

**The Impact of Information-Seeking Strategies and Social Presence on the Interaction between  
Customers and Conversational Agents**

**Thai Ha Nguyen**

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**Department of Business Information Systems  
Faculty of Business, Economics and Law**

**Primary Supervisor: Dr Lena Waizenegger  
Secondary Supervisor: Dr Angsana Techatassanasoontorn**

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## ATTESTATION OF AUTHORSHIP

"I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgments) nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning."

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## ABSTRACT

Many organisations in different industries have jumped on the bandwagon and implemented conversational agents (CAs) to support customer service operations. Although CAs are found to offer many benefits to their customers, they also pose various challenges, which raises several concerns about their effectiveness. Many CA implementation projects have failed to meet initial expectations. This high failure rate in CA implementation indicates a lack of understanding about customer-CA interactions. Therefore, it is necessary to understand how the interactions take place and why many of them fail, in order to close the gap between organisations' expectations and the actual performance of CAs.

This study takes a close look at the role of information-seeking strategies and social presence in shaping the interaction process by investigating the nature of customer-CA interactions and their success and failure factors. The following research question was addressed: "How do information-seeking strategies and social presence shape the outcome of interactions between customers and conversational agents?" Informed by the social information seeking model and the concept of social presence, this research examined the effects of information-seeking strategies and social presence on how interaction outcomes are shaped. The analysis involved investigating the interaction logs of 507 conversations between customers and a chatbot, which is a form of CAs that communicate with customers using text-based messages. The chatbot was implemented on the website of an electric power company to serve customer online services. By taking an abductive qualitative research approach and adopting a configurational thinking methodology, the researcher identified five distinct information-seeking strategies that customers used to interact with CAs: complete-sentence strategy, fragmented strategy, keyword search strategy, FAQ strategy and social reciprocity strategy. These strategies represent configurations of four interrelated factors that influence the strategy selection: context-related factors, goal-related factors, information-related factors, and technology-related factors.

The selected strategies were found to reciprocally interact with the degree of social presence to form outcomes. Factors involved in the interplay are indicated as those that contribute to the success and failure of the customer-chatbot interactions. This study proposes a process model that illustrates the interplay between information-seeking strategies and social presence in customer-chatbot interactions. This explains the intricate interplay of the various factors in shaping the interaction outcomes.

**Keywords:** conversational agents; customer-conversational agent interaction; information-seeking strategies; social presence.



## 1. INTRODUCTION

We are in the midst of the cognitive era, in which cognitive technology has been transforming every aspect of humans' lives. Cognitive technology is defined as the approach of humanising machines by mimicking humans' ways of thinking (Hurwitz, Kaufman, and Bowles, 2015). The evolution of cognitive technology resulted from the rapid development of processing power, Big Data, and artificial intelligence (AI) (Raub, 2018). The advancements in AI in particular, have empowered cognitive technology to learn continuously and reason (Sangaiah, Thangavelu, and Sundaram, 2018), which has created a leap in machines' cognition processing. The infusion of AI in many applications supports countless daily life activities of its users. For instance, AI-based virtual assistants, Google Home and Amazon Alexa, can accomplish tasks with minimal human intervention, including switching on devices, retrieving data, or reading notifications. Another example is the intelligent tutoring system, AutoTutor, which provides students with one-on-one tutorial sessions (Graesser, Lu, Jackson, Mitchell, Ventura, Olney, and Louwerse, 2004).

In recent years, AI-enabled technologies are experiencing a high uptake, in which they are being utilised to optimise business process automation, predominantly in customer self-service. Organisations across industries have implemented these technologies, especially conversational agents (CAs), to enhance their interactions with customers. CAs are known as intelligent autonomous systems that can emulate human communication behaviours (Cassell, 2000; Graesser, Li, and Forsyth, 2014; Radziwill and Benton, 2017). In the literature, there are a plethora of terms referring to CAs, such as chatbots, virtual assistants, digital assistants, and embodied conversational agents (Waizenegger, Seeber, Dawson, and Desouza, 2020). The various terms for the same technology make it hard to follow the discussion in this research field. Therefore, in this study, 'conversational agents' (CAs) will be used as an umbrella term when referring to the AI-technology that has the ability to communicate with humans using natural language.

Being known for their capability of sensing, information processing, decision-making, and learning to adapt to their contexts (Seeber, Waizenegger, Seidel, Morana, Benbasat, and Lowry, 2019), CAs are implemented into many organisations' online portals, such as websites or social media, to facilitate different customer service functions. This online implementation allows customers to easily connect with the organisations and get their queries addressed with minimal human agent intervention and a shorter response time. Since they are available 24/7, act autonomously, quickly process information and maintain a broad knowledge base (Beun, De Vos, and Witteman, 2003; Cassell, Bickmore, Campbell, and Vilhjálmsón, 2000; Gnewuch et al., 2017; Roda, Angehrn, Nabeth, and Razmerita, 2003), customers can have their problems solved at any time or even let the CAs make decisions on their behalf. Overall, CAs

serve as an online service assistant that empowers customers with decision-making, reduces their purchasing efforts, and offers them with a high-speed and personalised experience (Birnbbaum, 2019; Goasduff, 2020).

Due to several benefits that CAs are promised to bring, more and more organisations across industries, such as airlines, banking, retail, and tourism, have started to implement CAs to their service operations. Predominantly, customers use CAs as a search engine to help them seek information related to their services (Xu, Liu, Guo, Sinha, and Akkiraju, 2017). Their ability to understand human natural language enables CAs to identify customers' information needs and provide appropriate information. For instance, Air New Zealand's chatbot, 'Oscar,' that was implemented in 2017, is well-known for its ability to help customers to search for flight schedules, book flight tickets and navigate them to the information source. Another example is 'Jamie' – a CA implemented by ANZ Bank to help customers with answering frequently asked questions. The growth in the number of CA use cases does not show any signs of slowing down.

As the interaction between customers and CAs takes place, there are some social aspects that catch the attention of researchers, especially the manifestation of social presence. Social presence is defined as the extent to which a social actor is perceived as "real" by the others (Gunawardena, 1995). In the customer-CA communication context, the social presence concept reflects how real the CA is from the customer's perspective. Several studies found the positive impacts of social presence on customer experience (Choi, Lee, and Kim, 2011; Hess, Fuller, and Campbell, 2009; Li and Mao, 2015), such as increasing customer satisfaction, affinity, intention to use and follow the CAs' recommendations. Social presence is triggered by the exchange of social cues between customers and the CAs. CAs were found to use both verbal and non-verbal social cues while interacting with customers (Cassell, 2000; Cassell, Sullivan, Churchill, and Prevost, 2000; Han, Campbell, Jokinen, and Wilcock, 2012). These social cues, such as self-referencing, voice and gesture, can positively influence customer perception and elicit reciprocal behaviour towards the CA (Benbasat, Dimoka, Pavloi, and Qiu, 2020; Diederich, Lembcke, Brendel, and Kolbe, 2020; Morana, Gnewuch, Jung, and Granig, 2020). Non-verbal social cues were claimed to have dominant effects on customer engagement and affinity, compared to verbal cues (Wagner, Nimmermann, and Schramm-Klein, 2019). Based on the type of social cues used, CAs are broadly classified into two categories: embodied CAs and text-based CAs. While text-based CAs can only interact with users through text-based inputs, embodied CAs designed with body movements and sophisticated interfaces can communicate with their users using speech, gestures and facial expressions. With a wider range of embedded non-verbal cues, such as voice pitch, appearance, displayed gender and body movements,

embodied CAs attract more attention from customers, increasing their engagement, and eliciting more social responses (Cassell, 2001; Morana et al., 2020; Lee and Marsella, 2006). Unlike embodied CAs, text-based CAs attract customers through their conversational functionalities (Adam and Klumpe, 2019; Meyer von Wolff, Hobert, and Schumann, 2019). Many scholars, however, believe that there are several aspects that text-based CAs need to improve in order to achieve a higher degree of human-likeness (Araujo, 2018; Diederich, Brendel, Lichtenberg, and Kolbe, 2019; Liu, Xu, Sun, Wang, Wang, Wong, and Zhang, 2018). Regardless of which type of social cues are used, CAs, in general, are designed to carry out conversations with customers and provide them with adequate support.

Despite the many promising benefits that CAs are predicted to bring, many CA implementation projects have failed to meet the original expectations of organisations (Bryan, 2019). This high failure rate indicates a lack of understanding of customer-CA interactions. While the number of online consumers is increasing, along with the rising number of CA implementation, it is important to understand how the customer-CA interactions take place and why many of them have failed. By examining the role of information-seeking strategies and social presence in the interactions, this study is intended to investigate the nature of customer-CA interactions and identify their success and failure factors. In doing so, the following research question is addressed: “How do information-seeking strategies and social presence shape the outcome of interactions between customers and conversational agents?”

Based on the insights from the open coding that was conducted in the first phase of the data analysis, adequate theories were searched to further analyse and explain the patterns that emerged from the data. As a result, the social information seeking model (Ramirez, Walther, Burgoon, and Sunnafrank, 2002) and the concept of social presence (Schultze and Brooks, 2019) were deemed as suitable theoretical lenses that guided the further analysis of this study. Informed by the two theoretical lenses, this study was conducted to develop a more refined understanding of the nature of customer-CA interactions. Findings derived from this study will contribute to the body of knowledge of empirical research on human-technology interactions. It extends existing studies by explaining (i), which factors influence the information-seeking strategies and (ii), how the use of information-seeking strategies and social presence lead to different interaction outcomes. Moreover, this study also makes some practical implications that could be found useful by customers, organisations that are using CAs and those intending to implement them. It provides customers with an overview of how interacting with CAs might look and which strategies can be used to best utilise them. From the findings of this study, organisations can understand how a typical customer-CA interaction takes place and which factors contribute to its success or failure. This

understanding is important for organisations to increase the success rate of their CA implementation projects.

The rest of this study is structured as follows. Chapter 2 presents extant literature about CAs, their applications and their interactions with customers. Chapter 3 introduces the theoretical lenses, social information-seeking process model and the concept of social presence, and outlines the integrated model that will be used to guide the data analysis procedures. The research methodology and approach adopted for data analysis are explained in Chapter 4. Chapter 5 reflects the patterns derived from the data, findings of which are deliberated in Chapter 6, along with the theoretical and practical contributions of the study. Chapter 7 concludes this study by outlining limitations and suggests avenues for future research.

## 2. LITERATURE REVIEW

### 2.1. Conversational agents (CAs)

In the literature, a plethora of different definitions for CAs can be found. These definitions also depend on which context the CAs are used. For the ease of discussion, this study refers to the definition by Cassell (2000) that defines CAs as intelligent systems that can simulate human behaviours in communication, including speaking, facial expressions, and body gestures. There are various types of CAs, ranging from simple text-based chatbots to sophisticated embodied digital assistants. Along with an increase in the diversity of CA is the rising number of organisations that have jumped on the bandwagon and utilised them to enhance their service quality. The growing demand for fast customer service requires organisations to pay close attention to their customers' experience, especially with their newly implemented CAs. Concerning their high uptake, CAs are promised to help organisations run their services without human intervention (Moore, 2018).

### 2.2. CAs in customer self-service

Although customer experience is considered to be a core factor in achieving competitive advantages, many organisations show a lack of understanding of how their customers perceive their services (Meyer and Schwager, 2007). This gap implies that it requires more than their current effort to achieve customer satisfaction. The growing number of digital consumers, i.e. those who demand more advanced technologies to facilitate their purchase of products and services, has expanded the means available to communicate with organisations, such as emails, online chat and live support (McGinnis, 2019). To reduce the increasing pressure on front-line staff and the queuing time of customers, organisations have increased their self-service offerings, allowing customers to resolve their own issues. The benefits of online self-service have been acknowledged for providing real-time support and a quick resolution (Grewal, Levy, and Kumar, 2009; Scherer et al., 2015). Leveraging the advances of AI-based technology, organisations have implemented CAs to their websites, social network platforms and mobile apps to boost their self-service channels. The list of cases using them range from simple text-based chatbots, like Google Assistant, to embodied CAs with animated movements, such as ASB's Josie. Among them, chatbots are the most common form of CAs, which are well-known for their ease of use, allowing users to interact using simple text-based inputs (Choque-Diaz, Armas-Aguirre, and Shiguihara-Juarez, 2018). It can be customised and integrated into several platforms easily, enabling organisations to connect with more customers from the channels that they are already using, like Facebook Messenger (Batish, 2018). Embodied CAs are more sophisticated compared to chatbots as they are equipped with facial and body movement features. They not only communicate through text messaging, but they can also exchange information with their users

via speech. Either getting chatbots, embodied CAs, or any other forms of CA, the implementations promise to provide a tailored experience and enhance customer engagement with the brands (Sneiders, 2009; Zhu, Nakata, Sivakumar, and Grewal, 2007).

Although chatbots possess fewer advanced characteristics, they are still taking up \$2.6 billion of the market size in 2019 (Nguyen, 2020). Chatbots are user-friendly, easy to build and are compatible with several platforms, which allows chatbot-designers to implement them on multiple channels that have already been used by many customers, such as text messages, companies' websites, or Facebook Messenger. Due to the beneficial characteristics, chatbots have become the most commonly used CAs in customer self-service. Nowadays, compared to other forms of CAs, like embodied CAs, chatbots with their ease of use and flexibility have been implemented by increasingly more organisations. Despite the benefits that CAs have promised to offer, there has been a high failure rate of CA implementation, including chatbots. In 2017, Facebook Messenger's chatbots failed to handle 70% of customer requests (CB Insights, n.d.). Moreover, about 25% of organisations that had already implemented AI solutions, such as chatbots, reported a 50% failure rate in 2019 (Press, 2019). In order to reduce this undesirably high failure rate, it is important for organisations to understand what causes the failure in their chatbot implementation. Therefore, this study was intended to examine the use of chatbots to gain a sound understanding about how the interaction between customers and chatbots take place and how the success or failure of the outcome of the interaction is shaped.

### 2.3. Benefits and challenges of CAs

CAs have been offering organisations and customers many benefits alongside some inevitable challenges. Exploring the advantages of utilising CAs, Meyer von Wolff, Hobert, and Schumann (2019) conducted a literature review listing their fundamental functionalities and benefits, which includes supporting information seeking, automating customer self-service, assisting education, supporting training processes, and facilitating collaborative works. The high uptake of CA, especially in the customer service context, directed research attention towards their beneficial characteristics, especially the ability to communicate in different social contexts naturally.

