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Beyond words: the influence of congruent emojis on chatbot's perceived competence and customer satisfaction

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ABSTRACT

This research explores the impact of using semantically congruent emojis in chatbot communications on customer satisfaction within customer service contexts. As companies increasingly shift resources from human assistants to AI-driven avatars, understanding the factors that enhance customer satisfaction becomes crucial. An online experiment was conducted among 278 respondents to explore the relationship between the use of congruent emojis by chatbots and customer satisfaction. The study employs a controlled experimental design to investigate how these emojis influence perceived competence of the chatbot, and subsequently, customer satisfaction. The results indicate that messages from chatbots containing semantically congruent emojis are perceived as more competent, which in turn enhances customer satisfaction. These findings provide actionable insights for designing more effective virtual assistants, emphasizing the importance of incorporating paralinguistic elements to enhance user experience within online contexts.

Keywords: chatbots, emojis, congruent emojis, customer satisfaction, competence, anthropomorphic cues, linguistic cues, customer service, paralanguage

CHAPTER 1: INTRODUCTION

1.1 Phenomenon, Managerial Relevance and Problem

In today's fast-paced technological environment, mastering innovative technologies is essential for corporate success. Artificial Intelligence (AI), a cornerstone of this evolution, has become integral to various business and societal functions (Haenlein & Kaplan, 2019). AI's significant impact on customer experience, particularly through AI-enabled customer service, enhances personalized experiences and engagement (McKinsey & Company, 2023). McKinsey & Company (2020) estimated that, in global banking alone, artificial intelligence advancements hold the potential to yield an additional $1 trillion in annual value, with a notable portion attributed to the enhancement of customer service. Within this dynamic landscape, one of the most widespread and impactful applications of AI emerges, a technology that bears significance on both social and managerial fronts: chatbots. These conversational agents are programmed to simulate dialogues with human users, using Natural Language Process (NLP) techniques.

Chatbots serve numerous functions across marketing, customer service, technical support, and education (Smutny & Schreiberova, 2020). In addition to being highly versatile, chatbots are adaptable to varying purposes and usage situation, allowing for modifications in language, design, and other aspects to suit specific needs and settings. As chatbot technology continues to advance, its application in business is on the rise, notably in streamlining processes, particularly within customer service and personalization domains (Przegalinska et al., 2019). Projections point out a significant growth in the global chatbot market, with an anticipated compound annual growth rate (CAGR) of 23.3% from 2023 to 2030 (Grand View Research, 2023). Forecasts indicate a substantial shift in online service interactions, with an expected 95% transition to AI chatbots by 2028 (Chong et al., 2021). This underscores the increasing prevalence and effectiveness of chatbots in shaping and enhancing various aspects of business operations. Notably, chatbots are increasingly taking the place of human customer-service agents across digital platforms (Crolic et al., 2022). This aligns with estimates predicting potential savings of up to $80 billion for companies by 2026 through the integration of conversational artificial intelligence within contact centers (Gartner, 2022). Moreover, chatbots contribute to enhanced engagement by swiftly addressing customer requests (Gnewuch et al., 2018) and maintaining round-the-clock availability for user inquiries (Li & Zhang, 2023). This not only benefits customers but also alleviates the workload for employees (Deloitte, 2019).

Notwithstanding these advantages, it is imperative to recognize that chatbots are not flawless tools. According to CGS (2019), 86% of consumers still prefer interacting with a human agent. This inclination is attributed, in part, to miscommunication that occurs between users and chatbots (Sheehan et al., 2020), that can lead to responses that fall short of meeting consumer expectations and effective performance standards (Luo et al., 2022). Consequently, users may perceive such issues as indicative of a lack of competence in the chatbot. Competence, the ability to execute tasks efficiently (Cuddy et al., 2008), plays a crucial role in this context. Indeed, consumers hesitancy and resistance towards chatbots often arise from negative experiences marked by a lack of perceived competence and authenticity in the customer-chatbot interaction (Nguyen et al., 2023). In the perspective of addressing these problems, uncertainties persist concerning the optimal cues to enhance their efficacy and improve customer satisfaction. Therefore, managers face the challenge of effectively integrating chatbots while ensuring that customer satisfaction remains uncompromised.

1.2 Current Research and Gaps

Previous research explored the concept of competence, one of the two dimensions within the Stereotype Content Model (SCM) (Cuddy et al., 2008), which represents the ability to carry out intensions (Aaker et al., 2012). Since competence perceptions reflect many positive attributes, it is unsurprising that studies have linked it to enhanced satisfaction (Grandey et al., 2005). However, only a limited part of the literature has extended this construct to chatbots. As mentioned earlier, many issues related to the use of these conversational agents stem from discomfort due to their inability to efficiently resolve issues (CGS, 2019). Therefore, understanding how to improve users' perception of chatbots' competence - defined as being capable, knowledgeable, reliable, and effective in providing services (Følstad & Brandtzaeg, 2020) - is crucial. In this endeavor, it is prudent to heed the guidance offered by existing research.

Specifically, an examination of the literature reveals two main areas that have been extensively explored. Due to the inherent design of chatbots to replicate human-to-human communication, a considerable number of studies have examined a variety of anthropomorphic cues integrated into chatbots (e.g., Gnewuch et al., 2018; Go & Sundar, 2019; Zogaj et al., 2023). Furthermore, given the predominantly text-based nature of chatbots, a substantial body of research is dedicated to investigating the effects of different communication elements, with a specific focus on linguistic features and tone (e.g., Kull et al., 2021; Sands et al., 2021; Jiménez-Barreto et al., 2023). Considering this dual nature of chatbots, it is conceivable a pivotal aspect for enhancing their effectiveness, or competence, could be found within this domain. Emojis are an element that simultaneously intersects both anthropomorphic-based and text-related facets of the subject matter. They play a significant role in adding emphasis to messages emotional or contextual meaning, thereby enhancing the communication's appeal to the recipient (Bai et al., 2019). Moreover, a segment of the existing literature has delved into the impact of emojis based on their semantic alignment with accompanying text (e.g., Christofalos et al., 2022). Studies have explored how using an emoji that is synonymous of a certain word can facilitate text processing (Daniel & Camp, 2020). For instance, research has shown that employing congruent (e.g., "My tall coffee is just the right temperature ☕") instead of incongruent (e.g., "My tall coffee is just the right temperature 🍺") non-facial emojis increases the speed of message comprehension (Barach et al., 2021). Despite their evident potential, there remains a dearth of research elucidating how emojis can improve chatbots performance. No analysis has extended the knowledge on congruent emojis - those that align with the message conveyed in a text - to the realm of chatbots.

Thus, limited studies exist on perceived competence of chatbots as well as their congruent emoji use. Going deeper, an investigation of the effects of the use of congruent emojis by chatbots on perceptions of competence, and therefore on customer satisfaction, is lacking.

1.3 Contributions

The present work contributes to the existing literature by (1) extending the studies on the use of semantically congruent emojis to the realm of chatbots, trying to understand if their usage within a conversation can improve the overall customer satisfaction, and (2) expanding the knowledge about the relevance of chatbot perceived competence, testing its role as a potential mediator in the relationship between the use of congruent emojis by chatbots and customer satisfaction. Moreover, this Master Thesis provides insights concerning potential solutions to the misalignment between customer emotional and executional needs and the effective performance of chatbots.

Therefore, this study aims to address two interconnected research questions. Firstly, it seeks to ascertain how the integration of congruent emojis by chatbots influences customer satisfaction within the customer service field. Additionally, the research endeavors to examine the potential mediating role of perceived competence of chatbots in the relationship between their use of congruent emojis and customer satisfaction.

CHAPTER 2: LITERATURE REVIEW & HYPOTHESES DEVELOPMENT

2.1 Chatbots

The term "chatbot" originates from the combination of "chat" and "robot," initially proposed as "chatterbot" to denote robots capable of engaging in conversations with humans (Luo et al., 2022). Essentially, chatbots are computer programs endowed with natural language processing capabilities, designed to engage in dialogue with human users (Maudlin, 1994). They are predominantly deployed in customer service settings, where they directly interact with consumers (Chung et al., 2020). Within this context, they often serve as the primary point of contact, offering readily accessible assistance and information for frequently encountered queries and support tasks (Nordheim et al., 2019). Consequently, recent research has explored how AI-powered chatbots perform when used within a customer service context, for example in terms of response to user's need of human interaction (Sheehan et al., 2020). While chatbots offer various benefits such as cost-effectiveness, round-the-clock availability, and rapid response times (Gnewuch et al., 2017; Meuter et al., 2005; Adam et al., 2021), they also present several challenges. These challenges include initial distrust, misunderstanding, physical distance, discomfort, confusion, and interactions that may feel dehumanized (Zamora, 2017; Sands et al., 2021; Sheehan et al., 2020; Luo et al., 2019; Castillo et al., 2021; Kaneshige & Hong, 2018). Consequently, existing literature endeavors to explore methods for improving chatbot performance by addressing these issues while preserving their inherent advantages.

Given chatbots' intrinsic design to emulate human-to-human interaction, a considerable portion of studies in this field focuses on exploring the effects of imbuing these conversational agents with human-like characteristics (e.g., Schanke, 2021). Furthermore, due to their predominant text-based nature, a substantial body of research is dedicated to investigating the effects of different communication elements implemented in chatbot design (e.g., Xu et al., 2022). This is particularly important, since understanding how to improve these linguistic features not only allows to manipulate perceived anthropomorphism of the bot but could also improve the quality of the communication between the human and the computer, for instance making the conversation less confused and less boring (Saarem, 2016). It has been found that specific combinations of design cues, including verbal and human identity aspects, impact perceived anthropomorphism, highlighting the importance of considering task types and users' predispositions for effective conversational agents' design (Seeger et al., 2021). Moreover, Assink (2019) showed that the implementation of anthropomorphic visual and linguistic features in chatbots resulted in increased user satisfaction. Hence, as emphasized by Luangrath & Wang (2023), in such contexts it is crucial to consider not just the content (the verbal aspects of what is written) but also the style of communication (how something is written).

