the chatbot; and (2) the participants' experiential responses (i.e., sensory, intellectual, affective, behavioral, and social). The axial coding highlighted elements considered central to the participants' quotes (i.e., the degree to which the agentic and communal roles enabled or constrained the experience). Finally, with selective coding, we thoroughly analyzed the codifications that determined the final subthemes to test the ideas and concepts rooted in the participants' narratives linked to theory.

4.1.2. Results of Study 1

The roles identified in the interaction were classified with coding based on the agency of both elements in the interaction (i.e., the customer' ability to affect the chatbot and the chatbot's ability to affect the customer) and the functionality obtained as a result of the interaction (communalities) (see Table II).

[Insert Table II about here]

Three types of customer–chatbot relationships, including an agency–communion combination, were observed. The first relationship type was characterized by the participants' high agentic role, the chatbot's low agentic role, and by both parties having sufficient communion (i.e., a master–servant complementary relationship; Novak and Hoffman, 2019). In this relationship, the participants perceived that they had high control over the interaction with the chatbot. The second relationship type was characterized by the low agentic and communal roles of both the participants and the chatbot (i.e., the partners' isomorphic acomplementary style; Novak and Hoffman, 2019). The interaction associated with this relationship was perceived by several participants as problematic, frustrating, and useless for finding information, even though it was presented as fluid.

The third relationship type was characterized, although to a lesser extent, by the participants' high agentic and communal roles and by the chatbots' low agentic and communal roles (i.e., a non-correspondent master–servant relationship style; Novak and Hoffman, 2019). In this relationship, the participants questioned the chatbot's interactive functionality to help them achieve informational goals.

We also observed how the three relationship types extracted can be defined in the form of the participants' perceptions of competence, autonomy, and relatedness. We conclude that the master–servant complementary relationship allowed participants to feel high autonomy and relatedness during the interaction with the chatbot but low levels of competence. This means that customers can feel themselves in control and connection with the chatbot, but the overall value of the conversation does not amplify individuals' knowledge and searching capabilities. In contrast, for the partners' isomorphic acomplementary and non-correspondent master–servant relationship types, the levels of competence, autonomy, and relatedness were described as low. This means that the participants who developed these two relationships with the chatbot demonstrated limited self-determination to interact with the chatbot.

In addition, five dimensions theoretically linked to customer experiential responses emerged from the participants' narratives: sensory, intellectual, affective, behavioral, and social. The affective response to the chatbot emerged as the most important dimension at the experiential level (see Table II). The participants repeatedly reported feelings of frustration, risk, confusion, and mistrust at the idea of interacting with a chatbot. The few participant quotes that reflected positive emotions were related to the chatbot's personality traits (i.e., the politeness and friendliness with which it dealt with customers' issues). The participants' sensory responses were evaluated based on the quotes that highlighted the importance of the chatbot's visual elements. The chatbot's coordinated use of text, images, and emojis made the interaction more attractive for the senses and more immersive.

The intellectual responses captured in the participants' quotes queried or praised the chatbot's ability to respond to their complex questions. In addition, the participants highlighted the chatbot's ability to make them reflect on the linguistic adjustment needed to develop the conversation. The behavioral responses were related to the perceived comfort of the information search undertaken with the help of the chatbot and the customers' motivation to carry out a greater number of actions, for example, visit the airline's website.

Finally, the social responses were identified through the chatbot's textual capabilities to simulate high or low levels of human warmth and to motivate participants to develop and maintain the conversation.

4.2. Study 2

Study 2 used the same simulated visual stimulus as in Study 1, this time accompanied by an intentionally problematic narrative that was not fluid (see Figure III). The analytical coding elements also related to the roles and capacities expressed by the consumers in their interactions and to their experiential responses. The participants constituted a new recruited sample of 59 US residents (paid US $1.05; 55% female; mean age 30; 27% with university degrees) from MTurk. We included in the analysis the narratives of 34 participants after observing data saturation with the 34th participant.

[Insert Figure III about here]

4.2.1. Results of Study 2

First, the predominant relationships observed in the participants' narratives were the customers' high agentic and communal roles and the chatbot's low agentic and communal roles (i.e., the non-correspondent master–servant relationship type). Second, other participants expressed a low agentic role and communal role for both themselves and the chatbot (i.e., the partners' isomorphic acomplementary relationship type). Third, to a lesser extent, some participants expressed narratives based on a relationship characterized by the customer having a high agentic role and a low communal role in combination with the chatbot having low agentic and communal roles (i.e., the master–servant complementary relationship). As in Study 1, the Study 2 participants also demonstrated that self-determined motivation to interact with a chatbot is stronger in perceived autonomy, competence, and relatedness with a master–servant complementary relationship type (see Table III).

Regarding the experiential response, the negative and problematic elicitation of the customer's conversation with the chatbot evoked strong negative emotions. The participants reported frustration, perceived risk, and distrust in their interactions with the chatbot. The other experiential responses observed in Study 2 were similar to those observed in Study 1 (see Table III).

