How Artificial Intelligence impacts the customer experience

Auteur : Knidiri, Hiba
Promoteur(s) : Dessart, Laurence
Faculté : HEC-Ecole de gestion de l'Université de Liège
Diplôme : Master en sciences de gestion, à finalité spécialisée en international strategic marketing
Année académique : 2020-2021
URI/URL : http://hdl.handle.net/2268.2/13565

HOW ARTIFICIAL INTELLIGENCE IMPACTS THE CUSTOMER EXPERIENCE

Jury:

Promoter:

Laurence DESSART

Readers:

Maarten BOSMA; Florian PETERS

Dissertation by

Hiba KNIDIRI

For Master's degree in Management

specializing in International Strategic Marketing

Academic Year 2020/2021

TABLE OF CONTENTS

ACKNOWLEDGMENTS

The present work has been prepared with great care and attention to detail. But it would not have been possible without the people who have contributed to its production. It is only natural to express my gratitude to these people who have also made it a growth experience.

First, I would like to thank my academic advisor, Mrs. Laurence Dessart, for her guidance throughout the process.

Additionally, I would like to acknowledge Mr. Maarten Bosma and Mr. Florian Peters for the time spent reading this thesis and for their valuable feedback.

I owe a great debt of gratitude to my friend Mohammed Abdelbaki. Thanks to his development skills, we were able to turn this academic research into a work experience.

I would like to express my sincere gratitude and appreciation to my entire family of HEC Liege who made my journey to HEC possible.

Last but not least, I would like to thank my friends and beloved family in Morocco for their unconditional love. Their love and care during this difficult time is the greatest encouragement for all my efforts.

One last big thank you to everyone who took 5 minutes to fill out my thesis questionnaire!

ABSTRACT

The increasing use of AI technologies such as chatbots by retailers is leading academics and practitioners to recognise their impact on the customer experience. Although research shows that consumers generally prefer to deal with humans rather than robots, it has also shown that embedding virtual agents into online retail and service websites leads to positive customer outcomes. In this paper, we investigate the presence of intelligent, disembodied virtual agents (i.e., AI chatbots) in an online shopping context and extend the study to include human-like cues such as conversational style and avatar that can improve the customer experience. We conduct two online experiments (N = 77 and 143) with real chatbot conversations in a simulated online store to test the premises of our study. Study 1 showed no differences between the presence and absence of a chatbot on participants' customer experience. The interaction effect in Study 2 (conversation style x avatar type) also proved to be non-significant. Nonetheless, in line with previous studies, significant evidence of perceived humanness, personalization, and social support was found, opening the door for further research. The paper concludes with practical implications for retailers using AI chatbots for their customers.

Keywords:

AI Chatots – Online Customer Experience – Interaction Style – Avatar – Online Shopping

CHAPTER 1. GENERAL INTRODUCTION

This chapter provides an overview of the topic chosen for this thesis, its implications and scope.

1.1 Context

With the immense growth of digitization, artificial intelligence is the game changer that companies are banking on to boost their organizational performance. According to **?** recent survey on the topic, artificial intelligence is on the rise, with 37% of companies reporting that they are already using artificial intelligence. In practice, AI applications and tools are widely used by companies in all industries and are therefore ubiquitous. They are not only changing business processes but also customer behavior. Ameen et al. (2021) recently published an article that provides examples of common AI applications and how they improve and enhance the customer experience. For example, intelligent recommendation agents as AI-powered tools can improve customers' convenience by providing personalized recommendations that presumably profile their preferences (e.g., Netflix, Spotify). In retail, AI technologies for virtual fitting are also a case worth mentioning, as they help reduce and limit errors in online clothing purchases, from size to color to fashion preferences (Yang et al., 2020) . One example of the AI technology broadly used by by businesses to enable more efficient interactions with customers is chatbots[1], also known as (disembodied) conversational agent.

Chatbots are usually defined as computer programs with text or voice interface, based on natural language and specifically designed to provide faster and more natural access to information to facilitate and enhance user interaction (Jain et al., 2018). The chatbot revolution is in full swing,

[1]The term chatbot and conversational/virtual agent are not identical in meaning but will be used interchangeably henceforth.

appearing and disappearing from the limelight depending on how good their capabilities are. However, advances in artificial intelligence, natural language processing (NLP), and machine learning are the reason why chatbots are making a comeback and becoming more adept and intelligent (Gnewuch et al., 2017) . Given these improvements, the use of chatbots has expanded and can be found in various industries and sectors such as healthcare, tourism, and e-commerce. AI chatbots make it possible to access customer-related data, interpret it correctly, and adapt it in a flexible manner (Kaplan and Haenlein, 2019). By gaining such insights, companies can improve their potential knowledge of customer needs and optimize their decision-making in response,making AI chatbots an innovative way to add value not only for marketers but also for customers.

There is a plethora of AI chatbot use cases in marketing and sales. These often include answering frequently asked questions, handling customer service requests, recommending new offers, capturing customer inquiries, etc. Therefore, AI chatbots can be considered as interaction brokers, i.e., a point of contact between businesses and customers. Customers interact with chatbots to get information in the pre-purchase phase, to get assistance during the purchase phase, and finally to get their questions answered in the post-purchase phase. Previously, this required customers to either fill out forms, write formal emails, or call hotlines with often long queues.In summary, chatbots are touchpoints that allow customers to interact effortlessly and save time and money throughout the purchase phase (Gnewuch et al., 2018; Adam et al., 2019; Moriuchi, 2020; Prentice et al., 2020) .In line with research, the internal and subjective responses customers receive from similar interactions are referred to as customer experience. Therefore, it can be inferred that chatbots have an important impact on customer experience.

In today's retail service environment, where customers are more in control than ever, marketing scholars and practitioners agree that a largely pleasant customer experience represents a significant long-term competitive advantage for any business. It follows that CX is a key aspect of differentiation and engagement, making it one of the most important areas of research in marketing. And although customer experience is increasingly shifting to technology-based online touchpoints, there are only few studies investigating this new phenomenon (De Keyser et al., 2020; Becker and Jaakkola, 2020) . This growing attention has led to calls for research to better understand this trend in science and practice.

1.2 Research aim and objectives

As mentioned earlier, AI-based chatbots's omnipresence in customer-business encounters is pushing both scholars and practitioners to understand how these technologies impact customer experience in particular Jain et al. (2018) , but little is known about how customers respond to their use. The technology behind chatbots is growing, but understanding of chatbot interactions is not growing at the same rate. The development of a successful chatbot largely depends on these two factors, i.e. technological and social factors. In addition, while chatbots provide faster and more natural access to information, they often fail to meet customer expectations if they do not provide interactions as engaging, entertaining, and complex as interpersonal conversations in messaging apps Pérez et al. (2020). This means that more knowledge about the interaction between customers and chatbots is needed to achieve positive results for customers.

Based on these insights, the purpose of this study is to understand the impact of introducing an intelligent chatbot that performs search support functions in an online shopping context. More specifically, this study examines the difference between AI conversational user interface (i.e.,chatbot) and graphical user interface (website) in assisting customers to find the right products. In other words, we want to evaluate the difference between the presence and the absence of an AI chatbot in online shopping context in terms of customer experience (Study 1). Despite the different types and designs of chatbot interfaces (e.g., embodied, avatar, etc.), scholars and practitioners still disagree on which elements should be considered or disregarded when designing chatbots to achieve a better conversation with customers. These factors are related to human-computer interaction and are crucial for a positive customer experience. The study (2) addresses conversational and visual anthropomorphic cues in chatbots and examines their impact on customer experience, which is very relevant given the increasing prevalence of chatbots.

1.3 Contribution

The literature review of this paper does not include a study that examines the direct impact of AI chatbots and their features on customer experience. This gap motivates the author of this paper to provide meaningful insights to marketing scholars and managers and hopefully suggest directions for future research. Furthermore, it is not intended to provide definitive and conclusive answers regarding the causality of the variables studied, but rather to explore the research questions. Thus, the relevance of this work is firstly at the functional level for developers of chatbots by uncovering the potential impact of design elements on the experience. Secondly, at the management level for marketers testing chatbots on their landing pages to create a better and smoother online experience. And finally, at the academic level, adding to existing scientific knowledge and laying the groundwork for future studies on chatbots, such as understanding the underlying factors that might influence chatbot adoption.

Chatbots tend to be disembodied CAs in that they interact with customers primarily via messaging-based interfaces through verbal (e.g., conversational style) and nonverbal cues (e.g., three animated dots) that enable real-time dialogue, with generally a static profile picture. Apart from two exceptions that focused on verbal ADCs (Araujo, 2018; Go and Sundar, 2019), this study is, to our knowledge, one of the first to examine virtual agents in the form of AI chatbots (as opposed to other forms, such as interactive avatars) and to incorporate visual conversational cues to investigate their impact on the online customer experience in an online shopping environment (Adam et al., 2019).

1.4 Approach

This paper begins with a literature review explaining the concepts of the study (i.e. AI chatbots, customer experience). This section serves to enhance the understanding of the topic by allowing the researcher to map and analyze the current intellectual terrain and define the research question to add to the existing body of knowledge. Next, the major theories on the topic are highlighted and incorporated into the development of the hypotheses and the creation of the conceptual model. Finally, the research design and data collection process for this thesis are defined and the results are revealed and addressed to determine the managerial and scientific significance of this analysis and its potential implications for further study.

CHAPTER 2. LITERATURE REVIEW

In this chapter, a literature review important to establishing the research questions and assumptions that underpin the study design is presented to explain and clarify all constructs, terms and core theories that will form the basis for the development of the corresponding hypotheses and conceptual model for this thesis.

For expositional ease, we use the terms “interaction style” “conversational style” interchangeably throughout the paper.

2.1 Customer Experience

Holbrook and Hirschman (1982) were the first to challenge the traditional consumer decision-making process that assumed the customer was purely rational (Bhattacharaya), and instead recognized the "experiential" dimension of consumption, which includes symbolic, hedonistic, and esthetic factors. Later, in Pine and Gilmore’s "experience economy", experience becomes an important offering by firms to customers, similar to goods, commodities and services. However, the first serious discussion and analysis of customer experience in marketing emerged with a major study by Schmitt (1999), which extended the work of Pine and Gilmore. Schmitt (1999) presented a distinction between traditional marketing and experiential marketing based on five strategic experiential modules (SEMs) in the form of "sense", "feel", "think", "act" and "relate", which he used to argue that experiences occur when a consumer encounters and lives through things that convey relational, emotional, sensory, behavioral and cognitive values(Verhoef et al., 2009)

Since the conceptual focus of SEMs developed by Schmitt (1999), customer experience has received growing attention in academia with numerous conceptual and empirical studies on the topic.

Various definitions and conceptualizations have emerged, most of which share some elements with the model proposed by Schmitt (1999) (Berry et al., 2002; Gentile et al., 2007; **?**; Pine 2nd. and Gilmore, 1998) . However, despite their contrasting perspectives, these studies agree that customer experience is a complex, multifaceted concept defined differently depending on the approach and context, that involves a person (subject) interacting with a firm or its offerings (object) at different levels.(De Keyser et al., 2020; Jain et al., 2018) Customer experience is defined as a state that is evoked in an individual in response to a stimulus Poulsson and Kale (2004) . For Becker and Jackola, customer experience is the ”subjective response or interpretation of any direct or indirect contact with the elements of service, such as the provider, offering, brand, environment, or process”, while (Gentile et al., 2007, p.397) defines CX as ” set of interactions between a customer and a product, a company, or a part of its organization which provoke a reaction).Against these different definitions of customer experience (Lemon and Verhoef, 2016; Becker and Jaakkola, 2020) , there seems to be some agreement that customer experience reflects the customer's internal reaction and subjective response to all direct and indirect encounters with a company's products, service, or brand (Gentile et al., 2007; Becker and Jaakkola, 2020) . Indirect contact usually includes unplanned encounters with representatives, word of mouth, advertisements, news reports, or product reviews, while direct contact occurs in the course of a customer's purchase, use, or service and is usually initiated by the customer.

