Master Thesis

Unravelling the Hospitality Confusion: Understanding Customer Experience through Chatbots

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Abstract

Nowadays, firms are investing more and more into chatbots to enhance the customer experience which creates new touchpoints in the customer journey. This is also the case for Online Travel Agencies (OTA), where chatbots are implemented with increasing amounts. This industry is about to grow and therefore customers might become confused by the many options that are offered. This study provides insights into how customer confusion affects the outcomes of Customer Experience (CX). Moreover, it explains how the CX, in particular utilitarian value and Seeking Information Behaviour, mediates this relationship. Therefore, a one-factor, between-subjects experiment was conducted using a Wizard-of-Oz approach. Participants were randomly assigned to one of the two conditions. In both conditions participants were asked to buy a fictional product. However, in only one condition participants were intentionally confused to examine the differences in confusion. SmartPLS was used to analyse the serial mediation model. The research shows differentiating results. In contrast to the literature, customer confusion does not affect the customer experience outcomes directly, however this relationship is negatively mediated by utilitarian value. Moreover, customer confusion does affect the overall CX negatively. The study provides a better understanding of how customers experience confusion in a chatbot encounter and its effects on the outcomes. The findings provide several directions for future research avenues, such as including a fictional product that OTA's usually offer. Moreover, it recommends managers with practical guidance to develop chatbots and therefore enhance the CX during chatbot encounters.

Keywords: Chatbot, Customer Experience, Customer Confusion, Utilitarian Value, Seeking Information Behaviour, Online Travel Agencies

Contents

Introduction

The size of the global internet travel market was estimated to be around USD 433 billion in 2021 and USD 691 billion by 2026. Expedia and Booking.com were the biggest Online Travel Agencies by revenue worldwide (Statista, 2022). According to past research, it becomes difficult for the customer to overlook this market because the number of online offers increases fast (Matzler & Waiguny, 2005). As a result, customer confusion emerges when booking a hotel online. Customer confusion occurs when information is too similar, unclear or too much (Mitchell et al., 2005). This phenomenon has a negative effect on the outcomes of customer experience (CX). In particular, it significantly negatively impacts customer satisfaction and customer loyalty (Rosadi & Tjiptono, 2013).

For businesses, it is essential to understand the CX across time (Lemon & Verhoef, 2016). According to a study of Accenture (2015), the number one priority of businesses is improving the CX. CX is being impacted by technological advancements that are altering the way firms manage their interactions with customers (Chung et al., 2020). As a result, the CX will change in most businesses. New touchpoints will be created during the customer journey, and existing ones will be rearranged (Hoyer et al., 2020). To enhance a good relationship with customers, a technology must reach utilitarian and hedonic goals (Fiore et al., 2005). Both goals have a relation to behaviour. Hedonism refers to the pleasure, fun, and fantasizing whereas utilitarianism refers to rational, planned, and goal-oriented behaviour (Scarpi, 2020). Utilitarian customers apply a deliberate Information Seeking Behaviour to reach their goals quickly (Hoffman & Novak, 1997; Janiszewski, 1998).

Self-service technologies (SSTs) are an example of technological advancements and this service alters the manner in which customers engage with businesses (Meuter et al., 2000). Chatbots are an example of a self-service technology (Albayrak et al., 2018). The ability of chatbots to build an emotional connection with users is one of its most enticing features (Shum et al., 2018). The importance of chatbots in determining customer satisfaction is crucial (Magno, 2021). When customers' expectations are not exceeded, this could negatively influence customer satisfaction (Lemon & Verhoef, 2016). According to a new study of Precedence Research, the global chatbot market size is expected to be worth USD 4.9 billion by 2032 from valued at USD 0.84 billion in 2022. In addition, the annual growth rate is 19.29% from 2023 to 2032 (Precedence Research, 2023). From research about the adoption of AI chatbots in the hospitality and tourism industry can be concluded that customers are comfortable using chatbots for travel planning. Hence, they find chatbots accessible and can

converse comfortably with them (Pillai & Sivathanu, 2020). According to a recent study of Magno & Dossena (2022), organizations must be aware that customers do not expect technical perfection but the quality of information perceived and the emotion derived by their relationship with chatbots is more important. The quality of the information perceived by the chatbot is related to the Expectations Disconfirmation Theory (EDT), where a difference is made between the expected performance and the observed performance of a service, called disconfirmation (Oliver, 1980). When disconfirmation occurs, customer confusion arises. In past research, customer confusion was measured by looking into an experience's outcomes, such as customer satisfaction. However, there is still a lack of information about the actual experience of a customer (Fitzgerald et al., 2019). Despite Magno & Dossena (2022) stated that the hedonic elements outweigh in regards to customer satisfaction, it still remains unclear how the utilitarian elements play a role when a customer is being confused by a chatbot.

1.1 Research Objective

This paper aims to extend existing literature by researching about the experience that customers have when being confused in two ways. Firstly, by examining what effect customer confusion has on the outcomes of CX while interacting with a chatbot. Secondly, by investigating how CX mediates the relationship between customer confusion and customer experience outcomes. The main research question will therefore be:

How does customer confusion in a chatbot environment influence customer experience and its outcomes?

1.2 Relevance

Theoretical

Technology is an innovative advancement for the travel and tourism industry (Pillai & Sivathanu, 2020). Chatbots are an increasingly popular aspect of technology that has led to a greater understanding of the customer interaction with organizations. From previous research can be derived that customer confusion has a negative impact on customer experience outcomes (Rosadi & Tjiptono, 2013); however, there is a lack of knowledge about the actual experience of customer confusion (Fitzgerald et al., 2019). Moreover, the increasing use of chatbots across industries has increased the need to comprehend how customers interact with these systems and how they experience confusion during the interaction (Nguyen & Sidorova, 2018). Therefore, this study can fill the gap on the customer experience that customers have when being confused during a chatbot encounter.

Managerial

This contribution not only generates a better understanding of the academic field but also has practical implications. The hospitality and tourism sector is one of the most suitable industries where chatbots can be implemented (Ivanov & Webster, 2020). It is clear from the literature that customer confusion occurs while booking a hotel through an Online Travel Agency (OTA) (Matzler & Waiguny, 2005; Xue et al., 2020). To mitigate these confusing experiences, OTA's need to understand the customer needs when designing a chatbot (Ciechanowski et al., 2019). According to Blazevic & Sidaoui (2022) three aspects are important to consider when designing a chatbot, namely "the service logic, technology design and the customer experience". By researching the CX that is derived from confusion, OTA's can take strategies to improve the design and implementation of chatbots and enhance the CX throughout the entire process (El Bakkouri et al., 2022). For example, managers might create chatbots that give information about specific hotel guest inquiries which alleviates pressure on the concierge service.

1.3 Outline

The rest of the thesis will be as follows. The next chapter presents the theoretical framework following by the hypothesis. Afterwards, the thesis will elaborate on the methodology employed. Then, the results of the experiment are discussed. Lastly, the theoretical and managerial implications of the findings will be presented, along with limitations of the study and suggestions for future research.

Literature review

The second chapter will contain a theoretical framework for chatbots, customer experience, and customer confusion. At the end of the chapter, a conceptual model is given, and the individual hypotheses are formulated.

2.1 Chatbots

For a customer it is important to reach a company with minimum effort of time (Suwono & Sihombing, 2016). Therefore, businesses are investing more in digital services nowadays to enhance customer experiences. An example is e-service agents, such as chatbots (Trivedi, 2019). A chatbot is a computer program able to entertain a natural language-based conversation

with a human (Calvaresi et al., 2021). They mimic human interactions by interacting, speaking in a natural language, and striving to convey emotions in addition to providing information (Hoyer et al., 2020). Its purpose is to satisfy customers in a similar way as offline service agents do (Chung et al., 2020). Chatbots are a result of technological advancements, but firms must not forget that the experience is more important than technical perfection (Magno & Dossena, 2022).

Moreover, the use of chatbots in customer assistance for enterprises has grown in popularity. It is capable of interacting with a large number of clients at once and can partially address their needs. This substantially lowers the cost of providing customer assistance (Ranoliya et al., 2017). Moreover, chatbots are available 24/7 and it can analyse conversations to improve future conversations and to meet customer needs better (Winkler & Söllner, 2018).

Also, in the tourism and hospitality industry, these services are becoming more popular (Jiménez-Barreto et al., 2021). The most used OTA is Booking.com (Statista, 2022). They use a support chatbot, the booking assistant. With this chatbot, Booking.com handles 30% of customer questions, including payment, transportation, arrival and departure times, date changes, cancellation requests, parking information, extra bed requests, pet policies, Wi-Fi and internet availability (Booking, 2017).

2.2 Customer Experience

Nowadays, the amount of time customers spend in digital environments increases (Jenneboer et al., 2022). In the meantime, firms are challenged by competition, and it becomes more difficult to retain customers and to maintain positive CX (McLean & Wilson, 2016). Consequently, CX is becoming more important while firms adapt more to technological changes (Chung et al., 2020). CX is a multidimensional construct focusing on a customer's cognitive, emotional, behavioural, sensorial, and social response to a firm's offerings during the customer's entire purchase journey (Lemon & Verhoef, 2016). By enhancing the CX, expectations of customers can be exceeded which lead to the customer experience outcomes customer satisfaction and customer loyalty. Customer satisfaction happens if the product or service exceeds the expectations of a customer (Oliver, 1980). Moreover, customer loyalty refers to what extent customers keep using the product or service even when alternatives are around (Ludin & Cheng, 2014). With respect to CX, this research is focused on the cognitive experience and the behavioural response, in particular Seeking Information Behaviour (ISB).