[Insert Table III about here]

In conclusion, it should be noted that in both the fluid and the problematic interactions, similar elements were observed in the roles and capacities expressed by the participants and in their experiential responses. This evidence confirms the possibility of going deeper into the relationships between the expression of certain roles and capacities in chatbot interactions (i.e., the customer's perceived competence, autonomy, and relatedness), the experiential responses, and the individual's attitudes toward and satisfaction with the chatbot.

4.3. Study 3

The main objective of Study 3 was to examine the relationships between self-determined interactions, customer experience, attitude toward, and satisfaction with the chatbot. A new sample of 370 US residents was recruited through the MTurk platform (paid US $1.05; 42% female; mean age 31; 30% with university degrees). The participants were asked to freely ask Oscar, the Air New Zealand chatbot, for flight information, prices, and routings for travel between New Zealand and the US. They were subsequently asked to complete a questionnaire to measure the constructs under analysis (using the Qualtrics platform). The time participants spent in their online interactions with the chatbot was controlled, and an attention check question evaluated the quality of the responses. Those participants who navigated for fewer than two minutes or who answered the question incorrectly were eliminated from the analysis. Our final sample comprised 205 US residents (49% female; mean age 31; 29% with university degrees).

4.3.1. Measurement and model Estimation

As the goal of Study 3 was to determine the capacity of self-determined interactions to predict customer experience with and responses to a chatbot, the relational model was estimated using partial least square-structural equation modeling (PLS-SEM) (Usakli and Kucukergin, 2018). Self-determined interaction was operated as a formative second-order construct type II (reflective-formative; Hair *et al.*, 2018) with three reflective first-order components (i.e., competence, autonomy, and relatedness) adapted from Deci *et al*. (2001). Customer experience with the chatbot was also assessed with a second-order formative structure (type II) with five reflective first-order components (sensory, intellectual, affective, behavioral, and social) adapted from Bleier *et al.* (2019). Attitude and satisfaction were measured as reflective first-order constructs adapted from Makarem *et al*. (2009) and Rosen *et al*. (2013) respectively. The participants rated all the variables on a 7-point Likert-type scale (see Table IV).

[Insert Table IV about here]

We followed Ringle *et al.*'s (2012) recommendation of developing a two-stage approach to estimate our higher-order constructs (self-determined interaction and customer experience with chatbots) using SmartPLS software. In the first stage, we used the repeated indicator approach, in which first-order latent variables are formed with their related items, to estimate our model. Then, the second-order latent variables were developed with the manifest variables of the first-order variables, through which we obtained the first-order latent variable scores. In the second stage, we operated these scores as manifest variables representing the second-order constructs. We confirmed the reliability and validity of all the reflective scales according to Cronbach's alpha (range 0.81–0.93) and the composite reliability (range 0.89–0.95) reference limits of 0.70 (Hair *et al.*, 1998). All the constructs showed an acceptable average variance extracted (AVE; range 0.73–0.86) higher than 0.5 (Fornell and Larcker, 1981).

Similarly, we examined the suitability of each construct's factor by verifying the significance of the loadings with a value higher than 0.70 in each proposed theoretical construct (all p values < 0.001). Regarding discriminant validity, we corroborated the square root of the AVE per latent variable as higher than the correlations between each pair of constructs (Table V). Furthermore, all the constructs returned satisfactory discriminant validity based on the heterotrait-monotrait ratio (HTMT < 0.90) (Henseler *et al.*, 2015), indicating that the measurement model of the first-order constructs was suitable. After this analysis, we evaluated our model using the latent scores of the first-order constructs as the components of self-determined interaction and customer experience with the chatbot (our second-order constructs).

[Insert Table V about here]

Subsequently, we evaluated the validity of the formative scales. First, we conducted a collinearity test among the components of the formative constructs. All variance inflation factors were lower than 5 (see Table VI), indicating that there were no multicollinearity issues (Diamantopoulos and Winklhofer, 2001). Second, we examined the contribution of the first-order indicators for each second-order construct (i.e., self-determined interaction and customer experience with chatbots) to confirm whether they were valid components of the formative constructs (Hair *et al.*, 2018). We then conducted a non-parametric test with a bootstrapping procedure consisting of 10,000 samples, with no sign change. The bootstrapping approach revealed that all the indicators had a significance of at least 95% for self-determined interaction and at least 90% for the customer experience with the chatbot, except for the social dimension. As the contribution of the social dimension was not significant for the second-order formative construct of the customer experience, we continued with our experiential model, which included only four dimensions (i.e., sensory, intellectual, affective, and behavioral). This change improved the overall fit of our relationship model from a standardized root mean residual (SRMR) indicator of 0.028 to a final SRMR value of 0.023. Therefore, the resulting PLS-SEM measurement model showed an adequate fit based on the SRMR indicator cutoff rule (Henseler *et al.*, 2015).