These internal responses and subjective reactions are a set of sensations and mental states that can be described as the dimensions of the customer experience construct Rose et al. (2012). Notwithstanding the varying number of CX dimensions that exist depending on the context and the research setting, recent studies, in line with Smith's work, have extended the dimensionality approach from two dimensions, i.e. affective and cognitive (Rose et al., 2012; Danckwerts et al., 2019), to other dimensions such as sensory, behavioral and relational (Gentile et al., 2007; Schmitt, 1999). CX is thus a multidimensional construct composed of individuals' cognitive, affective, sensory/physical, social/relational, and behavioral/pragmatic responses to a service at every possible point of contact, i.e., touchpoints outside and within the control of the retailer or company.

All in all, a more dynamic perspective on customer experience states that CX is the amalgamation of small, incremental, bounded experiences that evolve throughout the customer journey Lemon and Verhoef (2016) .In similar vein, De Keyser et al. (2020) presents a comprehensive conceptualization of CX: the customer experience is formed through interactions with "touchpoints" (firm-controlled vs. non-firm-controlled and direct vs. indirect) within "phases" (pre-purchase, purchase, post-purchase) conditioned by a broader "context" (individual, social, environmental, etc.) and characterized by a set of "qualities" (strength, duration, valence, etc.) that together result in a value judgment by the customer.

The different conceptualizations of customer experience in terms of scope and dimensions, antecedents and consequences also complicate the operationalization of the construct in a holistic manner. Despite the associated concerns about measurement validity and results generalizability, scholars recommend that customer experience measurement tools should be adapted to fit the context (Waqas et al., 2021) .That being said, two influential scales are extensively used in CX research in view of their applicability in multiple, wide-ranging contexts in marketing (e.g., tourism,retail). These scales include the brand experience scale (Josko, 2009) and Experience quality scale (EXQ) (Klaus et al., 2013; Maklan and Klaus, 2011) The Brand Experience Scale follows the conceptual focus on SEMs developed by Schmitt (1999) to measure customer experience with a brand, using four dimensions: intellectual, sensory, affective and behavioral. The Experience Quality Scale (EXQ), on the other hand, includes four dimensions (product experience, outcome focus, moments of truth, and peace of mind) based on evaluative judgments about the service. The latter approach has been criticized by scholars considering that evaluative concepts such as perceived service quality, satisfaction, and motivational concepts such as engagement should be distinguished from the definition of CX and that this link deserves further investigation.(e.g.,) (Becker and Jaakkola, 2020; De Keyser et al., 2020; Lemon and Verhoef, 2016)

2.2 AI-enabled Customer Experience

Due to technological advancements and the proliferation of digital services, customer interactions are shifting to online channels and touchpoints. As a result, companies are expected to provide better service in the online environment and maximize the capabilities of each digital touchpoint to enhance the customer experience in the online context. However, it is becoming increasingly difficult to create a superior online customer experience (OCE) as customers become more aware of the competition. The main advantage of online stores is that retailers can operate their business 24/7 and customers can access the store from anywhere in the world, but one of the biggest disadvantages is the naturalness of the interaction with the retailer: when a customer enters the website, they should have the same feeling as when they enter a physical store. Therefore, the online customer experience should resemble the offline environment, where products and services are easy to find and help is always nearby.

Moreover, due to the lack of natural connection between retailers and online customers, most online stores resemble vending machines rather than real stores. Online stores, based only on graphical user interfaces, do not allow retailers to persuade potential customers to buy products and do not give customers the opportunity to ask questions and learn more details about products than they would with a human salesperson. There is no doubt that communication is crucial to attracting, serving and retaining customers. One of the most beneficial ways to engage customers anywhere, anytime, and provide them with an easy and natural interaction is to use a conversational user interface, i.e. chatbots.

To clarify, chatbots are computer programmes that simulate human-like interaction by understanding user queries and performing a limited number of tasks without undue delay, much as consumers would if they were talking to a real person. Chatbot systems have become much more sophisticated thanks to significant advances in artificial intelligence (AI). When supported by AI-related technologies such as Natural language understanding (NLU), chatbots can better discern the intent behind users' input and learn more complex ways to simulate human conversations, such as asking open-ended questions, interpreting users' free-text responses, and prompting for answers when needed (Hussain; Klopfenstein et al., 2017) . These technologies can be trained to learn from each interaction with a customer to improve their performance in the next one and eventually become more intelligent.

Virtual agents (i.e. AI chatbots) are needed wherever assistance is needed during or after a purchase: They are used to assist customers in online transactions on websites by providing them with additional information, personalized advice and recommendations (Araujo, 2018; De Cicco et al., 2020; Verhagen et al., 2014) and also technical support such as shipping or product returns. Therefore, these agents can be used strategically to enable companies to interact with their customers on a personal level and support them on a full-time basis. With this in mind, it can be concluded that chatbots aim to provide customers with an effortless online experience that is time and cost efficient (Gnewuch et al., 2018; Adam et al., 2019; Moriuchi, 2020; Prentice et al., 2020).

Empirical research on online customer experience started to emerge with seminal work of Novak et al. (2000). During this time, researchers investigated the phenomenon of customer experience in Internet environments (Waqas et al., 2021) . Only recently, with the rapid growth of online retailing, is research on digital touchpoints catching up (Bleier et al., 2019; Rose et al., 2012; Kaatz et al., 2019) . Nevertheless, a review of the extant literature shows that research is still sparse and at an early stage, and that more in-depth research on online customer experience in different online environments, e.g. shopping environments, including the measurement of this experience and its impact, is needed.

Earlier, the online customer experience was studied by Novak from a cognitive perspective and defined as "a cognitive state experienced during online navigation", i.e. "flow" (Novak et al., 2000). While the author focused only on the antecedents of online flow (i.e., telepresence, challenge, skill, and interactive speed), later studies extended this work and incorporated affective state into the conceptualization of OCX with new hedonic variables as antecedents of OCX (Rose et al., 2012) .

Consistent with these studies, the literature review shows that most research conducted in the field of OCX have described customer experience as consisting of two dimensions (Danckwerts et al., 2019). In contrast, other research based on previous notable work in the field of offline experiences has considered additional elements of a customer experience in an online environment, such as sensory and physical dimensions that include technology-related features such as a user-friendly interface and clear design (Ameen et al., 2021; Bleier et al., 2019; Waqas et al., 2021) . Similarly, social elements were captured that relate to the influence of others online, such as online forums, reviews, and virtual agents (e.g., avatars, chatbots) (Chattaraman et al., 2012) .

Since the context of analysis in this paper is online shopping, CX is inherently determined by the direct interaction between customers and the online environment. Therefore, a more comprehensive measurement such as Service Experience Quality EXQ (Klaus et al., 2013), which captures CX in three stages, or Brand Experience Scale (Josko, 2009; Schmitt, 1999), which focuses only on the "brand-related stimuli" (Lemon and Verhoef, 2016, p.70), cannot accurately explain CX in the online environment (Kuppelwieser and Klaus, 2021) . As mentioned earlier, there is no work that attempts to develop an all-encompassing measurement tool to capture all CX qualities holistically and dynamically across the customer journey, but work that tailors CX measurement to specific contexts (Waqas et al., 2021). Therefore, this paper analyzes CX as it is lived in the online environment using the operationalization of Bleier et al. (2019).

As recommended by most CX researchers(e.g.) (Lemon and Verhoef, 2016; Schmitt, 1999; Verhoef et al., 2009) , Bleier et al. (2019) based the OCX scale on the four dimensions of experience most commonly used in the literature: cognitive, affective, social and sensory, omitting by that the physical and behavioral dimensions. Indeed, several studies claim that responses to sensory stimuli are closely related to clients' physical well-being, implying that the sensory dimension is inextricably linked to the physical dimension. On the other hand, according to the definition of Kaatz et al. (2019). the behavioral component is: "the flexibility of customers to enter the store at any time and from any place", which is a given condition for the success of the experiments of this research. Accordingly, this study will limit the conceptualization and operationalization of OCX to that proposed by Bleier et al. (2019).

Online experiences are created through the internal reactions (cognitive, affective, social, sensory) that occur when customers perceive and interpret online stimuli, in this case, the nature of the interface (Study 1) and its features, i.e. anthropomorphic cues (Study 2). Respectively, cognitive dimension of OCX or *"Informativeness"* referred to by Bleier et al. (2019) . captures the functional aspect and value of the experience Verhoef et al. (2009), and is defined as "the extent to which a website provides consumers with helpful and useful information Bleier et al. (2019); Li and Unger (2012) .Customer interactions with the online environment can also elicit affective responses: The affective dimension or*"Entertainment"* reflects the immediate enjoyment of the experience, independent of its ability to facilitate a particular shopping task. The social dimension, i.e. *3Social Presence3*, refers to the warm, social and human contact that a website provides . Finally, the sensory dimension, *"Sensory Appeal"*, refers to "the representational richness of a mediated environment as defined by its formal features" (Bleier et al., 2019) . Sensory responses in the online environment can be elicited for example by visual design elements (e.g., colors, photos, videos).

2.3 Theoretical framework

In the context of human-computer interaction, social-response theory assumes that individuals respond to technology endowed with human-like features such as speech, voice, and interactivity with anthropomorphic impressions and socially desirable behavior (Nass and Moon, 2000) . The well-established social response theory has paved the way for several studies in digital contexts showing how humans apply social rules to anthropomorphically designed computers. Although many studies have been conducted on chatbots and conversational user interfaces, most of them have focused on their technical elements, such as improving natural language processing algorithms, Conversely, the understanding of chatbot interaction is not growing at the same rate. In line with HCI, chatbots have the ability to mimic interpersonal interactions and can therefore be considered as social and not just functional technologies (Følstad and Brandtzaeg, 2020).

Among the few research papers that have examined how users respond to social cues from chatbots and other systems with conversational user interfaces (e.g., embodied conversational agents) are those that examine the effect of visual cues like avatar (virtual representations of real persons) attractiveness (Holzwarth; Jin and Bolebruch, 2009), Other types of social cues have also been found to influence users' perception of a chatbot, such as interaction style (Chattaraman et al., 2019) and the degree of interactivity (Schuetzler et al., 2014). Actually, according to many, interactivity is a social cue that elicits social responses and can be explained by user's perception of interpersonal interaction and sense they are in the presence of a social other (Wang et al., 2007; Kim and Sundar, 2012). Along the findings of previous authors we argue that the presence of virtual agents elicits higher perceptions of interactivity.

Consistent with Zhang et al. (2020) , this study defines social support as a multidimensional construct consisting of informational and emotional support. Informational support refers to the cognitive feelings triggered by an online material in the form of recommendations, instructions, or useful advice that help customers overcome difficulties. Emotional support, on the other hand, refers to the affective experience of emotional concerns such as caring, understanding, and empathy. Indeed, a chatbot can provide the customer with response feedback (i.e., Nice to you meet you), social acknowlegments (i.e.,Thanks, i'm glad i could help) and deal with user excuses (i.e, no worries, want to start over). Similar to Chattaraman et al. (2019) we believe that social support through procedural and navigational instructions provided by a conversational user interface that simulates human-like conversations has the potential to give customers the feeling or experience of being cared for, helped, and responded to compared to a graphical user interface (Zhang et al., 2020).

Personalization is the customer's perception of the flexibility of the website to meet their preferences in an online environment. According to Komiak and Benbasat (2006), personalization has a positive effect on the adoption of recommendation agents, even if they're rudimentary. Furthermore, Verhagen et al. (2014) argue that CAs can reduce the lack of interpersonal interaction in online environments by evoking perceptions of social presence and personalization (Adam et al., 2019) . Finally, in line with previous authors, personalization of CA has been shown to positively affect cognitive experience state and affective experience state. In particular, it's worth noting that intelligent chatbots can collect a range of textual data to increase personalization, which significantly improves customers' virtual experiences. For example, they can remember the user's name and address him with it throughout the interaction, remember the user's choices and provide him with personalized information based on his needs and profiles. In this sense, we can say that conversational agents provide a higher level of personalization than a website when shopping online.