The aim of cognitive experiences is to encourage customers to utilize their creative and problem-solving abilities, thereby facilitating a re-evaluation of their assumption about a

product or service through experiences that engage their thinking and conscious mental processes (Schmitt, 2010). The thinking process involves gathering and analysing facts, theories, and information. Additionally, thinking allows for the evaluating of options and thus making effective decisions (Balasubramanian et al., 2011). To enhance a good relationship with customers, a technology must reach utilitarian and hedonic goals (Fiore et al., 2005). Cognitive elements guide utilitarian goals, which are oriented towards problem-solving (Dhar & Wertenbroch, 2000). As the research is focused on the CX element thoughts, only utilitarian value is included in the model.

Utilitarianism stems from the Technology Acceptance Model (TAM) by Davis (1989). The model shows that several factors impact customers' decisions about how and when to utilize new technologies. The main concepts of TAM are utilitarian and are called perceived usefulness and perceived ease of use (Dimitrijevic & Devedzic, 2021). The components of utilitarian value are directly linked to the analytical features of the technology.

Utilitarian experiences satisfy customers by fulfilling fundamental needs (Loureiro et al., 2014). Customer satisfaction measures how well your company's whole offering meets a set of customer expectations (N. Hill et al., 2003). This can be linked to the Expectations Disconfirmation Theory (EDT). EDT argues that post-purchase pleasure results from the combination of expectations and perceived performance. Two disconfirmations can be distinguished, positive and negative disconfirmation. Positive disconfirmation leads to post-purchase satisfaction when a product or service exceeds expectations. Customers are dissatisfied if a product or service fails to meet their expectations which refers to negative disconfirmation (Oliver, 1980).

Customers experience utilitarian value when a utilitarian good accomplishes a functional or practical task (Strahilevitz & Myers, 1998). To enhance a good relationship with a customer in a chatbot encounter, it is important for a company to invest in service quality, system quality and information quality (DeLone & McLean, 1992; Hoyer et al., 2020). All these factors contribute to the overall utilitarian value of a customer. Several examples regarding chatbots are providing sufficient information and answers (Lo Presti et al., 2021), fast customer support which is 24/7 available and efficient services (Trivedi, 2019).

When customers recognize a product's potential to meet their specific needs, solve problems or deliver desired outcomes, they are motivated to gather more information to validate and improve their perception of utilitarian value (Chiu et al., 2014). Gathering more information to complete a goal is called ISB (Tubachi, 2018). The goal of utilitarian customers while shopping is to reach a specific goal or task, as efficient as possible, so they can make

well considered decisions (Babin et al., 1994). As a result, they select a search behaviour that is deliberate and focused on achieving that goal or task (Hoffman & Novak, 1997; Janiszewski, 1998). Since utilitarian customers want to achieve a goal as fast as possible, they have a strong incentive to gather relevant information (Wu et al., 2015).

2.3 Customer confusion

However, the CX does not always go flawless (Bhatia & Priya, 2021). Service failure happens unfortunately often with customers (Lewis & McCann, 2004). An example of a service failure is customer confusion which negatively effects CX (Rosadi & Tjiptono, 2013). Customer confusion emerges when continuous cognitive work is interrupted by novel or unexpected circumstances that cannot be instantly resolved or integrated into existing mental models (Blum et al., 2020). Most marketing researchers have defined confusion by its cause (Fitzgerald et al., 2019). According to the conceptual framework of Mitchell et al. (2005), customer confusion consists of three types of confusion: overload, similarity and ambiguity. Overload confusion refers to customers facing challenges when presented with an overwhelming amount of product information and alternatives. This makes comparing and comprehending them difficult (Mitchell et al., 2005). The term similarity confusion describes the phenomenon when customers may mistakenly evaluate a brand due to perceived physical similarities between products or services (Mitchell et al., 2005). Ambiguity confusion is defined as a situation in which customers experience a lack of understanding that requires them to re-evaluate and potentially adjust their current beliefs or assumptions about products or the purchasing environment (Mitchell et al., 2005). Fitzgerald et al. (2019) argued that these definitions do not explain the experience of confusion. Confusion is a ‘hybrid’ emotion because it includes both thoughts and feelings (Ellsworth, 2003). Based on this argument, literature suggests that customer confusion is a state of mind characterized by negative emotions and cognitive challenges, resulting from a lack of comprehension or understanding of various stimuli in the marketplace (Fitzgerald et al., 2019).

When customer confusion reaches an intolerable level, customers will adopt a variety of techniques to decrease this unclarity (Leek & Kun, 2006). Mitchell & Papavassiliou (1997) concluded that there are several confusion reduction strategies (CRS), namely (1) do nothing, (2) postpone/abandon the purchase, (3) involving others, (4) clarify the buying goals, (5) seek additional information, (6) narrow down set of alternatives. Seeking additional information is the most common strategy customers use to behave regarding their confusion (Drummond,

2004), which refers to ISB (Krikelas, 1983). Information seeking begins when the knowledge of a customer is insufficient to address a problem and ends when that knowledge is gathered. This can either result in satisfaction or dissatisfaction (Al-Suqri & Al-Aufi, 2015). An important concept which is related to ISB is reaction time (Deary et al., 2001; Pachella, 2021). Reaction time in cognitive psychology refers to the period between the stimulation to a subject and the subject's response (Pachella, 2021). The cognitive overload results in a longer reaction time because a person needs more time to process and integrate the information (DeLeeuw & Mayer, 2008). According to J. Hill et al. (2015), customers communicate longer with chatbots then they do with real humans.

Within OTA's, all three dimensions of customer confusion can be expected. Overload confusion can occur at 22 choices or more. Booking.com already has over 28 million listings of accommodations (Booking, 2022). OTA's are look-alike websites and offer mostly the same information (Matzler & Waiguny, 2005) As a result, similarity confusion may occur (Lu et al., 2016). Ambiguity confusion may happen when customers have a low level of trust in websites or when it is hard to find the needed information (HongWei & ShiDai, 2019; Matzler & Waiguny, 2005).

2.4 Hypothesis

Customer confusion and Customer experience outcomes

To influence the CX, an increasing number of businesses are now using chatbots in customer interactions (Okuda & Shoda, 2018). Chung et al. (2020) explored that customers are more satisfied if they consider chatbots to be accurate. However, when a chatbot does not meet customers' expectations, this often results in a service failure (Sheehan et al., 2020). As mentioned earlier, a form of service failure is customer confusion. According to Rosadi & Tjiptono (2013), confusion results in additional processing, which decreases customer satisfaction. In addition, it is more difficult for companies to establish a good customer loyalty when customers are confused (Turnbull et al., 2000). Thus:

H1a: *Customer confusion negatively influences customer satisfaction.*
H1b: *Customer confusion negatively influences customer loyalty*.

Customer confusion and Customer experience

In a chatbot encounter, utilitarian elements, such as the perceived information quality by a chatbot (Trivedi, 2019), is important for a customer to evaluate the service (Kesari & Atulkar,

2016). When those elements are as expected, customers tend to become less confused and thus customers have less need to look for alternative products or service providers (Vieira et al., 2018). As stated earlier, customers deploy CRS to limit their confusion of which the most common strategy is ISB. According to Bai et al. (2008), they seek for additional information to clarify the choice they will make. According to J. Hill et al. (2015), when customers experience confusion they tend to response slower to questions because their cognitive load is high. As a result, customers need more time to process the information (DeLeeuw & Mayer, 2008). Therefore, the hypotheses are:

H2: *Customer confusion negatively influences utilitarian value.*
H3a: *Customer confusion positively influences Information Seeking Behaviour.*
H3b: *Customer confusion positively influences customers reaction time.*

Customer experience elements

A service, such as a chatbot, has a high utilitarian value if it is designed to solve a problem (Wang, 2010). Perceived information quality, which refers to utilitarianism, by a chatbot is important for customers (Magno & Dossena, 2022). If the need of a product or service is high, customers seek for additional information. So, offering a chatbot with a high utilitarian value will therefore not create a need to clarify information perceived. Thus:

H4: *A decrease in utilitarian value increases customer Information Seeking Behaviour.*

Simple mediations

A customer can develop a cognitive perspective of a product or service when comparing the expectations and the observed performance, also called disconfirmation (Oliver, 1980). This phenomenon affects the satisfaction and loyalty of a customer (Zhou, 2011). In this study, positive disconfirmation arises when the quality perceived from the chatbot is better than the expected quality. In contrast, negative disconfirmation happens if the experience in the chatbot encounter does not meet the expected quality. Hence, the greater customers' utilitarian expectations, the greater the likelihood that they would be negatively disconfirmed. As a result, it is more difficult for a company to satisfy customers with greater expectations, and vice versa (Liu et al., 2020). When a customer is confused by a chatbot, the performance of a chatbot does not meet the expectation of the customer and as a result the customer is not satisfied. According to a study of Serenko & Stach (2009), which was conducted in respect to the travel and tourism

industry, the loyalty of Expedia (OTA) users decreased after a negative disconfirmation. They concluded that a positive disconfirmation has a significantly effect on customer loyalty. Therefore:

H5: *Utilitarian value negatively mediates the relationship between customer confusion and the customer experience outcomes.*

Information can assist in changing the level of knowledge and recognizing a need, or solving a problem (Afzal, 2009). By seeking additional information, individuals attempt to resolve their confusion and achieve a greater level of comprehension. The widespread options for acquiring information quickly and easily have greatly boosted search behaviours, however it can lead to information overload which degrades the quality of information processing (G. & Asokan A., 2017). As a result, dissatisfaction happens (Walsh et al., 2007). Since satisfaction influences loyalty (Lin, 2006), ISB contributes negatively to the relationship between customer confusion and customer experience outcomes. Thus:

H6: *Seeking Information Behaviour negatively mediates the relationship between customer confusion and customer experience outcomes.*

2.4.1 Covariates

Four variables are included as covariates to test the effect of customer confusion on the customer experience outcomes. The covariates consist of two personality traits, namely tolerance of ambiguity and confusion avoidance. Furthermore, age and gender are analysed. Tolerance of ambiguity refers to how an individual deals with ambiguous situations when they experience an unfamiliar or complex situation (Furnham, 1994). From a research of Lu & Gursoy (2015) can be concluded that customers experience confusion more when they have a high ambiguity tolerance. This may be due to their diminished capacity to comprehend novel situations.