As depicted in Table 1, studies encompassing both identified macro-categories, namely anthropomorphic cues and linguistic features, often include an examination of chatbots' use of emojis. This is because emojis represent an element that somewhat integrates the two aforementioned aspects which constitute the essence of this dual nature of chatbots. Indeed, emojis hold the capacity to enhance the message conveyed by a given text and also offer the ability to capture and express non-verbal elements of communication, such as facial expressions or gestures (Bai et al., 2019). This is also linked to the fact that emojis are a facet of what is called textual paralanguage (TPL). Textual paralanguage encompasses nonverbal auditory, tactile, and visual components conveyed in written form, and involves the use of symbols, images, words, and other elements to complement or substitute written language (Luangrath & Barger, 2017). Despite this, just a very scarce part of the literature has studied the effects of emojis usage by chatbots (Fadhil et al., 2018; Beattie et al., 2020; Y. Liu et al., 2023; D. Liu et al., 2023; Yu & Zhao, 2024). Furthermore, existing research tends to focus on face emojis, neglecting the impact of non-facial emojis, which can also enhance the ability to simulate human conversation. Focusing on non-face emojis allows for an examination of how consumers attribute judgments related to chatbots' efficacy in task accomplishment, particularly competence, while the majority of existing studies concentrate on emotional dimensions like warmth and empathy. Therefore, although research shows that emoticons, representing facial expressions or emotions, enhance the perceived warmth of the sender (Li et al., 2019), it is reasonable to expect that other types of emojis, namely non-facial ones, may influence perceived competence. In this context, the present study aims to address this gap by investigating the effects of semantically congruent emojis in customer service contexts. Specifically, the work aims to explore how such emojis lead to higher customer satisfaction (H_1), with perceived competence mediating this effect (H_2). Additionally, as opposed to the common emphasis on service failure recovery procedures in existing analysis, here the focus is on general customer support, since overlooking this aspect could inadvertently lead to service failure situations.

Table 1 - Personal elaboration: summary of some recent studies about chatbots within customer service with a specific focus on anthropomorphic cues and linguistic features

Study	Focus	Service interaction	Research perspective	Main Findings
Faster is not always better: understanding the effect of dynamic response delays in human-chatbot interaction (Gnewuch et al., 2018)	Anthropomorphic cues	Chatbot only	Response delays as a mean for anthropomorphizing the chatbot	Dynamic response delays increase users' perception of humanness and social presence, and lead to greater satisfaction with the overall chatbot interaction
Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions (Go & Sundar, 2019)	Anthropomorphic cues	Human vs. chatbot	Influence of various cues (identity, visual, etc.) on chatbot humanness perceptions	High message interactivity can compensate for low anthropomorphic visual cues, while identifying the agent as human raises user expectations for interactivity
Blame the Bot: Anthropomorphism and Anger in Customer–Chatbot Interactions (Crolic et al., 2022)	Antropomorphic cues	Chatbot only	Chatbot anthropomorphism effects depending on customer's emotional state	When the customer is in an angry emotional state, chatbot anthropomorphism negatively affects customer satisfaction, firm evaluation, and purchase intentions due to expectancy violations
It's a Match! The effects of chatbot anthropomorphization and chatbot gender on consumer behavior (Zondaj et al., 2023)	Anthropomorphic cues	Chatbot only	Chatbot designed gender: congruent or divergent with user's gender	When there is a congruence between chatbot designed gender and user's gender, this positively impact on purchase intentions
How may I help you? Driving brand engagement through the warmth of an initial chatbot message (Kull et al., 2021)	Linguistic features	Chatbot only	Tone of the initial message of a chatbot: warmth or competent	Warm chatbot-initiated messages lead to increased brand engagement compared to competent and neutral ones
Managing the human–chatbot divide: how service scripts influence service experience (Sands et al., 2021)	Linguistic features	Human vs. chatbot	Service scripts type (educational or entertaining): comparing their effects on human and virtual agents	Using an educational script boosts satisfaction and purchase intent with human service agents over chatbots. Conversely, with an entertaining script, both human agents and chatbots perform similarly
How chatbot language shapes consumer perceptions: The role of concreteness and shared competence (Jiménez-Barreto et al., 2023)	Linguistic features	Human vs. chatbot	Language concreteness' impact on chatbots' and human agents' performances	Heightened chatbot language concreteness enhances perceptions of competence, satisfaction, and shopping efficiency
Task-oriented vs. social-oriented: Chatbot communication styles in electronic commerce service recovery (Wang et al., 2023).	Linguistic features	Chatbot only	Chatbot communication style: social or task oriented	A social-oriented chatbot communication style is more effective than a task-oriented one, enhancing consumer satisfaction by increasing trust levels
A bot and a smile: Interpersonal impressions of chatbots and humans using emoji in computer-mediated communication (Beattie et al., 2020)	Both	Human vs. chatbot	Facial emojis effects depending on the message source: a human agent or a chatbot	Participants rate emoji-using chatbots similarly to human sources, with both perceived as more socially attractive and credible compared to verbal-only message senders
How do consumers react to chatbots' humorous emojis in service failures (Y. Liu et al., 2023)	Both	Chatbot only	Humor positive effects on message sources: focus on facial humorous emojis and their impact on chatbots	Using humorous emojis in chatbot service recovery increases consumers' willingness to reuse them, with perceived intelligence partially mediating this effect
This study	Both	Chatbot only	Effects of the semantic congruence between text and non-facial emojis on chatbots' performances	A chatbot using semantically congruent emojis in a customer service context leads to higher customer satisfaction, with perceived competence mediating this effect

Notes: the literature review presented in the table is not intended to be exhaustive, but it selectively includes influential articles within each categorized research perspective, offering valuable insights into various aspects of the field.

2.2 Congruent emojis

Emojis are graphic symbols with predefined names and codes (Unicode), that encompass representations of facial expressions, abstract concepts, emotions, animals, plants, activities, gestures, and objects (Rodrigues et al., 2018). They can be divided into two main categories: human-face emojis, like the yellow-face emojis 😊, 😞, and 😠, or non-human face emojis, which encompass objects, symbols, gestures, body parts, plants, and animals, such as ⚽, 🚫, 👍🏼, 🌸, and 🦁 (Jaeger et al., 2019). Pictographs are extensively used in many forms of computer-mediated communication (Dresner & Herring, 2010), with 92% of users worldwide including emojis into their online interactions (Kaye et al., 2017). This widespread adoption can be attributed to the numerous benefits associated with emojis, including the ability to convey additional emotional or contextual nuances in communication (Bai et al., 2019), enhance the appeal of messages to recipients (Cramer et al., 2016), and contribute to the perception of messages as having heightened emotional intensity and extreme valence (Erle et al., 2022).

The benefits of emojis become particularly evident and impactful when they align semantically or emotionally with the accompanying sentence, as illustrated by examples such as "I need a new dress 👗" or "I am angry for this 😡". While face emojis can correspond to the valence of the sentence (e.g., positive-positive, "I passed the exam 😀"), non-face emojis enhance semantic congruence by reinforcing the meaning conveyed by a text (e.g., "It is a brilliant idea 💡"). Consequently, a significant portion of research has focused on investigating the effects of using congruent emojis alongside text (e.g., Daniel & Camp, 2020; Boutet et al., 2021; Hand et al., 2022; Yang et al., 2022; Christofalos et al., 2022). Specifically, semantic congruence enhances message processing ease and fluency (Choi & Kang, 2013), thereby improving clarity (Reber et al., 2004). This effect is particularly pronounced with non-facial emojis, which convey non-verbal communicative aspects while reducing message ambiguity (Riordan, 2017). Indeed, Barach et al. (2021) demonstrated that using congruent non-facial emojis (e.g., a coffee cup emoji in the statement "My tall coffee is just the right temperature ☕") instead of incongruent ones (e.g., a beer emoji in the same statement “My tall coffee is just the right temperature 🍺”) accelerates message comprehension speed. These findings are consistent with research demonstrating that textual paralanguage can evoke vivid mental images of gestures, sounds, or facial expressions, thereby making the message more concrete and realistic (Borst & Kosslyn, 2010).

2.3 Usage of congruent emojis by chatbots and customer satisfaction

The use of emojis, particularly those semantically congruent with the text, represents an unexplored dimension in the realm of chatbots despite their widespread adoption in computer-mediated communications. This avenue of research is particularly relevant considering the potential of semantic congruence to address challenges associated with chatbot utilization, such as misinterpretation and the inability to convey empathy or information clearly (Sheehan et al., 2020; Luo, 2019; Trivedi, 2019). By enhancing effectiveness of communication, semantic congruence in emoji usage may contribute to improving customer satisfaction with chatbot interactions.

Customer satisfaction stems from both cognitive and affective evaluations of a product or service (Giese & Cote, 2000). It holds significant importance in marketing literature as it is a key determinant of business success (Krivobokova, 2009). Research underscores that customer satisfaction is a primary motivator influencing repeat purchases (Oliver, 1980) and plays a pivotal role in fostering customer loyalty (Boulding et al., 1993; Leninkumar, 2017). Numerous studies have identified customer satisfaction as a key predictor of customer loyalty (Gronholdt et al., 2000), making it a fundamental aspect of attitudinal loyalty measures alongside metrics like the Net Promoter Score (NPS) (Ordenes et al., 2022).

Caruana (2002) asserts that service quality significantly impacts customer satisfaction, indicating that organizations delivering high-quality service tend to foster customer satisfaction. Therefore, when transitioning to an online customer service context, it becomes imperative to discern the determinants of quality within such an environment. While research demonstrates the potential of chatbots to enhance overall customer satisfaction (Krishnan et al., 2022; Chung et al., 2020), the satisfaction derived from chatbot interactions hinges on several key factors. These include responsiveness, assurance (professional communication skills), accuracy, personalization, and ease of use, which are indicative of the quality of service, information, and system (Jenneboer et al., 2022).

In light of this, it is crucial to emphasize that emojis play a pivotal role in facilitating positive perceptions and responsiveness, serving to diminish social distance and convey thoughtfulness toward the recipient (Coyle & Carmichael, 2019). Particularly noteworthy is the impact of non-facial emojis that align semantically with the accompanying text, significantly enhancing the text comprehension and processing speed (Barach et al., 2021). This effect can be also attributed to the reduction of message ambiguity and the enhancement of reader confidence associated with non-facial emojis (Riordan, 2017). Indeed, non-face emojis contribute to making text more vivid and specific (Peng & Zhao, 2021), attributes that contribute to language concreteness (Hansen & Wänke, 2010), which is linked to increased customer satisfaction (Packard & Berger, 2021). Furthermore, the inclusion of gesture-based emojis by chatbots could serve to humanize these agents (Gawne & McCulloch, 2019), thereby elevating the overall customer experience and personalization, ultimately leading to heightened customer satisfaction (Ashfaq et al., 2020; Araujo, 2018; Carvajal et al., 2011).

Considering these linkages between factors determining customer satisfaction and the effects of emoji usage, particularly those congruent with the text, it seems logical to propose the following hypothesis:

H_1 *The use of emojis semantically congruent with the text by a chatbot, as opposed to neutral ones, or to the absence of emojis with the same text, has a positive effect on customer satisfaction with the chatbot itself.*

2.4 The mediating role of perceived competence

The Stereotype Content Model (SCM) offers a framework for understanding how individuals judge others in social interactions, focusing on two primary dimensions: warmth and competence (Cuddy et al., 2008). Competence perceptions encompass attributes like intelligence, skill, confidence, and efficacy (Fiske et al., 2007), with this notion being relatively consistent across cultures (Cuddy et al., 2009). This perception of competence extends to virtual agents as well (Demeure et al., 2011). Notably, Hu and peers (2021) discovered that users' assessments of an AI assistant's warmth and competence are pivotal factors in their ongoing engagement with the system. This aligns with the Media Equation Theory and the CASA (Computers Are Social Actors) paradigm (Reeves and Nass, 1996; Nass et al., 1994), which suggest that individuals, despite recognizing media agents as artificial, still engage in social interactions with robots that exhibit human-like characteristics.