2.4 Proposed model and hypotheses development

2.4.0.1 Study 1

Websites present an environment of increased cognitive load when performing search tasks (Chattaraman et al., 2019). In this context, customers strive to obtain information about a product or service, compare alternatives, or find a better price (Bleier et al., 2019). According to cognitive load theory, individuals select the most relevant information from a variety of sources during a learning process. In line with this theory, more and more customers are using omnichannel services to complete the shopping process. However, recent research has shown that incongruence between channels leads to the need to complete multiple tasks simultaneously, which increases the cognitive effort required to switch from one channel to another. Information channels may therefore naturally become contrained with with diminished attentional capacity and cognitive resources, which impairs performing digital tasks like navigating through pages (Gao et al., 2021; Kaatz et al., 2019). Instead, Ciechanowski et al. (2019) point out the importance of recognizing how "interactive interfaces mediate the redistribution of cognitive tasks between humans and machines." In other words, the cognitive effort required to find a product is reduced by the presence of a virtual agent, and the efficiency of the customer's shopping process is appealed to the intellect. We therefore propose that the virtual agent assists the consumer in the purchase decision, which involves reasoning, conscious mental processing, and usually problem solving (Gentile et al., 2007; Bleier et al., 2019; Josko, 2009).Consequently, we propose the following hypotheses:

H1a : Chatbot (vs website) interface will yield a better cognitive customer experience in an online shopping environment.

Qiu and Benbasat (2010) show in a laboratory experiment that the use of recommendation agents with verbal and nonverbal anthropomorphic design cues in online stores strongly influences consumers' perception of social presence. This increased customers' trust, their enjoyment of the virtual agent, and ultimately their intention to use it as a decision-making tool. In another study by Chattaraman et al. (2019), it was found that perceived enjoyment of the robot increased when the virtual assistant provided social cues, i.e., social conversation, and conveyed the desired information in a personable manner, making the shopping process entertaining and enjoyable for the consumer. This also corroborates the findings of Zhang et al. (2020) who established that entertainment or playfulness can influence the success of human-computer interactions and thus the user experience. Entertainment or affective experience, according to Bleier et al. (2019) involves an appreciation for "spectacle" on the website, incorporates fun and play into online purchases, and offers more than just performance and goal-oriented purchase decisions. Consistent with Bleier et al. (2019) conceptualization, the above empirical studies suggest that virtual agents can stimulate customers' affective states and influence their online experience. Hence, it is hypothesized:

H1b : Chatbot (vs website) interface will yield a better affective customer experience in an online shopping environment.

Despite the absence of a real human presence, the use of a conversational agent capable of simulating a two-way conversation, i.e., understanding and responding to online customers in the form of natural language dialogs, can create a sense of sociability during the interaction by assuming the role of a sales representative in online stores, thus enhancing the sense of social presence. Social presence is described as the extent to which the online environment makes customers feel that there is a personal, sociable and intimate human contact (Bleier et al., 2019). Research on online agents in marketing has shown that simulated interactions facilitated by virtual agents can enhance perceptions of social presence. Social cues on a website can evoke feelings of social presence. However, since the chatbot can reduce social distance and is imbued with more social cues (e.g., interactivity, personalization, social support), as mentioned earlier, we propose in line with the results:

H1c : Chatbot (vs website) interface will yield a better social customer experience in an online shopping environment.

Unlike conventional brick-and-mortar retail, which provides opportunities for social connections (salespeople and peer customers) and physical experiences (browsing, touching, and feeling products), customers evaluate products online not through physical interaction but through verbal and visual stimuli on product pages. The customer performs cognitive and affective processing of incoming sensory information from the online environment, resulting in the impression being created and stored in the customer's memory (Josko, 2009; Rose et al., 2012). Sensory appeal, the sensory dimension, refers to the way a website stimulates the senses (Bleier et al., 2019), and regardless of the limited scope of sensory experiences in the online environment, sensations can be evoked by images (e.g., pictures, videos), although colors, shapes, fonts, and designs usually lead to sensory experiences. These sensory experiences can be enhanced through social interactions with textual and visual content and personalized greetings (Hassanein and Head, 2005) supported by virtual agents.Thus, we propose the following hypothesis:

H1d : Chatbot (vs website) interface will yield a better sensory customer experience in an online shopping environment.

From the formulated hypotheses, we posit:

H1: Chatbot (vs website) interface will yield a better online customer experience in an online shopping environment.

2.4.0.2 Study 2

Regardless of their physical or virtual embodiment, the ability of virtual agents to communicate with users linguistically is a crucial human-like feature sufficient to evoke a sense of social presence and perception of humanness. The common basis of research in this area is that cues as minimal as response delays (Gnewuch et al., 2018), chatbot typos, capitalization of words in responses (Westerman et al., 2019), and adaptive responses to user input are sufficient to simulate social schemas in users' minds and thus evoke perceptions of humanness. Wirtz et al. (2018) hypothesize that the acceptance of CAs is generally dependent on perceived humanness. This is evidenced in research by the positive outcomes when perceptions of humanness are high. Jin and Bolebruch (2009) show that human-like visual features in a 3D virtual environment positively influence CAs' likability and enjoyment of the experience. In this sense, previous research by Holzwarth et al. (2006) on attractive features of CAs shows that anthropomorphism of virtual sales agents helps to increase entertainment, information value, and customer satisfaction with the retailer. On the other hand, Araujo (2018) proves that the linguistic style of a chatbot should be calibrated to optimize the experience, claiming that a text-based CA would benefit from a stronger perception of humanness. Similarly, De Cicco et al. (2020) suggests that a human-like CA with humanized conversational qualities, i.e., social-oriented can increase social presence, which in turn leads to a more satisfying user experience among a young population. These findings were confirmed in a previous study by Chattaraman et al. (2019) on an older population, in which a socially-oriented interaction style of CAs that emphasized empathy, personality, and friendliness led to better social outcomes than a task-oriented interaction style that used formal language and focused solely on functional goals. Accordingly, we hypothesize that a human-like CA will improve the experience, specifically :

H2: The effects of the Chatbot interface on customer experience will be stronger when the chatbot uses contextual (vs scripted) conversational style and human (vs robot) visual identity.

Based on these hypotheses, a graphical model (see Figure 2.1) was developed to provide a visual representation of the research questions. In brief, this work aims to investigate the impact of an independent variable, the type of type of interface, on a four-dimentional dependent variables: online customer experience an online shopping context. In addition, the study is extented to examine particular chatbot modalities (interaction style x avatar type) effect on online customer experience.

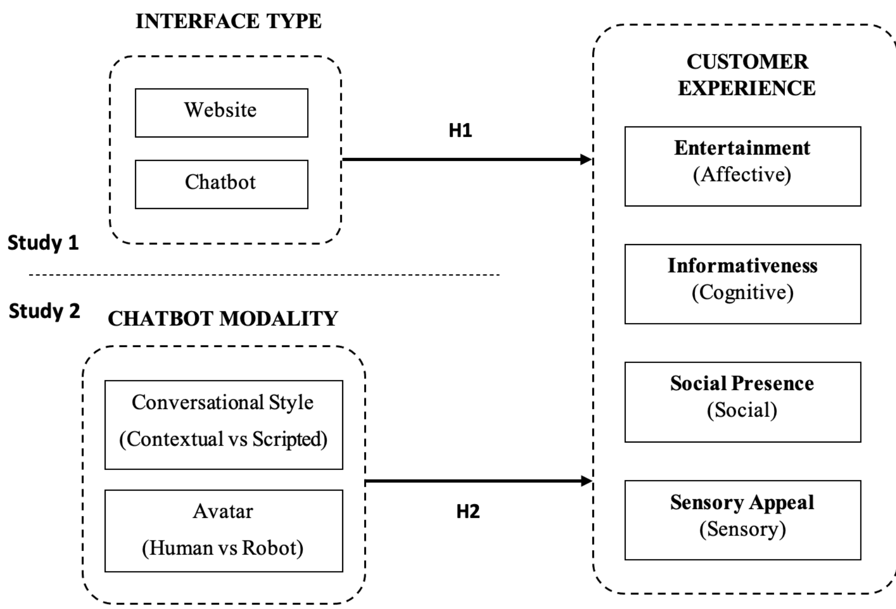


Figure 2.1 Research model

CHAPTER 3. STUDY 1

Study 1 investigated the impact of interacting with an AI chatbot that performs navigation support functions on the customer experience compared to traditional website navigation in the context of online shopping. For this purpose, an AI chatbot was developed on the open-source AI platform Rasa and connected to a mock website displaying real natural cosmetic products.

3.1 Method

This section presents the methodological scheme followed to answer the research questions of this study. In the following, we describe our experimental design, sample and the measures used in the post-experiment questionnaire.

In order to test the developed hypotheses and evaluate relationships between variables or, notably, an impact that one variable has on another, it is conventional to use causal research design (Malhotra et al., 2017; Eisend and Kuss, 2019) .Causal research is also clearly defined and highly structured in design. Moreover, since causal research aims to demonstrate causal relationships between variables as well as the nature of this relationship between the causal variables and the effect to be predicted, research shows that experimental designs are the best way to evaluate causal hypotheses.

Amongst the large array of experimental designs available (i.e., pre-experimental, true experimental, quasi experimental, statistical). Post-test only control group, was judged to be the most relevant for this study. Post-test only control group involves two groups. An experimental group is exposed to a particular treatment and a control group that serves for comparison (also called the testing effect) with no pretest measure to consider. This type of design is useful when participants are not available for a pretest and for a follow-up, which was the case for this study. At first, the researcher manipulates the independent variable, to create the two groups, and accordingly, randomly assigns participants to the experimental and the control group. The groups are then post-tested and compared in terms of their scores on the dependent variable after the experimental group has received the experimental treatment condition. The randomization of the different treatments allows the control of all extraneous variables and ensures that there are no systematic bias between the groups (Malhotra et al., 2017).

Thus, the manipulated variable of this study is the "type of interface" with an experimental condition (chatbot interface) and a control condition (website interface) that serves as an established baseline measure from which we can monitor and highlight the effects of the treatment, in this case the absence of the chatbot. In our online experiment, the stimuli, i.e., the type of interface (chatbot vs. website), were developed and mimicked the design of many modern chat and web interfaces. The website interface that hosted the chatbot was identical for both conditions for each page of the shopping task, including the home page, product list page, product page, shopping cart, shipping, and "return to questionnaire".The chatbot was developed using the Rasa platform, a conversational AI platform that provides developers with the necessary AI-based functional capabilities for natural language processing, understanding, as well as dialogue management, allowing them to design, script, and train conversational assistants. The chatbot is designed to support both search and navigation for online shopping using natural language. Once the user's input is sent, processed and understood, the virtual agent responds in a few seconds in the same natural way. Given the focus of this study, the agent did not have a profile picture and interacted with participants using text only.

As previously noted, both the control and experimental conditions provide the same information about the products. How users will access that information remains different.The control condition is regarded as a static delivery of information where users must click buttons, filters and tags to functionally navigate on a web page. Whereas, in the treatment condition, users can access content and services by the use of natural language in interaction with the virtual agent.The experience provided in the former is considered to be more interactive than the static access to the information. Also, the chatbot as compared to the website offers a functional support to users' specified query and a social support by assisting users and reducing their struggles. Moreover, the chatbot assists the users during their online shopping experience and reduces their struggles by asking relevant questions to tailor the corresponding fit to their input criteria. Accordingly, the treatment condition offers social and personalized support to the users in contrast with the control condition. Thus, the chatbot is regarded as a more interactive interface that offers higher levels of personalization and social support.

In an attempt to match real life experiences, real products of a young start-up specialized in natural cosmetics were displayed on the mock website. All products were rebranded to match the language of the research. The product database used for both interfaces was re-built from scratch, and a new design and packaging were used to better match the context of online shopping. No knowledge base was found with which to train the chatbot . Then, a series of sample dialogs with professionals and knowledgeable customers were conducted and validated with the conversation design fundamentals proposed by Rasa. Finally the conversations were tested with wizard of oz process to find the best conversational flow and translate natural speech into structured data, make the virtual assistant more helpful and natural. **(see key conversational skills)**

3.1.1 Participants and experimental procedure

A total of 101 people participated in the study. Only the cases with valid data for all the variables in the model were retained for hypothesis testing. Therefore, the final sample size for hypothesis testing was 77, including 46 males and 29 females (response rate = 76 %), with each experimental condition containing more than 20 observations Hair et al. (2006).The unequal distribution across the two conditions was due to the random assignment of participants by our experimental platform that did not account for participants who did not complete the study. The distribution of the demographic characteristics of participants is included in table 3.1.1.