Authors found that human-like sociability, autonomy, and quick resolution are the main useful characteristics that make CAs attractive to support online customer self-service. Firstly, human-like social behaviours of CAs are demonstrated by their ability to store their users' personal information and adapt their language style to fit users' communication traits (Liu et al., 2018; Wagner, Nimmermann, and

Schramm-Klein, 2019). This characteristic is leveraged to personalise the experience and helps increase customer engagement with organisations. Secondly, the autonomy of CAs has also been discussed in many papers (e.g. Araujo, 2018; Nguyen and Sidorova, 2018; Sullivan, de Bourmont, and Dunaway, 2020). They can respond autonomously to customer's queries and provide adequate issue resolution promptly (Dole, Sansare, Harekar, and Athalye, 2015; Sarikaya, 2017; Trivedi, 2019). Moreover, their 24/7 availability as well as polite attitude have been appreciated by customers (Michaud, 2018; Nuruzzaman and Hussain, 2018). Thirdly, as designed to provide instant online support, CAs can process information quickly and generate pre-programmed responses to address problems. This mechanism empowers CAs to quickly resolve customers' problems, significantly reduce their waiting time and be able to meet their expectations.

On the other hand, there exist some challenges that prevent organisations from achieving successful customer-CA interactions. Poor understanding of conversations, private information insecurity, and the adverse effects of human-likeness were found to be the main challenges in customer service posed by the use of CAs. First, while the sociability of CAs has been widely acknowledged as a huge benefit for companies utilising them, previous studies pointed out CAs' inability to emulate human natural language completely. As customers' intents might vary from context to context, there are cases in which CAs cannot fully capture the intent, misinterpret customers' meaning, and, hence, fail to communicate with customers naturally and fluently (Choque-Diaz et al., 2018; Diederich, Lembcke, Brendel, and Kolbe, 2020). Second, regarding the information security of interactions with CAs, authors were concerned about the vulnerability of customers' personal information provided in the interactions. While examining the technology behind CAs, Sarikaya (2017) also expressed his doubt about their capability to protect customers' personal information provided during the interaction, underscoring how much they should know about their users. Similarly, Følstad, Nordheim, and Bjørkli (2018) found that customers were wary that CAs might leak their personal information. There have been contrasting arguments about the impact of the degree of the CAs' human-likeness on customer experience. Concerning the users' perception of CAs, Skjuve et al. (2019) stated that customers might experience eeriness and repulsion while interacting with them. This reaction can be explained by the phenomenon of the uncanny valley, which refers to the point where the affinity for a technology drops drastically as it gets more human-like (Mori, MacDorman, and Kageki, 2012). The concept of the uncanny valley contrasted with early perspectives regarding the positive relationship between the technological affinity and the degree of human-likeness (Diederich, Brendel, Lichtenberg, and Kolbe, 2019, Wagner et al., 2019). The impacts of the uncanny valley, however,

can be overcome (Mori et al., 2012). Due to the contradictory opinions about the impacts of human-likeness on customer experience, the phenomenon has to be taken into careful consideration when designing CAs. Later studies rejected the effect of the uncanny valley on user affinity, arguing that the human-likeness of a CA is positively associated with customer satisfaction (Diederich et al., 2020; Merkle, 2019; Wagner et al., 2019).

CAs have not only offered more benefits but also posed several challenges to their customers and organisations. Due to these paradoxical views, it is difficult to understand how CAs can add value to the organisations' customer services. This lack of understanding drives the researcher to conduct a further investigation of how CAs interact with customers in order to shed more light on why some customers have a good experience with their CAs, but others do not.

#### 2.4. The nature of interactions with CA

Depending on the context and purpose of usage, people have formed different perceptions about their interactions with CAs. Studies have compared how customers perceive their interaction with CAs and that of human assistants. Customers were found to be more satisfied with their interactions with human staff than with CAs (Stock and Merkle, 2017 and 2018). However, Merkle (2019) argued that customers express greater empathy for CA's service failure and, therefore, are more satisfied with CA's failure recovery compared to that of human staff (Merkle, 2019).

Studies have also identified factors that influence customers' perception of their interactions with CAs. Aspects associated with customer satisfaction are: perceived controllability (Merkle, 2019), perceived irrationality (Abadie, Carillo, Fosso-Wamba, and Badot, 2019), engagement, transparency, informativeness, credibility (Li and Mao, 2015), pleasure, arousal, dominance (Zarouali, Van den Broeck, Walrave, and Poels, 2018), human-likeness (Merkle, 2019; Mou and Xu, 2017; Wagner et al., 2019) and perceived authenticity (Wuenderlich and Paluch, 2017). A CA's perceived usefulness was claimed to have particularly strong impacts on customer satisfaction and the intention to reuse it (Li and Mao, 2015; Stock and Merkle, 2017; Zarouali et al., 2018). Benbasat, Dimoka, Pavlou and Qiu (2020) suggested that customer affinity for CAs followed the rules of the similarity-attraction theory. This theory states that people tend to be attracted by those with whom they share some similarities (Byrne, 1971). Similar to the findings of Benbasat et al. (2020), Wagner et al. (2019) confirms the positive effects of perceived similarities between the CA and its users on a customer's intention to use CA. These perceived similarities could refer to communication styles, personal traits, or mutual interests. For instance, customers were



found to be more engaged with the CAs that have similar internet slang usage patterns (Li and Mao, 2015) or extroverted users could develop good relationships with CAs with extrovert personalities (Lee and Nass, 2003).

While some studies focused on user perceptions formed from one interaction only, others examined customers' perception of CAs after a few conversations. Results revealed that customers are likely to develop close relationships with the CA that they frequently interact with and subsequently gain more trust in it (Abadie et al., 2019; Portela and Granell-Canut, 2017). Higher trust can lead to higher customer affinity and the CA getting delegated to make decisions on behalf of the customer (Morana et al., 2020; Portela and Granell-Canut, 2017; Wagner et al., 2019). Findings derived from these studies indicated that customers were not viewing CAs as a tool but as a social partner, which has invoked a research stream concerning users' social behaviours towards CAs.

#### 2.4.1. Social behaviours towards CAs

Extant research was conducted on discovering how people behave towards the CA in their interactions. Studies found that customers are likely to adapt their communication style, such as language use and topics, to that of the CA (Mou and Xu, 2017; Thies, Menson, Magapu, Subramony, and O'Neill, 2017). By utilising the similarity-attraction theory (Byrne, 1971), Mou and Xu (2017) argued that users prefer to hold some commonalities with their social partners and, therefore, tend to change their communication style to fit with the others. This theory explains why customers have a tendency to adjust their behaviours during interactions with CAs. For instance, customers were found to use more profanities and shorter messages with CAs than with humans (Hill, Ford, and Farreras, 2015). Besides, Mou and Xu (2017) discovered that customers are less open and less confident during their CA encounters.

The sociability of the CA also influences customers' responses. By comparison to interacting with a human counterpart, customers tend to be less truthful when interacting with a responsive embodied CA by providing socially desirable responses instead of their real opinions (Schuetzler, Grimes, Giboney, and Nunamaker, 2018). Another study, however, found that customers have a high propensity for self-disclosing if their CA is able to sustain the conversation through interactive message exchanges (Adam and Klumpe, 2019). These findings suggested that customers' social behaviours towards CAs are diverse and complex, that there is no particular pattern of behaviours in this case.

#### 2.4.2. The impacts of social cues

While many researchers attempted to identify the differences in customers' behaviours towards CAs and other social individuals, the fact that humans tend to treat intelligent machines as social actors has been well-established. Nass, Steur, and Tauber (1994) who developed the Computer as Social Actors (CASA) paradigm proposed that social cues generated by computers can elicit mindless social responses in humans. These social cues are defined as stimulators that trigger information-seekers to socially respond, both verbally and non-verbally (Nass and Moon, 2000). Utilising the CASA paradigm, later studies found a wide range of computer's social cues, such as human-like personalities and etiquettes that the computer is designed to display, that result in users mindlessly applying social norms to their interaction, such as politeness (Reeves and Nass, 1996), reciprocity and self-disclosure (Nass and Moon, 2000).

Such behaviours were also found in human-CA interactions (Araujo, 2018; Diederich et al., 2019; Gnewuch et al., 2018; Han, Campbell, Jokinen, and Wilcock, 2012; Mou and Xu, 2017; Nunamaker Jr., Derrick, Elkins, Burgoon, and Patton, 2011; Portela and Granell-Canut, 2017; Thies et al., 2017). Similarly, CAs elicit customers' social responses using both verbal and non-verbal cues. Verbal social cues from CAs are delivered through text-based communication, such as greeting, giving advice, asking self-focused questions or sharing jokes (Feine, Gnewuch, Morana, and Maedche, 2019). More diverse in type, non-verbal cues of CAs can be demonstrated visually and audibly (Feine et al., 2019). Gender, voice (Nunamaker Jr. et al., 2011; Feine et al., 2019), body movement, facial expressions (Radziwill & Benton, 2017; Graesser, Li, & Forsyth, 2014, Feine et al., 2019), and identity (Wuenderlich and Paluch, 2017) are all displayed. These non-verbal cues can only be observed from non-text based CAs.

While studying the impacts of social cues on customer experience, Gnewuch et al. (2018a) found that response delays that emulate human delays in typing responses can increase customer satisfaction. Likewise, the observation of a CA typing indicator gets customers to perceive that the CA is socially present and, therefore, feel more engaged in the conversation (Gnewuch, Morana, Adam, and Maedche, 2018b). On the other hand, scripted social cues, such as providing pre-set answer options, adversely affect customer satisfaction as they reduce the human-likeness of the CA (Diederich et al., 2019). A CA's voice gender might trigger the application of gender stereotypes (Feine et al., 2019). The use of strong language and high confidence can make a CA more satisfactory and beneficial from the customer's perspective (Nass, Moon, Fogg, Reeves, and Dryer, 1995). Studies also suggested human-like designs for CAs, such as human natural language use or having a given name, can elicit more application of social rules (Araujo, 2018; Morana et al., 2020).

The social nature of customer-CA interactions has long been widely acknowledged. Several studies were conducted to examine the use of CAs in different contexts (refer to Table 1). The main findings of these studies are related to the benefits and challenges of utilising CAs, customer perception and behaviours towards their CAs. However, few studies demonstrate how the interaction between customers and CAs takes place. Moreover, while many aspects and types of social cues were claimed to influence the customer experience with CAs, which factors lead to a successful (or failed) interaction has not been explicitly identified. Even though studies have been exploring customer perception about the interaction with CAs, the literature has developed little empirical knowledge of how customers perceived CAs' messages and how they respond to them. While organisations are augmenting their customer self-services by leveraging the benefits of CAs, not every use case is as cost-effective and time-saving as it was anticipated. Particularly, most of the problems that are solvable at the self-service level get escalated to live support, which is time-consuming and cost organisations 80 times more than usual self-service interactions (Bryan, 2019). Along with that, a high failure rate of CA adoption still exists due to an insufficient understanding of organisations about how to deliver more satisfying customer experience through their CAs (Bryan, 2018). This issue evoked an interest to explore the nature of interactions and the strategies that customers use to interact with the CA in order to get their questions answered and problems solved. Therefore, this study was conducted to examine how customers use CAs for their information seeking and how the interaction outcomes are shaped.

**Table 1.** A summary of the literature

Authors	Models and Constructs	Methods	Findings
Abadie, Carillo, Fosso-Wamba, and Badot, 2019	Perceived irrationality, perceived control, perceived transparency, perceived consequences, perceived complexity, affective and cognitive trust, post-recommendation evaluation, intention to follow recommendations	Systematic literature review	<ul style="list-style-type: none"> <li>-Users tend to have a close relationship with the CA they frequently interact with.</li> <li>-Perceived irrationality and perceived control have negative effects on the intention to follow recommendations of the robot.</li> <li>-On the other hand, perceived consequences and cognitive trust positively impact the intention to follow the recommendations.</li> </ul>
Adam and Klumpe, 2019	User onboarding, social presence theory, social exchange theory	Post-experiment questionnaire	<ul style="list-style-type: none"> <li>-The chatbot's interactivity increases customers' self-disclosure propensity and plays a significant role in engaging and capturing prospective customers.</li> </ul>
Araujo, 2018	Computers as social actors, anthropomorphism	Experimental study	<ul style="list-style-type: none"> <li>-The use of human-like language or name can increase the social presence of the CA and elicit social responses in users.</li> <li>-Social presence can be triggered by anthropomorphic cue designs, such as the dialogue and messaging interface of the CA.</li> </ul>
Benbasat, Dimoka, Pavloi, and Qiu, 2020	Anthropomorphism, similarity-attraction theory, dissimilarity-repulsion theory	Experimental study	<ul style="list-style-type: none"> <li>-Users' affinity for a CA is affected by the ethnicity and gender demonstrated by the CA.</li> <li>-The affinity also follows the similarity-attraction and dissimilarity-repulsion rules.</li> </ul>
Cassell and Vilhjalmsson, 1999	Embodiment in distributed virtual Environment	Experiment	<ul style="list-style-type: none"> <li>-Conversations with an autonomous CA tend to be longer than with a text-based CA, indicating a high level of user engagement.</li> <li>-Users perceive an autonomous CA and interaction with it as more natural and expressive and more under their control than with a non-embodied CA.</li> </ul>

Diederich, Brendel, Lichtenberg, and Kolbe, 2019	Social response theory, CASA, social presence	Survey	-Providing pre-set answer options makes the chatbot less human-like, decreases its social presence and diminishes customer satisfaction.
Diederich, Lembcke, Brendel, and Kolbe, 2020	Social response, the uncanny valley theory	Experiment and questionnaire	-Customers interacting with a CA that fails to provide meaningful responses (response failure) might perceive a lower level of humanness, familiarity, and service satisfaction along with an increase in uncanniness. -Current anthropomorphic designs of CAs may achieve a level of human-likeness close to an uncanny valley response but yet not reaching it.
Gnewuch, Morana, Adam, and Maedche, 2018a	Social response theory, CASA, social presence	Post-experiment questionnaire	-Response delays increase customer satisfaction with the overall chatbot interaction. -Customers apply the same communication expectation on the chatbot as they do to humans.
Gnewuch, Morana, Adam, and Maedche, 2018b	CASA, the uncanny valley	Online experiment and survey	-Novice CA users found the typing indicator considerably affects the social presence degree of the CA. -A CA's graphical typing indicator results in a higher degree of social presence in comparison to the effect of the textual typing indicator. -Prior experience in using CAs might also influence the relationship between users and the CA.
Han, Campbell, Jokinen, and Wilcock, 2012		Experiments	-As people use non-verbal cues a lot in their communication, they are more likely to interact with a service bot that can utilise non-verbal channels. -There are several platforms and methods that help leverage non-verbal cues of robots, such as face detection, head nodding and shaking detection, conversational triggers and sonar sensors, etc.
Hill, Ford, and Farreras, 2015	Turing Test	MANOVA	-Humans tend to send more short messages and use more negative words (profanity, banned words, etc.) in conversations with chatbots than with other humans.