In the domain of customer service facilitated by chatbots, competence is often gauged through textual interactions. Users may evaluate a chatbot's competence based on its ability to convey confidence, clarity, and intelligence in its responses. According to research by Følstad & Brandtzaeg (2020), users regard chatbots as competent when they are perceived as capable, knowledgeable, reliable, and effective in providing assistance. Employing polite and reasoned arguments can be a strategy to demonstrate competence in online customer service interactions (Baltrukonis, 2023). However, in contexts where customers prioritize prompt and succinct responses (Følstad & Skjuve, 2019), lengthy messages may hinder efficiency. Therefore, integrating non-verbal elements like emojis could be advantageous to maintain message coherence without compromising response time. Notably, studies by Cuddy and colleagues (2011) suggest that non-verbal cues influence perceived competence in face-to-face social interactions. This finding suggests a plausible link between textual paralanguage and perceived competence extending even to online interactions. Emojis, especially those semantically congruent with a message, serve as a prime example of such non-verbal cues.

As highlighted earlier, these symbols, including gesture-based emojis, contribute to making chatbots more human-like. This becomes particularly relevant given studies indicating that when AI chatbots are personalized and exhibit anthropomorphic traits, they are perceived as more competent (Kim et al., 2023). Moreover, non-human face emojis are extraordinarily effective in adding vividness and concreteness to a message, thereby signaling competence (Hansen & Wänke, 2010). This aligns with research that investigates how language concreteness influences perceptions of competence in sources of information communication (Jiménez-Barreto et al., 2023).

At this point, it becomes evident that there exists a convergence between the factors influencing perceived competence and those impacting satisfaction when engaging with chatbots in online customer service settings. Therefore, it is not surprising that prior research across various sectors has identified a positive association between a service provider's perceived competence and consumers' trust and satisfaction (Coulter & Coulter, 2002; Andaleeb, 1998; Atouei & Theo, 2020). Considering this correlation, it is plausible to suggest that the use of congruent emojis by chatbots may contribute to enhancing perceived competence, thereby leading to increased customer satisfaction. This proposition forms the basis of the second hypothesis:

H_2 *Perceived competence will mediate the relationship between usage of congruent emojis and customer satisfaction. Consumers perceive higher levels of chatbot's competence when it uses congruent emojis compared to neutral ones or to text only.*

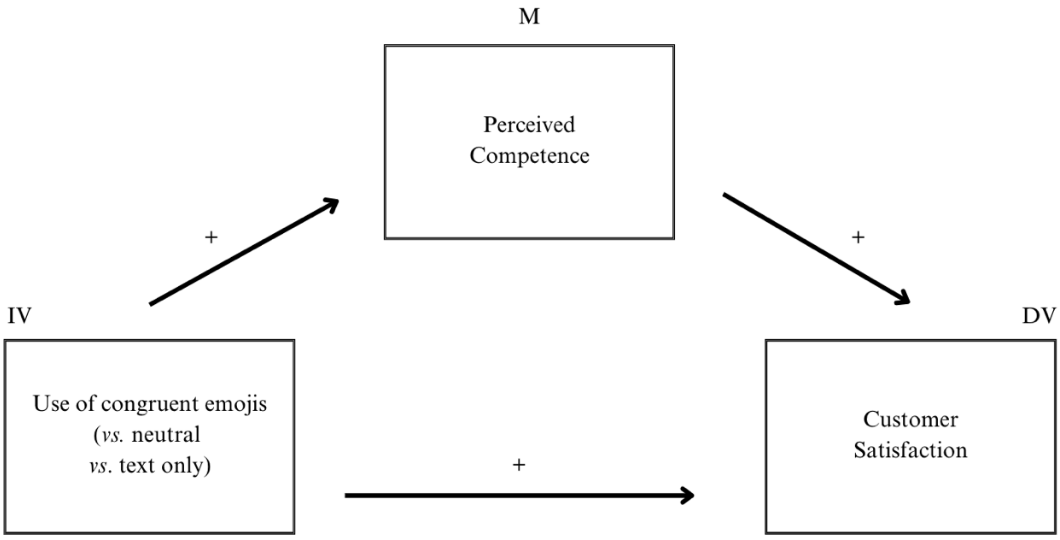

Figure 1 – Conceptual model

CHAPTER 3: METHODOLOGY

3.1 Overview

To test the hypotheses of the study, an online experiment was conducted. Initially, a pretest was conducted to confirm the effectiveness of the two independent variable manipulations: the presence of emojis and the congruence between emojis used by the chatbot and the accompanying text. Following the successful pretest, the main study proceeded with the pretested manipulations to investigate whether the use of congruent emojis by a chatbot enhances customer satisfaction (H_1) and whether this relationship is mediated by the chatbot's perceived competence (H_2).

The data collection involved administering a questionnaire through a survey conducted independently in Italy between April and May 2024 using the online platform Qualtrics XM. Participants were selected using a non-probabilistic sampling methodology, specifically a convenience sampling method, which facilitated easy and rapid access to elements of the population. Demographic variables such as age and gender were included without restriction, as they were not expected to significantly influence the experimental results statistically.

For conducting the online experiment, a sort of simulation has been crafted, in order to make the scenario as realistic as possible. Moreover, the messages generated by the chatbot draw inspiration from those typically employed by real travel websites, such as Expedia, Mariotta International, Ryanair, Lastminute.it, among others. Emojis are placed at the end of the sentences, and occasionally at the beginning. Notably, it has been demonstrated that emojis are usually positioned before or after the text (Provine et al., 2007). The chatbot functions as a customer service interface, a common feature on many websites. Typically, these chatbots initiate conversation after a brief period of browsing, offering assistance to users (Forbes, 2024). The selection of a travel website for this study is motivated by projections indicating that chatbot usage will experience the most significant growth within the travel and tourism industry from 2023 to 2030 (Grand View Research, 2023). Furthermore, emojis for the congruent condition were chosen based on their conventional meanings, selected via keywords or the overall message of the sentence (Emojipedia – Home of Emoji Meanings, n.d.). In the scenario with neutral emojis (not semantically congruent with the text), emojis were intentionally selected to be different from the context but not completely illogical or nonsensical. For instance, instead of using emojis related to cars, which would be semantically incongruent with booking a flight, emojis like fire, flower, or thumbs-up were chosen. This decision reflects a realistic approach, considering that companies typically avoid programming chatbots with entirely nonsensical emojis. However, it is possible for companies to implement chatbots using a limited number of neutral emojis, which can be suitable for various contexts. Based on the fact that some chatbots use emojis that are neutral in terms of their relationship to the text, such as those used by SSH, Air France, Zuppi, and other sites, this scenario was chosen to evaluate the cost-benefit analysis of using more popular and versatile emojis (e.g., standard ones used as Instagram story reactions) versus emojis specifically related to the accompanying text. To ensure the accurate neutrality (in terms of valence) of these emojis, the selection process relied on the Emoji Sentiment Ranking by Kralj Novak et al. (2015). This sentiment dictionary categorizes the 751 most commonly used emojis on social media, with human annotations assigning three sentiment values: negative, neutral, or positive, each rated on a scale from 0 to 1.

With regard to the structure and design of the questionnaire used for running the experiment, it was structured as follows. An introduction opened the survey, with two control questions to make respondents familiarize with the topic. Subsequently, participants were randomly but uniformly assigned to one of three conditions. Therefore, respondents in Condition 1 interacted with a chatbot sending text-only messages, while those in Condition 2 received messages containing emojis semantically congruent with the text, and those in Condition 3 received messages with neutral, non-semantically congruent emojis (see *Appendix 1*). After the simulation, participants responded to questions measuring the variables of interest. Finally, demographic data regarding age and gender were collected to provide additional information about the sample.

3.2 Pretest

A pretest was conducted with 83 participants (M_{age} = 26 years; SD_{age} = 8.76), comprising 56 females and 27 males, to assess the effectiveness of the manipulations involving the presence of emojis within text and the congruence between emojis and accompanying text. All 83 participants who completed the pretest survey met the study criteria and attention checks, and therefore they were included in the analysis. Participants were recruited via social media using a convenience sampling method and were randomly assigned to one of three experimental conditions. After the introductory section, respondents engaged in a simulated conversation with a chatbot to complete an operation on a travel website. Following the simulation, participants rated their perception of emoji presence within the chatbot's messages and the congruence of emojis with the text (only in conditions where emojis were present) using a 7-point Likert scale ranging from "Strongly disagree = 1" to "Strongly agree = 7" (see *Appendix 2A*).

The scale for assessing the presence of emojis was developed specifically for this study due to the absence of a pre-validated scale in the literature. To verify its validity and reliability, several analyses were conducted. The KMO test yielded a value of 0.713, indicating acceptable sampling adequacy for factor analysis. Bartlett's Test confirmed a significant correlation between variables ($p < 0.001$), supporting the suitability of the data for factor analysis. Examination of communalities revealed that all items exceeded 0.5, indicating each item contributed well to measuring emoji presence. Additionally, analysis of total explained variance revealed a single eigenvalue explaining over 70% of the variance, confirming that all scale items contribute effectively to measuring presence. Reliability analysis confirmed the scale's internal consistency. The Cronbach's Alpha coefficient was 0.967, exceeding the recommended threshold of 0.9, indicating excellent reliability. Item-total statistics indicated that no items needed removal, as this would decrease the Cronbach's Alpha value. Therefore, the scale demonstrated both validity and reliability for measuring emoji presence. The same analyses were applied to the scale measuring congruence, adapted from Speed & Thompson (2000). The KMO test yielded a value of 0.845, indicating good sampling adequacy. Bartlett's Test confirmed significant correlations between variables. Communalities and total explained variance analyses demonstrated that all scale items effectively measured congruence. Reliability analysis of the congruence scale revealed a Cronbach's Alpha coefficient of 0.952, indicating excellent internal consistency. Item-total statistics confirmed that no items needed removal to maintain scale reliability. Detailed tables presenting these analyses can be found in *Appendix 2B*.

Results of the pretest confirmed successful manipulations of the independent variables. The first independent t-test comparing congruent and neutral groups showed significant differences in ratings (M_{cong} = 5.62, SD_{cong} = 1.41; M_{incong} = 3.30, SD_{incong} = 2.05; $t(55) = 4.97$, $p < .001$), indicating successful manipulation of congruence. Similarly, the second independent t-test comparing text-only and text with emojis (both congruent and neutral) showed significant differences in ratings (M_{text} = 2.97, SD_{text} = 1.99; M_{emoji} = 5.72, SD_{emoji} = 1.48; $t(81) = -6.28$, $p < .001$), indicating successful manipulation of presence. Detailed tables presenting the pretest results can be found in *Appendix 2C*.