Another personality trait is confusion avoidance. When someone is confusion avoidance sensitive, he or she prefers to step back from confusing or difficult situations. An individual is then trying to minimize the feelings and difficult cognitive processes (Hoque et al., 2022). Thus, it is more presumably that confusion avoidance will affect the relationship between customer confusion and the customer experience outcome negatively.

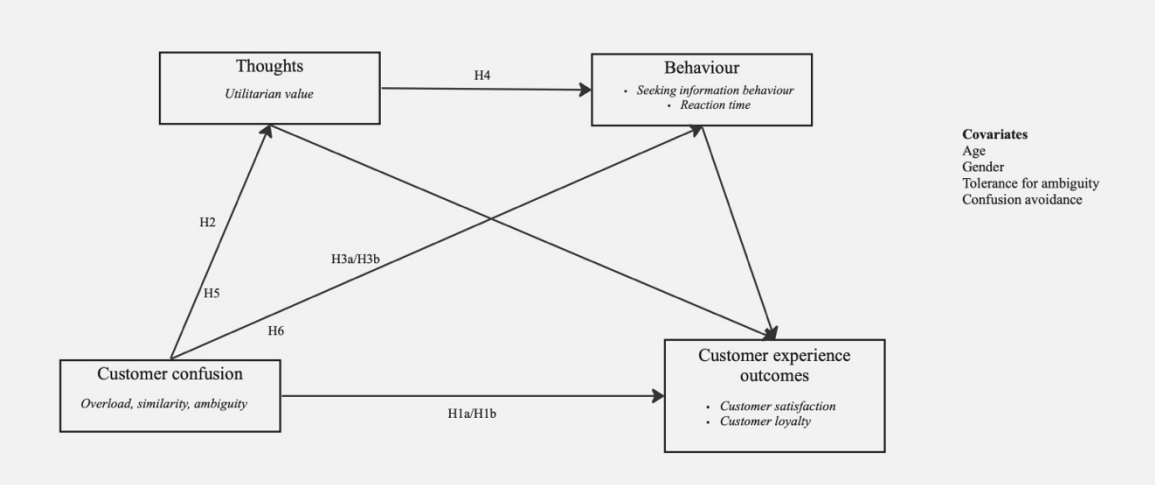
According to van der Goot & Pilgrim (2020), age groups may vary in their preference for communicating with chatbots over human contact. Leek & Chansawatkit (2006) found that elderly people's diminished cognitive capacities contributed to their increased likelihood of experiencing confusion. The rapid pace of the upcoming use of chatbots makes it harder for older people to make a purchase because they mainly rely on their established purchase habits. Therefore, it is likely that younger customers are less easily confused by a chatbot then older customers (Sharma et al., 2022).

Suggested from literature, females evaluate services and products more critically than males. Also, women enjoy gathering information by viewing various advertisements and view this activity as less time-consuming than men (Schreiner et al., 2019). As a result, they are confronted with more information, and they make themselves overwhelmed which can cause confusion (Wobker et al., 2015). Therefore, it is more likely that women are more sensitive to confusion.

2.4.2 Conceptual model

The conceptual model below shows the proposed hypotheses.

Figure 1: *Conceptual model of customer confusion on customer experience outcomes*



Methodology

The following chapter explains how the data is collected and how the analysis is performed. In addition, research ethics are explained at the end of the chapter.

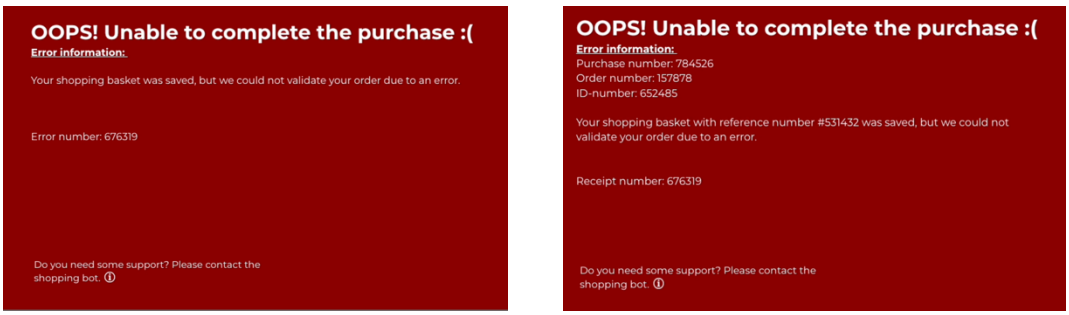
3.1 Research strategy

Quantitative and qualitative research is employed in this study, also called mixed-method research (Creswell, 1999). Quantitative method is the main approach to investigate hypothesized relationships, whereas qualitative research will be added research to look for several patterns in the answers to open-ended questions. There is chosen for an experiment because causal relationships are studied (Spencer et al., 2005). The independent variable customer confusion is manipulated to measure the effect on customer experience outcomes, the dependent variable. The data is obtained using a Wizard of Oz approach, in which a participant performs a task while an experimenter covertly substitutes for a piece of technology (Kelley, 1984). So, for this study, the researchers are the chatbot. The method is traditional and accepted to evaluate human behaviour (Steinfeld et al., 2009). The experiment took place at the Radboud University in Nijmegen and the data is collected in May and June 2023.

3.1.1 Procedure

The participants were asked to have a shopping experience with a shopping bot, a chatbot that assists customers with an online purchase (Sadeddin et al., 2007). The software that was used to interact with the participants is WhatsApp Business (WhatsApp Business, 2023). A non-contextual experience was designed by offering the participant a non-existing product. There were two different scenarios created for the experiment. One condition aimed not to confuse participants, and in the second condition, it was the intention to confuse participants. This was done by showing different error pages (Figure 2).

Figure 2: *No confusion (left) vs. Confusion (right)*



The shopping bot was named Cody. Cody assisted the participants in making an online purchase. After the participants placed the product in their basket, one of the error pages popped up. Cody asked for an error number which was seen on the page for the no confusion condition. In contrast, several numbers were displayed for the confusion condition, and none were explicitly called ‘error code’. After the shopping task, several closed and open-ended questions were asked. The full script can be found in Appendix A.

3.1.2 Sample

There was no specific sample group that needed to participate; however, since the experiment took place at the Radboud University in Nijmegen, primarily students and teachers from the University participated. The experiment used a one-factor, between-subjects experimental design. To select the participants, a form of non-probability sampling was used, namely convenience sampling (Malhotra et al., 2017). The participants were assigned randomly to one of the two conditions to ensure internal validity (Hair, 2019). Internal validity refers to how confident it is that a change in X cause changes in Y (Hair, 2019). Also, a pre-test was conducted before the experiment. A sample size of 100 participants per condition was desired. In total, 200 participants engaged in the experiment. Those 200 participants are divided into 100 in the no confusion and 100 in the confusion condition.

3.1.3 Software tools

To assess the reflective measurement model, the software SmartPLS 4 (Ringle et al., 2022) was used to perform structural equation modelling (SEM) and conduct a confirmatory factor analysis, including bootstrapping. Before this analysis, a manipulation check and missing value analysis was done using the program SPSS IBM v. 28 (Hair, 2019; IBM Corp., 2021).

To ensure that the answers to the open-ended questions were converted into quantitative data, sentiment analysis was used. This was managed through two different software's. The data analysis algorithms utilized in this thesis were constructed using an open-source programming language called Phyton (Python, 2023). To categorize the responses into positive, negative or neutral, TextBlob library was used. This library provides practical and precise natural language processing capabilities for sentiment analysis tasks. Moreover, it played a crucial role in standardizing the results of the analysis (TextBlob, n.d.; Loria, 2020).

As this study also aims for qualitative study regarding the open-ended questions, the software Atlas.ti is used. The software facilitates the organization and classification of qualitative data, making it simpler to identify patterns and relationships. AI coding was used to generate the codes (Atlas.ti, 2022; Woods et al., 2016).

3.2 Operationalization table

The measurements are suggested from existing literature. The constructs are explained in table 1. The concept thoughts was measured through the construct utilitarian value. Four closed-ended questions were asked using a seven-point Likert scale (Babin et al., 1994). Moreover, three open-ended questions were asked. The construct behaviour was measured by two

concepts using real time measurements. First, how many times a participant seeks for additional information through the information button and by asking the chatbot for help. Second, their reaction time in seconds. The concept customer experience outcome is divided into customer satisfaction (Chung et al., 2020) and customer loyalty (Reichheld, 2004). Both constructs were measured using a seven-point Likert scale. Customer satisfaction was measured by asking one item and for customer loyalty two items were asked. As mentioned earlier, four control variables are included. Age was measured by asking one open-ended question. Gender was measured by using a nominal scale (Reisner et al., 2014). Tolerance of ambiguity and confusion avoidance (Schweizer et al., 2006) were measured by asking three items and using a seven-point Likert scale. Lastly, the manipulation check questions used a seven-point Likert scale, and four items were asked (Sprotles & Kendall, 1986). An overview can be found in table 2.