Laumer, Maier, and Gubler, 2019	User acceptance	Interview	-Performance expectation, effort expectation, facilitating conditions, social influence, price value, and habit of using CAs influence customers' acceptance and use of CA for their services.
Li and Mao, 2015	Similarity-Attraction theory	Experiment and survey	<ul style="list-style-type: none"> <li>-The values of these virtual advisors lie in their hedonic aspects (engagement, transparency, and enjoyment) and utilitarian aspects (informativeness and credibility).</li> <li>-Users perceive a higher degree of informativeness, credibility, transparency, engagement and enjoyment when the communication style of the CA aligns with theirs.</li> <li>-The higher the perceived engagement and enjoyment, the more socially present the CA is.</li> <li>-Hedonic and utilitarian aspects influence users' reuse intention.</li> </ul>
Liu et al., 2018	User generated contents	Experimental study	<ul style="list-style-type: none"> <li>-Embedding personal information of users into the conversation would make the chatbot interaction more human-like.</li> <li>-Three factors that should be taken into consideration when improving human-chatbot interaction are context, personal information, and language style.</li> </ul>
Merkle, 2019	Uncanny valley, Wizard-of-Oz, attribution theory, the expectation-confirmation theory	Experimental study	<ul style="list-style-type: none"> <li>-The uncanny valley paradigm does not explain customer satisfaction towards their experience with either human staff or the service bot.</li> <li>-Customers interacting with CA have similar levels of satisfaction with the front-line employees.</li> <li>-The perception of controllability might increase anger and decrease customer satisfaction.</li> <li>-Upon service failure, customers are more satisfied with the performance of the CA than with that of the human staff.</li> </ul>

Meyer von Wolff, Hobert, and Schumann, 2019		Structured literature review	<p>-Chatbots can help users with information acquisition, customer support, self-service, education and training, and collaborative works.</p> <p>-In the digital workplace, chatbots are potentially utilised for supporting information search tasks and mapping standard routine processes.</p>
Morana, Gnewuch, Jung, and Granig, 2020	Social response	Experiment and questionnaire	<p>-The increase in a CA's anthropomorphism of the CA positively influences the user perception of the CA's social presence and its trustworthiness.</p> <p>-Perceived social presence has a positive effect on users' trust and their intention to follow the CA's recommendation.</p>
Mou and Xu, 2017	CASA	Experiment and questionnaire	<p>-Users will be less open and less extroverted if they are aware that they are interacting with a CA.</p> <p>-Users tend to fit their communication style with the CA's.</p>
Nunamaker Jr., Derrick, Elkins, Burgoon, and Patton, 2011	Power, composure, trustworthiness, expertise, likability	Experimental study and post-experiment questionnaire	<p>-Gender and demeanours have certain impacts on customer perception about the service.</p> <p>-Voice pitch can affect users' emotion during the interaction with the CA.</p>
Portela and Granell-Canut, 2017	Anthropomorphism, Uncanny valley, CASA	Experiment and survey	<p>-Users are sceptical about having a relationship with a CA.</p> <p>-After a few interactions, users gain more trust with the CA.</p>
Qiu and Benbasat, 2009	Social presence, technology acceptance model	Experiment and questionnaire	<p>-The CA's embodiment and voice increase customers' perception of its social presence.</p> <p>-As customers perceive a high level of social presence, they will perceive the CA as more useful, trustworthy and engaging, which positively influences customers' intention to use it.</p>
Salomonson, Allwood, Lind, and Alm, 2013	Turn management, communicative functions, communicative feedback, communicative	Case study	<p>-The CA tends to take longer turns and is unable to handle interruptions during conversations.</p> <p>-It can only respond based on a pre-planned format and cannot handle implicit communicative functions.</p>

	relevance, referential cohesion, informativeness		<p>-Since it does not have a collective memory, it is unable to capture a customer's intentions and link to their previous interactions.</p> <p>-It tends to overwhelm customers with too much information at a time, while also being unable to handle a large amount of information provided by customers.</p>
Schuetzler, Grimes, Giboney, and Nunamaker Jr., 2018	Self-disclosure, social desirability, social presence	Survey and interview	<p>-As customers perceive the CA as responsive, they will be likely to provide socially desirable responses.</p> <p>-The embodiment of a conversational agent does not affect the user's responses.</p>
Siddike, Spohrer, Demirkan, and Kohda, 2018	Cognition, intelligence, capability, performance	Interview	<p>-CAs assist users with their cognitive tasks and enhance their performance overall.</p> <p>-Trust, privacy, accuracy, ease of use and governance are the key issues that contribute to the success of a CA.</p>
Stock and Merkle, 2017	Robot acceptance model, role theory	Semi-structured interview and laboratory experiment	<p>-A prior interaction with CAs does not affect user acceptance.</p> <p>-Prior experience with human staff will have negative influences on customer acceptance for the CA.</p>
Stock and Merkle, 2018	Role theory, the expectation-confirmation theory	Laboratory experiment and interview	<p>-As a CA's performance exceeds customer expectation, customer satisfaction is achieved.</p> <p>-Customers are more satisfied when the CA demonstrates innovative service behaviours.</p> <p>-Customer satisfaction towards a human employee's innovative service behaviour are higher than those towards the CA.</p>
Thies, Menson, Magapu, Subramony, and O'Neill, 2017	Wizard-of-Oz	Experiment and Interview	<p>-Topics and communication styles of users change as their CA changes its own.</p> <p>-Although the use of emoticons is good, overuse of them may cause a user's irritation.</p>



			<ul style="list-style-type: none"> <li>-Users prefer a CA with various personalities so that their interaction can be more natural and engaging.</li> <li>-Customers prefer their personal information provided to the CA to be protected.</li> </ul>
Wagner, Nimmermann, and Schramm-Klein, 2019	Uncanny valley theory, CASA, user acceptance, similarity attraction theory, anthropomorphism	Online survey	<ul style="list-style-type: none"> <li>-The effect of the uncanny valley was refuted.</li> <li>-Customers' intention to use CA increases as they perceive a humanlike-fit or similarity between them.</li> </ul>
Wuenderlich and Paluch, 2017	Computer-mediated communication interactivity model, social presence	Interview and survey	<ul style="list-style-type: none"> <li>-Perceived authenticity of CA positively affects customers' behaviours.</li> <li>-Customers evaluate CAs' performance based on their use of social cues.</li> </ul>
Zarouali, Van den Broeck, Walrave, and Poels, 2018	Consumer acceptance technology (CAT) model, cognitive factors, affective factors, patronage intention	Survey	<ul style="list-style-type: none"> <li>-Cognitive and affective dimensions positively affect customers' attitude towards the organisation and their patronage intention.</li> <li>-Customers' cognitive and affective perceptions about a CA impacts how effectively they use it.</li> </ul>

### 3. THEORETICAL LENSES

In order to explore the strategies that customers use to interact with CAs and identify which interactions are successful and which have failed, two overarching theoretical lenses were adopted: the conceptual model of social information-seeking (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019). First, the conceptual model of social information-seeking developed by Ramirez et al. (2002) illustrates how the information-seeking process in a computer-mediated context takes place. The authors identified four main information-seeking strategies and distinct appraisals that influence the selection of these strategies. The model also suggested how the enactment of these strategies can affect the outcome of the interactions. Second, the concept of social presence (Schultze and Brooks, 2019) was used to explicate different degrees of social presence in interactions between humans and a technological artefact. Each degree of social presence was found to be associated with distinct behaviours. It also suggested how different degrees of social presence can be achieved in a human-computer interaction.

CAs are used as an information intermediate between customers and organisations. The knowledge domain of CAs is linked with the organisation's online knowledge base, such as frequently asked questions, which helps customers with getting their questions answered or problems solved. Customers, therefore, use CAs for information retrieval, website navigation, or information exchange with organisations (Cui, Huang, Wei, Tan, Duan, and Zhou, 2017; Kim, Hong, and Cho, 2007; Laranjo et al., 2018; Yang et al., 2018). The use of CAs for information-seeking has suggested that the strategies customers use can affect the entire interaction between them and the CA. In light of that, the social information-seeking model (Ramirez et al., 2002) would guide this study to explore which strategies are used and how they determine the outcome of customer-CA interactions.

The interaction between customers and CAs involve not only the information-seeking process but also the sociability factors influencing the interaction outcomes. Among the sociability dimensions of customer-CA interaction, social presence has been acknowledged as an important factor that contributes to the success of an interaction (Gunawardena and Zittle, 1997; Schultze and Brooks, 2019). The higher the degree of social presence, the more likely the interaction is to be successful (Adam and Klumpe, 2018; Diederich et al., 2019; Morana et al., 2020). As the concept of social presence (Schultze and Brooks, 2019) helps identify the social behaviours associated with each of its degrees, applying this concept to the empirical study would help the researcher to understand how different degrees of social presence can be achieved in customer-CA interactions and how they influence the interaction outcomes.

The researcher found that the two theoretical lenses complement each other. The social information seeking model (Ramirez et al., 2002) helps in understanding how interactions between customers and CAs take place throughout the information-seeking process. On the other hand, the concept of social presence (Schultze and Brooks, 2019) supports the understanding about the nature of the interactions by considering the social dimension of the conversations. Moreover, the two theoretical lenses both mention different factors that influence the outcomes of human-CA interactions. While the social information-seeking model (Ramirez et al., 2002) explains how the use of strategies determine the quality of desired information and, eventually, the outcome of the interaction process, the concept of social presence (Schultze and Brooks, 2019) clarifies how the degree of social presence influences customer perceptions and behaviours towards the CA. Therefore, the researcher adopted an integrative perspective of the conceptual model of social information-seeking (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019) to explore how the interactions take place and which factors affect their outcomes.

In the following sections, the researcher introduces each theoretical lens and explains how they complement each other to build the theoretical model for this study. Section 3.1 explicates the main ideas of the social information-seeking process (Ramirez et al., 2002), regarding how it is associated with the study context. In Section 3.2, the concept of social presence (Schultze and Brooks, 2019) is explained and applied to the customer-chatbot interaction. Section 3.3 illustrates how the two theoretical lenses will be integrated in order to guide the analysis.

### 3.1. Social information-seeking process

CAs have been substantially used to support the information-seeking process of customers (Quarteroni and Manandhar, 2007; Yang et al., 2018; Zamora, 2017). A customer-CA interaction for an information-seeking purpose have been considered as a social process because of the influence of numerous factors, such as the information-seekers' personality traits (Al-Samarraie, Eldenfria, and Dawoud, 2017), emotions (Arapakis, Jose and Gray, 2008; Savolainen, 2014), motivation (Savolainen, 2014; Weiler, 2005), engagement and credibility (Li and Mao, 2015). While many CAs are pre-programmed to follow their scripted scenarios, customers' behaviour during the process might vary according to the information-seeking context, the attributes of the desired information or to the strategies they use. Therefore, understanding why and how customers enact their information-seeking process through CAs can shed more light on how to achieve a successful customer-CA interaction in order to improve customer experience.

Information-seeking behaviours have been studied in numerous fields, such as academic research (Chowdhury, Gibb, and Landoni, 2011; Ellis, 1993; Spence, Reddy, and Hall, 2005), tertiary study (Catalano, 2013; Rieh and Hilligoss, 2008; Weiler, 2005), tourism (Fodness and Murray, 1999; Gursoy and McCleary, 2004; Gursoy and Umbreit, 2004), online services (Kiel and Layton, 1981; Peterson and Merino, 2003) and organisational problem-solving (Byström and Järvelin, 1995; Vakkari, 1999). Information is now becoming more accessible. Through the internet, people can get access to millions of information sources by simply typing their search terms. The development of computer-mediated channels has advanced and transformed the way people search for information. Although the online information-seeking process is perceived as task-oriented and impersonal (Walther, 1996), computer-mediated communication (CMC) and other technological advancements have offered alternative means for acquiring information that is not available in face-to-face contexts (Ramirez et al., 2002). While early perspectives had opted out of the impacts of social behaviours when studying the information-seeking process, due to the absence of social cues in some computer-mediated contexts (Walther, 1996), later studies argued how information seekers' behaviours can compensate for the constraints of social cues in human-computer communication (Ramirez et al., 2002).

Ramirez et al. (2002) proposed a conceptual model describing how information-seekers pursue desired information about a target via computer-mediated communication and new media. Since the information-seeking approach can substantially affect the perception of information-seekers about their interlocutors, Ramirez et al. (2002) focused on investigating why information-seekers choose a certain strategy, how they enact it and assess the acquired information. According to the model developed by Ramirez et al. (2002), there are four sets of strategies that information-seekers use to extract information: (i) interactive strategies, (ii) active strategies, (iii) extractive strategies, and (iv) passive strategies.

Interactive strategies are used when the information-seeker acquires information directly from the target. Different techniques could be used in order to get direct information, such as interrogating the target or self-disclosing information to elicit reciprocal disclosure. Active strategies entail acquiring information about a target from other individuals, for instance, from a third-party information source. In the CMC and new media contexts, active strategies are most likely to be used through exchanging emails or text messages with people acquainted with the target. Although they are less popular in CMC than in person, they are becoming more feasible due to the increasing uptake of online social networks and digital communication (Ramirez et al., 2002). Unlike interactive and active strategies, extractive strategies do not get the information-seekers to interact with others for information acquisition but to acquire desired

information through online search engines. These strategies allow information seekers to obtain information about the target without his or her knowledge. Whereas the abovementioned approaches involve the information-seeker to self-collect information, passive strategies allow information-seekers to acquire information through unobtrusive observation. According to Ramirez et al. (2002), passive seekers could be those within a group of "carbon copied" emails or new members of an online communication forum who prefer to take a glance of every available information before interacting with others to collect targeted information. Although there are many strategies that can be used in the computer-mediated and new media context, not all of these information-seeking strategies are applicable to this study context. Due to the nature of the interactions between customers and CAs, only interactive strategies are relevant to the analysis. Building from the main characteristics of the interactive strategies, this study extended the work of Ramirez et al. (2002) by providing a nuanced understanding of different interactive strategies that were used when customers interact with CAs.