As a result of these successful pretest manipulations, the main study proceeded as planned.

3.3 Main study

A 3 x 1 between-subjects experimental design was employed to test the hypotheses. The study involved 278 participants (M_{age} = 27 years; SD_{age} = 8.72), comprising 208 females, 68 males, 1 identifying as third gender, and 1 who preferred not to disclose the gender. All 278 participants who completed the survey met the study criteria and attention checks and were thus included in the analysis. Participants were recruited via social media using convenience sampling and randomly assigned to one of three experimental conditions. Following the introductory section, participants engaged in a simulated conversation with a chatbot to perform an operation on a travel website. After the simulation, participants rated their perception of the chatbot's competence and their satisfaction using a 7-point Likert scale ranging from "Strongly disagree = 1" to "Strongly agree = 7" (see *Appendix 3A*).

As for the pretest, scales validity and reliability were tested through various analyses. The scale for measuring chatbot’s perceived competence has been adapted from the research conducted by Awale and colleagues (2019), which focused on gauging perceived competence of an outgroup within a social context. The KMO test yielded a value of 0.866, indicating good sampling adequacy for factor analysis. Bartlett's Test confirmed a significant correlation between variables ($p < 0.001$), supporting the suitability of the data for factor analysis. Examination of communalities revealed that all items exceeded 0.5, indicating each item contributed well to measuring chatbot perceived competence. Additionally, analysis of total explained variance revealed a single eigenvalue explaining over 70% of the variance, confirming that all scale items contribute effectively to measuring competence. Reliability analysis confirmed the scale's internal consistency. The Cronbach's Alpha coefficient was 0.941, exceeding the recommended threshold of 0.9, indicating excellent reliability. Item-total statistics indicated that no items needed removal, as this would decrease the Cronbach's Alpha value. Therefore, the scale demonstrated both validity and reliability for measuring chatbot perceived competence. The same analyses were then conducted with the scale used for measuring satisfaction, which has been readapted from the work of McKinney and peers (2002), originally designed to assess customer satisfaction with websites. The KMO test yielded a value of 0.915, indicating excellent sampling adequacy. Bartlett's Test confirmed significant correlations between variables. Communalities and total explained variance analyses demonstrated that all scale items effectively measured satisfaction. Reliability analysis of the congruence scale revealed a Cronbach's Alpha coefficient of 0.942, indicating excellent internal consistency. Item-total statistics confirmed that no items needed removal to maintain scale reliability. Detailed tables presenting these analyses can be found in *Appendix 3B*.

To test H_1, a one-way ANOVA was conducted to examine the effect of chatbot text typology (text-only *vs*. with congruent emojis *vs*. with neutral emojis) on customer satisfaction. Results revealed a significant main effect ($F(275) = 59.465$, $p < 0.001$), indicating that the mean satisfaction scores differed across the three groups. Specifically, satisfaction was higher when chatbots used congruent emojis ($M_{cong} = 5.70$, $SD_{cong} = 1.59$). Conversely, satisfaction was lower when chatbots used neutral, non-semantically congruent emojis ($M_{incong} = 3.62$, $SD_{incong} = 1.31$) compared to text-only messages ($M_{text} = 4.86$, $SD_{text} = 1.00$). Therefore, H_1 is supported.

Moving on, a mediation analysis was conducted to examine H_2, using Model 4 of PROCESS. In this analysis, the predictor variable was the type of text used by the chatbot (where, according to ANOVA results, congruent_emoji was coded as 2, text_only = 1, incongruent_emoji = 0), perceived competence served as mediator, while customer satisfaction was the outcome variable. Results indicated a significant and positive effect of the independent variable on the mediator (ß = 1.0434, $p < 0.0000$). Additionally, the effect of the mediator on the dependent variable was positive and significant (ß = 1.0808, $p < 0.0000$), whereas the direct effect of the independent variable on the dependent one was not significant ($p = 0.1423$). Upon including perceived competence in the model, the indirect effect of text typology on customer satisfaction was positive and significant, with a confidence interval excluding zero (ab = 0.59, 95%CI(0.49, 0.68)). Thus, full mediation was observed, supporting H_2. Results of the analyses conducted to test the hypotheses can be found in *Appendix 3C*.

CHAPTER 4: CONCLUSIONS

4.1 General discussion

In light of the increasing prevalence of chatbots in the business world, it is crucial to understand how to optimize their performance to ensure customer retention, especially considering the associated risks.

This study investigates the impact of a simple paralinguistic cue, namely emojis, on customer satisfaction when interacting with chatbots. Through an online experiment, it was found that incorporating emojis that align semantically with the accompanying text enhances customer satisfaction with the chatbot. Furthermore, the analysis reveals that the perceived competence of the chatbot mediates this effect, underscoring the importance of congruent emoji usage in fostering positive customer experiences (see Table 2). Therefore, the findings of this experimental study validate the two initial hypotheses.

Table 2 – Personal elaboration: summary of hypotheses test results

Hypothesis	Result	Comment
H_1: The use of emojis semantically congruent with the text by a chatbot, as opposed to neutral ones, or to the absence of emojis with the same text, has a positive effect on customer satisfaction with the chatbot itself.	confirmed	The study finds that using emojis that align with the text contextually leads to the highest levels of customer satisfaction. However, the satisfaction levels decrease when chatbots use neutral, non-semantically congruent emojis compared to text-only messages.
H_2: Perceived competence will mediate the relationship between the usage of congruent emojis and customer satisfaction. Consumers perceive higher levels of chatbot's competence when it uses congruent emojis compared to neutral or text only.	confirmed	The results indicate that chatbot perceived competence acts as a mediator between the usage of congruent emojis and customer satisfaction. In other words, when chatbots use congruent emojis, customers perceive them as more competent, thereby enhancing satisfaction levels.

4.2 Theoretical contributions

The performed analysis significantly contributes to the existing literature on chatbots, focusing particularly on the utilization of a seemingly simple yet impactful paralinguistic cue prevalent in computer-mediated interactions: emojis. While previous research on chatbot effectiveness has predominantly emphasized anthropomorphic cues for optimizing design (e.g., Zogaj et al., 2023), or linguistic aspects to enhance message efficacy (e.g., Kull et al., 2021), this study advances the understanding of these domains by integrating both elements. Specifically, it demonstrates that emojis, when semantically congruent with the accompanying text, play a crucial role in increasing customer satisfaction with chatbots. This finding not only deepens our comprehension of how paralinguistic cues influence user interactions but also underscores the significance of considering congruence between emojis and text in chatbot design and communication strategies.

In addition, the present work addresses a gap in the existing literature by exploring the impact of non-facial emojis, particularly those that are semantically congruent with the accompanying text, on chatbot effectiveness. When discussing congruent emojis, we refer to emojis that align with the meaning of the text, whether from a semantic or emotional standpoint. Most existing research has primarily focused on studying facial emojis and how their usage in alignment with the accompanying text's sentiment can yield positive effects (e.g., Boutet et al., 2021). However, emojis can also be semantically congruent, thereby reinforcing the text's meaning, and this effect can be achieved using non-facial emojis, as demonstrated by study from Barach and peers (2021). Currently, few studies have extended the investigation of emojis to chatbots. For instance, Yu and Zhao (2024) recently found that using facial emojis positively influences warmth and satisfaction, but not competence. Therefore, this research extends the scope of previous studies on congruent emojis beyond traditional contexts to the realm of chatbots, revealing the applicability and effectiveness of such cues in enhancing user experiences with these platforms. This expansion of empirical evidence contributes to a more nuanced understanding of how emojis function as communicative tools in technologically mediated environments.

Furthermore, this study extends the analysis of the Stereotype Content Model (SCM) to the domain of chatbots, investigating whether the perceived competence of the chatbot serves as a mediating factor in the relationship between congruent emoji usage and customer satisfaction. This extension offers valuable insights into the underlying mechanisms driving user perceptions and behaviors in human-computer interactions, enriching our understanding of chatbot functionality and effectiveness.

In essence, the current analysis not only offers empirical evidence on the effectiveness of congruent emojis in chatbot interactions but also contributes to theoretical advancements by integrating insights from disparate strands of literature and extending established models to novel contexts.

4.3 Managerial implications

The findings of this study carry significant implications for practical application. Many prominent companies, including Nike, Kia, and Uber, have increasingly adopted chatbots as a means to provide customer assistance (Krishnan et al., 2022). Despite the myriad benefits offered by these virtual assistants (Meutet et al., 2005; Scherer et al., 2015), they also present several potential risks. These challenges, as previously discussed, are closely linked to customer dissatisfaction and perceived inadequacy, primarily stemming from issues related to competence and authenticity (Nguyen et al., 2023).

The results of the present work suggest that the content conveyed by chatbots significantly impacts user satisfaction. Specifically, incorporating emojis that align semantically with the accompanying text can enhance the perception of chatbot competence, subsequently increasing customer satisfaction. This finding underscores the potential of emojis as a practical solution to address challenges associated with chatbot usage, mitigating those factors that may discourage customer engagement and lead to negative brand perceptions (van der Goot et al., 2020; Altay et al., 2024; Shahzad et al., 2024).

When considering the managerial implications of this study, it is worth noting that the decision to prioritize emojis over other cues is partly due to its simplicity in real-world applications. Emojis offer an uncomplicated and cost-effective solution compared to alternative tools such as images or videos. Despite the rapid evolution of technology and the emergence of new tools, not all contexts progress at the same pace (Chinn et al., 2020). For instance, as highlighted in a 2023 study by Istat, Italy still faces significant levels of digital illiteracy. Various cultural, infrastructural, and sector-specific factors contribute to the challenges in implementing advanced and disruptive innovations. Consequently, it remains crucial for companies to focus on simpler yet effective tools like emojis.

4.4 Limitations and future research

Despite its theoretical and managerial contributions, this thesis has several limitations that suggest avenues for future research.

Firstly, the online experiment conducted in this study involved a simulated conversation with a virtual assistant on a travel website. However, the scope of the questions presented was limited, predominantly consisting of closed-ended queries for users. While efforts were made to make the simulation as realistic as possible, there are inherent differences compared to real interactions with live chatbots. Therefore, it would be valuable to investigate whether the findings of this research hold true in on-field experiments, where users engage with real chatbots on actual websites.

Another limitation pertains to the sample. Not only is the number of respondents not very large, but the primary concern lies in the utilization of convenience sampling methodology. This type of sampling, despite its practical advantages such as easy accessibility, geographic proximity, availability at a given time, or willingness to participate (Etikan et al., 2016), presents numerous potential biases and limitations. Therefore, future studies could concentrate on specific population segmentation to ascertain whether geographical or generational factors, combined with cultural elements, could influence the obtained results. It is plausible that younger customers, who are generally more inclined to use AI-driven tools (Forbes, 2023), would exhibit higher levels of satisfaction with chatbots compared to older individuals.