Descriptive statistics of demographics

Characteristics		%
Gender	Female	37.7%
	Male	59.7%
	Other	2.6%
Age	Under 20 years old	3.9%
	20 - 40	87%
	40 - 60	7.8%
	Over 60	1.3%
Level of education	High school graduate	7.8%
	Bachelor's degree	15.6%
	Master's degree	64.9%
	Doctorate degree	11.7%

The survey was created using the Qualtrics software program provided by HEC Liège. The survey of this study was slightly personalized using images, which could be beneficial for the psychological preparation of respondents (Malhotra et al., 2017) The survey offered alternative fixed-response questions that required respondents to select from a set of predetermined answers to control for variability in responses and simplify both data analysis for the researcher and the survey experience for respondents.

The main purpose of the experiment was not disclosed to the participants. Instead, participants were told that the study aimed to investigate people's knowledge about Moroccan cosmetics. Participants were randomly assigned to one of two conditions (i.e., treatment or control).Participants read a set of instructions describing the task they were to perform. In these instructions, participants in the chatbot condition were told to select one of two products and engage with the virtual agent to find the product, get more information about it, add it to the shopping cart, and click

"Return to questionnaire." Participants in the website condition, on the other hand, were asked to follow the same instructions by navigating the website. The manipulation check is asked directly after the last dependent variable measurement. Lastly attention check questions and demographic questions are kept for the end. An extensive explanation of the experimental setup, summarized in Table : experimental setup.

Table : Experimental setup

Group	Treatment group	Control group
Manipulation	Chatbot	Website
Shopping task Adapted from Chattaraman et al. (2019)	Both Argan oil and Prickly Pear Seed oil are becoming ever popular treatments thanks to their unparalleled benefits for men and women. Argan oil is a an excellent conditioner, mostly used to prevent hair breakage and hair loss. Prickly pear seed oil is an exceptional moisturizer that regenerates the skin and reduces ageing signs. Choose 1 of these oils and : 1- Look up its benefits and its price. 2- Look up information about shipping. 3- Add this product to cart. 4- Click on "Return to questionnaire".	
Manipulation	The participant is asked to interact with the chatbot to obtain the information described in the instructions	The participant is asked to obtain the information described in the instructions using the content on the pages of the website.

3.1.2 Measures

3.1.2.1 Independent variable

The independent variable in this study is the “type of interface” which is used as a stimuli in the experiment. The independent variable takes two conditions : (1) the chatbot condition and (2) the interface condition serving of a control group to the experiment.

3.1.2.2 Manipulation checks

To asses the assumed disparity between the two conditions A 7-item scale adapted from Chattaraman et al. (2012) was used to measure social support perceived by the participants from both conditions, perceived personalization was appraised with a scale from Danckwerts et al. (2019), and finally, perceived interactivity was measured using a 6-item interactivity scale with two subscales measuring two-way communication and synchronicity adopted from Chattaraman et al. (2019)

3.1.2.3 Dependent variable

The dependent variable of this research is "customer experience". In line with the work of Bleier et al. (2019), customer experience is composed of four dimensions: The affective (enjoyment), the cognitive(informativeness), the social (social presence) and the sensory experience (sensory appeal). In order to get an impression of the overall customer experience, all these components are assessed using the scales proposed by Bleier et al. (2019)

3.1.2.4 Control variables

To ensure the validity of our results, we accounted for some possible confounding variables in the questionnaire. First, after answering our construct-related questions, participants self-reported how familiar they were with the brand, which could potentially influence their response to a stimulus with familiar elements and thus their answers.

Next, familiarity with natural products and Moroccan natural cosmetics was examined, because if respondents are already well acquainted with the products, their answers may differ significantly, and the findings can't be generalizable to a population consisting of less knowledgeable individuals.Both control questions were measured on a 5-point Likert scale ranging from "very bad 1" to "very good = 5".

Participants' proximity to technology and virtual assistants could also influence the relationships examined in the model. In this case, two effects are expected: greater familiarity could enhance the interaction experience in the study, or it could impair the interaction due to the novelty effect, which decreases as familiarity increases. Technology propinquity was measured and chatbot use was measured using the same scale going from "very bad" to "very good".

In addition, we assessed participants' *Perceived Degree of Realism*. For this scale, participants were asked to rate how realistic the website was, using the two items "I could imagine an actual web page looking like the one I just saw" and "I believe this website could exist in reality" on a 7-point Likert scale with anchors ranging from "strongly disagree" to "strongly agree." We also asked them to indicate which device they used for the experiment, as the online environment and the size of the screen of a PC is not comparable to that of a smartphone.

The general profile of the respondents was portrayed thanks to a question related the age, gender and education of the participants. It is well-established that younger people are more open to new technology and that cosmetics' consumption is higher among female population. And finally, participants' English proficiency was also assessed using a 5-point rating scale ranging from "very bad" to "very good" .we asked participants to report the device (see A)

3.2 Analyses and results

This chapter describes the statistical approaches and analysis used to evaluate the hypotheses posed using the empirical data collected.The result are presented and commented.

3.2.1 Pre-test

Prior to the main experiment, a pretest was conducted to ensure that the manipulation was effective. Participants were randomly assigned to one of the conditions and 25 responses were retained for data analysis. The extent to which interaction with the chatbot was perceived as more personalized, interactive and offers more social support than the website interface. T-test results reveal that both personalization and social support were successfully manipulated whereas the interactive variable was not successfully manipulated. Table : Manipulation checks pre-test results shows the results.

Manipulation checks pre-test results

condition	n	P. Personalization	P. Interactivity	P. Social Support
		Mean	Mean	Mean
Website (Control)	37	2.805	4.902	4.166
Chatbot (Treatment)	40	5.333	5.307	5.604
Test statistic		t = -6.54, p = .000	t = -1.001, p = .342	t = -3.115, p = .005

3.2.2 Preliminary results

First of all, we performed a series of confound checks to control for the possibility that differences in our control variables like "Natural cosmetics familiarity" and "virtual agent usage" could have been equally distributed among the four conditions. A one-way ANOVA revealed no significant differences in terms of the control questions between the two groups ($p>0.05$). Next, we performed complementary robustness tests on RASA to check whether participants in the treatment group used and interacted indeed with the chatbot. Here, we verified the number of conversations against the number of our valid data-set.

Before turning to the research questions and starting the hypothesis testing, there are often several preliminary analyses to conduct (Sreejesh et al., 2014). The quality of the data and the measures used are to be appraised first. Checking the normality assumption is a prerequisite to many statistical tests. In this instance, A Shapiro-Wilk's test ($p < .05$) and a visual inspection of the histograms showed that the data significantly deviate from a normal distribution. However, our data are approximately normally distributed, in terms of skewness and kurtosis with values between -2 and 2 for all the items forming our measurement scales **??**, which is considered acceptable in order to assume normal distribution (Hair et al., 2006).

To examine the constructs' discriminant and convergent validity, we performed factor analysis with an oblimin rotation. The analysis performed on all the measures identified their unidimensionality. The analysis suggests the second item of the sensory appeal scale (sens2) to be removed, as it indicates a small loading of 0.47 that falls below the recommended threshold of 0.6 Hair et al. (2006) . This removal had no significant impact on the reliability of the scale.For a more accurate check, we computed the AVE of each contruct, with all results above 0.5 which is considered acceptable Hair et al. (2006). Similarly, the remaining items displayed adequate construct reliability and internal consistency. A complete list of variables, factor loadings and scale reliabilities is provided in Table : study 1 - factor analysis, with an adequate reliability demonstrating strong Cronbach's alphas (ranging from 0.86 to 0.94).

Study 1 : Factor analysis

Construct	Factor loading
Informativeness	
$\alpha = 0.86$; AVE= 0.68	
Information obtained from the Interface is useful	0.744
I learned a lot from using the Interface	0.675
I think the information obtained from the Interface is helpful	0.875
Entertainment	
$\alpha = 0.94$; AVE= 0.59	
Not Fun $\rightarrow$ Fun	0.942
Not enjoyable $\rightarrow$ enjoyable	0.950
Not entertaining at all $\rightarrow$ Very entertaining	0.954
Social Presence	
$\alpha = 0.93$; AVE= 0.66	
There is a sense of human contact in the interface	0.712
There is a sense of human warmth in the interface	0.811
There is a sense of human warmth in the interface	0.910
Sensory Appeal	
AVE = 0.73	
The product presentation on this interface is lively	0.613
This interface contains product information exciting to senses	0.610
Perceived Personalization	
$\alpha = 0.87$; AVE = 0.68	
The Interface can provide me with relevant product recommendations.	0.820
The Interface can provide me with product recommendations tailored to my preferences.	0.841
The Interface can provide me with personalized product recommendations	0.818
Perceived Social Support	
$\alpha = 0.91$; AVE = 0.58	
I would have enjoyed interacting with this service agent	0.728
This Interface really tries to help me	0.791
This Interface gives the help and support needed for shopping on it	0.884
This Interface is like a salesperson who is around when I am in need while shopping	0.728
This Interface is comforting to me	0.687
This Interface is comforting to me	0.766
This Interface is willing to help me make decisions	0.762

3.2.3 Manipulation checks

The manipulation checks were used in this study to make sure that the two treatments were correctly manipulated. The effectiveness of the manipulation relied on whether participants were led to perceive the chatbot as a more personalized interface and which provides higher levels of social support compared to the website. The manipulation check measures used (i.e., perceived personalization and perceived social support) were placed directly after the experiment with the hope of minimizing potential biases. Accordingly, we checked for the homogeneity of variance and tested for a significant difference between both conditions using Student's t-tests. Our results in Table reveal that there is a significant difference in perceived personalization and perceived social support between the two conditions with a $\bar{x}_{\text{Chatbot}}$=4.82 > $\bar{x}_{\text{Website}}$=3.54) which means that the chatbot interface higher levels of personalization and social support as against the website interface. Thus, the treatments were successfully manipulated. (see Table : Manipulation checks results

Manipulation checks results

condition	n	Perceived Personalization			Perceived Social Support		
		Mean	SD	SE	Mean	SD	SE
Website (Control)	37	3.549	1.108	.182	3.899	.872	.143
Chatbot (Treatment)	40	4.825	1.393	.220	4.803	1.283	.202
Test statistic		t = -4.420, p = .000			t = -3.637 , p = .001		

3.2.4 Hypotheses

Hypothesis 1 stated that the chatbot interface will yield a better customer experience than the website interface.That is, a better cognitive(a), affective(b), social (c) and sensory (d) experience. The expected mean difference is to be significant, with reported means for each customer experience component higher for the chatbot interface group than for the website interface. Therefore, We conducted an independent samples t-test to determine the effects of the presence (versus absence)of the chatbot. The results in table show that there is no significant difference between the groups as for the cognitive(a), affective(b), social (c) and sensory (d) experience. Altogether, there is no significant difference in the participants' customer experience between the two conditions. Hence, we conclude that H1 is not confirmed. (See Table : Descriptive results and test statistics for both conditions)

Descriptive results and test statistics for both conditions

condition	n	Informativeness		Entertainment		Social Presence		Sensory appeal	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Website (Control)	37	5.126	1.202	4.882	1.432	4.342	.266	5.00	1.974
Chatbot (Treatment)	40	5.150	1.186	5.116	1.600	5.00	.233	4.67	1.671
Test statistic		t = 1.125, p = .264		t = -.824, p = .412		t = -.673, p = .503		t = -.888, p = .930	
Hypothesis		H1a not confirmed		H1b not confirmed		H1c not confirmed		H1d not confirmed	

3.2.5 Relationship between variables

Multiple regressions is a relevant method of analysis relationships between a metric dependent variable and one or more independent variables.Here, to uncover some potential interrelations between the different variables and constructs the significant models are to be commented in the following.

First, *"Perceived Social Support"* and *"Perceived Personalization"* together were found to have significant impact on all four customer experience dimensions ($p<0.05$). Overall the models were significant, most of which explain more than 10% of the variance. Indeed perceptions of interactivity and personalization positively explain the informativeness, enjoyment, social presence and sensory appeal of an experience online.