3.3 Research ethics

During the experiment, several principles were considered. Before the experiment, any potential risks were mentioned, and steps were taken to minimize those steps. First, an informed consent was sought from all participants (Tavakol & Sandars, 2014). This consent included statements where is explained that the obtained data will be kept secure and secret, and that participant anonymity will be maintained throughout the study to adhere to privacy compliance. Second, they were informed well through an explanation of the nature and aim of the study (Malhotra et al., 2017; Tavakol & Sandars, 2014). In addition, participants were advised of their ability to withdraw at any moment (Malhotra et al., 2017). In order to limit potential harm or discomfort to participants, the study was developed with their time and well-being in mind. Participants were debriefed after the experiment by explaining what was tested. Finally, there was an opportunity for participants to ask questions and voice any concerns.

Results

In this chapter, an elaboration will be given on the results of the analysis. In particular, data preparation, manipulation check, assessing of the structural and measurement model and the analysis of the hypotheses will be explained.

4.1 Data preparation

Before the start of the analysis, a data preparation was done. In particular, a missing value analysis was conducted, and the validity and reliability were assessed. Every participant finished the experiment, so in total the data of 200 participants was collected and put in SPSS.

The items CA_3, Confusion_2 and Confusion_3 were reversed because they were stated in the opposite direction.

To check the data, a missing value analysis was performed. A distinction is made between missing values completely at random (MCAR) and missing values at random (MAR). If the analysis states that MAR occurred, this can indicate that the missing values are not systematically associated with other missing values.

According to Field (2009), the univariate statistics need to be <10%. For all values, this was the case except for Reactiontime_EM. This variable had a percentage of exact 10%. The reason is that during the experiment participants in the no confusion condition gave the error code immediately and the chatbot continued the conversation without asking for an error code. Thus, there is no reaction time registered from the message of the chatbot until the next answer. To fix this, an imputation method was added. Since the data of this variable is skewed, a missing value was changed by the median, namely 17. After conducting this, the percentage missing was 9.5% which is sufficient to continue. The Little MCAR test (Little, 1988) showed that the test is insignificant ($\chi^2 = 115.135$, df = 114, $p = 0.453$). Therefore, the missing values are completely at random, and the analysis was continued.

Moreover, the item confusion was adjusted to allow this item to be analysed. An extra variable was created for this variable, a dummy variable. The no confusion condition was coded with a '0' and the confusion condition with a '1'.

4.2 Manipulation check

The participants were randomly assigned to the two different conditions. One condition stated for the no confusion condition and the other one for the confusion condition. Four items were added in the chatbot-survey to assess that these conditions were measured correctly. The analysis of the manipulation check was performed via an independent samples t-test in SPSS. All items were measured with a seven-point Likert scale (see table 2). The results of the test showed that there was a statistically significant difference between the two conditions for all the four questions. Moreover, they were all significant (see table 3). So, it can be concluded that the manipulation check was successful.

***Table 3**: Group statistics no confusion and confusion*

Question	Mean no confusion	Mean confusion	Significance
1	3.60	5.24	$p = <.001$
2	2.85	4.94	$p = <.001$
3	3.53	5.74	$p = <.001$
4	3.13	4.13	$p = <.001$

4.3 Assessing measurement model

4.3.1 Main constructs

To test the validity and reliability, a confirmatory factor analysis (CFA) was conducted. SmartPLS was used to perform the CFA. The reflective measurement model was assessed by looking at the indicator loadings. According to Hair et al. (2019), loadings above 0.708 are recommended. The indicator 'ISB_button', scored very low, namely -0.046. Moreover, the item reactiontime_EP scored also low with a value of 0.285. As a result, these indicators were deleted from the data. The construct behaviour was separated into a latent variable called reaction time and a latent variable called ISB since both concepts were measured differently. Moreover, customer satisfaction and customer loyalty were separated as the R^2 improved by this. Loyalty had two indicators, namely the questions for customer loyalty and NPS. The indicators NPS, Thoughts_C1 and all the open-ended questions of the construct thoughts also scored below the threshold of 0.708; however, since they were all above 0.5, the factor analysis was continued.

To assess the internal consistency reliability, Cronbach's alpha and the composite reliability can be used. The composite reliability was used for this analysis because this is the recommended measure, as Cronbach's alpha is less precise (Hair et al., 2019). The threshold for this measure is that scores between 0.60 and 0.70 are considered acceptable and scores between 0.70 and 0.90 are recommended. All scores were between 0.70 and 0.90, except for the open-ended questions of the construct thoughts. Therefore, this construct was eliminated from the data as well. The reason that the composite reliability was not met for this construct may be due to the sentiment analysis that was done. Thoughts frequently entail expressing facts, giving justifications, or talking about abstract subjects without clear emotional content (Tye, 2008). Therefore, it is difficult for the software to categorize the answers into a clear positive or negative statement. As a result, a neutral score was given to a lot of answers.

Afterwards, the convergent validity was checked. The metric used to evaluate this validity is the average variance extracted (AVE). The acceptable threshold is 0.50 or higher (Hair et al., 2019). All constructs scored higher than 0.50 which made it acceptable to continue with these constructs.

The Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larcker criterion assess the discriminant validity (Hair et al., 2019). The threshold for HTMT is a value under 0.90. This was not the case for customer loyalty (0.910). As the outer loading of the NPS indicator scored the lowest of this construct, this item was deleted to ensure that the discriminant validity was also accepted. An overview of the values can be found in table 4. After deleting this indicator, the HTMT threshold was met. The Fornell-Larcker criterion was also met, where the shared variance for all model constructs should not be larger than their AVE's (Fornell & Larcker, 1981). These values can be found in table 5. Hereafter, a one-tailed bootstrapping was conducted to show the significance of the indicators. All the values were significant; thus, the variables were good to continue.

At last, the model fit was checked by looking at the SRMR. The threshold for this value is <0.08 (Byrne, 1998). The results showed an SRMR score of 0.045, which shows a sufficient fit.

4.3.2 Control variables

After performing the CFA for the constructs, a CFA is also performed for the control variables. The questions regarding credibility (Alternative1), distraction (Alternative2) and problem-solving reference (Alternative3) are taken into account to rule out any alternative explanations. The outer loadings of CA_2 and CA_3R were very low, namely below 0.40. As a result, these two indicators were eliminated. Moreover, the outer loadings of the Tolerance of ambiguity construct were also below the threshold, however when deleting ToA_2, the other indicators increase immensely (ToA_1: 0.483 to 0.929, ToA_3: 0.248 to 0.633).

The composite reliability of all control variables was between 0.70 and 0.90, thus maintaining reliability. Regarding the convergent validity, all values of the AVE were above 0.50. For the discriminant validity, the HTMT threshold was met for all constructs and the Fornell-Larcker criterion.

After this, a one-tailed bootstrapping was done to determine the statistical significance (Hair et al., 2019). The bootstrap showed that indicator ToA_3 was insignificant and therefore eliminated from the data. The outer loadings can be found in table 6.

4.4 Assessing structural model

Collinearity must be examined before evaluating the structural relationships to ensure that it does not affect the regression results. This is done by assessing the VIF scores. Preferably, the VIF score is close to 3 or lower (Mason & Perreault, 1991). All VIF scores in the model do pass this threshold. So, this means that there is no problem regarding collinearity.

The R-squared (R^2), also known as the coefficient of determination, is another value to assess the structural model. This measures how much of the variable of the independent variable is explained by the dependent variable (Hair, 2019). The R^2 of satisfaction and loyalty is moderate, 0.591 and 0.578 whereas for reactiontime, SIB and utilitarian value are between weak and moderate, 0.311, 0.323 and 0.329.

4.5 Analysis

4.5.1 Hypotheses

To test the hypotheses, a SEM-PLS analysis with 5000 one-tailed bootstrapped samples was conducted using SmartPLS 4. A one-tailed bootstrapping was performed since the effects are hypothesizes in only one direction (Kock, 2015). Table 7 shows the output of the mediation analysis, including the covariates. The R^2 of some of the latent variables improved by adding the control variables. The mediation model can be found in Figure 3.

Customer confusion → Customer satisfaction (H1a)

After conducting the analysis including the covariates, the coefficient of determination for satisfaction is medium to large: 0.591. It can be concluded that the effect is not significant (p = 0.293). Thus, the hypothesis is not supported. Therefore, there is no strong enough evidence to reject the null hypothesis. A potential clarification is that the shopping bot and the participant solved the problem together. So, confusion or no confusion, in both cases, the error was solved.

Customer confusion → Customer loyalty (H1b)

The R^2 of customer loyalty is 0.580 which indicates a medium to large effect. Customer confusion has a positive significant effect on customer loyalty; however, it is not very strong (β = 0.241, p = 0.026). Since the effect is positive, the hypothesis is not supported. As stated earlier, the error was resolved in both conditions and could have affected loyalty in a positive way. Age has a negative significant effect (β = -0.095, p = 0.035). It is rather small; however, a relationship has been found. The older someone is, the more loyal that person is towards a product or service.

Customer confusion → Utilitarian value (H2)

Without connecting the control variables to the construct thoughts, the R^2 is weak, namely 0.153, however adding the control variables double the amount of variation from the IV on the DV, 0.329. Customer confusion has a significant negative effect on utilitarian value, (β = -0.518, p = 0.000). Therefore, the hypothesis is supported. If a customer is confused, the utilitarian value is less positive. Looking at the effects of the control variables, it can be stated that age (β = -0.126, p = 0.033), confusion avoidance (β = 0.173, p = 0.038) and alternative3 (β = -0.375, p = 0.000) has a significant effect on utilitarian value. Age has a significant negative effect, so the older someone is, the less positive someone was about the experience. Confusion avoidance effects utilitarian value significant positively, thus the more confusion avoidance someone is, the more positive the utilitarian value. Alternative3, regarding problem solving preference, has a significant negative effect and therefore the more someone prefers to talk to a human instead of a chatbot, the lower the utilitarian value.