Ramirez et al. (2002) introduced five classes of factors that determine the selection of information-seeking strategies, which are (i) communicator-related factors, (ii) context-related factors, (iii) goal-related factors, (iv) information-related factors, and (v) technology-related factors. Communicator-related factors are associated with the information-seeker's self, such as his characteristics, skills, or his information-seeking behaviour. Context-related factors entail the situational effects on the information-seeking process. They might be the availability of the target or the accessibility of the information sources. Goal-related factors reflect the characteristics of the goals of the information-seeker. These factors refer to the duration of the goal (i.e. short-term, long-term) or the type of goal. Information-related factors are comprised of the characteristics of the desired information, which might affect how information-seekers pursue it. These factors include information quantity, qualities, and how the information needs are defined. Technology-related factors refer to aspects of the information-seeking process that are directly influenced by the use of an information and communication medium. Examples of these factors are the technological efficacy of the medium, such as its efficiency and ease of use.

The above appraisal factors influenced the use of information-seeking strategies, which determines the efforts that customers had to put in to acquire information and the matching level between the acquired information and desired information. Evaluation for alternative strategies will take place regarding the acquired information. Information-seekers will assess the quantity and quality of acquired information and note their experiences in enacting the strategies and the discrepancies between desired and acquired information (Ramirez et al., 2002). The outcomes of the assessment will determine subsequent

behaviours of the information-seekers, including re-evaluating initial factors and modifying information-seeking strategies.

The model provides a comprehensive view of the social information-seeking process via CMC and new media, which especially considers the behavioural adaptation of information-seekers upon the limited social cues of the contexts. Drawing from this social information-seeking model, this paper aims to develop a refined understanding of how different interactive information-seeking strategies were used and how these strategies shaped the outcomes of interactions.

### 3.2. Social presence theory

Many scholars have been investigating different social factors that influence humans' social behaviours in human-CA interactions. Studies found a strong link between a CA's social presence and human's social responses towards it (Nowak and Biocca, 2003; Qiu and Benbasat, 2005; Lee, Peng, Jin, and Yan, 2006; Verhagen, van Nes, Feldberg, and van Dolen, 2014; Araujo, 2018; Gnewuch et al., 2018; Diederich et al., 2019).

The concept of social presence was first introduced as a psychological communication term referring to the degree of salience of a social actor and the impacts of one's salience on social interactions (Short, Williams, and Christie, 1976). It was primarily used to demonstrate how real a person is perceived in a mediated communication, which was said to vary among different interlocutors by the social cues that they render and how they are delivered (Gunawardena, 1995). The perceived degree of social presence was found to elicit certain social behaviours in customers and, therefore, influence how the interactions take place.

By utilising social presence theory, recent studies suggested that humans also perceived a certain degree of social presence when interacting with computers and other technological artefacts, including CAs (Nowak and Biocca, 2003; Hwang and Park, 2007; Schultze and Brooks, 2019). People can perceive a degree of social presence through human-like social cues of the CAs, such as voice and personalities (Lee and Nass, 2003) or through how interactive and engaging they are (Li and Mao, 2015). The manifestation of social presence of CAs has been acknowledged to have various positive influences on customer satisfaction (Gnewuch, Morana, Adam, and Maedche, 2018; Hess, Fuller, and Campbell, 2009; Morana, Gnewuch, Jung, and Granig, 2020; Wuenderlich, and Paluch, 2017). A high degree of social presence can result in higher levels of perceived warmth and positively influence the trust of customers towards a CA (Dorn et al., 2017; Hess, Fuller, and Campbell, 2009). Social presence also has mediating impacts on customers' intention to revisit a virtual advisor (Choi, Lee, and Kim, 2011; Li and Mao, 2015). Although the

level of social presence determines the quality of customer-CA interactions, little is known about how customers form their sense of social presence towards the CA. Most of the previous studies used quantitative approaches to study customers' awareness of the CA's social presence without considering the interactivities that customers and the CA have during the interactions (Choi, Lee, and Kim, 2011; Hess et al., 2009; Schuetzler, Grimes, Giboney, and Nunamaker Jr., 2018; Morana et al., 2020; Verhagen et al., 2014).

### ***An interactional perspective of social presence in customer-CA interaction***

The interactional perspective of social presence in customer-CA interaction refers to how the interplay between different concepts influences the degree of social presence (Schultze and Brooks, 2019). Adopting the interactional view, Schultze and Brooks (2019) developed a model describing how different levels of social presence can be achieved in a virtual space. The three degrees of social presence are introduced by utilising the concepts of co-presence, involvement obligation and interlocking involvement obligation. Co-presence is defined as the sense of being collocated with the other in the same virtual space (Biocca, Harms, and Burgoon, 2003; Goffman, 1963; Zhao, 2003). Upon the sense of colocation, the focal actors perceive the other's availability for interaction and ability to monitor their behaviours (Bulu, 2012; Goel, Johnson, Junglas, and Ives, 2013; Rettie, 2005). Co-presence of the other in a focused interaction gets the social actors to establish involvement obligation. According to Goffman (1967), involvement obligation takes place when interlocutors pay attention to each other and are engaged in the joint task which they are endeavouring to accomplish. Interlocking involvement obligation is a higher level of involvement obligation, at which social participants not only support each other's involvement but also acknowledge and validate the social self of others (Schultze and Brooks, 2019), such as reflecting each other's emotional states and similarities (Nowak and Biocca, 2003).

Drawing on the social presence theory, Schultze and Brooks (2019) highlighted that the concepts outlined above are respectively associated with a low, medium, and high degree of social presence in a computer-mediated conversation. First, a low level of social presence, the focal actor can perceive the co-presence and mutual monitoring of the social other in an unfocused situation. Second, a medium degree of social presence is reached when the focal actor perceives the joint engrossment and involvement obligation of the other to the shared task. As they participate in a focused interaction, in which they share the same endeavour to accomplish a joint activity, the social actors establish involvement obligation. The interactional involvement is evidenced by the meaningfulness of the other's responses allows both social actors to be involved cognitively and emotionally, i.e. joint engrossment.

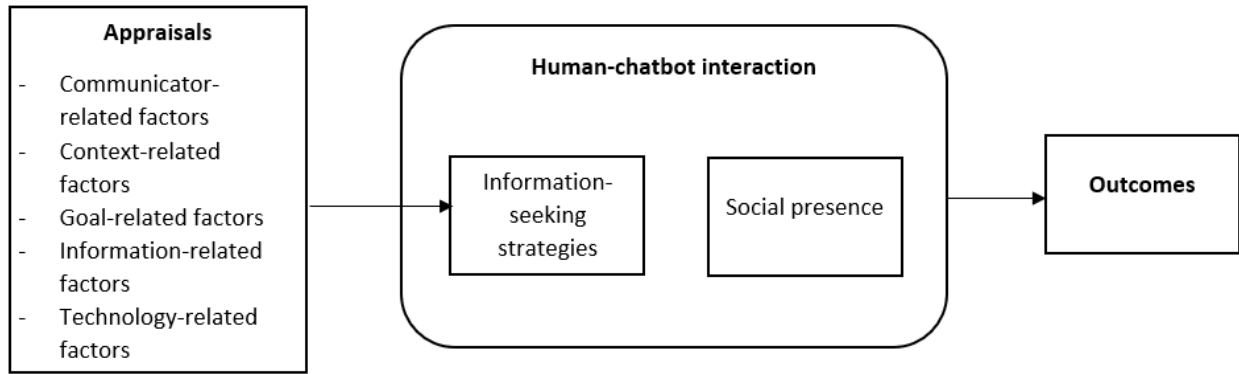
Finally, a high degree of social presence is reached when there is interlocking involvement obligation between the social actors, in which the focal actor supports the other's involvement with the joint task and honours the social self of the other.

This interactional perspective (Schultze and Brooks, 2019) has shed light on how each degree of social presence is achieved in a CMC. Moreover, as the degree of social presence is acknowledged as one of the key contributors to a successful customer-CA interaction, the concept of social presence (Schultze and Brooks, 2019) will help identify how customers would react to the CA at different degrees of social presence.

### 3.3. The integrated theoretical model

The social information seeking model (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019) complement each other in certain ways. The researcher understood that the conceptual model of social information-seeking (Ramirez et al., 2002) could help in illustrating how the interactions between customers and CAs take place. From the model, this study would be able to elucidate the strategies that customers enact for their interactions with CAs and the factors that stimulate these strategies. As the interactions are taking place, this is where the social presence concept (Schultze and Brooks, 2019) comes into play to illuminate the conversational aspects of the interactions. According to both lenses, the outcome of the interactions is influenced by the enacted information-seeking strategies and the degree of social presence. This study, therefore, considers the mutual impacts of the two factors on how the outcome of the interactions is shaped. In the context of this study, the analysis concentrated on the interaction between customers and chatbots (a text-based CAs). As a result, the researcher integrated the model of social information seeking and the concept of social presence into one model (see Figure 1 below), depicts the interactions of different factors derived from the two overarching theoretical lenses in shaping the outcomes of customer-chatbot interaction.





**Figure 1.** The integrated model of the customer-chatbot interaction

## 4. METHODOLOGY

This section describes the methodology and approach used to answer the research question, “How do information-seeking strategies and social presence shape the outcome of the interactions between customers and conversational agents?” It explains my underlying theoretical assumptions and justification for choosing a qualitative approach with an abductive reasoning to guide the research process.

### 4.1. Research design

In order to address the research question, “How do information-seeking strategies and social presence shape the outcome of interactions between customers and conversational agents?” there are two main points that need to be addressed: (i) how customers use the information-seeking strategies in their interaction with CAs and (ii) how the interplay between information-seeking strategies and social presence influences the outcomes of the interaction.

First, since the information-seeking strategies reflect how customers interact with the CAs in order to acquire their desired information effectively, an understanding of the information-seeking behaviours will shed light on the nature of the customer-CA interaction. Therefore, the researcher intends to investigate which strategies customers have been using to extract information from the CAs, how they select the strategies and what their intentions are underlying each choice.

Second, because the information-seeking strategies and social presence are both found to have certain impacts on how customers and CAs respond to each other, understanding their mutual impacts on how customers interact with the CAs for information seeking will provide a more thorough explanation for how an interaction outcome is shaped. For that reason, this study is intended to explore how customers enact the information-seeking strategies, how different degrees of social presence are established and how the information-seeking strategies and social presence interact to shape the outcomes of interactions.

Since this objective of this study is to understand customers’ information-seeking behaviours and their intentions, the researcher builds on the philosophical underpinnings of interpretivism to conduct this study. The interpretivism stance has long been used for studies about human behaviours (Cazeaux, 2017; Creswell, 2014) and refers to “culturally derived and historically situated interpretation of the social life-world” (Crotty, 1998). This approach seeks to understand individuals within their society, the meanings attached to their actions, the intentions behind each choice, possible reactions reviews, and an eventual action selected (O’Reilly, 2008). In this study context, undertaking an interpretivist approach, the

researcher will examine how customers choose and enact their information-seeking strategies, i.e. their choice of actions, in order to interpret what is intended when they make their decisions (O'Reilly, 2012). By doing so, the researcher will be able to discover how the information-seeking strategies are used by customers to seek information from the CAs.

Moreover, this stance also holds that the human's social world is complex and that their behaviours are impossible to predict (Gray, 2018; Williams and May, 1996). Interpretivism claims that an outcome is shaped by certain contributory factors that, if removed, will lead to a completely different outcome (O'Reilly, 2012). Following an interpretivist approach, the researcher will investigate how different factors, i.e. the information-seeking strategies and the degree of social presence, influence the interactions between customers and the CAs. This approach will allow the researcher to identify the interplay between the information-seeking strategies and social presence and how it shapes different outcomes of the interactions.

For the reasons above, this study was guided by the epistemological underpinnings of constructivism. Constructivism emphasises the complexity of perspectives on a phenomenon that is shaped by the study subject's norms (Creswell, 2014). Therefore, to attentively capture customers' perceptions regarding their CA-encounters, the researcher's preconceptions about the CAs were put aside and, at the same time, she objectively observed the interactions between customers and the CAs so that the focus could be bound to the subjective view of customers (Crotty, 1998). In this study, the researcher observed customer-CA communication through an interaction log and applied the theoretical lenses to understand how the interactions took place. The observation allowed the researcher not only to discover the strategies that customers used to interact with the CA but also to explore how the outcome of the interactions was formed in different cases. Results derived from the analysis are discussed within the interpretation of the researcher from the observation.

In line with the philosophical perspective, the researcher chose to conduct a qualitative research method to investigate the nature of customer-CA interactions. The analysis was intended to explore emergent patterns of customers' information-seeking behaviour in their interactions with the CA. These patterns would provide insights on the identification of factors shaping the outcome of the interactions. The analysis process followed abductive reasoning. The abduction research logic refers to the process of conceptualising meanings to form an understanding or develop an explanation of a phenomenon (Eriksson and Kovalainen, 2016). The abductive approach allowed the researcher to discover the

relationship between the appraisal factors and selected information-seeking strategies and the interaction between the selected strategies and social presence on the basis of the underlying theoretical lenses (Dubois and Gadde, 2002). The integrated model of social information seeking process and the concept of social presence was utilised to guide the coding process. Using abductive reasoning enabled the researcher to identify the patterns of how customers used the CA for information-seeking and its outcomes, conceptualise these patterns and explain their relationships to demonstrate how the outcomes of customer-CA interactions were formed.

#### 4.2. Data collection

In order to address the knowledge gap, this study was intended to examine the nature of the customer-CA encounter from an interactional viewpoint. The collected dataset should demonstrate the actual conversations taking place. Hence, for the purpose of this study, a customer-chatbot interaction log was used as the dataset for the analysis. The research proposal was sent to a chatbot provider company that have been offering conversation platforms and building chatbots for several organisations in New Zealand. The company then connected the researcher with one of its own client companies which is a large electric power company in New Zealand and owns a chatbot that had been implemented to its website for more than two years. After reaching a non-disclosure agreement regarding pseudonymising and redacting private information, the client company agreed to grant the researcher access to the dataset, which are interaction logs between its customers and the chatbot.

The dataset was saved locally and pseudonymised under an Excel file. Any private information about the customers were also redacted. The provided dataset entails interaction lines demonstrating how customers and the chatbot were taking turns during the interactions, with 8154 rows of 1000 interactions. Among the 1000 interactions, 493 interactions were dropped off by customers, leaving 507 interactions that are meaningful for the analysis. Drop-off conversations are those that were started by customers through the 'Get started' option but were abandoned without any request or query posted. These interactions took place from May 2018 to December 2019. Each row represents a turn taken either by customers or by the chatbot. Data cleaning was needed for the ease of successive data analysis stages. The dataset included some redundant or meaningless characters and symbols due to the modification of file format. These characteristics and symbols were removed from the dataset to make it easier for the data analysis process and to avoid any misunderstanding. The order of interaction lines was mixed up as they were sorted by timestamps rather than by interactions. Since each interaction was given a separate

user ID, the dataset was reordered by user ID, then by timestamp. After being sorted, each interaction was numbered to signal at which line the interaction was initiated and ended.