[Insert Table VI about here]

4.3.2 Hypotheses testing

The standardized load coefficients, *t*-statistics, and standard errors were computed through a bootstrapping process (resampling size of 10,000). To evaluate the model's explanatory and predictive capacity for the global sample, the R^2 and Q^2 values were calculated. The R^2 parameter showed that self-determined interaction and customer experience with the chatbot explained 65% of the variance in attitude toward the chatbot, and the three constructs as a whole explained 78% of the satisfaction with the chatbot. Additionally, self-determined interaction explained 66% of the variance in customer experience. The positive Q^2 values higher than 0.20 in the dependent variables (range 0.49–0.77) showed that the global model demonstrates predictive relevance.

The results confirm the positive direct influence of self-determined interaction on the customer experience with chatbots ($\beta = 0.81$; $p < 0.001$; supporting H1). Similarly, they also confirm that self-determined interaction exerts a positive direct influence both on attitude toward the chatbot ($\beta = 0.35$; $p < 0.001$; supporting H3a) and on satisfaction with the chatbot

($\beta = 0.43$; $p < 0.001$; H3b is supported). In turn, customer experience positively and directly influences attitude toward ($\beta = 0.48$; $p < 0.001$; supporting H2a) and satisfaction with the chatbot ($\beta = 0.23$; $p < 0.001$; supporting H2b). Finally, the positive direct effect of attitude on satisfaction with the chatbot is confirmed ($\beta = 0.28$; $p < 0.001$; supporting H4).

Path estimates and their significance indicate that self-determined interaction could have an indirect effect on individuals' attitudes toward and satisfaction with the chatbot through customer experience. The specific indirect effects derived from the bootstrapping procedure using SmartPLS with 10,000 subsamples confirmed that customer experience had a mediation effect in three cases: (1) between self-determined interaction and attitude ($\beta = 0.40$; 95% confidence interval (CI) 0.21–0.51; $p < 0.001$); (2) between self-determined interaction and satisfaction with the chatbot ($\beta = 0.19$; 95% CI 0.08–0.30; $p < 0.01$); and (3) between self-determined interaction, attitude, and satisfaction ($\beta = 0.11$; 95% CI 0.04–0.17; $p < 0.01$). In addition, we confirmed the mediation of attitude toward the chatbot between self-determined interaction and satisfaction with the chatbot ($\beta = 0.10$; 95% CI 0.04–0.18; $p < 0.01$) and between customer experience and satisfaction ($\beta = 0.14$; 95% CI 0.05–0.24; $p < 0.01$).

5. Conclusions

The adoption by hospitality and tourism service companies of AI-based technologies, such as chatbots, underlines the need for more research on customer experiences (Pillai and Sivathanu, 2020; Tussyadiah, 2020). In our study, we proposed and evaluated a hybrid model that integrates both human- and interaction-centric customer experience approaches.

First, we observed the roles and capacities expressed by individuals in their interactions with chatbots. The qualitative findings show that the roles and capacities expressed by customers in their interactions with chatbots can be categorized into three types of relationships. The first relationship type was characterized by the customers' high agency when they made requests to the chatbot and the chatbot's sufficient agency to return answers, which allowed the customers to obtain basic information. A second relationship type was characterized by the customers and the chatbot having similar capacities for agency and communion: the customers were reluctant to interact with the chatbot, which they perceived as having limited functionality. In the third relationship type, the customers trusted their ability to interact with the chatbot but questioned the ability of the chatbot to provide sufficiently complete, secure, and satisfactory responses.

Second, our qualitative analysis indicated that the customer experience with a chatbot is formed around five experiential dimensions: sensory, intellectual, affective, behavioral, and social. Fluid interactions are mainly driven by an individual's intellectual, affective, behavioral, and social responses to the stimuli emitted by the chatbot. In contrast, problematic interactions with chatbots are fundamentally characterized by the generation of negative emotions in customers (affective responses).

Third, in the quantitative study, customer roles and capacities were represented by their basic psychological needs (competence, autonomy, and relatedness). Thus, following the SDT, the dimensions of the customer's perceived competence, autonomy, and relatedness in conversation with the chatbot were considered in the conceptualization of self-determined interaction as a second-order construct (Gilal *et al*., 2019). Similarly, customer experience was assessed as a second-order construct based on the identification in the two qualitative studies of five experiential dimensions (i.e., sensory, intellectual, affective, behavioral, and social—the latter was non-significant). Using a relational-predictive model, the results confirm that self-determined interaction effectively predicts customer experience, attitude toward, and satisfaction with the chatbot.

5.1. Theoretical implications

Prior studies in hospitality and tourism call for a better understanding of how technological assistants improve customer experiences (Belanche *et al.*, 2020b; Chiang, 2020; Tung and Au, 2018). In response to more research on customer experience with chatbots, the proposed model with service companies' chatbots extends prior hospitality and tourism studies' knowledge through three main theoretical contributions.