Moreover, while this study is centered on a travel website, it is conceivable to anticipate varied outcomes depending on the sector or industry. Indeed, across various marketing domains, differences in consumer behaviors are observed based on the nature of the product or service, whether utilitarian or hedonic (e.g., Pozharliev et al., 2023; Barrett et al., 2024). Therefore, future research endeavors could delve deeper into this aspect.

Furthermore, although this study focuses on chatbots for customer service assistance, many chatbots are also deployed for aiding in service failure procedures. Hence, it would be intriguing for subsequent studies to investigate whether there are distinct consumer behaviors in these scenarios. It is plausible to anticipate that using emojis, even if congruent, might not yield the same positive outcomes. Indeed, research indicates that when a customer is in an angry state, it could adversely affect their predisposition and satisfaction with anthropomorphized chatbots (Crolic et al., 2022).

Another noteworthy aspect is that, in formulating the tested hypotheses, numerous connections were drawn with elements such as anthropomorphism and concrete language. Consequently, future research could contemplate incorporating additional variables into the model to ascertain if they would enhance its explanatory power.

Finally, it is pertinent to mention the growing predominance of unstructured data, such as images, videos, and audios, in current marketing strategies (Wang et al., 2024). Therefore, incorporating these tools into chatbot design could offer a means to integrate additional and potentially more effective paralinguistic cues into computer-mediated conversations. Subsequent research endeavors could investigate the impact of these elements on human-chatbot interactions.

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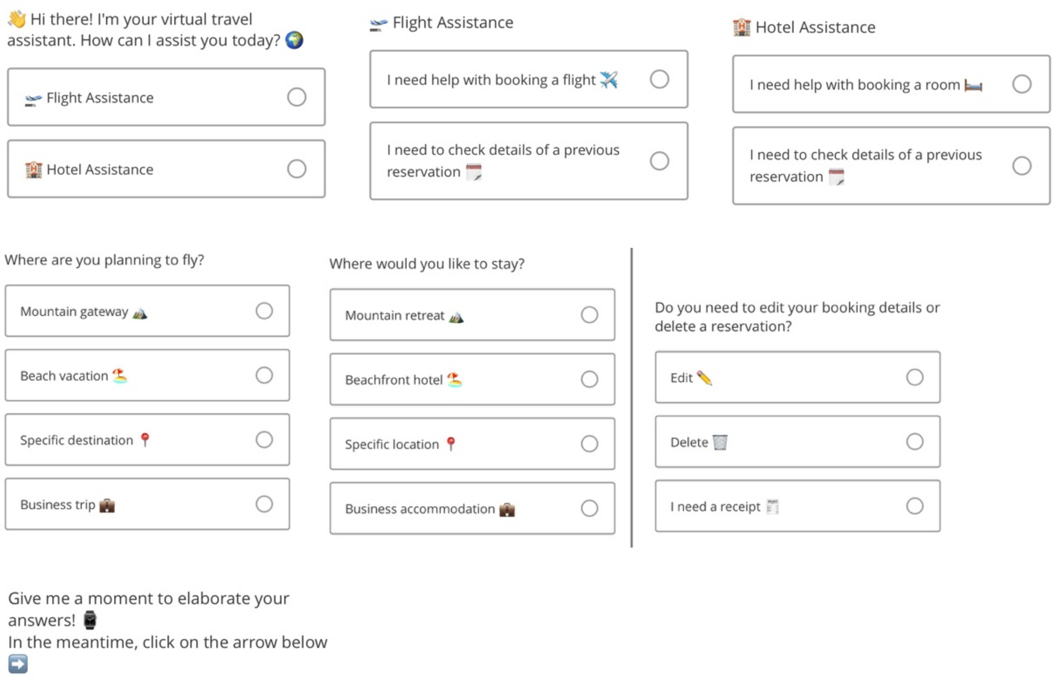
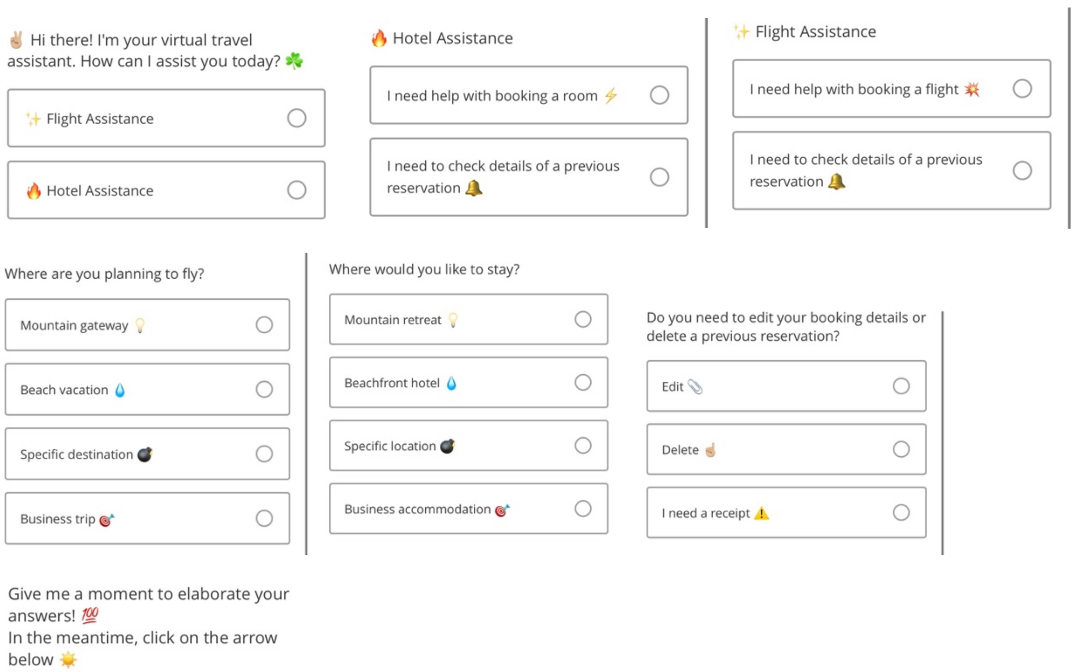
APPENDIX

Appendix 1 – Stimuli

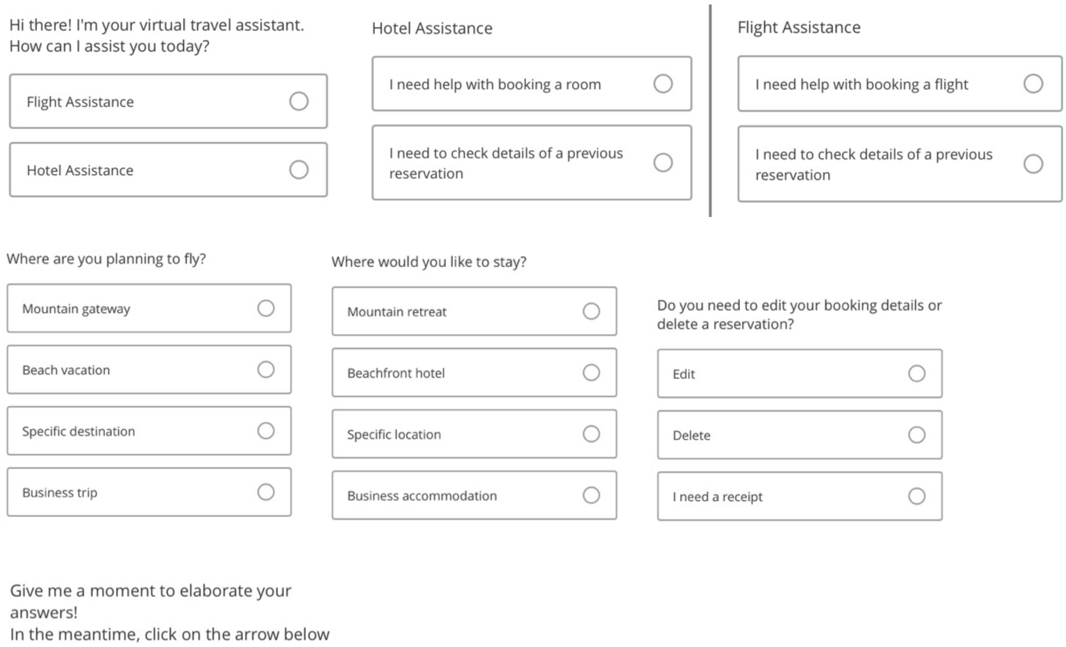
Scenario 1



Scenario 2



Scenario 3



Appendix 2A – Scale Items (Pretest)

Construct	Items	Source
Congruence/fit	• There is a logical connection between the text and the emojis used by the chatbot • The image of the texts and that of the emojis are similar • The sentences and the emojis used by the chatbot fit together well • The sentences and the emojis sent by the chatbot stand for similar things • It makes sense to me that those emojis accompany those texts	Speed, R., & Thompson, P. (2000)
Presence	• Emojis are present in the messages sent by the chatbot • There are emojis in the messages sent by the chatbot • I can find emojis in the messages sent by the chatbot	Personal elaboration

Appendix 2B – Validity and Reliability analyses (Pretest)

<u>Presence scale</u>

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		.713
Test della sfericità di Bartlett	Appross. Chi-quadrato	120.682
	gl	3
	Sign.	<.001

Comunalità

	Iniziale	Estrazione
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Sono presenti emoji nei messaggi inviati dal chatbot	1.000	.963
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Ci sono emoji nei messaggi inviati dal chatbot	1.000	.973
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Posso trovare emoji nei messaggi inviati dal chatbot	1.000	.887

Metodo di estrazione: Analisi dei componenti principali.

Varianza totale spiegata

	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
Componente	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	2.823	94.103	94.103	2.823	94.103	94.103
2	.165	5.507	99.609			
3	.012	.391	100.000			

Metodo di estrazione: Analisi dei componenti principali.

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Correlazione multipla quadratica	Alpha di Cronbach se viene eliminato l'elemento
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Sono presenti emoji nei messaggi inviati dal chatbot	5.96	14.438	.956	.976	.936
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Ci sono emoji nei messaggi inviati dal chatbot	6.08	16.474	.970	.978	.924
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Posso trovare emoji nei messaggi inviati dal chatbot	5.81	17.442	.875	.774	.966

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
.967	.968	3

<u>Congruence scale</u>

Analisi fattoriale

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		.845
Test della sfericità di Bartlett	Appross. Chi-quadrato	130.787
	gl	10
	Sign.	<.001

Varianza totale spiegata

	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
Componente	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	4.276	85.513	85.513	4.276	85.513	85.513
2	.491	9.814	95.328			
3	.103	2.058	97.386			
4	.084	1.671	99.057			
5	.047	.943	100.000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - C'è una connessione logica tra testo ed emoji usati dal chatbot	1.000	.855
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - L'immagine dei testi e quelle delle emoji erano simili	1.000	.909
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Le frasi e le emoji utilizzate dal chatbot stanno bene insieme	1.000	.931
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Le frasi e le emoji utilizzate dal chatbot rappresentano cose simili	1.000	.896
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Per me ha senso che quelle emoji accompagnano quei testi	1.000	.684

Metodo di estrazione: Analisi dei componenti principali.