3.3 Discussion

In relation to the manipulation variable, the results suggest that the AI-driven digital assistant is perceived as a more personalised and "socially supportive" tool when shopping online. Existing literature has shown that the use of anthropomorphic cues with utilitarian value, such as providing real-time dialogue, and hedonic value, such as tailored communication and online assistance, positively influence the shopping experience (Qiu and Benbasat, 2014; Verhagen et al., 2014; Roy and Naidoo, 2021) , which wasn't the case in our study. That's, the online experience of using a chatbot to navigate a shopping environment and arrive at a desired piece of information wasn't perceived as more efficient or enjoyable than the website. Specifically, the chatbot wasn't able to provide a better cognitive, affective, social, and sensory experience. This could be due to the fact that the customers' evaluation was altered by the stimulating effect of the website attributes. In other words, the website where the interaction takes place in the absence of the chatbot and the customers reach the information by clicking, scrolling or swiping is interspersed with sensory and social information, i.e. aesthetic images of different social environments. In line with the literature, the presence of human images (i.e. the human element) is sufficient to arouse senses and create perceptions of social presence among users (Hassanein and Head, 2007) . Thus, reduce the difference between the two interfaces (website vs. chatbot) in terms of online customer experiences.

CHAPTER 4. STUDY 2

Study 2 is an extension of Study 1, which aimed to investigate the impact of chatbot modality on customer experience. Specifically, the effects of conversational and visual anthropomorphic cues, i.e. conversational style and avatar type. The experiment examined conversational style (social-oriented/contextual vs. task-oriented/menu-based) x avatar type (human vs. robot) in the context of online shopping.

4.1 Method

This section presents the methodological scheme that will be used to answer the research questions of this study. The experimental design, sample, and measures used in the post-experiment questionnaire are described below.

4.1.1 Experiment and stimulus development

To test the hypotheses of Study 2, we conducted an online experiment with a 2 (interaction style of the digital assistant: social vs. task-oriented)) × 2 (avatar type: human vs. robot-like) between-subjects design, where the interaction between the conversational style of the assistant and the avatar type was the focus of the current study. Participants were randomly assigned to one of four groups. Accordingly, four simulated virtual agents were designed based on the same algorithm and interaction scripts as in Study 1, but with human and robotic avatars, respectively, and with button (menu-based) or contextual (text) interaction styles. A total of 143 participants were recruited, representing more than 30 subjects in each treatment group. **Hair et al.**

As mentioned above, the stimuli were similar to those in Study 1. The chatbot was set up to interact with users, answer their questions, and address their concerns in natural language. The main changes involved manipulations of the avatar and interaction style used in Study 1. First, instead of using a logo image, we attempted to use avatars that would be perceived as high and low in humanness. In this case, the avatar was manipulated by either a human-like (high) or a robot-like (low) image. The human-like treatment photos were selected from an online photo database. We chose a female human avatar because it is perceived as more competent than the male human avatar (Pfeuffer, 2019). For the robot-like avatar, we chose a common chatbot avatar as used on websites.

In contrast to previous operationalizations of virtual agent interaction style in experiments Chattaraman et al. (2019); Go and Sundar (2019), the development of this manipulation was based on Chattaraman et al. (2019) with a task-oriented chatbot that uses buttons instead of natural language. In other words, to achieve a stronger manipulation of humanness, the task-oriented (menu-based) virtual agent was designed to interact with the participants using a formal computer-like language, which means that participants use buttons instead of natural language. The menu-based chabot focuses on goal achievement, speaks in a goal-oriented manner, and structures the conversation in contrast to the contextual (socially-oriented) bot, which uses informal language, has a human name (Anika), initiates and concludes the interaction using informal and friendly conversational cues (e.g., "hey there !" "my bad, I'm afraid I didn't learn that yet") (Chattaraman et al., 2019).

In summary, the experiment was a conversation style (low and high) × avatar type (low and high) design. Thus, the interaction style and avatar type served as stimulus material and experimental manipulation in this study. The manipulations were made to affect the perception of humanness. The conversational style was manipulated by using either a social-oriented/contextual (high) or a task-oriented/menu-based (low) interaction, and on the other hand, the avatar type was manipulated by using a human-like (high) or robot-like (low) image. The four chatbots desgined for this study are shown in 4.1

4.1.2 Participants and experimental procedure

In all other respects, the procedure was identical to Study 1. Before beginning to interact with the chatbots, participants read the same set of set of intsructions (study1: chatbot condition). 143 participants (out of 203) took part in the experiment and were randomly assigned to one of the four experimental conditions. In an identical environment, they were asked to complete the same shopping task as in Study 1 (searching for one of two cosmetic products) with the help of Anika (virtual assistant). After subjects were exposed to the chatbot manipulation, they returned to the questionnaire and answered a different manipulation check question than in our first study. Subsequently, subjects completed the questions on key variables - cognitive, affective, social, and sensory experience - which were measured with similar items as in study1.(see Experimental conditions)

Characteristics		%
Gender	Female	49.0%
	Male	50.3%
	Non-binary	0.7%
Age	Under 20 years old	2.1%
	20 - 40	92.3%
	40 - 60	5.6%
Level of education	High school graduate	2.1%
	Bachelor's degree	21%
	Master's degree	60.8%
	Doctorate degree	16.1%

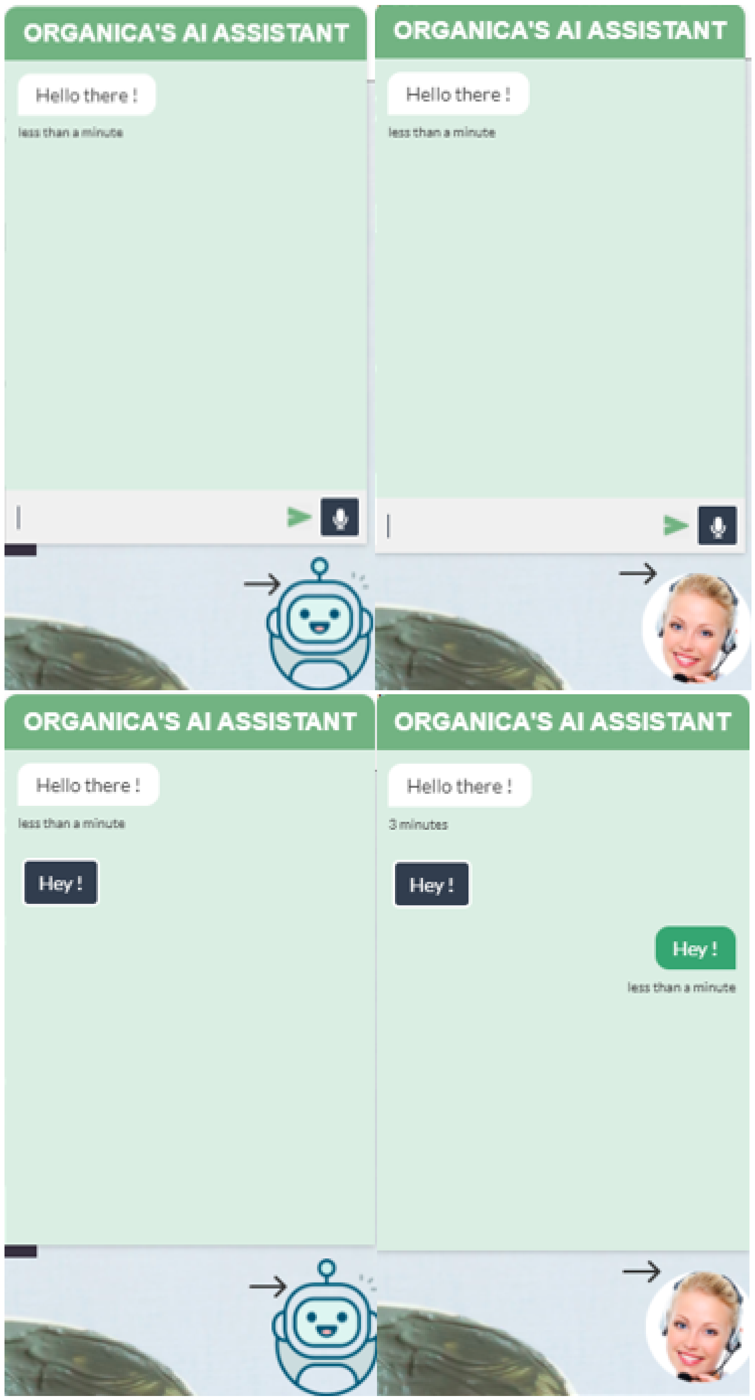


Figure 4.1 Four experimental conditions

4.1.3 Measures

4.1.3.1 Independent variable

As mentioned earlier, the independent variable "chatbot modality" was controlled within the survey by randomising the four different chatbot interfaces (i.e., contextual with human-like avatar; contextual with robot-like avatar; menu-based with human-like avatar; menu-based with robot-like avatar).

4.1.3.2 Manipulation check

To assess the hypothesised disparity between the four conditions, Perceived humanness was measured on a 9-point semantic differential scale adapted from Gnewuch et al. (2018) and executed the scales developed by , which consist of a nine point semantic differential scale, ranging from extremely nonhuman to extremely human. This was used to measure the degree of humanness participants perceived in each of their assigned conditions.

4.1.3.3 Dependent variable

As previously stated, the dependent variable is the same as in Study 1. Customer experience (affective (enjoyment), cognitive (informativeness), social (social presence), and sensory (sensory appeal)) was assessed using the scale developed by Bleier et al. (2019). The scales are listed in the table.

4.1.3.4 Control variable

All control measures used in study 1 are used in study 2. Namely, participants's *Technology proximity*, *English Proficiency*, *Familiarity With Natural Cosmetics*, *Familiarity With Moroccan Natural Cosmetics*, *Chatbot Usage* A

4.2 Analyses and results

This chapter explains the statistical procedures and analyses used to test the hypotheses against the empirical data collected, as well as the results and comments.

4.2.1 Pre-test

Before the main experiment, we conducted a pretest to ensure that the manipulation was effective (Chattaraman et al., 2019; De Cicco et al., 2020) We randomly assigned 35 students to one of the two conditions. We randomly assigned 35 students to one of the conditions. The extent to which the interaction with the chatbot was perceived as human was measured by asking participants how much they thought the chatbot was human-like,skilled,polite,thoughtful,responsive,engaging from Gnewuch et al. (2018) on a 9 point differential scale. The responses were averaged to create a variable score .As expected, findings revealed that the chatbot was perceived more human in high conditions with significant main effect and interaction effect **(see table)**.

4.2.2 Preliminary checks

Several analyses of variance confirmed the successful random assignment to the different experimental conditions: We did not observe any significant differences in terms of participant's Gender, Age, Technology propinquity and Natural cosmetics familiarity across the groups (all $p>0.05$), suggesting that these (control) variables did not confound our dependent variables.

Before turning to the research questions and starting the hypothesis testing, there are often several preliminary analyses to conduct (Sreejesh et al., 2014) . The quality of the data and the measures used are to be appraised first. Checking the normality assumption is a prerequisite to many statistical tests. In this instance, A Shapiro-Wilk's test ($p <.05$) and a visual inspection of the histograms showed that the data significantly deviate from a normal distribution. However, our data are approximately normally distributed, in terms of skewness and kurtosis with values between -

2 and 2 for all the items forming our measurement scales(**see Appendix**), which is considered acceptable in order to assume normal distribution (**George Mallery, 2010**) **(see table)**

Several preliminary analyses are frequently required before moving on to the research topics and hypothesis testing. (Sreejesh et al., 2014). First, the quality of the data and the measures used must be examined. Checking the normality assumption is a prerequisite for many statistical tests. In this case, a Shapiro-Wilk test and visual inspection of the histograms showed that the data deviated significantly from a normal distribution ($p<0.05$). However, our data are approximately normally distributed in terms of skewness and kurtosis, with values ranging from -2 to 2 for all items making up our measurement scales (see Appendix), which is considered acceptable for the assumption of a normal distribution (George Mallery, 2010) (See table).

Factor analysis conducted for all measures revealed their unidimensionality, with all scales having acceptable values except for the perceived humanity scale. One item (ph1: extremely inhuman/extremely human-like) was removed because it had a low loading of 0.53, which is below the recommended threshold of 0.6. This removal helped to achieve a better reliability of the scale of 0.91. The AVE calculated thereafter also showed acceptable values above 0.5 for construct validity. All items showed adequate construct reliability and internal consistency, with all scores having strong Cronbach's alphas (ranging from 0.82 to 0.91). The list of variables, factor loadings, and scale reliabilities with adequate reliability can be found in the Appendix.