First, regarding the human-centric approach to the customer experience (Hoyer *et al.*, 2020), we observe that current airline chatbot assistants based on AI can provoke experiential responses from customers that are fundamentally behavioral, followed by intellectual, sensory, and affective, with a non-significant effect of social responses. This means that customer interaction with chatbots could enhance customers' motivation and curiosity to know about a certain service that the chatbot is capable of introducing. The lower contribution of the social dimension to the customer experience construct may indicate that current tourism industry chatbots, such as Oscar, might improve their capacity to prompt customers to ask more complex questions, as well as make the conversation more human-like. This finding is consistent with existing literature. Recent studies indicate that chatbots are still limited in their ability to provide favorable social outcomes to consumers (Gursoy *et al.*, 2019), because chatbots' social presence is usually embedded within websites, social media platforms, or message applications (Chi *et al.*, 2020).

Second, for the interaction-centric approach to customer experience (Hoffman and Novak, 2018), we demonstrated that individuals' expressed roles and capacities in interaction with chatbots can be understood and measured through the SDT dimensions of perceived competence, autonomy, and relatedness. In this sense, we offer new interpretations of human interaction with AI-based assistants, as we empirically translated qualitatively observed customers' roles and capacities into measurable dimensions of customers' self-determined interaction with chatbots formed after real interactions with smart technology. Here, considering existing hospitality and tourism literature about the use of chatbots in customer services, we observe that the more connected, autonomous, and competent customers feel in their interactions with chatbots, the more positive their experiences, attitudes toward, and satisfaction with chatbots will be.

Finally, and in line with other studies (e.g., Adam *et al*., 2020), the results indicate that the success of human-chatbot interactions is based on multiple factors. These are the chatbot's esthetic appeal, its ability to bond with the customer intellectually and emotionally, and the behavioral activation that the conversation conveys (e.g., to book a flight or ask more questions).

5.2 Practical implications

We suggest that hospitality and tourism managers can develop chatbots for customer service on the basis of the interaction assemblage. This means that effective chatbots must offer a fluid and agile conversation in which consumers feel competent in achieving their informational goals and perceive that they have control over what is shared during the conversation. Managers can check the effectiveness of customer–chatbot conversations by measuring individuals' self-determined interaction.

In the context of our study, self-determined interaction with chatbots is fundamentally defined by the dimensions of relatedness and autonomy, followed to a lower degree by competence. The lower weight of perceived competence may indicate an individual's limited capacity to process informational tasks with the chatbot due to a lack of knowledge or having not previously used chatbots while looking for a flight.

Second, managers must consider certain aspects of the chatbot configuration, such as having a visually attractive interface and a high conversational and problem-solving capacity, which are the main drivers that produce behavioral motivations and induce thinking and creativity in customers. We also detected that the social response to the chatbot can be improved by setting chatbot parameters that enhance its capacity to promote the generation of complex requests and become sensible to customers' emotional states. One way to improve chatbots' social presence could be based on developing their emotional intelligence using psycholinguistic models, which could help capture customers' emotional tones through text and, consequently, provide adapted responses (Wiak and Kosiorowski, 2010).

5.3 Limitations and future research

Our study focused on the application of a motivational model of customer experience with chatbots in the passenger air transport sector. Therefore, an important limitation of our research is the need to apply the model in different hospitality and tourism service contexts. Future studies might analyze the chatbot interaction model longitudinally. Taking a longitudinal perspective might detect whether customers' previous motivations, in terms of the idea of interacting with chatbots to obtain information, change as a result of the interaction experience. Another limitation is that we did not consider any moderating variables, such as customer characteristics, that could affect the relational model. It would be interesting to determine whether differences emerge in the proposed relationships when comparing individuals with high/low motivation and high/low resistance to using new technologies. In this sense, different types of interactions (positive or negative) with a chatbot could also drive or limit multiple engagement behaviors, such as customers' purchases, recommendations, or referrals (Bilro and Loureiro 2020). Hence, future research may explore the role of customer engagement in the motivational customer experience with chatbots.

Finally, future studies might analyze the customer's motivational experience in a dual-communication scenario with the chatbot, that is, when human personnel from the service company intervene to overcome the chatbot's limitations or enhance its capacities.