Customer confusion → Information Seeking Behaviour (H3a)

The explained variance without control variables is 0.254 and with it is 0.324. Customer confusion shows a positive moderate effect on SIB (β = 0.529, p = 0.000). The hypothesis is thus supported. When someone is confused, he or she shows SIB. Only the control variable age had a negative significant effect on seeking more information (β = -0.116, p = 0.032). The older someone is, the less they will seek for more information.

Customer confusion → Reaction time (H3b)

The R^2 without control variables was 0.295 and by adding the control variables the R^2 did improve slightly: 0.311. None of the control variables were significant. The effect size of customer confusion on reaction time was significant positive (β = 1.157, p = 0.000), so the hypothesis is supported. The more confused customers are, the slower they respond. The path coefficient shows a value above one which can cause problems regarding the collinearity, however after assessing the structural model with VIF (Mason & Perreault, 1991), it can be stated that there were no problems regarding this aspect. Therefore, conclusions are based on this path coefficient.

Utilitarian value → Information Seeking Behaviour (H4)

By adding the control variables, the R^2 has a value of 0.324. The path coefficient is negative and significant (β= -0.302, p= 0.000). Since the effect is negative, the hypothesis is supported. If the utilitarian value is high, customers will not seek for additional information.

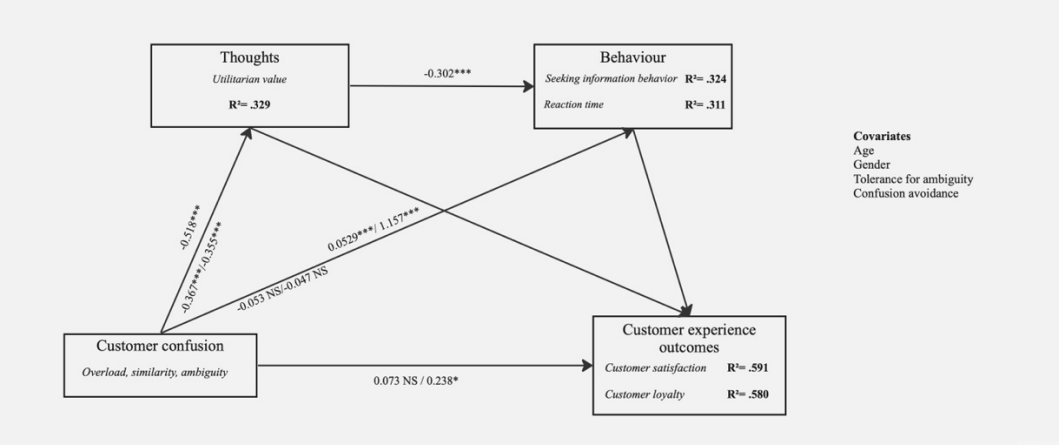
Simple mediation (H5/H6)

Since loyalty and satisfaction were separated during the analysis, they are analysed apart from each other. Utilitarian value is a mediator between the effect of customer confusion on satisfaction and the effect of customer confusion on loyalty. Both effects are significant negative and therefore hypothesis H5 is supported (Satisfaction: β = -0.367, p = 0.000; Loyalty: β = -0.355, p = 0.000). Confusion leads to a low level of utilitarian value and therefore the satisfaction and loyalty decreases.

However, there is a difference regarding to what extent thought can explain the relationship. Since the effect of confusion on satisfaction is insignificant, utilitarian value fully explains the variation of confusion by satisfaction, also called full mediation (Baron & Kenny, 1986; Zhao et al., 2010). The indirect effect of confusion on loyalty through utilitarian value is a so-called partial mediation because the direct effect is significant (Baron & Kenny, 1986; Zhao et al., 2010). So, utilitarian value only partially explains the effect from confusion on loyalty.

The mediation effect of SIB on the relationship between customer confusion and customer experience outcomes is not significant and therefore H6 is not supported. (Satisfaction: β = -0.038, p = 0.191; Loyalty: β = -0.050, p = 0.073). A reason for this can be because the construct is only measured by one indicator.

Figure 3: *Serial mediation with covariates*



*Symbol meaning: NS = p ≥ 0.05; * = p ≤ 0.05; ** = p ≤ 0.01; *** = p ≤ 0.001*

4.5.2 Additional qualitative analysis

As mentioned by assessing the measurement model, the open-ended questions of the construct thoughts were eliminated due to the weak composite reliability value, however the data was used to do an additional qualitative analysis. All the codes can be found in Appendix F.

In the analysis of the hypotheses, it is discussed that hypotheses H1a and H1b were not supported and that a possible clarification may be that the error was solved both for the no confusion condition as for the confusion condition. The suggested explanation can be followed up by the codes that occurred from the qualitative analysis. An interesting pattern that occurred in the confusion condition was customer satisfaction. Examples of quotes are: *"At first it wasn't clear to me that I had to make a purchase, but you were helpful in what I had to do and you helped me through the process."* or *"I was a bit confused at first, but figured out just to reach out with the error codes"*. Thus, it can be stated that even participants who received the error page in the confusion condition, were still satisfied after resolving it together with the shopping bot.

Moreover, H3a was supported. From the qualitative analysis, it can be concluded that customers will adopt SIB when confused. A pattern arises called: seeking help. Examples of quotes are: *"... so I tried to be as clear as possible by providing you with the fact that the purchase failed and the corresponding error number. I expected you would be able to use just that information to help me."* and *"I assumed that i was suppose to place the order. This was not possible on the web. So for me the only solution was to ask for help."*

Another interesting finding from the qualitative analysis is that one of the main patterns that occurred in the no confusion condition was *"*confusion*"*. Examples of answers are: *"i was confused on what happened, i first thought that i had to refresh the page for example or that i was being tricked into a fake purchase"* or *"At first I was confused that the site give me an error, but after asking you for help it worked quickly so I did not put any more thought into it"*. The reason that people were confused could be that they already felt confused by seeing an error page because it was something they did not expect to happen.

For the construct behaviour, an extra qualitative analysis was conducted for the question: *"What actions crossed your mind in the process of resolving this error?",* to see what participants wanted to do while confused. Even though one of the indicators of SIB had to be eliminated, namely clicking on the information button, the answers on the open-ended questions can cover this construct. Participants were looking for more information via the information button. Some examples of quotes are *"look for a help button or something like that"* and *"I clicked on the information button to look for more information about the error"*.

Moreover, a pattern that occurred was problem-solving. Participants had the tendency to cancel the purchase, refresh the page or redoing the purchase. Examples are *"Refreshing the page or going back in the website."* and *"to refresh the page and do it again"*. These responses occurred in both conditions. It could be that participants already were confused by seeing the error page which made them wanted to do these behavioural actions in both conditions.

Discussion

This chapter elaborates on the findings of this study. The theoretical and managerial implications are discussed regarding the previous research. Finally, the limitations of the research are discussed followed by the direction for future research.

5.1 Theoretical implications

This research extends the literature by adding more knowledge towards how customers experience confusion during a chatbot encounter.

Hypotheses H1a and H1b have shown an insignificant and significant effect which are not in line with existing research, however the limitations will explain the shortcomings of the specific research design that negatively impacted the results of these hypotheses.

The results confirm the literature regarding how customer confusion influences the CX. The data supported the hypothesis regarding thoughts that customer confusion negatively influences the utilitarian value (H2). This result is in line with previous research that state that customers become confused when the perceived information quality is not clear (Vieira et al., 2018). Moreover, in terms of CX dimension behaviour, both hypotheses supported the literature review. First, customer confusion has shown a positive significant effect on ISB (H3a). This is in accordance with the study of Mitchell & Papavassiliou (1997), where was studied which strategies customers applied to reduce their confusion. The most used strategy in this study was SIB. Therefore, the results of this study build upon this theory. This result seems logical as humans are naturally inclined to search for information when confused. Second, a positive significant effect has been found between customer confusion on reaction time (H3b). The results expands the literature of J. Hill et al. (2015) which stated that if the cognitive load of customers is high while confused, it generates a longer reaction time.

The results show an effect between the two CX dimensions, thoughts and behaviour. It supports the hypothesis that when the utilitarian value decreases, customers apply ISB (H4). The results are in agreement with the literature which state that utilitarian customers select a

search behaviour which is deliberate and goal-oriented to achieve a goal as fast as possible (Babin et al., 1994; Chiu et al., 2014; Wu et al., 2015). This seems reasonable as if the utilitarian value of a product or service is high, they are closer towards their goal and less additional information is needed.

The outcomes of this study confirm previous studies that negative disconfirmation influences customer experience outcomes negatively (Oliver, 1980). The data supported the hypothesis that the relationship between customer confusion and customer experience outcomes is negatively mediated by utilitarian value (H5). So, if the quality of the product or service is not better than expected, it will affect the customer experience outcomes negatively (Oliver, 1980). Utilitarian value fully explains the variation of the relationship between customer confusion and satisfaction whereas utilitarian value only partially explains the relationship between customer confusion and customer loyalty. This suggests that other variables which are not included in this study might mediate this relationship.

Even though this study indicated a negative mediating effect of ISB on the relationship between customer confusion and the customer experience outcomes (H6), the p-value indicated that the effect is non-significant. Therefore, it cannot agree with the findings that are mentioned in the literature which do find a significant negative effect (G. & Asokan A., 2017).