Table 2 below presents an example of how an interaction looks like in the data set. The chatbot's name, company's name and user ID were redacted. As the contents of messages exchanged between customers and the chatbot were the focus of this study, later quotes of interactions from the data set would only display the source and the message text columns.

**Table 2.** *An example of the data set*

Interaction number	User ID	Source	Message text	Timestamps
1	XXXX-XXXX-XXX	Customer	Get started	19/11/2018 01:22:20
1	XXXX-XXXX-XXX	Bot	Hi, I'm [chatbot name] from [company name].	19/11/2018 01:22:22
1	XXXX-XXXX-XXX	Bot	I can help you find information you need, and we can chat about who [company name] is and what we do.	19/11/2018 01:22:24
1	XXXX-XXXX-XXX	Bot	How can I help?	19/11/2018 01:22:26
1	XXXX-XXXX-XXX	Customer	Hi	19/11/2018 01:22:30
1	XXXX-XXXX-XXX	Bot	Hello there.	19/11/2018 01:22:30
1	XXXX-XXXX-XXX	Bot	What else can I help you with? If you'd like to give feedback, just type feedback.	19/11/2018 01:22:32

### **About the chatbot**

The chatbot is a text-based CA that can only process text-based inputs from customers. It was launched in 2018 on the company's website to assist customers with their online self-service. At the time of data collection, the chatbot was trained in a small range of topics, such as check for outages, report outages, company's contact details, and application processes. As customers navigate to the homepage of the website, a small icon on the bottom right will pop up, suggesting customers seek help from the chatbot. Customers can initiate their conversations with it by clicking on the icon and selecting "Get started" option. Running on a natural language processing algorithm, the chatbot is able to understand the intents of customers through even just a few simple search terms. For example,

Customer: *Outage*  
 Bot: *Sounds like your power may be out – I’m sorry to hear that  
 You can get in touch with [Company name] by phoning [phone number]  
 ([Company name]) or at the contact details linked below | [attached links]  
 How else can I help?*

From one search term, the chatbot was able to understand that the customer wanted to make a request regarding outages and, therefore, provided appropriate links and contact numbers for further support. Moreover, along with receiving text-based inputs from customers, it also offers pre-set options that allow customers to post their inquiries more quickly with less effort. As pre-designed by the company, the chatbot provides some pre-set options at the beginning of the conversations. These options represent frequently asked questions, which include getting connected, check outages, and the company’s contact details. Each option has a pre-programmed response that will be provided once customers select it. For example,

Customer: *(select ‘Getting connected’ option)*  
 Bot: *The process of getting connected to the Vector network has several stages:  
 1. You make an application to Get Connected.  
 2. We send you a quote.  
 3. After the quote is accepted and paid, we commence work.  
 4. The connection is built, and any reinstatement work is done.  
 Start the connections quote process... | [‘Apply now’ option]*

Not only can it answer service-related questions, it is also designed to sustain informal conversations, such as greeting and sharing jokes.

#### 4.3. Data analysis

In order to analyse the data, an abductive approach was applied. The abductive approach refers to the development of the theory by conceptualising real-life observation on the basis of existing frameworks (Van Hoek, Aonsson, Kovács, and Spens, 2005), which is well suited for the purpose of this study. Guided by the abductive approach, the researcher utilised the two theoretical lenses, the social information-seeking model (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019), to guide the analysis. The analysis process was divided into two phases.

In the first phase, the researcher conducted a thematic analysis (Braun and Clarke, 2006) with the help of NVIVO 12 software. The analysis was started with the researcher getting familiarised with the data set. Any important excerpts or remarks were noted down for later coding. By reading through the data set twice, the researcher found some interesting ideas and emergent patterns describing the nature of

customer-chatbot conversations. After data familiarisation was done, the researcher carried out an open coding process. Open coding involved the researcher coding data slices in accordance with the research focus. At this stage, no preconceived theoretical frameworks were involved (Fernández, 2004). This step helped to form an understanding of how the interactions had taken place. For example, the expression of the chatbot, “I don’t understand that I’m sorry”, was evidence that the chatbot failed to identify the intention of the customer, which was coded as “chatbot’s inability to understand customers’ intents”. This code demonstrated one of the deficiencies of the chatbot and, therefore, should be one of the potential factors that shape an interaction failure. A similar approach was used to code the entire data set, which produced a list of 44 open codes (Appendix A). The next step involved theme generation and revision. This was done by collating the open codes with similar patterns into the same theme. A constant comparison process was conducted to categorise all open codes into their coherent themes. The outcome of this step should be a list of distinct themes that would be theorised to address the research problem. For example, by performing the analysis at a higher level of abstraction, besides the open code labeled as “chatbot’s inability to understand customers’ intents”, other deficiencies of the chatbot were identified, including “chatbot’s misinterpretation of customers’ requests”, “chatbot’s repeated errors”, and “chatbot’s repeating scripted response”. These codes were found to point to the miscommunication between the chatbot and customers and, therefore, were grouped into the same theme labeled “customer-chatbot miscommunication”. The researcher applied the same approach to recognise all emergent themes from the open code list.

From the coding process conducted in the first phase, the researcher searched for adequate theories that could help further analyse the emerged patterns. As the emerged patterns evolved around the information-seeking behaviour of customers towards the chatbot, the open codes provided hints that the social information-seeking model (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019) should be useful to further explain the relationship of these patterns. The integrated model of these two theoretical lenses (Section 3.3) was utilised as a guiding framework to re-analyse the data.

Based on the integrated model, the researcher attempted to explicate how information-seeking strategies were utilised by customers to extract information from the chatbot and how the strategy, together with the impacts of social presence, shaped the outcome of customer-chatbot interactions. The emergent themes were theorised by aligning them with the components of the integrated model. For example, the “Staff support availability” theme fits into the definition of context-related factors in the information-seeking process (Ramirez et al., 2002). Therefore, it was categorised as a context-related

factor. “Mutual awareness”, “Limited mutual monitoring”, and “Low level of interactional involvement” themes, all refer to a low degree of social presence and, hence, were put under the “Low social presence” category. Similar logic was applied to other themes to group them into distinct categories. The theoretical lenses also helped refining the labels of open codes and themes in order to align with the constructs of the adopted theories. For example, the “customer-chatbot miscommunication” theme consisted of open codes that are close to the low degree of mutual monitoring between customers and the chatbot. Therefore, the theme was re-named as “Limited mutual monitoring” to align with the concepts of the guiding theory. Following this approach, the researcher was able to generate a complete list of 8 categories, which included the following: context-related factors, goal-related factors, information-related factors, technology-related factors, interactive strategies, low social presence, medium social presence, and interaction outcomes (Appendix A).

After finishing coding, the researcher then clustered the appraisals, including context-related factors, goal-related factors, information-related factors, and technology-related factors, in terms of their causal relationship with the information-seeking strategies by adopting a configurational approach (Fiss, 2011). The configurational approach refers to a systematic method of classifying distinct factors of multi-dimensional constellations in order to discover their interdependence and depict patterns across them (Meyer et al., 1993). The idea of the configurational thinking is that all factors within an entity take their meaning from the whole and should not be considered in isolation (Meyer et al., 1993; Misangyi, Greckhamer, Furnari, Fiss, Crilly, and Aguilera, 2017). The underlying principles of the configurational approach are the coherence between factors and the holistic nature of the entity (Meyer et al., 1993). The systematic classification should demonstrate the correlation between factors from which coherent patterns emerge. Additionally, the patterning of these factors should be the focus of the study rather than their interconnectedness. Moreover, the approach accentuates the reciprocal and nonlinear relationships among factors (Meyer et al., 1993), indicating that there are some factors that have a stronger causal relationship with the outcome of interest than others. In line with that, Fiss (2011) proposed that there are core and peripheral conditions that play a role in shaping the outcome of interest. According to Fiss (2011), core factors are those that show strong causal relationships with the outcome whereas peripheral factors are those that have weaker causal impacts on the outcome. Moreover, the approach also suggested the notion of neutral permutations stating that a core factor can be supported by more than one constellation of distinct peripheral factors.



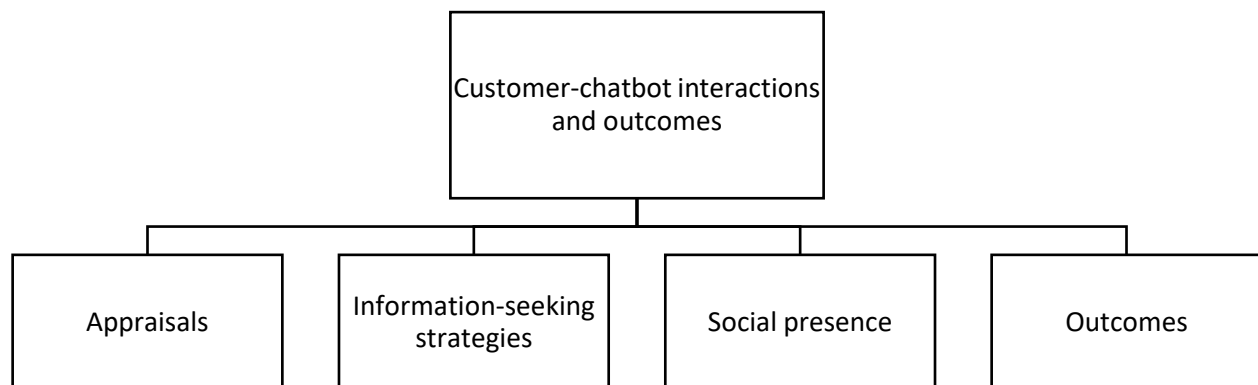
Applying the idea of this configurational approach, the researcher classified appraisals based on their core-peripheral influences on the information-seeking strategy selection. Specifically, when an appraisal was found to influence the use of a strategy and all or most interactions initiated by the strategy were influenced by it, the appraisal was classified as a core factor. On the other hand, an appraisal was identified as a supporting factor of a strategy when it influenced the use of the strategy but was not present in most of the cases in which the strategy was applied. For example, when analysing the influence of appraisals on complete-sentence query strategy, the researcher found that out of 325 interactions using complete-sentence queries for the information search, 320 interactions were influenced by the chatbot's open-domain question answering ability. Hence, this technology-related factor was classified as a core factor that determines the use of complete-sentence query strategy. However, 102 of those interactions were affected by the office-hour inquiry factor and 223 interactions were influenced by the after-hours inquiry factor. These factors are part of the context-related factors that refer to the situational effects on the information-seeking strategies. Although these two factors were found to affect the selection of complete-sentence strategy to some extent, their influence did not cover most of the interactions. Therefore, office-hour and after-hours inquiry factors were identified as supporting factors. A similar approach was applied to classify the effects of appraisals on the strategies. A summary of the systematic classification is presented in Appendix B.

## 5. FINDINGS

This chapter presents the categories which emerged from the analysis and illustrates how they were constructed to answer the following research question: “How do information-seeking strategies and social presence shape the outcome of interactions between customers and conversational agents?” Guided by the social information -seeking model (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019), the researcher performed data analysis and identified eight main categories revolving around the interactions between customers and the chatbot. These include context-related factors, goal-related factors, information-related factors, technology-related factors, interactive information-seeking strategies, low social presence, medium social presence, and interaction outcomes. Under each category are its aggregated themes that were developed, based on the open codes identified from the analysis.

### 5.1. A framework of customer-chatbot interactions and outcomes

The representation of the findings of this study will be based on a framework. Figure 2 depicts the framework, by which the main categories and their sub-categories will be discussed and summarised in the sections below. It includes (i) the appraisals theme that entails ‘context-related factors’ category, ‘goal-related factors’ category, ‘information-related factors’ category, and ‘technology-related factors’ category, (ii) the information-seeking strategies theme representing the ‘interactive information-seeking strategies’ category, (iii) the social presence theme including ‘low social presence’ category and ‘medium social presence’ category, and (iv) the outcomes theme with the ‘interaction outcomes’ category.



*Figure 2. A framework of the customer-chatbot interactions and outcome*

#### 5.1.1. Appraisals

First, context-related factors refer to the external effects on the information-seeking process. They might relate to the availability of the subject target or the accessibility of the information sources. Under the ‘context-related factors’ category, two sub-categories emerged, which are staff support unavailability and

staff support availability. Staff support unavailability is related to requests that were posted after office hours, whereas staff support availability refers to those queries posted during office hours.

Second, goal-related factors reflect the characteristics of the goals of customers. They could be the duration or the type of customer's goals. Two sub-categories of 'goal-related factors' are task-oriented goals and non-task-oriented goals. Task-oriented goals include those interactions that involved accomplishing intended tasks that customers have in mind. This sub-category entails problem-solving goals, incident investigation goals, and information confirmation goals. For example, queries such as "I have an outage. What should I do?" would be considered a task-oriented goal since it refers to actions required to address the problem. The non-task-oriented goals theme refers to those goals that are not associated with any task accomplishments, such as general information request goals and entertainment goals. A customer's request for joke sharing or for general information about the application process to get connected to the company's power network were specifically classified as non-task-oriented goals.

Third, information-related factors refer to the characteristics of the desired information, which might affect how customers pursue it. Five sub-categories of the 'information-related factors' category are as follows: broadly-defined information needs, narrowly-defined information needs, navigational information needs, high-priority information needs, and psycho-emotional information needs. First, the broadly-defined information needs sub-category is composed of both construction information needs and orientation information needs. Construction information needs referred to the desire to seek information that helps to form new opinions about a topic of interest or to solve a problem. This type of need usually referred to an outage report. Orientation information needs are defined as the need to acquire information that explains what is taking place. Checking an address for an outage is an example of an orientation information need. Second, the narrowly-defined information needs sub-category includes re-orientation information needs. This type of information need is defined as the need to search for information that helps customers to build on their understanding about an incident. Re-orientation information needs were instigated by customer inquiries checking for the accuracy of the information that customers already knew. For example, the customer's query, "Is there still a planned outage for my area today?" was classified as re-orientation information as the customer wanted to be assured that his knowledge about the planned outage is still correct. Third, the navigational information needs sub-category is consisted of chatbot-related information, company-related information, information location, and procedural information. These concepts refer to general information about different topics that customers were found to be interested in. Fourth, the high-priority information needs sub-category

includes information importance and information urgency. Information importance was expressed by customers inferring how important the desired information was in their situation. For instance, a customer claimed that he wanted to know the time at which the power would be restored because the outage seriously affected his restaurant business; the desired information was coded as information importance. Information urgency reflects the need to acquire information urgently to solve a problem due to its seriousness. For example, searches for “Gas safety” or “a car crashed onto the pole” were coded as information urgency. Finally, the psycho-emotional information needs sub-category refers to the information with casual and random contents, such as jokes, compliments or simple greetings.