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Figure. 1

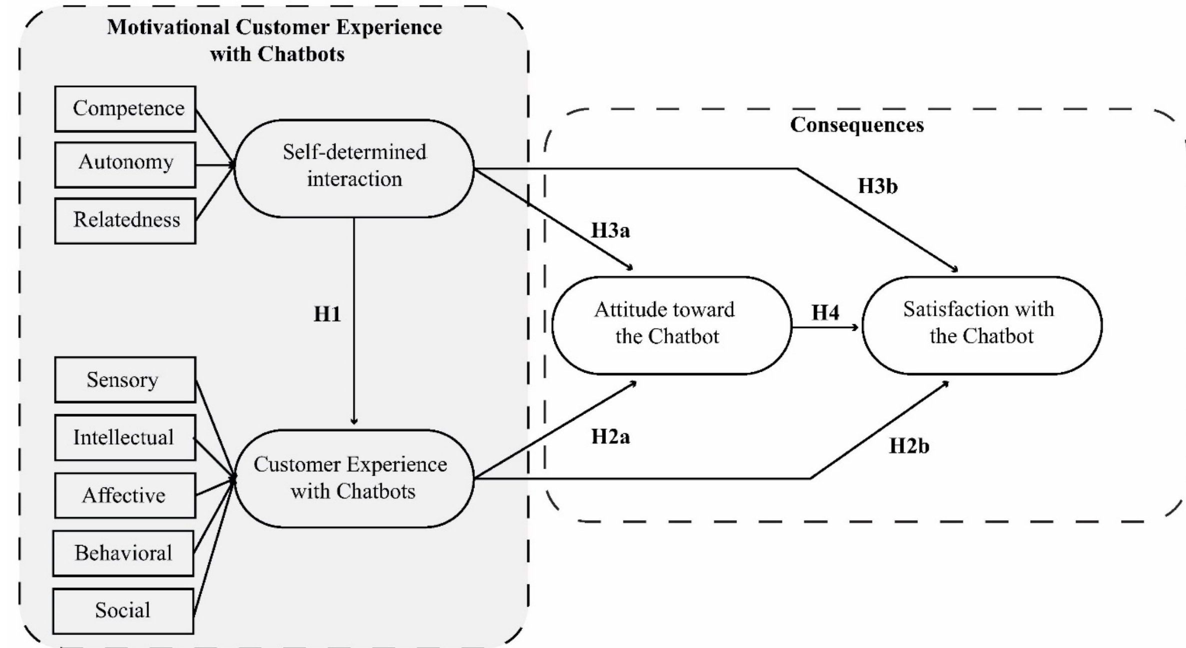
Motivational Customer Experience with Chatbots
Competence
Autonomy
Relatedness
Self-determined interaction
H1
Sensory
Intellectual
Affective
Behavioral
Social
Customer Experience with Chatbots
Consequences
H3b
H3a
Attitude toward the Chatbot
H4
Satisfaction with the Chatbot
H2a
H2b

Figure 2.

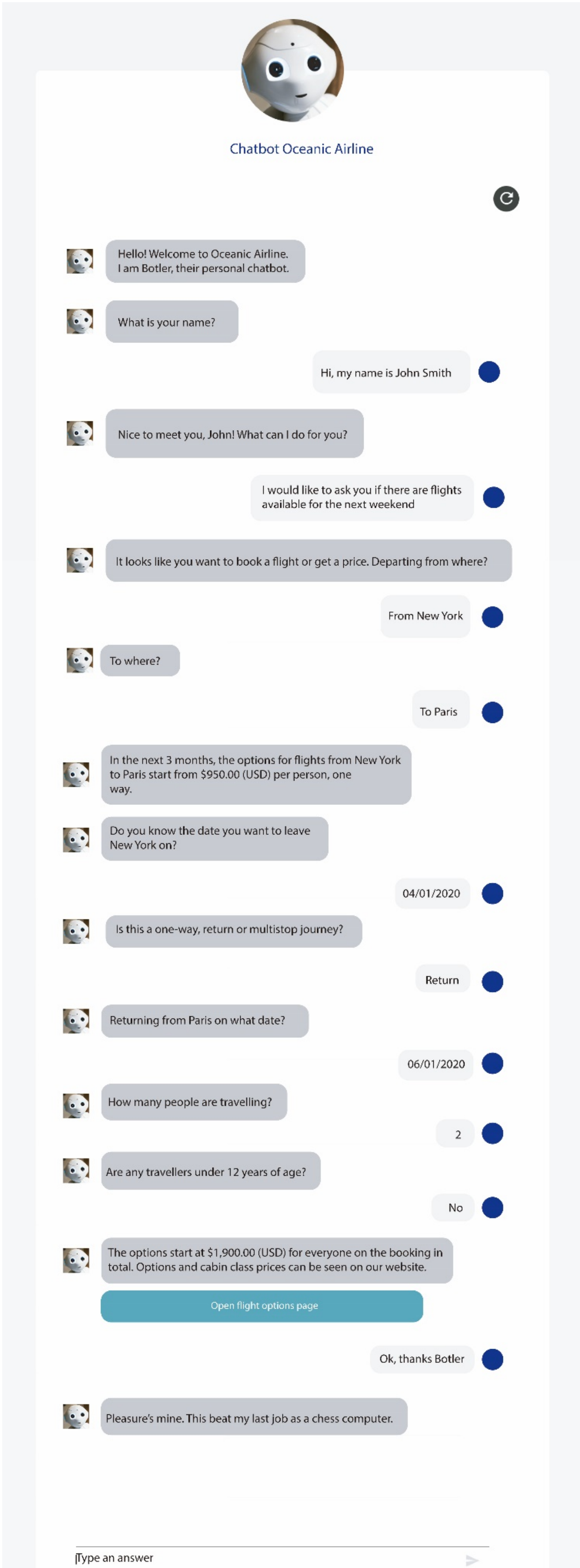
Chatbot Oceanic Airline
Hello! Welcome to Oceanic Airline.
I am Botler, their personal chatbot.
What is your name?
Hi, my name is John Smith
Nice to meet you, John! What can I do for you?
I would like to ask you if there are flights available for the next weekend
It looks like you want to book a flight or get a price. Departing from where?
From New York
To where?
To Paris
In the next 3 months, the options for flights from New York to Paris start from $950.00 (USD) per person, one way.
Do you know the date you want to leave New York on?
04/01/2020
Is this a one-way, return or multistop journey?
Return
Returning from Paris on what date?
06/01/2020
How many people are travelling?
2
Are any travellers under 12 years of age?
No
The options start at $1,900.00 (USD) for everyone on the booking in total. Options and cabin class prices can be seen on our website.
Open flight options page
Ok, thanks Botler
Pleasure's mine. This beat my last job as a chess computer.
Type an answer