4.2.3 Manipulation check

As mentioned earlier, manipulation checks were used in a pilot study to ensure that treatments were manipulated correctly. The efficacy of the manipulation depended on the extent to which participants perceived the chatbot as more human-like in the high conditions and less human-like in the low conditions. As reported in the pretest, there is a significant main effect of avatar type

Study 2 : Factor analysis

Construct	Factor loading
Informativeness	
$\alpha = 0.92$; AVE = 0.66	
Information obtained from the Interface is useful	0.853
I learned a lot from using the Interface	0.782
I think the information obtained from the Interface is helpful	0.815
Entertainment	
$\alpha = 0.91$; AVE = 0.76	
Not Fun $\rightarrow$ Fun	0.844
Not enjoyable $\rightarrow$ enjoyable	0.840
Not entertaining at all $\rightarrow$ Very entertaining	0.913
Social Presence	
$\alpha = 0.92$; AVE= 0.75	
There is a sense of human contact in the interface	0.843
There is a sense of human warmth in the interface	0.940
There is a sense of human warmth in the interface	0.835
Sensory Appeal	
$\alpha = 0.82$; AVE = 0.67	
The product presentation on this interface is lively	0.862
I can acquire product information on this interface from different sensory channels	0.812
This interface contains product information exciting to senses	0.789
Perceived Humanness	
$\alpha = 0.91$; AVE = 0,73	
Extremely unskilled $\rightarrow$ Extremely skilled	0.846
Extremely unthoughtful $\rightarrow$ Extremely thoughtful	0.837
Extremely impolite $\rightarrow$ Extremely polite	0.896
Extremely unresponsive $\rightarrow$ Extremely responsive	0.867
Extremely unengaging $\rightarrow$ Extremely engaging	0.884

and conversational style, and a significant interaction effect of the two factors. This means that the level of conversational style depends on the level of avatar type. In the main study, the same results were obtained, with all effects significant at a $p < 0.05$. Thus, we conclude that the treatments were also successfully manipulated. (See Figure 4.2)

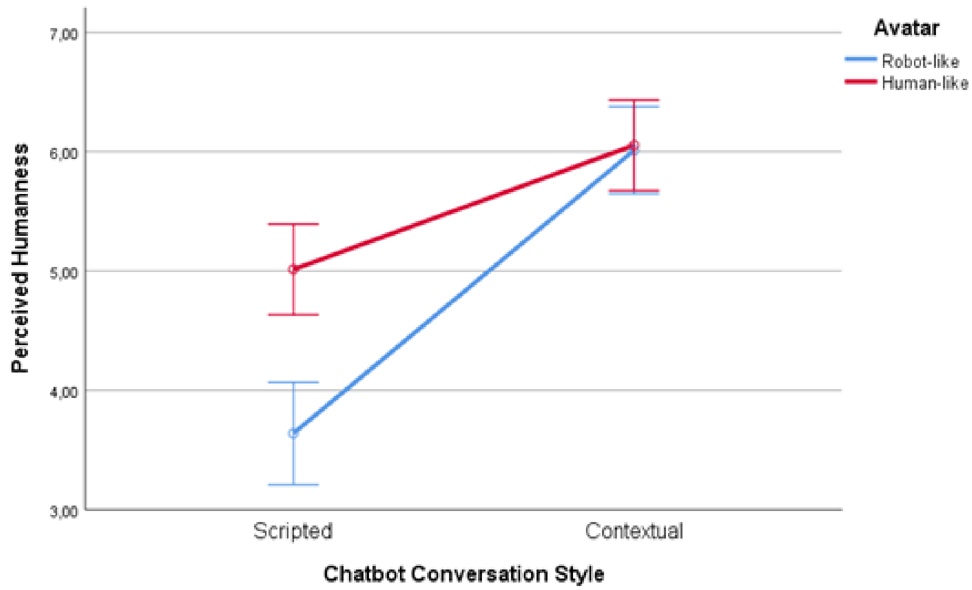


Figure 4.2 Perceived humanness interaction effect

4.2.4 Hypotheses

The influence of Conversational style and Avatar type:

A series of two-way analyses of variance (ANOVAs) and pairwise comparisons shown in **the table** were conducted to compare the effects of contextual vs. menu-based conversational style and human-like vs. machine-like avatar on (a) cognitive experience (b) affective experience, (c) social experience and sensory experience(i.e., customer experience).

4.2.4.1 Main effect of Conversational Style

When looking exclusively at the conversational style, graphically, we could see some differences from the low (menu-based) to the high (contextual) conditions. However, when comparing the Contextual chatbot with the Menu-based chatbot for each component of CX separately using Pairwise comparisons with Bonferroni adjustment the differences are not significant with all $p>0.05$. Therefore, the main effect for conversational style was not significant for customer experience.

4.2.4.2 Main effect of Avatar Type

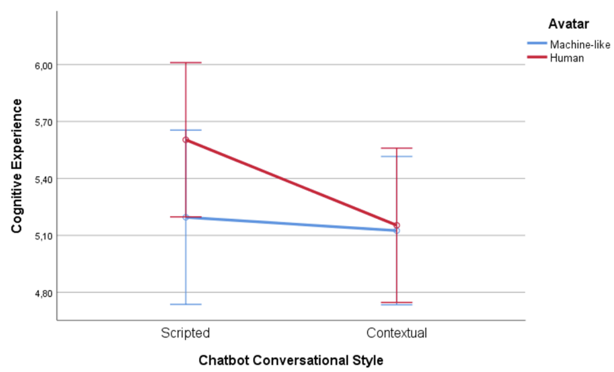
The main effect for type of avatar (human vs. machine-like) was not significant for all components of customer experience, despite the differences shown in the graphical representations.Pairwise comparisons with Bonferroni adjustment indicate that, when comparing the human with the machine-like separately (human-vs. machine-like agent), the differences are not significant (all $p> 0.05$). Thus, the avatar type has no main effect.

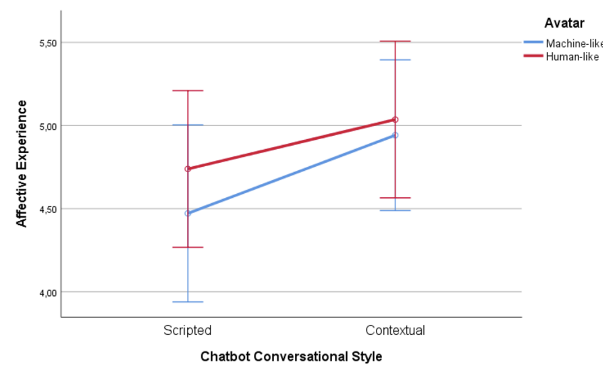
4.2.4.3 Interaction effect

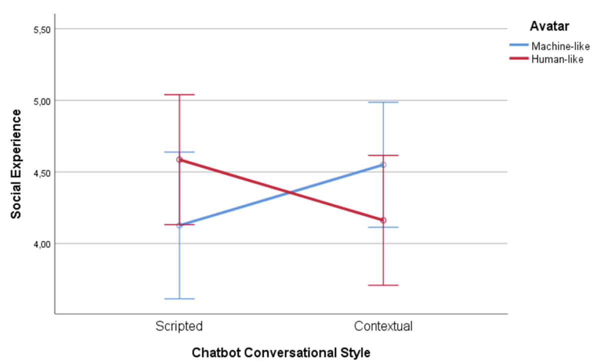
Beyond the reported results of main effects, we did not register any effect of a factor that is contingent upon the level of the other, with all $p> 0.05$.Although, the interaction between Conversational style * Avatar type was almost nearly significant for the social experience, $F=3.4$,$p=0.07$. Thus, eventually, we conclude that there are no interaction effect for any of the manipulations used (i.e., Conversational style and Avatar type).

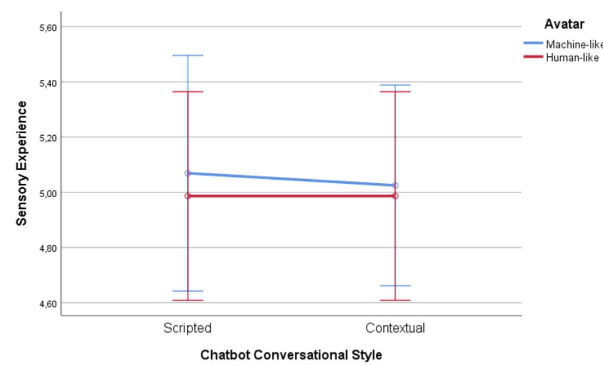
Study 2 : Pairwise comparison

Dependant variable	Avatar	Chatbot Interaction Style		Interaction effect p-value
		Task-oriented	Social-oriented	
		M	M	
Cognitive experience	Robot	5.19	5.60	.368
(Informativeness)	Human	5.12	5.15	
Affective experience	Robot	4.74	4.94	.724
(Entertainment)	Human	4.73	5.03	
Social experience	Robot	4.12	4.55	.074
(Social presence)	Human	4.58	4.16	
Sensory experience	Robot	5.06	5.02	.911
(sensory appeal)	Human	4.98	4.98	









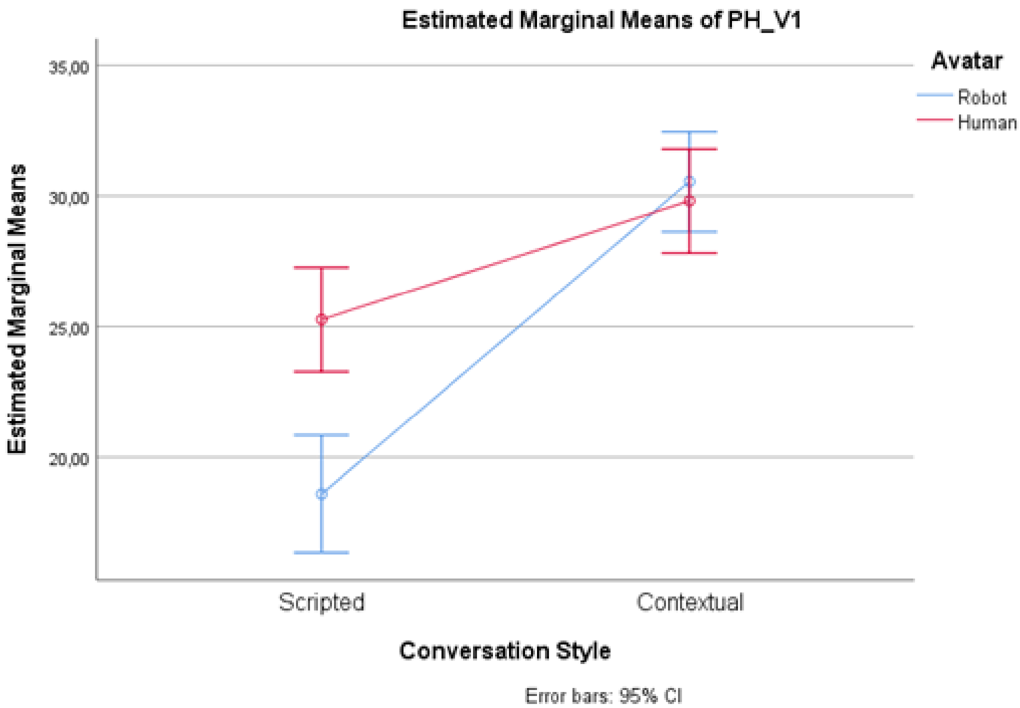


Figure 4.3 Perceived humanness interaction effect

4.2.5 Relationship between variables

A series of two-way analyses of covariance (ANCOVAs) were conducted to compare the effects of human-like vs. robot-like agent and social vs. task oriented interaction style on cognitive, affective, social and sensory experience with gender, age and chatbot usage were included as covariates. the main effects and the other interaction effects results were evaluated. No main effects emerged for the independent variable, digital assistant interaction style, on any of the outcome measures. Further, no main or interaction effects emerged all $p > 0.05$.

Although non-hypothesized, a series of simple linear regression were conducted to explore the effects of the manipulation variable *"Perceived Humanness"* on the online customer experience measures. the results show that perceived humanness significantly impacts informativeness ($F=11.080, p<0.05$), entertainment ($F=13.028, p<0.05$),sensory appeal ($F=8.293, p<0.05$). This mean that the more humanized the chatbot seems to people, the better their cognitive, affective and sensory experience is. Interestingly, the effect of perceived humanity on social presence was almost significant (p: 0.052), implying that the perception of how human-like the chatbot is doesn't imply that there's a sense of presence in the interaction environment.