Fourth, the ‘technology-related factors’ category is composed of two sub-categories: natural language and colloquial language. Under the natural language sub-category, open-domain question answering ability and clickable buttons are the two concepts which emerged from the analysis. Open-domain question answering ability reflects the chatbot’s capability to understand the customer’s questions in the form of text-based inputs and autonomously reply with adequate answers. Additionally, the chatbot is also designed with clickable buttons that represent topics of frequently asked questions. These buttons, when clicked, will generate appropriate responses that were pre-programmed by the chatbot’s designer. Colloquial language, on the other hand, is defined as the chatbot’s conversational capabilities to sustain conversations using embedded social cues, such as jokes and expressions of empathy with a customer’s feelings.

#### 5.1.2. Information-seeking strategies

Information-seeking strategies refer to the approaches that customers used to extract their desired information from the chatbot. The analysis shows that only interactive information-seeking strategies were applicable in the study context. Interactive strategies are those that involved customers acquiring information about the company through direct interaction with the chatbot. Two sub-categories identified under this category are information interrogation strategies and social reciprocity strategies.

First, information interrogation strategies include approaches allowing customers to acquire pre-defined information from the chatbot, which are complete-sentence strategy, fragmented strategy, keyword search strategy, and FAQ strategy. Queries posed by the complete-sentence strategy are in the form of a full sentence, for example, “I want to report an outage,” or, “Can I get an LPG bottle delivered?” The fragmented strategy made queries be broken into small information pieces and posted them on separate interaction rows. In the example below, the customer provides pieces of information about the incident on different conversation rows, instead of giving the details all at once.

Customer: *my power pole fell down*

Bot: *I'm sorry, I didn't understand that. These are some of the things I can currently help you with. | [options provided]*

Customer: *lightning hit the pole outside my house*

Bot: *You can help keep our network safe by reporting damaged equipment, pipeline or cable exposure by calling [phone number]. If this is an emergency, please call 111.  
Damaged network | ['More info' option] –  
What else would you like to know? If you'd like to give feedback, just type feedback.*

Customer: *It's on fire*

Bot: *I'm sorry, I didn't understand that. These are some of the things I can currently help you with. | [provided options]*

Customer: *I think I heard some kind of explosion*

Bot: *I'm sorry, I didn't understand that. These are some of the things I can currently help you with. | [provided options]*

Customer: *The transformer just blew up and took out a car*

Bot: *I'm sorry, I didn't understand that. These are some of the things I can currently help you with. | [provided options]*

Customer: *It's chaos - people running for their lives.*

Bot: *I'm sorry I couldn't be of more help. Please call us directly so we can assist further.*

The keyword search strategy was activated when a customer used short phrases to search for their desired information, such as 'outage' and 'undergrounding'. Finally, the FAQ strategy refers to the use of pre-set options, each of which represents a frequently asked topic. The topics could be, for example, "Getting connected" that refers to the application process to get connected to the company's power network or "Contact [Company name]" in regards to the contact details of the company.

Second, the social reciprocity strategies consist of those that were utilised to carry out casual and random conversations with the chatbot. These strategies might eventually end up with information needs emerging later in the interactions. Conversation following the social reciprocity strategy can look like the following:

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *How are you?*

Bot: *I'm feeling good today. How are you today?*

Customer: *grumpy?*

Bot: *Ah – That's too bad. Can I brighten up your day?*

Customer: *Joke*  
 Bot: *Two atoms were walking down the street one day, when one of them exclaimed, "Oh no - I've lost an electron!" "Are you sure?" the other one asked. "Yes," replied the first one, "I'm positive."*  
 Bot: *What else can I help you with? If you'd like to give feedback, just type feedback.*

### 5.1.3. The degree of social presence

The next categories regard the different degrees of social presence in the interactions, low social presence and medium social presence. Under the 'low social presence' category, there are three main sub-categories found from the analysis: mutual awareness, limited mutual monitoring, and low interactional involvement. First, the 'mutual awareness' sub-category reflects the customers' perceptions of the collocation of the chatbot. Second, the 'limited mutual monitoring' sub-category describes the miscommunication took place during the interactions, such as misunderstanding or misinterpretation of the intents of the customers. For instance, when a customer asked a simple question and the chatbot failed to understand it, it demonstrated a miscommunication between them and, therefore, a limited mutual monitoring level:

Customer: *Why are you here?*  
 Bot: *I don't know how to answer that I'm sorry.*

Finally, the 'low level of interactional involvement' sub-category demonstrates the chatbot's lack of commitment to solving the customers' problems. This can be expressed by the fact that the chatbot was unable to provide answers but directed customers to other information sources to sort out the problems themselves.

The next category, 'Medium social presence' consists of two sub-categories: high level of interactional involvement and joint engrossment. The 'high level of interactional involvement' sub-category entails those codes that describe the chatbot's attempts to address customers' problems and are evidenced by its adequate resolution process. The 'joint engrossment' sub-category reflects the engagement of customers with the conversations they had with the chatbot. For example, customers' self-disclosure demonstrates that they are emotionally involved in the conversation with the chatbot and are willing to share their personal emotions.

#### 5.1.4. Interaction outcomes

From the observation of the interaction between information-seeking strategies and social presence, four main sub-categories of interaction outcomes were found, including absolute failure, failure, subtle success and success. These types of outcome represent how much effort customers invested in the interactions and how the acquired information matched the desired information.

Table 3 below lists the eight main categories found in the analysis and their sub-categories. These categories and sub-categories will be further examined regarding their interactions and relationships in shaping the answers to the research question, “How do information-seeking strategies and social presence shape the outcome of interactions between customers and conversational agents?”

**Table 3.** List of categories and sub-categories

No.	Categories	Sub-categories	Concepts
1	Context-related factors	Staff support unavailability	After-hours inquiries
		Staff support availability	Office-hour inquiries
2	Goal-related factors	Task-oriented goals	<ul style="list-style-type: none"> <li>• Problem-solving</li> <li>• Incident investigation</li> <li>• Information confirmation</li> </ul>
		Non-task-oriented goals	<ul style="list-style-type: none"> <li>• General information request</li> <li>• Entertainment</li> </ul>
3	Information-related factors	Broadly-defined information needs	<ul style="list-style-type: none"> <li>• Construction</li> <li>• Orientation</li> </ul>
		Narrowly-defined information needs	Re-orientation
		Navigational information needs	<ul style="list-style-type: none"> <li>• Chatbot-related information</li> <li>• Company-related information</li> <li>• Information location</li> <li>• Procedural information</li> </ul>
		High priority information	<ul style="list-style-type: none"> <li>• Information importance</li> <li>• Information urgency</li> </ul>
		Psycho-emotional information	Informality
4	Technology-related factors	Natural language	<ul style="list-style-type: none"> <li>• Clickable buttons</li> <li>• Open-domain question answering ability</li> </ul>
		Colloquial language	Social cues
5	Interactive information-seeking strategies	Information interrogation strategies	<ul style="list-style-type: none"> <li>• Complete-sentence strategy</li> <li>• Fragmented strategy</li> <li>• Keyword search strategy</li> <li>• FAQ strategy</li> </ul>
		Social reciprocity strategies	Social reciprocity strategy
6	Low social presence	Mutual awareness	<ul style="list-style-type: none"> <li>• Greeting the chatbot</li> <li>• Curiosity about the chatbot</li> <li>• Politeness towards the chatbot</li> </ul>
		Limited mutual monitoring	<ul style="list-style-type: none"> <li>• Chatbot's inability to capture customer's intents</li> <li>• Chatbot's misinterpretation of customer's requests</li> <li>• Chatbot's repeated errors</li> <li>• Customer's repeated requests</li> </ul>
		Low level of interactional involvement	<ul style="list-style-type: none"> <li>• Navigating customers to other websites</li> <li>• Escalating customer requests</li> <li>• Suggesting customers seek human agent support</li> <li>• Scripted responses to pre-set options</li> </ul>



7	Medium social presence	High level of interactional involvement	<ul style="list-style-type: none"> <li>• Chatbot's adequate problem-solving attempts</li> <li>• Chatbot's adequate responses</li> <li>• Chatbot's willingness to help</li> </ul>
		Joint engrossment	Reciprocal self-disclosure
8	Interaction outcomes	Absolute failure	Acquired information not matching desired information and requiring additional effort
		Failure	Acquire information not matching desired information and requiring minimal effort
		Subtle success	Acquired information matching desired information and required additional effort
		Success	Acquired information matching desired information and required minimal effort

The following sections of this chapter present the patterns that show how distinct appraisals influenced the use of information-seeking strategies and how the interaction between these strategies and social presence shaped the outcomes of customer-chatbot interactions. The different sub-categories under the first four categories – context-related factors, goal-related factors, information-related factors, and technology-related factors – interacted with each other and composed distinct appraisal sets that were found to have affected the selection of information-seeking strategies. Under each appraisal set, there were main factors that showed strong causal relationships with the selected strategy and supporting factors that displayed weaker causal relationships. Elements classified as main factors are those that were found to have influenced the strategy and that all or most of the information-seeking strategies found in the data were influenced by them. In other words, if one of the main factors in an appraisal set is removed, the effects of the appraisal set will be different. On the other hand, supporting factors are those that influenced a strategy enactment, however, not many of the information-seeking strategies found in the data were affected by them. Therefore, supporting factors are considered to be non-essential to the strategy selection and can be opted out of without affecting how the appraisal set shapes information-seeking strategies.

The information-seeking strategies were selected under the influence of the appraisal sets. The strategies and the degree of social presence during the interactions were found to shape the outcome of the customer-chatbot interactions. Five main patterns were derived from the analysis that shed light on how different information-seeking strategies were selected and how their interactions with social presence affected the outcomes of customer-chatbot interactions. The next section, Section 5.2, explains the information-seeking strategy patterns which emerged from the analysis and how the appraisal sets influenced each strategic pattern. In Section 5.3, different degrees of social presence found in the analysis are discussed. Finally, Section 5.4 describes how the interactions between the selected information-seeking strategies and social presence shaped the outcomes of customer interactions with the chatbot.

## 5.2. Information-seeking strategies under the impact of appraisal factors

Five patterns of the use of information-seeking strategies were identified from the analysis, including (i) complete-sentence strategy, (ii) fragmented strategy, (iii) keyword search strategy, (iv) FAQ strategy, and (v) social reciprocity strategy. These patterns demonstrate how customers leveraged the chatbot for their information seeking, which reflects how customers initiate the conversations and the characteristics of their queries.

### 5.2.1. Complete-sentence strategy

The complete-sentence strategy is used when a customer poses his queries in full sentences. Complete-sentence queries could be in the form of a question. In the example below, the customer informs the chatbot about the outage location and states his desired information, which is the underlying explanation associated with the outage. This is done using a full-sentence question:

Customer: *[Street address] – Do you know why power is out?*  
Bot: *Outages – Here's some handy links about outages. If your outage isn't shown on our map then you can report it to us by calling [phone numbers]. | [attached links]*

Complete-sentence queries are also posted in the form of an informative statement. The customer in the example below describes his problem by a statement, “My power is out in [home address]”, that is interpreted as a request for an outage check:

Customer: *Power is out in [home address]. What happened?*  
Bot: *I can help you check you check your address for an outage. Is [home address] the correct location?*  
Customer: *Yes*  
Bot: *We are not aware of an outage in your area. Please report it to us via the link below so we can investigate. | [attached links]*

This strategy, whether in the form of a question or an affirmative statement, gives customers the ability to describe the problems they are facing in detail and precisely express their information needs. It is the most used strategy in the data set as more than 64% of the interactions were initiated by complete-sentence queries.

Despite its advantages, lengthy sentences with too much information might be difficult to interpret for the chatbot, causing misunderstanding or misinterpretation of the intentions of customers, for instance,

Customer: *The streetlight across the road from [home address] has been out for a few weeks. I contacted Auckland Transport but haven't heard anything from them. I noted this morning on their website, they only deal with above ground issues, and I'm thinking this may be a below ground fault. Can this be looked into as it's become a danger. Thanks.*  
Bot: *Outage Centre – The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | [attached links]*

Five main factors and eight supporting factors were found to have influenced the selection of the complete-sentence strategy (see Table 4 below). First, no essential influence from context-related factors,

including after-hours inquiries and office-hour inquiries, were identified. The analysis did not find any significant differences between the interactions activated during and after office hours.

Second, problem-solving and incident investigation serve as the main goal-related factors that influence the selection of the complete-sentence strategy. Problem-solving goals urge customers to seek information that provides them with new knowledge to resolve their issues. However, incident investigation goals encourage customers to search for information that provides them with details about the situations they are facing. These factors, problem-solving and incident investigation, are the concepts of the task-oriented goals sub-category that refers to purposes of accomplishing some tasks. Besides the essential influences of these factors on most complete-sentence strategy interactions, the general information request was found to be a supporting goal-related factor. Although this type of goal has some effect on the strategy, only a small number of complete-sentence strategy interactions are associated with it.

Third, with the goals above, customers seek information that can help them to solve their problems or to understand what was happening. This explains the essential influences of construction and orientation information needs, which are the two information-related factors that are under the 'broadly-defined information needs' sub-category. Construction information needs could be reflected by queries asking about how to report an outage. On the other hand, orientation information needs refer to those queries asking about how long an outage would be. There are five supporting information-related factors that influence the complete-sentence strategy but are not found associated with many interactions. These factors are re-orientation information needs, information urgency, chatbot-related information, company-related information, and procedural information. Re-orientation information needs supported the orientation information needs by motivating customers to seek additional details to bolster the information they already knew about the incidents. The other supporting factors, such as chatbot-related information, company-related information, and procedural information, support the construction information needs by encouraging the search for new information about a topic of interest. These factors belong to the 'navigational information needs' sub-category that refers to general information that is not specific to any particular customer cases.

Fourth, to fulfill the goals and information needs above, customers would choose a strategy that allows instant and detailed information exchange in order to get their open-domain questions answered.

Therefore, the main technology-related factor driving customers to use the complete-sentence strategy was the open-domain question answering ability of the chatbot.