Other interesting findings are regarding the control variables on the endogenous variables. Age had a significant negative effect on customer loyalty, ISB and utilitarian value. This is in line with the literature since older customers have more difficulties in situations where they need to interact with advanced technologies, such as chatbots (Sharma et al., 2022). However, the effects might be reversed when they talk to a real life human. Moreover, two effects have been found on the construct utilitarian value, namely problem-solving preference and confusion avoidance. Problem-solving preference significant negatively impacts utilitarian value. As problem solving preferences reflects the preference of talking to a human instead of with a chatbot, this seems to indicate that the participant wants to include hedonic values in the conversation as opposed to utilitarian values (Babin et al., 1994). Confusion avoidance influences utilitarian value significantly positive. In order to avoid confusion logically someone will look at factual information which is related to utilitarian value (Hoque et al., 2022).

5.2 Managerial implications

Next to the theoretical implications, the results of this study are a contribution to the practical field as well. The OTA industry is an industry where chatbots can make a huge difference.

Developers of a chatbot in the OTA industry need to note that customer confusion negatively influences the overall customer experience. Therefore, they need to keep the service quality, information quality and system quality in mind so it exceeds the expectation of the customers and positive disconfirmations occur. For example, booking information is clear and easy to find and the booking service does not provide too many choices to prevent customer from being confused. As a result, customers are satisfied and will keep continue using the service provided.

Moreover, a chatbot can function as a constantly updated database for the managers of an OTA. When the chatbot is used often for a specific object during the booking process, the chatbot can gather this information and redirect it towards the managers so they can improve the service provided. For example, if the chatbot identifies that the majority of customers experience difficulties with the payment system, the managers can specifically target this issue.

Finally, the research has provided valuable confirmation that older age groups need to be approached differently than younger age groups when confused during a chatbot encounter. Therefore, managers can consider approaching these groups differently. For example, older people care less about utilitarian value; therefore, a manager can implement indicators so that the chatbot will behave more emotional instead of rational and goal oriented when interacting with these older groups.

5.3 Limitations

Even though, this study provides contributions, it has several limitations. First, the experiment was executed with a non-contextual shopping experience since the data is used for other studies. As a result, a fictional product was used for the experience. Therefore, it was unclear for participants what the product was. As a result, it made participants already confused. This could have affected the results regarding the two different conditions.

Second, an error page was given in both conditions after putting the product in their basket. From the answers on the open-ended questions could be concluded that even though they were in the no confusion condition, they got confused by the error page because the error page already was an unexpected given. Unless the manipulation check was successful, it could have affected the internal validity.

Third, as mentioned, the results of hypotheses H1a and H1b were not significant and not supported which is contrary towards the literature. According to Rosadi & Tjiptono (2013), customer confusion negatively influence the customer experience outcomes. The error page was different for the no confusion and confusion condition; however, the error was solved in

both conditions. As a result, participants could have still felt satisfied and loyal after the experience.

Fourth, since the experiment was conducted at the Radboud University in Nijmegen an age group between 18 and 25 years old mostly participated. In addition, the majority was classified as student. As a result, the experiment is not as representative as it should be.

Fifth, by doing the analysis it became clear that lots of indicators and all the open-ended questions of the construct thoughts needed to be eliminated. As a result, most concepts, except for the closed-ended questions of thoughts, are only explained by one indicator. This decreases the external validity because it is harder to generalize the results to a larger population.

Last, for the construct behaviour, a distinction was made between SIB and reaction time because the loadings scored better. Reaction time was measured in seconds, however how slow or fast someone types was not taken into account. This has resulted in a decrease in reliability and construct validity.

5.4 Future research

Next to the theoretical and managerial implications, several directions for future research are proposed. First, it is recommended to replicate this study using a contextual experiment. As mentioned earlier, the experiment is conducted with a fictional product. Since the results of this study are reflected towards OTA's, it is beneficial to redo the experiment in a context that a participant is booking a hotel via an OTA. This will improve the credibility because participants can empathize more into the shopping experience. In addition, redoing the experiment in other contexts is suggested as well, because the results can be different among industries. For example, in healthcare, retail or e-commerce.

Second, the theory and practice would benefit from analysing the control variables more extensively. From the analysis can be concluded that Alternative3, regarding if someone prefers to talk to a human instead of a chatbot while solving a problem, has a negative significant effect on utilitarian value. This variable was only taken into account to rule out any alternative explanations, but this unexpected effect is interesting to study more in the future regarding chatbots. Moreover, from the literature it is stated that customers with a high tolerance of ambiguity are confused more because they have a reduced ability to understand new situations. Since the control variable tolerance of ambiguity was left out the model after assessing the measurement model it is suggested to look at this personality trait in more depth and to test the existing literature.

Third, because the sentiment analysis may have difficulties by categorizing the answers to the open-ended questions of thoughts it is recommended to conduct qualitative research to evaluate more in-depth the detailed insights about the experience of customers when being confused. Moreover, qualitative research regarding how customers behave would be a beneficial contribution to the literature. It will give a deeper exploration of why participants wanted to refresh the page, cancel, or redo the purchase.

Conclusion

This study provides an understanding of the effects of customer confusion on customer experience, in particular utilitarian value and Seeking Information Behaviour. Moreover, it gives insights about how these experiences mediate the relationship between customer confusion and the customer experience outcomes. The results show that customer confusion does not affect customer satisfaction directly and that it affects customer loyalty positively. In addition, the results show a negative significant mediation effect of utilitarian value on the relationship between customer confusion and customer satisfaction and loyalty. The research question ‘’*How does customer confusion in a chatbot environment influence customer experience and its outcomes?’’* can therefore be answered with customer confusion negatively influences the customer experience and as a result decreases the satisfaction and loyalty.

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Appendix

Appendix A: Script experiment

1. Please interact with our Radboud shopping bot as you would normally in an online environment –
2. Hi, I am Cody, and will be your shopping assistant for the day. Before we begin, could you please provide me with your assigned participant ID?
   Participants sends participant ID
3. Great, thank you! How are you doing today?
   a. ***Answer with a positive or neutral expression: ***
      i. Great, let's continue then.
   b. ***Answer with a negative expression: ***
      ii. That is unfortunate. I still hope you can help me out, let's continue.
   c. ***Completely inappropriate answer: ***
      iii. Okay, thank you for sharing, let's continue.
4. I am thankful that you are helping me today to improve my design. As a shopping bot my purpose is to enhance your shopping experience and help you complete a purchase. Let's start shopping, I will provide you with a link to a website where we can make the purchase.
5. Send link for specific condition.
6. ***Delete the link when they have entered the site***
   a. ***When asking why the link was deleted*:**
      i. The link has expired, but you can still continue on the website.
   b. ***When asking what to do***
      iv. Please add the purchase to your basket.
7. *Wait for the error screen AND for the participant to contact shopping bot*
   a. ***Not respond within 1 min of encountering the error***:
      v. Oops something went wrong with adding the item to your basket 😕. Please send me the error number you see on the screen so I can try to solve the error for you.
   b. ***Asks what they should do/ask for a number for the first time*:**
      vi. It seems you stumbled upon an error when adding the item to your basket. Please send me the error number you see on the screen so I can try to solve the error for you.
   c. ***Asks again for clarification etc. *:**
      vii. I cannot provide further assistance without you providing me with the error number you see. Please send me the error number you see on the screen so I can try to solve the error for you.

*IF NON-CONFUSION: * ***Accept any code/number the participants answers***
*IF CONFUSION:

8. ***3x when they send a number***
   a. I am unable to use this number, please provide me with an alternative displayed error number so I can try to solve the error for you.
   b. ***If the participant repeats the same number(s) *:**
      i. You have already provided me with this number, but I am unable to use it. Please provide me with an alternative displayed error number so I can try to solve the error for you.
9. I think I managed to sort the problem out, can you please confirm to me if the purchase has been completed by checking this link https://shorturl.at/DFY47
10. ***Wait for the participant to confirm ***

a. *** If participant does not respond within 30 seconds *:**
Is there something wrong? I am confident that I managed to fix the error for you, can you please check this link and confirm https://shorturl.at/DFY47

11. *** If participant confirms the purchase has been made *:**
    a. Great to hear, it looks like we managed to resolve the issue together. To learn from this experience and help me improve for the next time, please help me in answering some questions. I would like you to reflect on your shopping experience with me. Please tell me how strongly you agree or disagree with my upcoming questions by typing in the corresponding numbers (when applicable). Let's get started.
12.
    a. ***When answering in another way than a number*:**
        ix. I was expecting a number, please reply to me with the respective number indicating your closest choice.
    b. ***When participant answer off scale for example "8" *:**
        x. Your choice is not reflected in the answer possibilities, please reply to me with the respective number indicating your closest choice.
    c. ***When participant don't understand question***:
        xi. I am afraid I am unable to provide you with further assistance. Please answer with the best of your abilities.
13. How strongly do you agree that the more information you sought, the harder it seemed to complete the purchase?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
14. Ok, and to what extent do you agree that the provided information was clear enough to complete the purchase?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
15. I see, and how strongly do you agree with: the information provided was so ambiguous that you often felt confused?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
16. Alright, and to what extent do you agree: that seeking more information made completing your purchase less confusing?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
17. Ok and moving on, to what extent do you agree that you had enough time to complete the purchase?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
18. Sounds good, and how strongly do you agree that you felt like you were under time pressure while making the purchase?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
19. Interesting… and to what extent do you agree that the presence of a timer made you feel rushed during the purchase?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
20. Ok, thank you for sharing. To help me further, please take me through what you were thinking as you were attempting to help me resolve the purchase error we encountered.
21. I see, and what actions crossed your mind in the process of resolving this error?
22. That is insightful thank you, and would you please elaborate by telling me what was valuable in achieving the outcome of the shopping experience and how?
23. I see, so to what extent do you agree that we have accomplished what we wanted from this purchase?