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Correlazione multipla quadratica	Alpha di Cronbach se viene eliminato l'elemento
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - C'è una connessione logica tra testo ed emoji usati dal chatbot	22.77	23.994	.876	.907	.944
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - L'immagine dei testi e quelle delle emoji erano simili	22.91	25.610	.927	.883	.930
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Le frasi e le emoji utilizzate dal chatbot stanno bene insieme	22.55	27.498	.946	.929	.929
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Le frasi e le emoji utilizzate dal chatbot rappresentano cose simili	22.64	28.433	.912	.874	.936
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Per me ha senso che quelle emoji accompagnano quei testi	22.59	29.110	.736	.738	.951

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
.952	.957	5

Appendix 2C – Pretest results

Congruence manipulation

Test t

Statistiche gruppo

	group	N	Media	Deviazione std.	Errore standard della media
meancongruence	1.00	28	5.6214	1.41562	.26753
	2.00	29	3.3034	2.05470	.38155

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie							
						Significatività				Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	P unilaterale	P bilaterale	Differenza della media	Differenza errore std.	Inferiore	Superiore
meancongruence	Varianze uguali presunte	4.204	.045	4.943	55	<.001	<.001	2.31798	.46897	1.37815	3.25781
	Varianze uguali non presunte			4.974	49.813	<.001	<.001	2.31798	.46599	1.38192	3.25404

Dimensioni effetto campioni indipendenti

		Standardizzatore[a]	Stima del punto	Intervallo di confidenza 95%	
				Inferiore	Superiore
meancongruence	D di Cohen	1.77004	1.310	.731	1.878
	Correzione di Hedges	1.79464	1.292	.721	1.853
	Delta di Glass	2.05470	1.128	.524	1.717

a. Il denominatore utilizzato per stimare le dimensioni dell'effetto.
La d di Cohen utilizza la deviazione standard raggruppata.
La correzione di Hedge utilizza la deviazione standard raggruppata, piu un fattore di correzione.
Il delta di Glass utilizza la deviazione standard del campione del gruppo di controllo (ovvero il secondo).

Presence manipulation

Test t

Statistiche gruppo

	GROUP	N	Media	Deviazione std.	Errore standard della media
meanpresence	1.00	26	2.9744	1.99092	.39045
	2.00	57	5.7251	1.48821	.19712

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie							
						Significatività				Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	P unilaterale	P bilaterale	Differenza della media	Differenza errore std.	Inferiore	Superiore
meanpresence	Varianze uguali presunte	7.045	.010	-7.003	81	<.001	<.001	-2.75079	.39277	-3.53228	-1.96929
	Varianze uguali non presunte			-6.289	38.258	<.001	<.001	-2.75079	.43739	-3.63604	-1.86554

Dimensioni effetto campioni indipendenti

		Standardizzatore[a]	Stima del punto	Intervallo di confidenza 95%	
				Inferiore	Superiore
meanpresence	D di Cohen	1.65969	-1.657	-2.183	-1.124
	Correzione di Hedges	1.67526	-1.642	-2.162	-1.114
	Delta di Glass	1.48821	-1.848	-2.419	-1.267

a. Il denominatore utilizzato per stimare le dimensioni dell'effetto.
La d di Cohen utilizza la deviazione standard raggruppata.
La correzione di Hedge utilizza la deviazione standard raggruppata, piu un fattore di correzione.
Il delta di Glass utilizza la deviazione standard del campione del gruppo di controllo (ovvero il secondo).

Appendix 3A – Scale Items (Main Study)

Construct	Items	Source
Competence	• I think the chatbot is competent • I consider the chatbot capable • The chatbot is efficient • I believe the chatbot is skillful • In my opinion, the chatbot is intelligent • The chatbot is confident	Awale, A., Chan, C. S., & Ho, G. T. (2019)
Satisfaction	• I feel satisfied by my experience of using the chatbot • I am pleased by my experience of using the chatbot • I am contented of my experience of using this chatbot • I feel delighted my experience of using this chatbot • I will recommend it to my friends • I will reuse it	McKinney, V., Yoon, K., & Zahedi, F. M. (2002)

Appendix 3B – Validity and Reliability analyses (Main Study)

Competence scale

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		.866
Test della sfericità di Bartlett	Appross. Chi-quadrato	573.358
	gl	15
	Sign.	<.001

Varianza totale spiegata

	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
Componente	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	4.667	77.778	77.778	4.667	77.778	77.778
2	.614	10.238	88.015			
3	.325	5.420	93.435			
4	.197	3.281	96.716			
5	.129	2.148	98.864			
6	.068	1.136	100.000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Penso che il chatbot sia competente	1.000	.698
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Considero il chatbot capace	1.000	.904
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Il chatbot è efficiente	1.000	.887
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Credo che il chatbot sia intelligente	1.000	.792
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Secondo me il chatbot è abile	1.000	.841
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Il chatbot è sicuro di sé	1.000	.545

Metodo di estrazione: Analisi dei componenti principali.

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Correlazione multipla quadratica	Alpha di Cronbach se viene eliminato l'elemento
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Penso che il chatbot sia competente	27.97	35.619	.760	.728	.938
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Considero il chatbot capace	28.16	31.463	.916	.903	.918
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Il chatbot è efficiente	27.97	31.249	.911	.864	.919
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Credo che il chatbot sia intelligente	28.48	31.405	.835	.747	.929
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Secondo me il chatbot è abile	28.47	32.013	.876	.793	.923
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: – Il chatbot è sicuro di sé	28.09	35.079	.654	.571	.940

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
.941	.941	6

Statistiche degli elementi di riepilogo

	Media	Minimo	Massimo	Intervallo	Massimo/minimo	Varianza	N. di elementi
Correlazioni tra gli elementi	.727	.440	.887	.447	2.017	.015	6

<u>Satisfaction scale</u>

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		.915
Test della sfericità di Bartlett	Appross. Chi-quadrato	890.439
	gl	15
	Sign.	<.001

Varianza totale spiegata

Componente	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	5.462	91.037	91.037	5.462	91.037	91.037
2	.190	3.169	94.207			
3	.124	2.068	96.275			
4	.105	1.752	98.027			
5	.070	1.159	99.186			
6	.049	.814	100.000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Mi sento soddisfatto della mia esperienza di utilizzo del chatbot	1.000	.900
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Sono compiaciuto della mia esperienza con il chatbot	1.000	.930
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Sono contento della mia esperienza di utilizzo del chatbot	1.000	.934
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Mi sento felice della mia esperienza con il chatbot	1.000	.895
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Lo raccomanderei ai miei amici	1.000	.913
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Lo riutilizzerei	1.000	.890

Metodo di estrazione: Analisi dei componenti principali.

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
.942	.949	6

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Correlazione multipla quadratica	Alpha di Cronbach se viene eliminato l'elemento
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Mi sento soddisfatto della mia esperienza di utilizzo del chatbot	18.19	41.725	.861	.915	.927
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Sono compiaciuto della mia esperienza con il chatbot	18.61	41.271	.868	.820	.926
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Sono contento della mia esperienza di utilizzo del chatbot	17.73	47.352	.831	.942	.934
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Mi sento felice della mia esperienza con il chatbot	17.48	48.170	.827	.895	.936
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Lo raccomanderei ai miei amici	18.66	39.422	.846	.871	.932
Su una scala da 1 (completamente in disaccordo) a 7 (completamente d'accordo), valuta le seguenti affermazioni: - Lo riutilizzerei	18.04	43.318	.822	.870	.932

Appendix 3C – Main study results

ANOVA

Descrittive

Satis

	N	Medio	Deviazione std.	Errore std.	95% di intervallo di confidenza per la media		Minimo	Massimo
					Limite inferiore	Limite superiore		
.00	87	4.8640	1.00243	.10747	4.6503	5.0776	1.33	7.00
1.00	93	5.7079	1.59021	.16490	5.3804	6.0354	1.00	7.00
2.00	98	3.6241	1.31218	.13255	3.3611	3.8872	1.00	7.00
Totale	278	4.7092	1.58547	.09509	4.5220	4.8964	1.00	7.00

Tests di omogeneità delle varianze

		Statistica di Levene	gl1	gl2	Sig.
Satis	Basato sulla media	13.501	2	275	<.001
	Basato sulla mediana	3.945	2	275	.020
	Basato sulla mediana e con il grado di libertà adattato	3.945	2	233.515	.021
	Basato sulla media ritagliata	10.987	2	275	<.001

ANOVA

Satis

	Somma dei quadrati	df	Media quadratica	F	Sig.
Tra gruppi	210.219	2	105.109	59.465	<.001
Entro i gruppi	486.083	275	1.768		
Totale	696.302	277			

Dimensioni effetto ANOVA[a]

		Stima del punto	Intervallo di confidenza 95%	
			Inferiore	Superiore
Satis	Eta quadratico	.302	.213	.379
	Epsilon quadratico	.297	.208	.374
	Effetto fisso omega quadratico	.296	.207	.373
	Effetto casuale omega quadratico	.174	.115	.230

a. Eta quadratico e epsilon quadratico vengono stimati in base al modello a effetto fisso.