For example, the customer in the interaction below wants to check the duration of an outage. The goal of this conversation is to know what is happening, i.e. incident investigation. The desired information refers to gaining more understanding of the incurring outage, i.e. orientation information needs. To do so, detailed information exchange between the two parties is required. Therefore, the chatbot's ability to process text-based questions and provide adequate answers would allow the customer to easily raise his query and receive understandable responses.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *When will the power in [street address] likely be coming back?*

Bot: *Outage Centre – The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | [attached links]. What else would you like to know? If you'd like to give feedback, just type feedback*

**Table 4.** Complete-sentence strategy and its appraisal set

Appraisals	Main factors	Supporting factors
<i>Context-related factors</i>	–	<ul style="list-style-type: none"> <li>• After-hours inquiries</li> <li>• Office-hour inquiries</li> </ul>
<i>Goal-related factors</i>	<ul style="list-style-type: none"> <li>• Problem-solving</li> <li>• Incident investigation</li> </ul>	<ul style="list-style-type: none"> <li>• General information request</li> </ul>
<i>Information-related factors</i>	<ul style="list-style-type: none"> <li>• Orientation</li> <li>• Construction</li> </ul>	<ul style="list-style-type: none"> <li>• Re-orientation</li> <li>• Urgency</li> <li>• Chatbot-related information</li> <li>• Company-related information</li> <li>• Procedural information</li> </ul>
<i>Technology-related factors</i>	<ul style="list-style-type: none"> <li>• Open-domain question answering ability</li> </ul>	–

Overall, context-related factors play a supporting role in shaping the use of the complete-sentence strategy. Task-oriented goals, including the problem-solving and incident investigation goals, show more dominant effects on the complete-sentence strategy than non-task-oriented goals. Moreover, customers with broadly-defined information needs are likely to use the complete-sentence strategy for information-seeking, in which case the desired information is case-specific. This type of information is the

opposite of general information that is not related to any specific case and every customer would receive the same responses. By contrast, case-specific information would be different from case-to-case and, therefore, different customers would receive different responses. For example, customers requesting outage checks would receive a different outcome depending on their address. On the other hand, customers looking for information about contact details of the company would receive the same responses, as the desired information is unrelated to the customers' situations. Since the desired information is case-specific, the chatbot's ability to answer open-domain questions in natural language would help customers to acquire their desired information. Therefore, when customers embark on interactions that were influenced by these appraisal factors, they had a tendency to use the complete-sentence query strategy as an approach to search for information.

### 5.2.2. Fragmented strategy

The fragmented strategy refers to the information-seeking approach that involves putting in fragments of details about a topic through a series of interactions. Instead of posting all information in a full sentence, customers choosing the fragmented query strategy for information-seeking broke their queries down into small pieces of information and provided each piece in a separate conversational turn. This type of request could be fragments of short phrases as in the example below. The customer tries to provide as many details as possible to help him describe how severely the outage affected his work.

Customer: *Can I confirm whether there is gas in the following address:*  
Bot: *To find out an estimation on how much it will cost to get gas connected simply use our gas estimator tool below.*  
*['Gas estimator' option] | ['Get an estimate' option] -*  
Bot: *What else can I help you with? If you'd like to give feedback, just type feedback.*  
Customer: *(input home address)*  
Bot: *It looks like you've entered an address. Did you want to check for outages, get a new connection or organise a disconnection?*

Fragmented queries could also be pieces of information stated in a sentence followed by another. In the following example, each sentence represents a piece of information about the customer's incident. Because fragmented pieces of information were given separately, the chatbot was unable to grasp the situation and failed to provide adequate responses.

Customer: *My power pole fell down*  
Bot: *I don't know how to answer that I'm sorry. These are some of the things I can currently help you with. | [provided options]*

Customer: *Lightning hit the pole outside my house*

Bot: *You can help keep our network safe by reporting damaged equipment, pipeline or cable exposure by calling [phone number]. If this is an emergency please call 111. | ['Damaged network' option] | ['More info' option]*

Bot: *What else would you like to know? If you'd like to give feedback, just type feedback.*

Customer: *It's on fire*

Bot: *I don't know how to answer that I'm sorry. These are some of the things I can currently help you with. | [provided options]*

Customer: *I think I heard some kind of explosion*

Bot: *I'm sorry, I didn't understand that. These are some of the things I can currently help you with. | [provided options]*

Customer: *The transformer just blew up and took out a car*

Bot: *I don't know how to answer that I'm sorry. These are some of the things I can currently help you with. | [provided options]*

Customer: *It's chaos - people running for their lives.*

Bot: *I don't know how to answer that I'm sorry. These are some of the things I can currently help you with. | [provided options]*

Some customers are aware of the chatbot's inability to process multiple information pieces at once and, therefore, rephrased their queries to make it easier for the chatbot. The example below shows that the chatbot can interpret the intention of the customer and suggested appropriate actions to address the issues after all information was later provided in one turn.

Customer: *Outage*

Bot: *Sounds like your power may be out – I'm sorry to hear that  
You can get in touch with [Company name] by phoning [phone number]  
([Company name]) or at the contact details linked below | [attached links]  
How else can I help?*

Customer: *At [street address]*

Bot: *It looks like you've entered an address. Did you want to check for outages, get a new connection, or organise a disconnection?*

Customer: *An outage at [street address]. Need to know the time we will get the power back*

Bot: *Sounds like your power may be out – I'm sorry to hear that  
You can get in touch with [Company name] by phoning [phone number]  
([Company name]) or at the contact details linked below | [attached links]  
How else can I help?*

Interactions that involved fragmented strategy show a high failure rate because it involved more turn-takings between the chatbot and customers, which, however, did not guarantee whether the chatbot can fully understand the customers' intention. Moreover, in the examples above, customers did not provide

sufficient information in one turn, making it difficult for the chatbot to interpret their intentions. Therefore, customers did not show much interest in using this strategy as the analysis shows only a small percentage (2.5%) of the interactions were carried out by fragmented queries.

Four main factors and five supporting factors were found to have influenced the fragmented strategy (see Table 5 below). First, similar to the complete-sentence strategy pattern, no significant impacts of context-related factors were identified. This is because there are no significant differences between the interactions that were initiated by the fragmented strategy during and after office hours.

Second, problem-solving is the main goal-related factor that influences most fragmented strategy interaction. It is a concept related to the 'task-oriented goal' sub-category. This type of goal could refer to a report of an emergency or question about how to cancel a request. Besides that, the analysis also found the supporting influences of the incident investigation goals on the use of the fragmented strategy. This task-oriented goal is associated with the search for information that helps customers understand more about their incidents. Incident investigation goals were found to influence the fragmented strategy but were only exhibited in a few fragmented strategy interactions.

Third, to fulfil the goals above, customers want to acquire information that meets their construction and orientation information needs, which are the concepts of the 'broadly-defined information needs' sub-category. Construction information needs drive customers to seek information giving them instructions on solving the problems they incurred. Orientation information needs, on the other hand, encourage customers to look for information that offers them more details about what is happening. These information needs, construction and orientation, are the main information-related factors found to influence the fragmented strategy. Along with the main factors, two other supporting information-related factors are found, including information importance and information location. First, information importance refers to how significant the desired information is to the customer. The importance of the desired information was found to support the construction information needs because it explains why getting the problem solved is important. It is usually associated with their safety, such as gas safety or network damages. Second, details about information location are related to where the desired information is stored. This supporting factor was found to be closely linked with the orientation information needs as the information location helps customers to locate the information that explains the incidents that have occurred. Information importance and information location, however, did not



influence many interactions in which fragmented queries were used. Therefore, they only play a supporting role in shaping the use of the fragmented strategy.

Finally, the goals and information needs outlined above indicate that there would be intense information exchanges between customers and the chatbot to get their questions answered. Therefore, the open-domain question answering ability of the chatbot is the main technology factor that stimulated the use of the fragmented strategy.

The example below depicts an interaction in which the customer wants to report an outage. This is a problem-solving goal that aims at finding solutions to the power outage the customer is experiencing. The desired information should give the customer instructions on how to pose an outage report, which reflects a construction information need. As the incident refers to addressing an open-domain problem, the chatbot's ability to answer open-domain questions helps the customer to easily communicate his problems and receive appropriate answers.

Customer: *No power*

Bot: *Outage Centre – The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | [‘Go to Outage Centre’ option]*  
*What else can I help you with? If you'd like to give feedback, just type feedback.*

Customer: *[street address]*

Bot: *It looks like you've entered an address. Did you want to check for outages, get a new connection, or organise a disconnection?*

Bot: *[company name] | [‘Check for outages’ option] – [‘Apply for a connection’ option] – [‘Order a disconnection’ option]*

Bot: *What else would you like to know? If you'd like to give feedback, just type feedback.*

**Table 5.** *Fragmented strategy and its appraisal set*

<b>Appraisals</b>	<b>Main factors</b>	<b>Supporting factors</b>
<i>Context-related factors</i>	–	<ul style="list-style-type: none"> <li>• After-hours inquiries</li> <li>• Office-hour inquiries</li> </ul>
<i>Goal-related factors</i>	<ul style="list-style-type: none"> <li>• Problem-solving</li> </ul>	<ul style="list-style-type: none"> <li>• Incident investigation</li> </ul>
<i>Information-related factors</i>	<ul style="list-style-type: none"> <li>• Orientation</li> <li>• Construction</li> </ul>	<ul style="list-style-type: none"> <li>• Importance</li> <li>• Information location</li> </ul>
<i>Technology-related factors</i>	<ul style="list-style-type: none"> <li>• Open-domain question answering ability</li> </ul>	–

Overall, context-related factors only play a supporting role in influencing the use of the fragmented strategy. All interactions that involved the fragmented strategy are influenced by task-oriented goals that were found to be the main goal-related factor. Broadly-defined information needs factors, including construction and orientation, play an essential role in influencing the use of the fragmented strategy. The chatbot's ability to answer open-domain questions in natural language is the main technology-related factor influencing the selection of this strategy. This ability allows customers to precisely describe the situations, state the questions and receive appropriate replies from the chatbot. Therefore, when these main factors collectively influence the interaction, customers are likely to choose the fragmented query strategy for information-seeking.

### 5.2.3. Keyword search strategy

The keyword search strategy refers to the information-seeking strategy that uses key search terms about the topics of interest to look up the desired information. Applying this strategy, customers input a few keywords as the search terms. Two types of search terms are used by customers to pose their queries. The first type is a short description of the topics of interest that might refer to an object, such as "Grantee for [company name] easement", or to an action, like "Change of postal address." In most cases, the short search terms are used to describe the situation customers were facing. In the example below, the customer states his problem which is a power outage. Based on the keyword 'outage', the chatbot could interpret his intention and reply accordingly:

Customer:        *Outage [street address]*  
Bot:                *Sounds like your power may be out - I'm sorry to hear that. You can get in touch with [company name] by phoning [phone number] or at the contact details linked below. | [attached links]*

The second type of keyword search strategy is using lengthy phrases to declare the desired information needs. The search terms in the example below are both lengthy and rambling, so consequently the chatbot fails to understand the intention of the customer.

Customer:        *The Physical Risks from Climate Change Report of Findings for [Company name] Limited (November 2017)*  
Bot:                *I'm sorry, I didn't understand that. These are some the things I can currently help you with. | [provided options]*

Moreover, for those topics that are not pre-programmed for the chatbot, it is likely that the chatbot would fail to provide adequate responses. In the interaction below, because the search topic is not within the

knowledge domain of the chatbot, it is unable to understand the intent of the customer despite his attempt to rephrase his queries to make them more understandable.

Customer: *Painting of transformers*

Bot: *I'm sorry, I didn't understand that. These are some of the things I can currently help you with. | [provided options]*

Customer: *(select a pre-set option) Something else*

Bot: *What can I help you with?*

Customer: *Paint finish of substation*

Bot: *I'm sorry, I didn't understand that. These are some of the things I can currently help you with. | [provided options]*

The above examples indicate that the results of the interactions can vary depending on the topics that customers are interested in and how they choose their search terms to pose their queries. Due to its ease of use, the keyword search strategy takes up to approximately 10% of the total interactions, making it the third most used strategy.

There were five main factors and four supporting factors found to have influenced the keyword search strategy (see Table 6 below). First, context-related factors, including after-hours inquiries and office-hour inquiries, did not show a strong causal relationship with the strategy, which is similar to those of the complete-sentence strategy and fragmented strategy. The analysis shows no significant differences between the interactions carried out by the keyword search strategy during and after office hours.

Second, problem-solving and general information requests are the two main goal-related factors that influence the keyword search strategy. Problem-solving goals refer to the intentions of customers to request information that helps them to address their issues, such as outage reporting and safety instructions. This is a concept related to the 'task-oriented goals' sub-category that refers to the goals of accomplishing certain tasks. General information request goals refer to the intention of looking for general information, such as contact numbers. It is a concept associated with the 'non-task-oriented goals' sub-category that does not involve any task accomplishments.

Third, to meet the goals above, customers wish to look for information that either helps them solve their problems or addresses their general information requests. This explains why construction and orientation information needs are the two main information-related factors that shape the use of the keyword search strategy. They are under the 'broadly-defined information needs' sub-category. Construction information needs drive customers to search for information that provides them with instructions on how to solve

their problems or to form an understanding of the topics of their interest. Orientation information needs motivate customers to look for more details that explain what is happening in their situation. Additionally, the analysis found the supporting effects of information location and procedural information on the keyword search strategy. They both represent the ‘navigational information needs’ sub-category that refers to general information that is not specific to any problems that customers face. Information location is related to the location that stores the contents that customers are searching, such as where the outage map is. Procedural information describes the steps that customers need to take to complete a task, such as how to get connected to the power network of the company. Information location and procedural information were found to be closely related to the orientation information needs, that provides them with details about what is taking place in their situations. Since only a few interactions were influenced by the information location and procedural information factors, they were coded as supporting factors.

Finally, the chatbot’s ability to understand and answer open-domain questions was identified as the main technology-related factor that triggered customers to apply this strategy. This factor is a concept under the ‘natural language’ sub-category that reflects the chatbot’s ability to communicate with customers in human natural language.

The example below illustrates a customer’s request for general information. The desired information, “sustainability,” reflects a construction information need. It shows that the customer wants to know more about the sustainability of the company – the topic about which he did not have much information. The chatbot’s open-domain question answering ability allows the customer to get his query answered properly.