Figure 3.

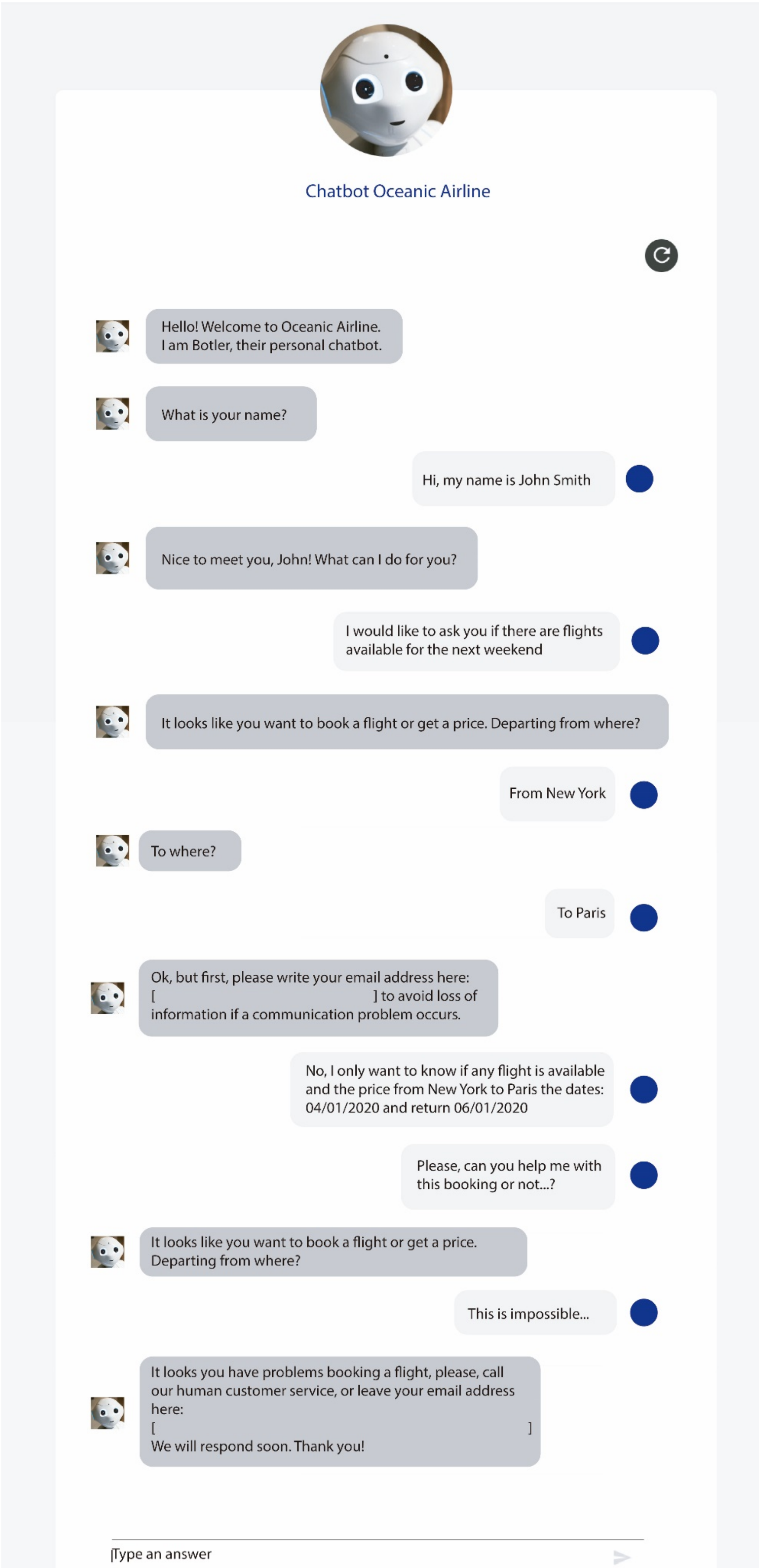
Chatbot Oceanic Airline
Hello! Welcome to Oceanic Airline.
I am Botler, their personal chatbot.
What is your name?
Hi, my name is John Smith
Nice to meet you, John! What can I do for you?
I would like to ask you if there are flights available for the next weekend
It looks like you want to book a flight or get a price. Departing from where?
From New York
To where?
To Paris
Ok, but first, please write your email address here: [ ] to avoid loss of information if a communication problem occurs.
No, I only want to know if any flight is available and the price from New York to Paris the dates: 04/01/2020 and return 06/01/2020
Please, can you help me with this booking or not...?
It looks like you want to book a flight or get a price. Departing from where?
This is impossible...
It looks you have problems booking a flight, please, call our human customer service, or leave your email address here:
[ ]
We will respond soon. Thank you!
Type an answer