MEDIATION ANALYSIS

```
Run MATRIX procedure:

*************** PROCESS Procedure for SPSS Version 4.2 beta ***************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Satis
    X  : IV
    M  : Comp

Sample
Size:  278

**************************************************************************
OUTCOME VARIABLE:
 Comp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6229      .3880     1.1876   175.0134     1.0000   276.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.6150      .1013    35.6704      .0000     3.4155     3.8145
IV           1.0434      .0789    13.2293      .0000      .8881     1.1987

Standardized coefficients
        coeff
IV      .6229

**************************************************************************
OUTCOME VARIABLE:
 Satis

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .9219      .8498      .3798   778.0462     2.0000   275.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.2087      .1357    -1.5377      .1253     -.4759      .0585
IV           -.0839      .0570    -1.4714      .1423     -.1961      .0283
Comp         1.0808      .0340    31.7538      .0000     1.0138     1.1478

Standardized coefficients
          coeff
IV       -.0440
Comp      .9486
```

```
************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 Satis

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5470      .2992     1.7657   117.8130     1.0000   276.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.6985      .1236    29.9293      .0000     3.4553     3.9418
IV           1.0439      .0962    10.8542      .0000      .8545     1.2332

Standardized coefficients
        coeff
IV      .5470


************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_cs
     1.0439      .0962    10.8542      .0000      .8545     1.2332      .5470

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_cs
     -.0839      .0570    -1.4714      .1423     -.1961      .0283     -.0440

Indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
Comp     1.1278      .1003      .9307     1.3253

Completely standardized indirect effect(s) of X on Y:
         Effect     BootSE   BootLLCI   BootULCI
Comp      .5909      .0473      .4953      .6818

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Executive Summary

In our contemporary milieu, technology has permeated every aspect of our lives, advancing at unprecedented pace. Consequently, a profound comprehension and effective management of this innovative landscape have become imperative for corporate success. Currently, AI stands as the apex of this technological evolution, with its applications spanning diverse domains of business and society (Haenlein & Kaplan, 2019), becoming a crucial factor in customer experience, too. Indeed, AI-enabled customer service represents the most effective and quickest way to deliver personalized experience that increase customer engagement (McKinsey & Company, 2023). Within this dynamic landscape, one of the most widespread and impactful applications of AI emerges, a technology that bears significance on both social and managerial fronts: chatbots. Chatbots, using Natural Language Processing (NLP), are versatile tools employed across numerous fields, such as marketing, technical support, and education (Smutny & Schreiberova, 2020). As chatbot technology continues to advance, its application in business is on the rise, particularly within customer service and personalization domains (Przegalinska et al., 2019). This is also highlighted by projections anticipating a compound annual growth rate of 23.3% from 2023 to 2030 in the chatbot market (Grand View Research, 2023), and expecting that 95% of online service interactions will be managed by AI chatbots by 2028 (Chong et al., 2021). Despite their numerous advantages, such as round-the-clock availability or rapidity in addressing customer requests, chatbots face many challenges too. According to CGS (2019), 86% of consumers still prefer interacting with a human agent instead of an AI-based system. This inclination is attributed, in part, to the perception that chatbots and virtual assistants pose challenges in efficiently resolving issues, due to instances of miscommunication (Sheehan et al., 2020). Therefore, consumers hesitancy and resistance towards chatbots often arise from negative experiences marked by a lack of perceived competence and authenticity in the customer-chatbot interaction (Nguyen et al., 2023). This underscores the need to address user concerns regarding chatbot performance and competence.

The concept of competence as defined within the Stereotype Content Model (SCM) (Cuddy et al., 2008), is crucial in understanding user satisfaction with chatbots. Competence perceptions are linked to the ability of an entity to fulfill its objectives effectively. Despite its importance, there is limited research on chatbot competence.

Therefore, given that the perception of chatbots' competence pertains to users' views of them as capable, knowledgeable, reliable, and effective in providing services (Følstad & Brandtzaeg, 2020), it is important to investigate how to improve it. Since chatbots are aimed to replicate human-to-human conversations and have a prominently text-based nature, studies on the topic are mainly focused on inquiries into anthropomorphism (e.g., Seeger et al, 2021; Go & Sundar, 2019) or on linguistic features (e.g., Kull et al., 2021). Considering this dual nature of chatbots, it is conceivable a pivotal aspect for enhancing their competence could be found within this domain. Emojis are an element that simultaneously intersects both anthropomorphic-based and text-related facets of the subject matter. They are a form of textual paralanguage that plays a significant role in augmenting messages. Specifically, when emojis align semantically with the accompanying text, many advantages have been demonstrated by previous research (e.g., Barach et al., 2021). Despite this, the potential of congruent emojis (those that align semantically with the text) to improve chatbot performance and user perceptions of competence has not been thoroughly investigated.

The present work aims to bridge the gap in the literature by examining the use of semantically congruent emojis in chatbot communications. It seeks to understand if these emojis can enhance customer satisfaction. Additionally, the study investigates the mediating role of perceived competence in the relationship between congruent emoji use and customer satisfaction. By addressing these research questions, this thesis contributes to both theoretical knowledge and practical insights. Offering potential solutions for aligning customer emotional and executional needs with the effective performance of chatbots, thereby enhancing overall customer satisfaction.

Chatbots are computer programs endowed with natural language processing capabilities, designed to engage in dialogue with human users (Maudlin, 1994). They are predominantly deployed in customer service settings, where they directly interact with consumers (Chung et al., 2020), offering readily accessible assistance and information for frequently encountered queries and support tasks (Nordheim et al., 2019). Consequently, recent research has explored how AI-powered chatbots perform when used within a customer service context, for example in terms of response to user’s need of human interaction (Sheehan et al., 2020). While chatbots offer various benefits, they also present several challenges. Consequently, existing literature endeavors to explore methods for improving chatbot performance by addressing these issues while preserving their inherent advantages. For this reason, previous studies explore how using anthropomorphic cues for optimizing chatbot performance (e.g., Schanke, 2021) or try to understand the effects of different communication elements implemented in chatbots design (e.g., Xu et al., 2022). This is particularly important, since enhancing these linguistic features can improve perceived anthropomorphism and communication quality, for instance making interactions less confusing and more engaging (Saarem, 2016). It has been found that specific combinations of design cues, including verbal and human identity aspects, impact perceived anthropomorphism, highlighting the importance of considering task types and users' predispositions for effective conversational agents' design (Seeger et al., 2021). Moreover, Assink (2019) showed that the implementation of anthropomorphic visual and linguistic features in chatbots resulted in increased user satisfaction. Therefore, finding a solution that integrates both human-like and linguistic cues could be a way for optimizing chatbots design. Emojis, for instance, represent a textual paralanguage element that somewhat integrates the two aforementioned aspects which constitute the essence of this dual nature of chatbots. Indeed, they hold the capacity to enhance the message conveyed by a given text and also offer the ability to capture and express non-verbal elements of communication, such as facial expressions or gestures (Bai et al., 2019). Despite this, just a very scarce part of the literature has studied the effects of emojis usage by chatbots. Furthermore, existing research tends to focus on face emojis, neglecting the impact of non-facial emojis, which can also enhance the ability to simulate human conversation. Focusing on non-face emojis allows for an examination of how consumers attribute judgments related to chatbots' efficacy in task accomplishment, particularly competence, while the majority of existing studies concentrate on emotional dimensions like warmth and empathy. Therefore, although research shows that emoticons, representing facial expressions or emotions, enhance the perceived warmth of the sender (Li et al., 2019), it is reasonable to expect that other types of emojis, namely non-facial ones, may influence perceived competence.

Emojis are graphic symbols with predefined names and codes (Unicode), that encompass representations of facial expressions, abstract concepts, emotions, animals, plants, activities, gestures, and objects (Rodrigues et al., 2018). 92% of users worldwide include them into their online interactions (Kaye et al., 2017). This widespread adoption can be attributed to the numerous benefits associated with emojis, for instance the ability to enhance the appeal of message to recipients (Cramer et al., 2016). The benefits of emojis become particularly evident and impactful when they align semantically or emotionally with the accompanying sentence. Consequently, a significant portion of research has focused on investigating the effects of using congruent emojis alongside text (e.g. Hand et al., 2022). Specifically, semantic congruence enhances message processing ease and fluency (Choi & Kang, 2013), thereby improving clarity (Reber et al., 2004). This effect is particularly pronounced with non-facial emojis, which convey non-verbal communicative aspects while reducing message ambiguity (Riordan, 2017). Indeed, Barach et al. (2021) demonstrated that using congruent non-facial emojis instead of incongruent ones accelerates message comprehension speed. These findings are consistent with research demonstrating that textual paralanguage can evoke vivid mental images, thereby making the message more concrete and realistic (Borst & Kosslyn, 2010).

Despite the widespread use of emojis in digital communication, their impact on chatbot interactions remains underexplored. Addressing semantic congruence in emoji usage could mitigate common chatbot issues, such as misinterpretation and the inability to convey empathy or information clearly (Sheehan et al., 2020; Luo, 2019; Trivedi, 2019). Enhancing communication effectiveness through semantic congruence in emoji usage may improve customer satisfaction with chatbot interactions. Customer satisfaction, a crucial determinant of business success, arises from cognitive and affective evaluations of a service (Giese & Cote, 2000; Krivobokova, 2009). It influences repeat purchases (Oliver, 1980) and fosters customer loyalty (Boulding et al., 1993; Leninkumar, 2017). High-quality service leads to higher customer satisfaction (Caruana, 2002). Therefore, when transitioning to an online customer service context, it becomes imperative to discern the determinants of quality within such an environment. The satisfaction derived from chatbot interactions, for instance, hinges on several factors such as responsiveness, assurance, accuracy, personalization, and ease of use (Jenneboer et al., 2022). In light of this, it is important to emphasize that emojis play a pivotal role in facilitating positive perceptions and responsiveness, serving to diminish social distance and convey thoughtfulness toward the recipient (Coyle & Carmichael, 2019). Particularly, non-face congruent emojis significantly enhance text comprehension and processing speed (Barach et al., 2021). This effect can be also attributed to the reduction of message ambiguity and the enhancement of reader confidence associated with non-facial emojis (Riordan, 2017). Indeed, non-face emojis contribute to making text more vivid and specific (Peng & Zhao, 2021), attributes that contribute to language concreteness (Hansen & Wänke, 2010), which is linked to increased customer satisfaction (Packard & Berger, 2021). Furthermore, the inclusion of gesture-based emojis by chatbots could serve to humanize these agents (Gawne & McCulloch, 2019), thereby elevating the overall customer experience and personalization, ultimately leading to heightened customer satisfaction (Ashfaq et al., 2020; Araujo, 2018; Carvajal et al., 2011). Considering these linkages between factors determining customer satisfaction and the effects of emoji usage, it is possible to hypothesize that the use of emojis semantically congruent with the text by a chatbot, as opposed to neutral ones, or to the absence of emojis with the same text, has a positive effect on customer satisfaction with the chatbot itself (**H_1**).