(1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree

24. Got it, and to what extent do you agree that we were effective in completing the purchase?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
25. Good, and to what extent do you agree that the way the error was resolved was useful?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
26. Moreover, how strongly do you agree that this shopping experience with me was valuable?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
27. Thank you for sharing, now in relation to how you felt, please tell me a bit about your feelings while attempting to help me resolve the purchase error.
28. Got it! And could you now please describe your overall feelings about the shopping experience outcome?
29. I see thank you for elaborating, so overall your shopping experience was …
    (1 = Extremely Displeasing, 2 = Very Displeasing, 3 = Moderately Displeasing, 4 = Slightly Displeasing, 5 = Neutral, 6 = Slightly Nice, 7 = Moderately Nice, 8 = Very Nice, 9 = Extremely Nice)
30. Clear, and in the end, how pleasant was your shopping experience?
    (1 = Extremely Unpleasant, 2 = Very Unpleasant, 3 = Moderately Unpleasant, 4 = Slightly Unpleasant, 5 = Neutral, 6 = Slightly Pleasant, 7 = Moderately Pleasant, 8 = Very Pleasant, 9 = Extremely Pleasant)
31. Got it, and how agreeable or disagreeable would you say your whole shopping experience was?
    (1 = Extremely Disagreeable, 2 = Very Disagreeable, 3 = Moderately Disagreeable, 4 = Slightly Disagreeable, 5 = Neutral, 6 = Slightly Agreeable, 7 = Moderately Agreeable, 8 = Very Agreeable, 9 = Extremely Agreeable)
32. Thanks for that, so this shopping experience left you feeling...
    (1 = Extremely Sad, 2 = Very Sad, 3 = Moderately Sad, 4 = Slightly Sad, 5 = Neutral, 6 =Slightly Happy, 7 = Moderately Happy, 8 = Very Happy, 9 = Extremely Happy)
33. Thanks for sharing how you felt with me. So as an outcome, to what extent would you say that you are satisfied with the shopping experience?
    (1) Strongly Dissatisfied (2) Dissatisfied (3) Somewhat Dissatisfied (4) Neither Dissatisfied nor Satisfied (5) Somewhat Satisfied (6) Satisfied (7) Strongly Satisfied
34. Ok, and how likely is it that you would use this shopping experience again?
    (1) Highly Unlikely (2) Unlikely (3) Somewhat Unlikely (4) Neither Unlikely nor Likely (5) Somewhat Likely (6) Likely (7) Strongly Likely
35. Thanks for sharing, and how likely is it that you would tell a friend or colleague about this shopping experience?
    (1) Highly Unlikely (2) Unlikely (3) Somewhat Unlikely (4) Neither Unlikely nor Likely (5) Somewhat Likely (6) Likely (7) Strongly Likely
36. Thank you and moving on, to what extent do you agree that you prefer situations in which there is some ambiguity?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
37. Alright, and how strongly would you agree that you enjoy tackling problems that are complex enough to be ambiguous?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
38. Great, and to what extent do you agree that you generally prefer novelty to familiarity?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
39. Got it, and to what extent do you agree that providing clear information is the basis for avoiding confusion?

(1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree

40. Ok, and to what extent do you agree that you want to see unambiguous information when resolving confusing issues occurring in shopping experiences?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
41. Moreover, to what extent do you agree that you enjoy tackling issues pertaining to confusion occurring from ambiguous information?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
42. Almost done, a few questions more. To what extent do you agree that I behaved like an automated assistant?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
43. Got it, and to what extent do you agree that you sensed something in your surroundings that hindered you from fully concentrating on your experience with me?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
44. Alright, and to what extent do you agree that you would have preferred chatting to a human agent as opposed to me when encountering the error we had?
    (1) Strongly Disagree (2) Disagree (3) Somewhat Disagree (4) Neither Disagree nor Agree (5) Somewhat Agree (6) Agree (7) Strongly Agree
45. Thank you so much for sharing this with me, a few last questions before you go. Compared to how you felt starting this experience with me, how would you describe feeling now? Can you elaborate on why you feel this way?
46. Thank you for elaborating, can you please provide me with your age?
47. Ok, before you go, what is the gender you identify with the most?
    (1) Male, (2) Female, (3) Other, (4) Prefer not to say.
48. Thank you for participating and being patient with me! This is the end of the experience. Please do not close any windows, stay seated, and wait till someone helps you.

Appendix B: Definition of constructs

Table 1: *Constructs*

Main concept	Construct	Definition	Source
	Customer confusion	When continuous cognitive work is interrupted by novel or unexpected circumstances that cannot be instantly resolved or integrated into existing mental models.	(Blum et al., 2020)
Thoughts	Utilitarian Value	The value that a customer receives based on a task-related and rational consumption behavior	(Babin et al., 1994)
Behaviour	Reaction time	The period between the stimulation to a subject and the subject's response	(Pachella, 2021)
	Seeking information behavior	The purposive seeking for information as a consequence of a need to complete some goal.	(Tubachi, 2018)
Customer experience outcomes	Customer Satisfaction	The product or service exceeds the expectations of a customer.	(Oliver, 1980)
	Customer loyalty	To what extent customers keep using the product or service even when alternatives are around	(Ludin & Cheng, 2014)

Appendix C: Operationalization

Table 2: *Operationalization of key concepts, control variables and manipulation check*

Main concept	Construct	Description	Measurement level	Source
Thoughts	Utilitarian value	To what extent do you agree that we have accomplished what we wanted from this purchase?	Seven-point Likert scale	(Babin et al., 1994)
		To what extent do you agree that we were effective in completing the purchase?	(1 = strongly disagree, 7 = strongly agree)	
		To what extent do you agree that the way the error was resolved was useful?		
		How strongly do you agree that this shopping experience with me was valuable?		
	Utilitarian value	Please take me through what you were thinking as you were attempting to help me resolve the purchase error we encountered.	Open questions	
		What actions crossed your mind in the process of resolving this error?		
		What was valuable in achieving the outcome of the shopping experience and how?		
Behaviour	Seeking Information Behaviour	Button clicks	Amount of clicks on information button	
		Asking for help	Total counts for asking help to the chatbot	
	Reaction time	Error page (the periode between the moment the error page appeared and the first reponse of the participant)	In seconds	
		Error message (the period between that the chatbot send the error message and the reponse of the participant)		
Customer experience outcomes	Customer satisfaction	To what extent would you say that you are satisfied with the shopping experience?	Seven-point Likert scale	
	Customer loyalty	How likely is it that you would use this shopping experience again?	Seven-point Likert scale (1 = Highly Unlikely, 7 = Strongly Likely)	Reichheld, 2004)
		How likely is it that you would tell a friend or colleague about this shopping experience?		
Control variables	Age	Can you please provide me with your age?		
	Gender	What is the gender you identify with the most? Male, (2) Female, (3) Other, (4) Prefer not to say		
	Tolerance for ambiguity	To what extent do you agree that you prefer situations in which there is some ambiguity?	Seven-point Likert scale (1 = Highly Unlikely, 7 = Strongly Likely)	McLain (2009)
		How strongly would you agree that you enjoy tackling problems that are complex enough to be ambiguous?		
		To what extent do you agree that you generally prefer novelty to familiarity?		
	Confusion avoidance	To what extent do you agree that providing clear information is the basis for avoiding confusion?	Seven-point Likert scale (1 = Highly Unlikely, 7 = Strongly Likely)	(Schweizer et al., 2006)
		To what extent do you agree that you want to see unambiguous information when resolving confusing issues occurring in shopping experiences?		
		To what extent do you agree that you enjoy tackling issues pertaining to confusion occurring from ambiguous information?		
Manipulation check	Confusion	How strongly do you agree that the more information you sought, the harder it seemed to complete the purchase?	Seven-point Likert scale	(Sprotles & Kendall, 1986)
		To what extent do you agree that the provided information was clear enough to complete the purchase?	(1 = strongly disagree, 7 = strongly agree)	
		How strongly do you agree with: the information provided was so ambiguous that you often felt confused?		
		To what extent do you agree: that seeking more information made completing your purchase less confusing?		

Appendix D: Confirmatory Factor Analysis

Table 4: *Values HTMT*

	Age	Alternative1	Alternative2	Alternative3	Confusion	CA	Gender	Loyalty	Reactiontime	Satisfaction	Seeking info	Thoughts	ToA
Age													
Alternative1	0.133												
Alternative2	0.053	0.065											
Alternative3	0.196	0.080	0.121										
Confusion	0.048	0.016	0.097	0.299									
CA	0.025	0.028	0.018	0.079	0.064								
Gender	0.058	0.031	0.028	0.075	0.004	0.045							
Loyalty	0.247	0.066	0.002	0.382	0.232	0.088	0.081						
Reactiontime	0.030	0.061	0.012	0.104	0.532	0.012	0.076	0.065					
Satisfaction	0.245	0.070	0.017	0.423	0.311	0.028	0.040	0.782	0.121				
Seeking info	0.039	0.009	0.019	0.213	0.404	0.297	0.022	0.353	0.157	0.350			
Thoughts	0.236	0.049	0.020	0.522	0.446	0.178	0.064	0.823	0.127	0.830	0.489		
ToA	0.013	0.060	0.010	0.069	0.081	0.060	0.056	0.052	0.008	0.072	0.118	0.104	