Table I. Roles and relationship types in the interaction with chatbots

	Agentic role	**Communal role**	**Relationship types enabling or constraining the overall experience**
			Master-Servant Customer/chatbots' agentic and communal roles are inversed (opposite agency; similar communion).
Enabling the experience	Customers/chatbots exercise their capacities and enables the development of the interaction.	Customers/chatbots internalize emergent capacities from the interaction.	Partners Customer/chatbots' agentic and communal roles are equivalent (similar agency; similar communion).
Constraining the experience	Customers/chatbots remove their capacities and limit the development of the interaction.	Customers/chatbots internalize the constrictions of any capacity from the interaction.	Non-correspondent Master-Servant Customer/chatbots' agentic and communal roles are crossed (opposite agency; opposite communion).
			Unstable Customer/chatbots' agentic and communal roles are unstable (similar agency; opposite communion).

Note: Adapted from Hoffman and Novak (2018).

Table II. Study 1. Examples of participants' expressed roles and experiential responses (fluid interaction with a chatbot)

Examples of open coding (Line–by–Line Coding)	Subthemes (Axial Coding)	Main Themes (Selective Themes)
Expressed Roles		
"not a lot of time researching online"; "did its job"; "inquiries on time."	Master-Servant relationship style	Master-servant and Partners isomorphic acomplementary are the central relationships that emerged while interacting with the chatbot.
"less capable"; "feel less comfortable"; "autogenerated responses"; "may be biased."	Partners isomorphic acomplementary relationship style	
"I do not believe"; "not sure"; "risking"; "people frustrated."	(residually) Non-correspondent master-servant relationship style	
Experiential Responses		
"using images"; "emojis"; "it is actually listening."	Sensory	Sensory, intellectual, affective, behavioral, and social are the central experiential responses while interacting with the chatbot.
"answer more complex questions"; "understand the information quickly"; "knowledgeable."	Intellectual	
"risking"; "frustrated"; "slightly anxious"; "little worry"; "the sake of feeling valued."	Affective	
"good verbal skill"; "conversation smoother"; "drop-down menu."	Behavioral	
"human warmth"; "slightly more personal"; "chatting with a human."	Social	

Table III. Study 2. Examples of participants' expressed roles and experiential responses (problematic interaction with a chatbot)

Examples of open coding (Line–by–Line Coding)	Subthemes (Axial Coding)	Main Themes (Selective Themes)
Expressed roles		
"did not seem to be responsive"; "bots are ruining customer service"; "taking away jobs."	Non-correspondent Master-Servant relationship style	Non-correspondent Master-Servant, Partners isomorphic acomplementary, and Master-Servant are the central relationships that emerged while interacting with the chatbot.
"chatbot could delay booking process"; "just to collect information on people"	Partners isomorphic acomplementary relationship style	
"pretty good idea"; "very accurate"; "it will reduce time."	Master-Servant relationship style	
Experiential responses		
"to listen "; "robot voice"; "I can see."	Sensory	Sensory, intellectual, affective, behavioral, and social are the central experiential responses while interacting with the chatbot.
"intelligent enough"; "become smarter."	Intellectual	
"very annoying"; "nothing but frustration"; "feel more comfortable"; "I love the idea."	Affective	
"unexpected response"; "respond to"; "feel more in control."	Behavioral	
"human like thoughts"; "unique personality."	Social	