4.3 Discussion

The results of our online experiment suggest that Avatar type (human-like vs robot-like) and conversational style positively affect customers perceptions of disembodied virtual agents in the form of chatbots.The findings, in line with response theory, support the assumption that the more the CA displays social cues the more "humanized" it will be perceived have a positive effect on the experience (Verhagen et al., 2014; Danckwerts et al., 2019; Araujo, 2018) . However, the thought-provoking finding of Study 2 is the fact that perception of humanness of the chatbot do not necessarily trigger social presence in constrast with the findings of (Jin and Bolebruch, 2009; Etemad-Sajadi, 2016; Holzwarth et al., 2006; Etemad-Sajadi, 2016). Actually, in comparable research, social presence (i.e., automated social presence) was reported to have better consumer outcomes (i.e.,conflict mitigation) when the avatar design is low in attractiveness. Along this line, De Cicco et al. (2020) in his study ascribes the ineffectiveness of avatars in enhancing feelings of social presence to the chat platform where avatars are not highly visible.Verhagen et al. (2014) suggest that a change in physical appearance does not elicit more social responses and that an increase in anthropomorphism from robot-like to human-like agents might be too small to find variance.On the other hand, higher conditions of interaction style was always reported to significantly generate feelings of social presence Roy and Naidoo (2021).Interestingly, the current research cannot support this statement. This may partially be explained by the manipulation of task-oriented chatbot which has taken the form of button rather than a limited formal interaction style as operationalized in the literature but mainly by the limited contingency (i.e., exchange of responses) of the conversations as instructed in the experiment.

A

.

CHAPTER 5. GENERAL DISCUSSION

5.1 Short Summary

In this study, chatbots are considered as a form of ubiquitous AI-powered application that disrupts the online customer experience. To understand this phenomenon, it is equally necessary to consider a key element: Anthropomorphism. In a self-developed web environment (website and chatbot), we conduct two different experimental studies. First, to study the impact of the presence (or absence) of an AI conversational agent on the customer experience, and second, to deepen the understanding of which anthropomorphic design cues (interaction style and avatar type) are more appreciated and improve the customer experience. With this in mind, Study 1 used a post-test design with a control (website) and a treatment (chatbot) condition, and Study 2 used a 2x2 between-subjects design with 4 experimental conditions (social or task-oriented interaction style, with either a human or robot-like avatar). Participants were conveniently recruited online and in both studies and randomly assigned to one of the respective conditions in each study.

In accordance with Chattaraman et al. (2019) and De Cicco et al. (2020), a pre-test was first conducted to see if the conditions were effectively manipulated. This resulted in some minor changes to the constructs used to check the manipulations, but also some adjustments to the experimental instructions to improve subjects' understanding before the main study questionnaire was created.

The results of Study 1 show that the AI conversational agent provides the same level of informativeness, entertainment, social presence, and sensory appeal as the website. This suggests that customers respond similarly to a conversational user interface as they do to a graphical user interface, although there are a number of differences between them. Similarly, no differences were recorded between the four conditions in study 2. The customer experience remain invariable irrespective of the visual or conversation cue used in chatbots.

Both results could be explained by either (1) the artificial environment in which the shopping task was performed despite the control of the environment: If customers want to buy something online, the need must come from themselves and not from an instruction. (2) Customers do not care how they get to the shopping goal as long as they reach it. (3) Selection and participant bias: only interested subjects participate and end up giving inaccurate answers These results lead to implications and suggestions for similar research studies.

5.2 Theoretical Implications of this study

First and foremost, the theoretical and empirical findings acknowledge that despite the emerging discourse of AI in the field of marketing, the research is still scarce and decentralized with most theoretical and empirical work on AI and chatbots only addressing the role of anthropomorphism of digital assistants. The theoretical basis for this is social response theory, which states that humans mindlessly adopt the same social behaviors when interacting with computers by displaying social cues, such as interacting with others using natural language. Therefore, no theory has yet been developed to examine the elements that underline the interaction between users and chatbots specifically.

Second,both studies conducted on conversational agents and online customer experience have shown that there's no significant relationship between the two: The presence of a chatbot doesn't improve online customer experience, nor does changing chatbot features and design (anthropomorphic cues). This is in contrast to most of the findings in the literature, where virtual agents in their various forms and in different environments, e.g., Animated avatars (Liew et al., 2017), interactive 3D avatars in virtual environments (Lin et al., 2021), and human-like animated customer service agents that mimic real salespeople (Verhagen et al., 2014), affect affective, social, cognitive, and functional outcomes, but consistent with these studies, the chatbot actually conveys perceptions of social support and personalization (Study 1) and humanness (Study 2) that positively impact the online experience holistically. These mixed results are suspected to originate from differences in the measurements used or the type of environment. As can be seen from the literature, trust is an important variable to explore when researching conversational assistants, as users have privacy concerns (Danckwerts et al., 2019).

Finally, customer experience is one of the most debated topics at the moment. Online customer experience, however, still lags behind in terms of both conceptualization and operationalization. Therefore, due to its significant impact on a company's competitive advantage and the increasing tendency of customers to use digital channels, OCX should be given more attention by practitioners and scholars.

5.3 Managerial Implications of this study

The main findings need further discussion, both in terms of the business implications for marketers and the practical implications for AI developers and chatbot designers. The current results suggest that adding an AI conversational interface to an online store does not lead to better customer experiences. This is the case if the website is already interactive and has sensorial and social stimuli (colors, images, videos). We suggest that the AI interface needs to provide a higher level of personalization and social support to differentiate itself from other interfaces.The exponential amount of consumer data makes marketing a natural beneficiary of these evolving technologies especially as customers' buying processes increasingly shift to online channels where they can compare different options (Jarek and Mazurek, 2019).A more proactive use of AI would allow marketers to leverage rich contextual consumer data, to customize future conversations and provide frictionless experiences. On the other hand, a better understanding of customer perceptions of chatbots use will allow chatbot developers and designers to design interfaces that could have a greater impact on the experience, i.e., more testing needs to be done to find out how customers ascribe meaning to the different anthropomorphic design cues and what kind of responses that elicits.

In summary, digital assistants are brilliant technologies that provide ongoing support to customers and enable businesses to build and maintain relationships with them. AI-based digital assistants can open up new ways for businesses to reach out to customers, interact with them, and customize how they communicate with them. However, as artificial intelligence technologies continue to evolve, the marketing landscape is likely to fundamentally change. Therefore, marketers need to start developing marketing strategies that engage customers and change their perception of chatbots and therefore add value to the interactions between businesses and customers.

5.4 Limitations and suggestions for further research

Our current work has several limitations that may stimulate future research. First, we focus on the study of natural cosmetics and in particular Moroccan natural cosmetics (e.g., argan oil, prickly pear seed oil). These products are often considered gender-specific and are more popular among women in general and Moroccan women in particular. In addition, natural cosmetics are characterized by properties that are difficult to evaluate (e.g. category, benefits, application). Future research should therefore investigate the impact of AI conversational agents as shopping assistants in a different context. Since the chatbot was newly developed, it could not be sufficiently trained, so we could not perform a robustness test to check in which conversations the chatbot failed and provided wrong answers, so we suggest that more control variables need to be considered when studying chatbot interactions (e.g. e.g. time of interaction, number of messages exchanged).We could also add, as mentioned earlier, the fictional task of shopping, which is quite dissimilar to a pre-purchase experience, and here we claim that similar experiments should be conducted in a less artificial way. Regarding the large discrepancies found in responses to control variables such as

Product Involvement, self-reported measurement should be done with more accurate scales: When asked about technology affinity, a software engineer and a cell phone user might both receive the same ratings and thus biased responses.Finally we contend that these type of type of experiments should be conducted on different generational populations as there will likely be strong differences in how consumers react to these technologies according to age as it has been shown that age impacts consumer acceptance and use of information technology (Khatri et al., 2018)

Bibliography

Adam, M., Wessel, M., and Benlian, A. (2019). AI-based chatbots in customer service and their effects on user compliance. page 19.

Ameen, N., Tarhini, A., Reppel, A., and Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, 114:106548.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior*, 85:183–189.

Becker, L. and Jaakkola, E. (2020). Customer experience: fundamental premises and implications for research. *J. of the Acad. Mark. Sci.*, 48(4):630–648.

Berry, L. L., Carbone, L. P., and Haeckel, S. H. (2002). Managing the Total Customer Experience. *MIT Sloan Management Review*, page 8.

Bleier, A., Harmeling, C. M., and Palmatier, R. W. (2019). Creating Effective Online Customer Experiences. *Journal of Marketing*, 83(2):98–119. Publisher: American Marketing Association.

Chattaraman, V., Kwon, W.-S., and Gilbert, J. E. (2012). Virtual agents in retail web sites: Benefits of simulated social interaction for older users. *Computers in Human Behavior*, 28(6):2055–2066.

Chattaraman, V., Kwon, W.-S., and Gilbert, J. E. (2019). Should AI-Based, conversational digital assistants employ social- or task-oriented interaction style? A task-competency and reciprocity perspective for older adults. *Computers in Human Behavior*, page 16.

Ciechanowski, L., Przegalinska, A., Magnuski, M., and Gloor, P. (2019). In the shades of the uncanny valley: An experimental study of human–chatbot interaction. *Future Generation Computer Systems*, 92:539–548.

Danckwerts, S., Meißner, L., and Krampe, C. (2019). Examining User Experience of Conversational Agents in Hedonic Digital Services – Antecedents and the Role of Psychological Ownership. *SMR*, 3(3):111–125.

De Cicco, R., e Silva, S. C., and Alparone, F. R. (2020). Millennials' attitude toward chatbots: an experimental study in a social relationship perspective. *IJRDM*, 48(11):1213–1233.

De Keyser, A., Verleye, K., Lemon, K. N., Keiningham, T. L., and Klaus, P. (2020). Moving the Customer Experience Field Forward: Introducing the Touchpoints, Context, Qualities (TCQ) Nomenclature. *Journal of Service Research*, 23(4):433–455.

Eisend, M. and Kuss, A. (2019). *Research Methodology in Marketing: Theory Development, Empirical Approaches and Philosophy of Science Considerations*. Springer International Publishing, Cham.

Etemad-Sajadi, R. (2016). The impact of online real-time interactivity on patronage intention: The use of avatars. *Computers in Human Behavior*, page 6.

Følstad, A. and Brandtzaeg, P. B. (2020). Users' experiences with chatbots: findings from a questionnaire study. *Qual User Exp*, 5(1):3.

Gao, W., Li, W., Fan, H., and Jia, X. (2021). How customer experience incongruence affects omnichannel customer retention: The moderating role of channel characteristics. *Journal of Retailing and Consumer Services*, 60:102487.

Gentile, C., Spiller, N., and Noci, G. (2007). How to Sustain the Customer Experience:. *European Management Journal*, 25(5):395–410.

Gnewuch, U., Morana, S., Adam, M. T. P., and Maedche, A. (2018). FASTER IS NOT ALWAYS BETTER: UNDERSTANDING THE EFFECT OF DYNAMIC RESPONSE DELAYS IN HUMAN-CHATBOT INTERACTION. page 18.

Gnewuch, U., Morana, S., and Maedche, A. (2017). Towards Designing Cooperative and Social Conversational Agents for Customer Service. page 14.

Go, E. and Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, 97:304–316.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., and Tatham, R. L. (2006). Multivariate Data Analysis: Pearson Prentice Hall. *Upper Saddle River, NJ*, pages 1–816.

Hassanein, K. and Head, M. (2005). The Impact of Infusing Social Presence in the Web Interface: An Investigation Across Product Types. *International Journal of Electronic Commerce*, 10(2):31–55.

Hassanein, K. and Head, M. (2007). Manipulating perceived social presence through the web interface and its impact on attitude towards online shopping. *International Journal of Human-Computer Studies*, 65(8):689–708.

Holbrook, M. B. and Hirschman, E. C. (1982). The Experiential Aspects of Consumption: Consumer Fantasies, Feelings, and Fun. *Journal of Consumer Research*, 9(2):132–140. Publisher: Oxford University Press / USA.

Holzwarth. The influence of avatars.