The Stereotype Content Model (SCM) offers a framework for understanding how individuals judge others in social interactions, focusing on two primary dimensions: warmth and competence (Cuddy et al., 2008). Competence perceptions encompass attributes like intelligence, skill, confidence, and efficacy (Fiske et al., 2007), and could be extended to virtual agents as well (Demeure et al., 2011). Notably, Hu and peers (2021) discovered that users' assessments of an AI assistant's warmth and competence are pivotal factors in their ongoing engagement with the system. In the domain of customer service facilitated by chatbots, competence is often gauged through textual interactions. Users may evaluate a chatbot's competence based on its ability to convey confidence, clarity, and intelligence in its responses. According to research by Følstad & Brandtzaeg (2020), users regard chatbots as competent when they are perceived as capable, knowledgeable, reliable, and effective in providing assistance. Integrating non-verbal elements like emojis could be advantageous to maintain message coherence without compromising response time. Notably, studies by Cuddy and colleagues (2011) suggest that non-verbal cues influence perceived competence in face-to-face social interactions. This finding suggests a plausible link between textual paralanguage and perceived competence, extending even to online interactions. Emojis, especially those semantically congruent with a message, serve as a prime example of such non-verbal cues. As highlighted earlier, these symbols, including gesture-based emojis, contribute to making chatbots more human-like. This becomes particularly relevant given studies indicating that when AI chatbots are personalized and exhibit anthropomorphic traits, they are perceived as more competent (Kim et al., 2023). Moreover, non-human face emojis are extraordinarily effective in adding vividness and concreteness to a message, thereby signaling competence (Hansen & Wänke, 2010). This aligns with research that investigates how language concreteness influences perceptions of competence in sources of information communication (Jiménez-Barreto et al., 2023). At this point, it becomes evident that there exists a convergence between the factors influencing perceived competence and those impacting satisfaction when engaging with chatbots in online customer service settings. Therefore, it is not surprising that prior research across various sectors has identified a positive association between a service provider's perceived competence and consumers' trust and satisfaction (Coulter & Coulter, 2002; Andaleeb, 1998). Considering this correlation, it is plausible to hypothesize that perceived competence will mediate the relationship between usage of congruent emojis and customer satisfaction; consumers perceive higher levels of chatbot's competence when it uses congruent emojis compared to neutral ones or to text only (**H_2**).

To test the hypotheses of the study, an online experiment was conducted. The data collection involved administering a questionnaire through a survey conducted independently in Italy between April and May 2024 using the online platform Qualtrics XM. Participants were selected using a non-probabilistic sampling methodology, specifically a convenience sampling method, which facilitated easy and rapid access to elements of the population. Demographic variables such as age and gender were included without restriction, as they were not expected to significantly influence the experimental results statistically. For conducting the online experiment, a sort of simulation has been crafted, in order to make the scenario as realistic as possible, with messages generated by the chatbot inspired by those typically employed by real travel websites. The choice of this sector is motivated by projections indicating that chatbot usage will experience the most significant growth within the travel and tourism industry from 2023 to 2030 (Grand View Research, 2023). Furthermore, emojis for the congruent condition were chosen based on their conventional meanings, selected via keywords or the overall message of the sentence (Emojipedia – Home of Emoji Meanings, n.d.). In the neutral scenario, emojis were intentionally selected to be different from the context but not completely illogical or nonsensical, considering that companies obviously avoid programming chatbots with entirely nonsensical emojis. However, it is possible for companies to implement chatbots using a limited number of neutral emojis, which can be suitable for various contexts. Based on the fact that some chatbots use emojis that are neutral in terms of their relationship to the text, such as those used by SSH, Air France, Zuppi, among others, this scenario was chosen to evaluate the cost-benefit analysis of using more popular and versatile emojis (e.g., standard ones used as Instagram story reactions) versus emojis specifically related to the accompanying text. To ensure the accurate neutrality (in terms of valence) of these emojis, the selection process relied on the Emoji Sentiment Ranking by Kralj Novak et al. (2015). With regard to the structure and design of the questionnaire used for running the experiment, it was structured as follows. An introduction opened the survey, with two control questions to make respondents familiarize with the topic. Subsequently, participants were randomly but uniformly assigned to one of three conditions. Therefore, respondents in Condition 1 interacted with a chatbot sending text-only messages, while those in Condition 2 received messages containing emojis semantically congruent with the text, and those in Condition 3 received messages with neutral emojis (see *Appendix 1*). After the simulation, participants responded to questions measuring the variables of interest. Finally, demographic data regarding age and gender were collected to provide additional information about the sample.

Initially, a pretest was run to confirm the effectiveness of the two independent variable manipulations. The pretest had 83 participants (M_{age} = 26 years; SD_{age} = 8.76), with 56 females and 27 males. Following the simulation, participants rated their perception of emoji presence within the chatbot's messages and the congruence of emojis with the text (only in conditions where emojis were present) (see *Appendix 2A*). Before analyzing the results, analyses to test the used scales validity and reliability where conducted (see *Appendix 2B*). The results of the pretest confirmed successful manipulations of the independent variables. The first independent t-test comparing congruent and neutral groups showed significant differences in ratings (M_{cong} = 5.62, SD_{cong} = 1.41; M_{incong} = 3.30, SD_{incong} = 2.05; $t(55) = 4.97$, $p < .001$), indicating successful manipulation of congruence. Similarly, the second independent t-test comparing text-only and text with emojis (both congruent and neutral) showed significant differences in ratings (Mtext = 2.97, SDtext = 1.99; Memoji = 5.72, SDemoji = 1.48; t(81) = -6.28, p < .001), indicating successful manipulation of presence. Detailed tables presenting the pretest results can be found in Appendix 2C. As a result of these successful pretest manipulations, the main study proceeded as planned.

A 3 x 1 between-subjects experimental design was employed to test the hypotheses. The study involved 278 participants (Mage = 27 years; SDage = 8.72), comprising 209 females, 69 males, 1 identifying as third gender, and 1 who preferred not to disclose the gender. After the simulation, participants rated their perception of the chatbot's competence and their satisfaction (see *Appendix 3A*). As for the pretest, scales validity and reliability were tested through various analyses (see *Appendix 3B*). To test H_1, a one-way ANOVA was conducted to examine the effect of chatbot text typology (text-only vs. with congruent emojis vs. with neutral emojis) on customer satisfaction. Results revealed a significant main effect (F(275) = 59.465, p < 0.001), indicating that the mean satisfaction scores differed across the three groups. Specifically, satisfaction was higher when chatbots used congruent emojis (Mcong = 5.70, SDcong = 1.59). Conversely, satisfaction was lower when chatbots used neutral emojis (Mincong = 3.62, SDincong = 1.31) compared to text-only messages (Mtext = 4.86, SDtext = 1.00). Therefore, H1 is supported. Moving on, a mediation analysis was conducted to examine H_2, using Model 4 of PROCESS. In this analysis, the predictor variable was the type of text used by the chatbot (where, according to ANOVA results, congruent_emoji was coded as 2, text_only = 1, incongruent_emoji = 0), perceived competence served as mediator, while customer satisfaction was the outcome variable. Results indicated a significant and positive effect of the independent variable on the mediator (ß = 1.0434, p < 0.0000). Additionally, the effect of the mediator on the dependent variable was positive and significant (ß = 1.0808, p < 0.0000), whereas the direct effect of the independent variable on the dependent one was not significant (p = 0.1423). Upon including perceived competence in the model, the indirect effect of text typology on customer satisfaction was positive and significant, with a confidence interval excluding zero (ab = 0.59, 95%CI(0.49, 0.68)). Thus, full mediation was observed, supporting H2. Results of the analyses conducted to test the hypotheses can be found in *Appendix 3C*.

This study investigates the impact of a simple paralinguistic cue, namely emojis, on customer satisfaction when interacting with chatbots. Through an online experiment, it was found that incorporating emojis that align semantically with the accompanying text enhances customer satisfaction with the chatbot. Furthermore, the analysis reveals that the perceived competence of the chatbot mediates this effect, underscoring the importance of congruent emoji usage in fostering positive customer experiences.

The performed analysis significantly contributes to the existing literature on chatbots, focusing particularly on the utilization of a seemingly simple yet impactful paralinguistic cue prevalent in computer-mediated interactions: emojis. They combine both anthropomorphic cues and linguistic aspects, typical of these agents. Specifically, the study demonstrates that emojis, when semantically congruent with the accompanying text, play a crucial role in increasing customer satisfaction with chatbots. This finding not only deepens our comprehension of how textual paralanguage influences user interactions but also underscores the significance of considering congruence between emojis and text in chatbot design and communication strategies. In addition, most existing research has primarily focused on studying facial emojis and how their usage in alignment with the accompanying text's sentiment can yield positive effects (e.g., Boutet et al., 2021). However, emojis can also be semantically congruent, thereby reinforcing the text's meaning, and this effect can be achieved using non-facial emojis, as demonstrated by study from Barach and peers (2021). Currently, few studies have extended the investigation of emojis to chatbots. For instance, Yu and Zhao (2024) recently found that using facial emojis positively influences warmth and satisfaction, but not competence. Therefore, this research extends the scope of previous studies on congruent emojis beyond traditional contexts to the realm of chatbots, revealing the applicability and effectiveness of such cues in enhancing user experiences with these platforms. Furthermore, this study extends the analysis of the Stereotype Content Model (SCM) to the domain of chatbots, investigating whether the perceived competence of the chatbot serves as a mediating factor in the relationship between congruent emoji usage and customer satisfaction.

Moreover, the findings of this thesis carry significant implications for practical application. The results of the present work suggest that the content conveyed by chatbots significantly impacts user satisfaction. Specifically, incorporating emojis that align semantically with the accompanying text can enhance the perception of chatbot competence, subsequently increasing customer satisfaction. This finding underscores the potential of emojis as a practical solution to address challenges associated with chatbot usage, mitigating those factors that may discourage customer engagement and lead to negative brand perceptions (van der Goot et al., 2020; Altay et al., 2024; Shahzad et al., 2024). When considering the managerial implications of this study, it is worth noting that the decision to prioritize emojis over other cues is partly due to its simplicity in real-world applications. Emojis offer an uncomplicated and cost-effective solution compared to alternative tools such as images or videos. Despite the rapid evolution of technology and the emergence of new tools, not all contexts progress at the same pace (Chinn et al., 2020). For instance, as highlighted in a 2023 study by Istat, Italy still faces significant levels of digital illiteracy. Consequently, it remains crucial for companies to focus on simpler yet effective tools like emojis.

While this study represents a significant step forward, it is not without limitations. While efforts were made to make the simulation as realistic as possible, there are inherent differences compared to real interactions with live chatbots. Therefore, it would be valuable to investigate whether the findings of this research hold true in on-field experiments, where users engage with real chatbots on actual websites. Another limitation pertains to the sample. Not only is the number of respondents not very large, but the primary concern lies in the utilization of convenience sampling methodology, which present many potential biases. Therefore, future studies could concentrate on specific population segmentation to ascertain whether geographical or generational factors, combined with cultural elements, could influence the obtained results. Moreover, while this study is centered on a travel website, it is conceivable to anticipate varied outcomes depending on the sector or industry. Indeed, across various marketing domains, differences in consumer behaviors are observed based on the nature of the product or service, whether utilitarian or hedonic (e.g., Pozharliev et al., 2023; Barrett et al., 2024). Therefore, future research endeavors could delve deeper into this aspect. Furthermore, although this study focuses on chatbots for customer service assistance, many chatbots are also deployed for aiding in service failure procedures. Hence, it would be intriguing for subsequent studies to investigate whether there are distinct consumer behaviors in these scenarios. Another noteworthy aspect is that in formulating the tested hypotheses, numerous connections were drawn with elements such as anthropomorphism and language concreteness. Consequently, future research could contemplate incorporating additional variables into the model to ascertain if they would enhance its explanatory power. Finally, it is pertinent to mention the growing predominance of unstructured data in current marketing strategies (Wang et al., 2024). Therefore, incorporating these tools into chatbot design could offer a means to integrate additional and potentially more effective paralinguistic cues into computer-mediated conversations. Subsequent research endeavors could investigate the impact of these elements on human-chatbot interactions.