Table 5: *Values Fornell-Larcker*

	Age	Alternative1	Alternative2	Alternative3	Confusion	CA	Gender	Loyalty	Reactiontime	Satisfaction	Seeking info	Thoughts	ToA
Age	1.000												
Alternative1	-0.133	1.000											
Alternative2	0.053	-0.065	1.000										
Alternative3	0.196	0.080	0.121	1.000									
Confusion	0.048	-0.016	-0.097	0.299	1.000								
CA	0.025	0.028	0.018	0.079	-0.064	1.000							
Gender	0.058	0.031	0.028	-0.075	-0.004	0.045	1.000						
Loyalty	-0.247	0.066	-0.002	-0.382	-0.232	0.088	0.081	1.000					
Reactiontime	0.030	-0.061	0.012	0.104	0.532	0.012	0.076	-0.065	1.000				
Satisfaction	-0.245	0.070	0.017	-0.423	-0.311	0.028	0.040	0.782	-0.121	1.000			
Seeking info	-0.039	0.009	-0.019	0.213	0.404	-0.297	-0.022	-0.353	0.157	-0.350	1.000		
Thoughts	-0.206	-0.001	-0.017	-0.464	-0.391	0.158	0.043	0.742	-0.107	0.747	-0.435	0.782	
ToA	-0.013	0.060	0.010	-0.069	-0.081	0.060	0.056	0.052	0.008	0.072	-0.118	0.069	1.000

Table 6: *Outer loadings*

	Age	Alternative1	Alternative2	Alternative3	Confusion	CA	Gender	Loyalty	Reactiontime	Satisfaction	Seeking info	Thoughts	ToA
Age	1.000												
Alternative1		1.000											
Alternative2			1.000										
Alternative3				1.000									
Confusion					1.000								
CA_1						1.000							
Gender							1.000						
Ractiontime_2									1.000				
Satisfaction										1.000			
Loyalty								1.000					
Seekinginfo											1.000		
Thoughts_C1												0.686	
Thoughts_C2												0.786	
Thoughts_C3												0.757	
Thoughts_C4												0.887	
ToA_1													1.000

Appendix E: Serial mediation analysis results

Table 7: *Results serial mediation by SmartPLS*

Predictors	*R2*	*coeff (b)*	*t*	*p*
Outcome: Customer satisfaction	.591			
Customer confusion (H1a)		0.075 NS	0.559	**0.288**
Thoughts		0.685	11.566	0.000
Reaction time		-0.042	0.682	0.248
Seeking information		-0.072	1.011	0.156
Age		-0.082	1.555	0.060
Gender		0.022	0.228	0.410
Confusion avoidance		-0.093	1.431	0.076
ToA		0.013	0.268	0.394
Alternative1		0.070	1.183	0.118
Alternative2		0.053	1.094	0.137
Alternative3		-0.084	1.513	0.065
Outcome: Customer loyalty	*.580*			
Customer confusion (H1b)		0.240	1.934	**0.027**
Utilitarian value		0.706	14.205	0.000
Reaction time		-0.030	0.534	0.297
Seeking information		-0.095	1.642	0.050
Age		-0.096	1.830	**0.034**
Gender		0.107	1.141	0.127
Confusion avoidance		-0.041	0.780	0.218
ToA		-0.007	0.127	0.449
Alternative1		0.061	1.097	0.136
Alternative2		0.035	0.691	0.245
Alternative3		-0.050	0.839	0.201
Outcome: Utilitarian value	.329			
Customer confusion (H2)		-0.521	4.488	**0.000**
Age		-0.125	1.842	**0.033**
Gender		0.025	0.205	0.419
Confusion avoidance		0.172	1.766	**0.039**
ToA		0.009	0.150	0.440
Alternative1		0.003	0.049	0.480
Alternative2		0.006	0.093	0.463
Alternative3		-0.374	6.110	**0.000**
Outcome: Seeking info	.324			
Customer confusion (H3a)		0.529	3.747	**0.000**
Utilitarian value (H4)		-0.301	3.991	**0.000**
Age		-0.116	1.847	0.032
Gender		0.029	0.234	0.408
Confusion avoidance		-0.229	1.433	0.076
ToA		-0.062	0.981	0.163
Alternative1		0.005	0.087	0.465
Alternative2		0.009	0.130	0.448
Alternative3		0.030	0.452	0.326
Outcome: Reactiontime	.311			
Customer confusion (H3b)		1.157	11.433	**0.000**
Utilitarian value		0.119	1.630	0.052
Age		0.014	0.224	0.411
Gender		0.135	1.150	0.125
Confusion avoidance		0.030	0.381	0.351
ToA		0.044	0.737	0.230
Alternative1		-0.049	1.018	0.154
Alternative2		0.068	1.110	0.133
Alternative3		-0.026	0.345	0.365
Indirect effect(s) of X on Y				
CC -> UV -> CS (H5)		-0.357	4.115	**0.000**
CC -> UV -> CL (H5)		-0.368	4.179	**0.000**
CC -> SIB -> CS (H6)		-0.038	0.872	0.191
CC -> SIB -> CL (H6)		-0.050	1.455	0.073

Note. sample size = 200; Y: CS (Customer Satisfaction), CL (Customer Loyalty);
X: CC (customer confusion); M1: UV (utilitarian value); M2: SIB (Seeking Information Behaviour);
Covariates: age, gender, confusion avoidance, ToA (Tolerance for ambiguity), Alternative 1 (credibility);
Alternative2 (distraction), Alternative2 (problem solving preference)

Appendix F: Codes generated for construct Thoughts

Table 8: *Codes Question 1 by Atlas*

NC	Counts	C	Counts
Anxiety	3	Ambiguity	1
Autonomy	1	Anxiety	1
Clarity	2	Assistance	1
Communication	2	Clarity	6
Confusion	21	Confusion	31
Control	2	Criticism	2
Convenience	1	Difficulty	4
Curiosity	1	Efficiency	1
Customer satisfaction	2	Effort	1
Customer service	1	Feedback	1
Decision making	1	Forgetfulness	1
Dependency	1	Frustration	21
Doubt	4	Helpful	2
Ease of use	1	Indifference	1
Efficiency	9	Insecurity	1
Expectation of expertise	1	Irritation	1
Fear	1	Mistake	3
Frustration	3	Misunderstanding	13
Gratitude	4	Negative emotions	1
Helpful	1	Overwhelmment	1
Impatience	1	Persistence	1
Impersonal communicat	1	Precision	1
Inadequate support	1	Problem-solving	5
Indecision	1	Regret	1
Insecurity	1	Relief	1
Lack of clarity	2	Request	1
Misunderstanding	2	Resourcefulness	1
Negative emotions	1	Self-blame	1
Order processing	5	Skepticism	1
Performance pressure	1	Stress	1
Problem-solving	13	Success	1
Questioning	2	Suggestion	1
Request for assistance	2	Surprise	1
Rushing	1	Technical issues	4
Technical issues	3	Time pressure	2
Uncertainty	6	Uncertainty	10

Note. Codes for Q1: Please take me through what you were thinking as you were attempting to help me resolve the purchase error we encountered; NC = No confusion; C = Confusion

Table 9: *Codes Question 2 by Atlas*

NC	Counts	C	Counts
Anticipation	1	Ambivalence	1
Anxiety	3	Anger	1
Attempt	1	Annoyance	1
Autonomy	1	Anxiety	3
Clarity	1	Attention to detail	10
Communication	4	Challenges	16
Communication	1	Clarity	5
Confusion	15	Communication	2
Convenience	1	Confusion	41
Curiosity	1	Criticism	2
Customer experience	7	Determination	1
Customer satisfaction	2	Difficulty	4
Customer service	1	Doubt	1
Doubt	2	EmotionalStates	4
Ease of use	1	Failure	1
Efficiency	4	Forgetfulness	1
Expectation	1	Frustration	24
Expectation of	1	Gratitude	1
Experience	1	Improvement needed	1
Frustration	4	Incompetence	1
Gratitude	3	Inefficiency	1
Helpfulness	1	Insecurity	1
Impatience	1	Lack of clarity	21
Inadequate support	1	Miscommunication	5
Insecurity	1	Mistake	3
Lack of explanation	2	Misunderstanding	5
Misunderstanding	1	Persistence	1
Negative emotions	1	Pressure	1
Obeying orders	1	Problem-solving	10
Performance pressure	1	Regret	1
Practicality	1	Resilience	6
Problem solving	20	Seeking information	3
Questioning	1	Self-Efficacy	1
Seeking information	17	Shopping	1
Speed	1	Skepticism	1
Spontaneity	1	Stress	1
Surprise	3	Suggestion	1
Technical Issue	2	Surprise	1
Time pressure	6	Technical issue	11
Uncertainty	5	Technical support	16
		Uncertainty	10

Note. Codes for Q2: What actions crossed your mind in the process of resolving this error?; NC = No confusion; C = Confusion

Table 10: *Codes Question 3 by Atlas*

NC	Counts	C	Counts
Achievement	1	Annoyance	1
Admiration	1	Appreciation	5
Annoyance	1	Communication	2
Apathy	1	Completion	1
Appreciation	4	Confusion	6
Clarity	4	Criticism	2
Comfort	1	Customer support	24
Confirmation	1	Disinterest	1
Confusion	2	Dissatisfaction	7
Consumer behavior	1	Distrust	2
Convenience	1	Encouragement	1
Customer satisfaction	10	Frustration	3
Dependency	1	Gratitude	7
Distrust	1	Indifference	1
Ease of use	3	Ineffectiveness	1
Efficiency	15	Negative sentiment	1
Frustration	2	Politeness	1
Gratitude	8	Positive attitude	1
Helpfulness	2	Preference for human in	1
Impulsivity	1	Problem-solving	2
Lack of motivation	1	Request for clarification	4
Mistake	1	Resignation	1
Misunderstanding	1	Skills	10
Problem-solving	3	Uncertainty	4
Regret	1		
Surprise	1		
Technical Problems	2		
Technology	1		
Uncertainty	1		

Note. Codes for Q3: What was valuable in achieving the outcome of the shopping experience and how?; *NC = No confusion; C = Confusion*