Holzwarth, M., Janiszewski, C., and Neumann, M. M. (2006). The Influence of Avatars on Online Consumer Shopping Behavior. *Journal of Marketing*, 70(4):19–36.

Hussain, R. Personalization, Customer Experience, and AI. page 4.

Jain, M., Kota, R., Kumar, P., and Patel, S. N. (2018). Convey: Exploring the Use of a Context View for Chatbots. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems - CHI '18*, pages 1–6, Montreal QC, Canada. ACM Press.

Jarek, K. and Mazurek, G. (2019). Marketing and Artificial Intelligence. *CEBR*, 8(2):46–55.

Jin, S.-A. A. and Bolebruch, J. (2009). Avatar-Based Advertising in Second Life: The Role of Presence and Attractiveness of Virtual Spokespersons. *Journal of Interactive Advertising*, 10(1):51–60.

Josko, B. (2009). Brand Experience: What Is It? How Is It Measured? Does It Affect Loyalty? page 18.

Kaatz, C., Brock, C., and Figura, L. (2019). Are you still online or are you already mobile? – Predicting the path to successful conversions across different devices. *Journal of Retailing and Consumer Services*, 50:10–21.

Kaplan, A. and Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1):15–25.

Khatri, C., Venkatesh, A., Hedayatnia, B., Gabriel, R., Ram, A., and Prasad, R. (2018). Alexa Prize — State of the Art in Conversational AI. *AIMag*, 39(3):40–55.

Kim, Y. and Sundar, S. S. (2012). Anthropomorphism of computers: Is it mindful or mindless? *Computers in Human Behavior*, 28(1):241–250.

Klaus, P., Gorgoglione, M., Buonamassa, D., Panniello, U., and Nguyen, B. (2013). Are you providing the "right" customer experience? The case of Banca Popolare di Bari. *Intl Jnl of Bank Marketing*, 31(7):506–528.

Klopfenstein, L. C., Delpriori, S., Malatini, S., and Bogliolo, A. (2017). The rise of bots: A survey of conversational interfaces, patterns, and paradigms. In *Proceedings of the 2017 conference on designing interactive systems*, pages 555–565.

Komiak and Benbasat (2006). The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents. *MIS Quarterly*, 30(4):941.

Kuppelwieser, V. G. and Klaus, P. (2021). Measuring customer experience quality: The EXQ scale revisited. *Journal of Business Research*, 126:624–633.

Lemon, K. N. and Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey. *Journal of Marketing*, 80(6):69–96.

Li, T. and Unger, T. (2012). Willing to pay for quality personalization? Trade-off between quality and privacy. *European Journal of Information Systems*, 21(6):621–642.

Liew, T. W., Tan, S.-M., and Ismail, H. (2017). Exploring the effects of a non-interactive talking avatar on social presence, credibility, trust, and patronage intention in an e-commerce website. *Hum. Cent. Comput. Inf. Sci.*, 7(1):42.

Lin, Y.-T., Doong, H.-S., and Eisingerich, A. B. (2021). Avatar Design of Virtual Salespeople: Mitigation of Recommendation Conflicts. *Journal of Service Research*, 24(1):141–159. Publisher: SAGE Publications Inc.

Maklan, S. and Klaus, P. (2011). Customer Experience: Are We Measuring the Right Things? *International Journal of Market Research*, 53(6):771–772. Publisher: SAGE Publications.

Malhotra, N. K., Nunan, D., and Birks, D. F. (2017). *Marketing research: an applied approach, 5th ed.* Pearson Education Limited. Accepted: 2020-10-22T01:13:40Z Journal Abbreviation: Revised edition of Marketing research, 2012.

Moriuchi, E. (2020). Engagement with chatbots versus augmented reality interactive technology in e-commerce. page 16.

Nass, C. and Moon, Y. (2000). Machines and Mindlessness: Social Responses to Computers. *J Social Isssues*, 56(1):81–103.

Novak, T., Hoffman, D., and Yung, Y.-F. (2000). Measuring the customer experience in online environments: A structural modeling approach. *Marketing Science*, 19(1):22–42.

Pine 2nd., B. and Gilmore, J. (1998). Welcome to the experience economy. *Harvard business review*, 76(4):97–105.

Poulsson, S. and Kale, S. (2004). The Experience Economy and Commercial Experiences. *ERA - Social, Behavioural and Economic Sciences*, 4.

Prentice, C., Weaven, S., and Wong, I. A. (2020). Linking AI quality performance and customer engagement: The moderating effect of AI preference. *International Journal of Hospitality Management*, 90:102629.

Pérez, J. Q., Daradoumis, T., and Puig, J. M. M. (2020). Rediscovering the use of chatbots in education: A systematic literature review. *Computer Applications in Engineering Education*, 28(6):1549–1565. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/cae.22326.

Qiu, L. and Benbasat, I. (2010). A study of demographic embodiments of product recommendation agents in electronic commerce. *International Journal of Human-Computer Studies*, 68(10):669–688.

Qiu, L. and Benbasat, I. (2014). Evaluating Anthropomorphic Product Recommendation Agents: A Social Relationship Perspective to Desig. page 39.

Rose, S., Clark, M., Samouel, P., and Hair, N. (2012). Online Customer Experience in e-Retailing: An empirical model of Antecedents and Outcomes. *Journal of Retailing*, 88(2):308–322.

Roy, R. and Naidoo, V. (2021). Enhancing chatbot effectiveness: The role of anthropomorphic conversational styles and time orientation. *Journal of Business Research*, 126:23–34.

Schmitt, B. (1999). Experiential Marketing. *Journal of Marketing Management*, 15(1-3):53–67.

Schuetzler, R., Grimes, M., Giboney, J., and Buckman, J. (2014). Facilitating Natural Conversational Agent Interactions: Lessons from a Deception Experiment. *Human Computer Interaction*, page 17.

Sreejesh, S., Mohapatra, S., and Anusree, M. R. (2014). *Business Research Methods*. Springer International Publishing, Cham.

Verhagen, T., van Nes, J., Feldberg, F., and van Dolen, W. (2014). Virtual Customer Service Agents: Using Social Presence and Personalization to Shape Online Service Encounters. *J Comput-Mediat Comm*, 19(3):529–545.

Verhoef, P., Lemon, K., Parasuraman, A., Roggeveen, A., Tsiros, M., and Schlesinger, L. (2009). Customer Experience Creation: Determinants, Dynamics and Management Strategies. *Journal of Retailing*, 85(1):31–41.

Wang, L. C., Baker, J., Wagner, J. A., and Wakefield, K. (2007). Can A Retail Web Site be Social? *Journal of Marketing*, 71(3):143–157.

Waqas, M., Hamzah, Z. L. B., and Salleh, N. A. M. (2021). Customer experience: a systematic literature review and consumer culture theory-based conceptualisation. *Manag Rev Q*, 71(1):135–176.

Westerman, D., Cross, A. C., and Lindmark, P. G. (2019). I Believe in a Thing Called Bot: Perceptions of the Humanness of "Chatbots". *Communication Studies*, 70(3):295–312.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., and Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, 29(5):907–931. Publisher: Emerald Publishing Limited.

Yang, G., Ji, G., and Tan, K. H. (2020). Impact of artificial intelligence adoption on online returns policies. *Ann Oper Res*.

Zhang, J., Oh, Y. J., Lange, P., Yu, Z., and Fukuoka, Y. (2020). Artificial Intelligence Chatbot Behavior Change Model for Designing Artificial Intelligence Chatbots to Promote Physical Activity and a Healthy Diet: Viewpoint. *J Med Internet Res*, 22(9):e22845.

APPENDIX A. Confound checks

	Study 1	Study 2
Gender	t= 1.621 ; p=0.109	F= 0.389 ; p=0.761
Age	t=-0.781 ; p=0.437	F=0.177 ; p=0.912
Education	t=0.368 ; p=0.714	F=0.614 ; p=0.607
English	t=0.608 ; p=0.545	F=0.557 ; p=0.644
New Technologies	t=0.080 ; p=0.937	F=0.189 ; p=0.904
Natural Cosmetics	t=-1.421 ; p=0.159	F= 1.343 ; p=0.263
Moroccan Cosmetics	t=-1.018 ; p=0.312	F=1.370 ; p=0.255
Chatbot Usage	t=0.941 ; p=0.350	F=2.527 ; p=0.060
Brand Recognition	t=0.794 ; p=0.430	F=1.176 ; p=0.321

Note : The mean difference between the two treatments in Study1 and across the four conditions in Study2 is not significant (p > .05)

APPENDIX B. Normality checks

Study 1

Scale	Items	Shapiro-Wilk		Skewness	Kurtosis
		Statistic	p-value		
Informativeness	inf1	.809	.000	-1.473	1.205
	inf2	.842	.000	-1.258	1,573.
	inf3	.845	.000	-1.323	1.372
Entertainment	ent1	.916	.000	-.537	-.190
	ent2	.917	.000	-.664	0.69
	ent3	.929	.000	-.501	-0.17
Social Presence	sp1	.908	.000	-.657	-.264
	sp2	.897	.000	-.657	-.232
	sp3	.920	.000	-.577	-.191
Sensory Appeal	sa1	.891	.000	-.843	.460
	sa2	.922	.000	-.546	.211
	sa3	.921	.000	-.627	.297
Perceived Humanness	ph1	.809	.000	-.289	-.583
	ph2	.961	.000	-.224	-.028
	ph3	.963	.001	-.185	-.198
	ph4	.950	.000	-.421	-.237
	ph5	.956	.000	-.313	-.511
	ph6	.959	.000	-.291	-.501

Study 2

Scale	Items	Shapiro-Wilk		Skewness	Kurtosis
		Statistic	p-value		
Informativeness	inf1	.874	.000	-.916	.629
	inf2	.935	.001	-.407	-.345
	inf3	.873	.000	-.944	.771
Entertainment	ent1	.909	.000	-.713	.316
	ent2	.896	.000	-.629	-.313
	ent3	.901	.000	-.775	.284
Social Presence	sp1	.918	.000	-.515	-.596
	sp2	.919	.000	-.497	-.640
	sp3	.922	.000	-.480	.642
Sensory Appeal	sa1	.903	.000	-.763	.066
	sa2	.921	.000	-.284	.650
	sa3	.908	.000	-.467	-.623
Perceived Personalization	per1	.924	.000	-.380	-.798
	per2	.928	.000	-.221	-1.014
	per3	.927	.000	-.916	-1.024
Perceived Social Support	soc1	.942	.002	-.160	-1.024
	soc2	.933	.001	-.095	-.818
	soc3	.923	.000	-.326	.679
	soc4	.943	.002	-.513	-.101
	soc5	.946	.003	-.127	-.871
	soc6	.942	.002	-.037	-.761
	soc7	.921	.000	-.480	-.587

APPENDIX C. Descriptive statistics of control variables

Controls	Study 1		Study 2	
	N=77		N=143	
	Mean	SD	Mean	SD
Proficiency in the English Language	4.55	0.68	4.55	0.64
Familiarity with New technologies	4.51	0.73	4,51	0,70
Familiarity with Natural Cosmetic Products	3.29	1.22	3.62	1.05
Familiarity with Moroccan Cosmetic Products	3.13	1.30	3.41	1.17
Chatbot Usage	2.82	1.33	2.78	1.09

Technique	Synopsis	Example
Response Feedback	Acknowledge a user's responses and provide positive feedback to encourage information disclosure	User: "I find all of this very interesting" Anika: "Thank you. We really appreciate the interest."
Response Prompting	Ask for more information	User: "Do you have hair products ?" Anika: "Would you be interested in a specific category of products ?" Anika: "Such as Serum , Styler or maybe Shampoo ?"
Response Probing	Probe answers to elicit deeper information	User: "Please add sesame oil to my bag" Anika: "Sesame Oil comes in 2 sizes : 50ml and 100ml" Anika: "Which one should i add to your bag ?"
Social Acknowledgement	Acknowledge a user's input to convey understanding and verbalize emotion	User: "I am doing great" Anika: "Happy to hear that"
Handle conversation flow	Probe answers to elicit deeper information	User: "Can we restart ??" Anika: "Alright. Sorry if i'm being confusing." Anika: "Shall we start over ?"
Handle User Excuses	Handle a user's excuses not to answer a question and encourage continuation	User: "I'm sorry" Anika: "Oh no it's fine" Anika: "May i still be of help ?"