Table IV. Study 3. Measurement Scales

Construct/Items	Mean	SD
Competence		
I felt that I could complete challenging tasks and projects.	4.42	1.56
I felt that I could take on and mastered hard challenges.	4.14	1.70
I felt competent in what I did.	4.91	1.48
Autonomy		
I felt that my choices were based on my true interests and values.	5.24	1.36
I felt free to do things my way.	4.94	1.59
I felt that my choices expressed my 'true' self.	4.83	1.48
Relatedness		
I felt that the chatbot understood my specific needs and requests.	4.88	1.55
I felt that the chatbot was able to solve my needs and requests.	4.93	1.57
I felt that the chatbot offered me recommendations that matched my needs and the situation.	5.30	1.37
Sensory		
I found the chatbot attractive to some of my senses (visual).	4.86	1.36
The chatbot provides information exciting to my senses.	4.41	1.45
The chatbot offered me a positive sensorial experience (visual).	4.83	1.45
Intellectual		
The chatbot made me think and reflect.	4.30	1.72
The chatbot generated me interesting ideas.	4.57	1.72
The chatbot facilitated me to learn more.	4.82	1.64
Affective		
The chatbot induced positive feelings and sentiments to me.	4.62	1.55
I experienced pleasant feelings and emotions while using the chatbot.	4.76	1.61
Using the chatbot produced me positive emotions.	4.70	1.60
Behavioral		
Using the chatbot was relaxing.	4.63	1.46
Using the chatbot was comfortable.	5.09	1.33
Using the chatbot produced me well-being.	4.49	1.55
Social *"During the interaction, the chatbot encouraged me..."*		
to continue developing the conversation.	5.10	1.52
to spend more time in the conversation.	4.66	1.58
to ask for more questions.	5.33	1.43
Attitude		
Unappealing/Appealing.	5.35	1.40
Bad/Good.	5.42	1.45
Unpleasant/Pleasant.	5.44	1.37
Unfavorable/Favorable.	5.33	1.43
Unlikeable/Likeable.	5.43	1.38
Satisfaction		
Overall. I am satisfied with the chatbot.	5.29	1.53
The chatbot exceeds my expectations.	4.74	1.80
The chatbot is close to my ideal customer service technology.	4.57	1.85

Table V. Study 3. Construct reliability and discriminant validity

Constructs		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Competence	(CA = 0.87; CR = 0.92; AVE = 0.80)	**0.90**	0.82	0.74	0.74	0.77	0.67	0.78	0.64	0.68	0.81
(2) Autonomy	(CA = 0.85; CR = 0.91; AVE = 0.78)	0.72	**0.88**	0.84	0.67	0.68	0.67	0.77	0.51	0.74	0.80
(3) Relatedness	(CA = 0.87; CR = 0.92; AVE = 0.79)	0.65	0.73	**0.89**	0.64	0.66	0.65	0.80	0.50	0.65	0.87
(4) Sensory	(CA = 0.83; CR = 0.90; AVE = 0.75)	0.62	0.52	0.57	**0.87**	0.82	0.75	0.78	0.65	0.72	0.73
(5) Intellectual	(CA = 0.86; CR = 0.91; AVE = 0.78)	0.68	0.59	0.58	0.67	**0.88**	0.82	0.79	0.60	0.72	0.76
(6) Affective	(CA = 0.92; CR = 0.95; AVE = 0.86)	0.61	0.60	0.60	0.61	0.74	**0.93**	0.83	0.50	0.74	0.75
(7) Behavioral	(CA = 0.88; CR = 0.93; AVE = 0.81)	0.70	0.68	0.72	0.64	0.69	0.75	**0.90**	0.67	0.80	0.86
(8) Social	(CA = 0.81; CR = 0.89; AVE = 0.73)	0.55	0.43	0.43	0.54	0.51	0.44	0.58	**0.86**	0.46	0.60
(9) Attitude	(CA = 0.93; CR = 0.95; AVE = 0.79)	0.62	0.67	0.72	0.57	0.65	0.70	0.73	0.41	**0.89**	0.86
(10) Satisfaction	(CA = 0.90; CR = 0.94; AVE = 0.84)	0.72	0.71	0.79	0.57	0.68	0.70	0.78	0.52	0.80	**0.92**

Notes: CA: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted. Fornell and Larcker's criterion (below the main diagonal) and the Heterotrait-Monotrait (HTMT) (above the diagonal). In the diagonal and in bold are the square root of AVEs.

Table VI. Study 3. Second-Order Constructs Assessment

Constructs	Weights	*t*-statistic	VIF
Self-determined interaction			
Competence	0.17	2.12**	2.23
Autonomy	0.40	4.82***	2.86
Relatedness	0.53	7.70***	2.44
Customer Experience			
Sensory	0.17	2.34**	2.61
Affective	0.16	1.77*	2.97
Intellectual	0.20	2.20**	2.80
Behavioral	0.58	7.23***	3.01
Social	0.01	0.02	1.64

Notes: *$p < 0.10$; **$p < 0.05$; ***$p < 0.001$; VIF: Variance inflation factor.