Bot:	<i>Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?</i>
Customer:	<i>Information on sustainability</i>
Bot:	<i>I'm sorry, I didn't understand that. These are some of the things I can currently help you with.   [provided options]</i>
Customer:	<i>Sustainability</i>
Bot:	<i>[Company name] is all about creating a bright future for Auckland. We're involved in all sorts of community projects from providing energy education programmes in schools, to working with Auckland Council to light up the harbour bridge. To find out more, check out our website, linked below.   [attached links]</i>

**Table 6.** Keyword search strategy and its appraisal set

Appraisals	Main factors	Supporting factors
<i>Context-related factors</i>	–	<ul style="list-style-type: none"><li>• After-hours inquiries</li><li>• Office-hour inquiries</li></ul>
<i>Goal-related factors</i>	<ul style="list-style-type: none"><li>• Problem-solving</li><li>• General information request</li></ul>	–
<i>Information-related factors</i>	<ul style="list-style-type: none"><li>• Orientation</li><li>• Construction</li></ul>	<ul style="list-style-type: none"><li>• Procedural information</li><li>• Information location</li></ul>
<i>Technology-related factors</i>	<ul style="list-style-type: none"><li>• Open-domain question answering ability</li></ul>	–

In general, context-related factors are considered to be supporting factors because they have a weak causal relationship with the keyword search strategy. The main goal-related factors, including problem-solving and general information requests, indicate that customers with either task-oriented goals or non-task-oriented goals may use search terms to extract information from the chatbot. Customers with broadly-defined information needs are likely to apply the keyword search strategy for information-seeking. The technology-related factor that allows customers to quickly pose their open-domain questions and get them answered by the chatbot drives the intention to use the keyword search strategy to attain their desired information.

#### 5.2.4. FAQ strategy

The company designed the chatbot with selected pre-set options at the beginning of the conversation for customers to choose from. Each option is linked to a frequently asked topic that customers might be interested in. The list of pre-set options includes “check outages,” “getting connected,” “what the company does,” “contact a person” and “something else.” The FAQ strategy refers to the use of these pre-defined options to pose frequently asked questions (FAQs) to the chatbot. Once an option is selected, the chatbot accordingly provides responses that were already pre-programmed by the company. The FAQ strategy gets customers to state their intents before any additional information is requested. For instance, in the interaction below, the customer only provides detailed information, i.e. his home address, after stating his intents by selecting the ‘Outage – Check my address’ option.

Customer: (select a pre-set option) Outages – Check my address  
Bot: I can help you check your address for an outage. You can type or send me your location (don't forget to click 'Allow'). What is your street address?  
Customer: (input home address)  
Bot: Choose your address or click on "Start again" to enter a new address.

*[home address]. Click on "Use this address" if this is the correct address / [attached links]*

Customer: *(confirm home address)*

Bot: *We are not aware of an outage in your area. Please report it to us via the link below so we can investigate. | [attached links]*

Once customers select a topic from the FAQ list, there are two possible subsequent scenarios: either the customer gets asked for supporting information as in the example above, or the use of the pre-set option is followed by another list of pre-set options:

Customer: *(select a pre-set option) Getting connected*

Bot: *The process of getting connected to the Vector network has several stages:*

- 1. You make an application to Get Connected.*
- 2. We send you a quote.*
- 3. After the quote is accepted and paid, we commence work.*
- 4. The connection is built and any reinstatement work is done.*

*Start the connections quote process... | ['Apply now' option]*

Bot: *Would you like any more details?*

Customer: *(select a pre-set option) Apply now*

*(Customer gets directed to another website)*

The FAQ strategy not only enables customers to precisely and quickly raise their queries but also gets the chatbot to generate responses that are close to the desired information of customers. Therefore, it was followed by 17.5% of interactions, making it the second most used strategy in the data set.

Four main factors and four supporting factors were found to have influenced the FAQ strategy (see Table 7 below). First, similarly to the previous strategies, the analysis did not find any major impact by context-related factors, including after-hours inquiries and office-hour inquiries, on the use of the FAQ strategy. This is because no differences were found between the interactions initiated by the FAQ strategy during and after office hours.

Second, the main goal-related factors are information confirmation and general information request goals. Information confirmation goals refer to the desire to search for information that confirms the accuracy of the information that customers already have. An example of the information confirmation goal would be a customer confirming with the chatbot the time at which an outage will be over. This type of goal is a concept related to the 'task-oriented goals' sub-category as it is concerned with acquiring information in order to accomplish certain tasks. General information request goals are associated with the intention to look for general information that is not related to any specific problems that customers

have, such as contact numbers and dividend dues. It is a concept under the ‘non-task-oriented goals’ sub-category that does not involve completing any tasks.

Third, with these goals in mind, customers aim to look for information that helps them confirm the accuracy of the information they already know and to understand what is taking place. Therefore, the orientation information needs are the main information-related factors that influence the FAQ strategy. Orientation information needs drive customers to search for information that explains what is happening in their situations. This type of information need is a concept of the ‘broadly-defined information needs’ sub-category. Additionally, information location and procedural information were found to have supporting influences on the FAQ strategy alongside the main effects of orientation information needs. The two supporting factors both belong to the ‘navigational information needs’ sub-category. Information location refers to the location where the contents that customers are looking for are stored. Procedural information describes the procedures that customers need to take to complete a specific task. These two supporting factors, information location and procedural information, were found to be closely associated with the orientation information needs as they refer to the information from which customers can have a grasp of what is happening in their cases. They play a supporting role in influencing the FAQ strategy because they did not show a strong causal relationship with most interactions initiated by the strategy.

Finally, the desired information was typically of the topics found in frequently asked questions, which were offered as clickable buttons throughout the chat. This technology-related factor encourages customers to use the buttons that refer to the topics of their interest in order to pose their requests with minimal effort.

The interaction below is a representation of the FAQ strategy’s appraisal set. In this example, the customer’s goal is to confirm whether his address is under a planned outage, which is of the information confirmation goal. His information needs direct him to search for information that explains why he is experiencing an outage, i.e. orientation information needs. The topic referring to an outage check is one of the frequently asked topics that were offered by the chatbot through clickable buttons at the beginning of the chat. Their ease of use attracts the customers attention when they embark on the conversations as they can quickly and easily pose their requests.

Customer:        *(select a pre-set option) Outages – Check my address*

Bot: *I can help you check your address for an outage. You can type or send me your location (don't forget to click 'Allow'). What is your street address?*

Customer: *(input home address)*

Bot: *Thanks. Is [home address] the correct location?*

Customer: *Yes*

Bot: *We are aware of an unplanned outage in your area, and the estimated restoration time is still being confirmed. To get the latest info as it becomes available, visit the link below and sign up for updates by TXT or email. | [attached links]*

**Table 7.** FAQ strategy and its appraisal set

Appraisals	Main factors	Supporting factors
<i>Context-related factors</i>	–	<ul style="list-style-type: none"> <li>• After-hours inquiries</li> <li>• Office-hour inquiries</li> </ul>
<i>Goal-related factors</i>	<ul style="list-style-type: none"> <li>• Information confirmation</li> <li>• General information request</li> </ul>	–
<i>Information-related factors</i>	<ul style="list-style-type: none"> <li>• Orientation</li> </ul>	<ul style="list-style-type: none"> <li>• Procedural information</li> <li>• Information location</li> </ul>
<i>Technology-related factors</i>	<ul style="list-style-type: none"> <li>• Clickable buttons</li> </ul>	–

In general, the context-related factors do not exert much influence on the FAQ strategy. The main goal-related factors, including information confirmation and general information request goals, indicate that customers with either task-oriented goals or non-task-oriented goals might use the FAQ strategy for their information search. Moreover, broadly-defined information needs have a strong causal relationship with the strategy. Clickable buttons offer quick question posing and, when activated, will provide appropriate answers in natural language, which was the main technology-related factor shaping the use of the FAQ strategy. Therefore, when an interaction influenced by the factors in this appraisal set, it will likely be carried out by the FAQ strategy.

#### 5.2.5. Social reciprocity strategy

Social reciprocity strategy involves both customers and the chatbot as social actors to reciprocally exchange information in order to sustain the conversations. Particularly, this strategy is usually used for informal and conversational interactions. Customers adopted this strategy to carry out friendly conversations with the chatbot without pre-defining their desired information. During a socially reciprocal interaction, customers and the chatbot alternately take turns to keep the conversation going until they specify their information needs.



In the example below, although the customer did not state his exact goals and information needs, it can be observed from the interaction that he wants to share his feelings and have an informal conversation with the chatbot. He continuously expressed his anger to the chatbot until it suggested him to seek human employee support.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *I'm angry*

Bot: *Ah – That's too bad. Can I brighten up your day? | [provided options]*

Customer: *Ok- now I'm angry*

Bot: *Ah – That's too bad. Can I brighten up your day? | [provided options]*

Customer: *I'm angry*

Bot: *Ah – That's too bad. Can I brighten up your day? | [provided options]*

Customer: *Angry angry angry*

Bot: *I'm sorry I couldn't be of more help. Please call us directly so we can assist further. | ['Contact [Company name]' option] | ['Get in touch' option] || [phone number] [email address] |[phone number] |['Call Us' option] |[email address] | ['Email Us' option] | [website link] | ['Contact us page' option]*

The analysis shows that customers who applied this strategy usually did not establish a clear agenda for the interactions in advance. The social reciprocity strategy was enacted in 6% of total interactions, which makes it one of the least used strategies.

Three main factors and three supporting factors were found to have influenced the social reciprocity strategy (see Table 8 below). First, the context-related factors, including after-hours inquiries and office-hour inquiries, did not exhibit an essential influence on social reciprocity. The analysis did not find any significant differences between the interactions initiated by the social reciprocity strategy during and after office hours.

Second, the main goal-related factor that was found to have a causal relationship with the social reciprocity strategy was entertainment goals, which is a concept associated with the 'non-task-oriented goals' sub-category. This type of goal drove customers to initiate conversations with random content and without involving any tasks to be done.

Third, customers may search for information that is casual, which fits their entertainment purposes. Therefore, informality is identified as the main information-related factor that influenced the selection of

the social reciprocity strategy. Informality is a concept under the ‘psycho-emotional information needs’ sub-category that refers to the need for information related to feelings and emotions, such as sharing jokes or reciprocal self-disclosure.

Finally, since the exchange of psycho-emotional information gets customers and the chatbot to be involved in the conversations both cognitively and emotionally, the social cues are the main technology-related factor that influence the social reciprocity strategy. Social cues are a concept related to the ‘colloquial language’ sub-category that refers to the chatbot’s ability to sustain a conversation. They trigger social responses from both customers and the chatbot and help maintain the intimacy between them during the interactions. Moreover, the analysis identified the chatbot’s ability to address open-domain questions as a supporting factor. When using the social reciprocity strategy, customers also posed open-domain questions to request entertainment information. Although the chatbot’s ability to answer open-domain questions was found to influence the social reciprocity strategy, not all social reciprocity interactions were affected by this factor. Therefore, the chatbot’s open-domain question-answering ability is considered to be a supporting technology-related factor.

The example below illustrates the appraisal set of the social reciprocity strategy. The conversation is started with no clear intention. The customer’s goal emerges when the chatbot offers help, which is a request for joke sharing. This request reflects the entertainment purpose of the customer. The emotional self-disclosure of the customer and his request of the chatbot to tell jokes indicates that the customer wants to look for casual information with a high level of informality. Moreover, the social cues embedded into the chatbot, such as intimate greetings and colloquial jokes, trigger the customer to use the social reciprocity strategy to interact with the chatbot.

Bot:	<i>Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?</i>
Customer:	<i>How are you?</i>
Bot:	<i>I'm feeling good today. How are you today?</i>
Customer:	<i>Sleepy</i>
Bot:	<i>Ah – That's too bad. Can I brighten up your day?</i>
Customer:	<i>Joke</i>
Bot:	<i>I have a joke to share: My mother believed I'd be a good electrician. She always said "You conduit!". What else can I help you with? If you'd like to give feedback, just type feedback.</i>
Customer:	<i>Tell me a joke</i>
Bot:	<i>I have a joke to share:</i>

Bot: *I finally managed to get rid of that nasty electrical charge I've been carrying. I'm ex-static!*  
*What else can I help you with? If you'd like to give feedback, just type feedback.*

**Table 8.** Social reciprocity strategy and its appraisal set

Appraisals	Main factors	Supporting factors
<i>Context-related factors</i>	–	<ul style="list-style-type: none"> <li>• After-hours inquiries</li> <li>• Office-hour inquiries</li> </ul>
<i>Goal-related factors</i>	<ul style="list-style-type: none"> <li>• Entertainment</li> </ul>	–
<i>Information-related factors</i>	<ul style="list-style-type: none"> <li>• Informality</li> </ul>	–
<i>Technology-related factors</i>	<ul style="list-style-type: none"> <li>• Social cues</li> </ul>	<ul style="list-style-type: none"> <li>• Open-domain question answering ability</li> </ul>

In general, the appraisal set of the social reciprocity strategy does not include any context-related factors as the main factors that influence the use of the social reciprocity strategy. An entertainment goal, which is a non-task-oriented goal factor, plays an essential role in shaping the use of the strategy. Customers looking for information with a high level of informality are likely to use the social reciprocity strategy for their search. The chatbot's social cues help customers easily engage in and sustain the conversations. This colloquial language factor also significantly influences this strategy. Hence, when customers embark on interactions that are influenced by this appraisal set, they are likely to apply social reciprocity strategy to interact with the chatbot.

The emergent information-seeking strategies and the main factors in their appraisal sets were summarised (refer to Table 9 below). The main factors of goal-related factors, information-related factors, and technology-related factors were presented alongside with their sub-categories, and the final column shows the information-seeking strategies identified from the analysis. Each row represents an interaction of the main factors and their associated strategy. For example, social reciprocity strategy was influenced by entertainment as a goal-related factor, informality as an information-related factor, and social cues as a technology-related factor.

**Table 9.** Summary of main appraisal factors

Appraisal sets						Interactive information-seeking strategies	
Goal-related factors		Information-related factors		Technology-related factors			
Sub-categories	Concepts	Sub-categories	Concepts	Sub-categories	Concepts		
Task-oriented goals	Problem-solving	Broadly-defined information needs	Orientation	Natural language	Open-domain question-answering ability	Complete-sentence strategy	Information interrogation strategies
Task-oriented goals	Incident investigation	Broadly-defined information needs	Construction				
Task-oriented goals	Problem-solving	Broadly-defined information needs	Orientation	Natural language	Open-domain question-answering ability	Fragmented strategy	
		Broadly-defined information needs	Construction				
Task-oriented goals	Problem-solving	Broadly-defined information needs	Orientation	Natural language	Open-domain question-answering ability	Keyword search strategy	
Non-task-oriented goals	General information request	Broadly-defined information needs	Construction				
Task-oriented goals	Information confirmation	Broadly-defined information needs	Orientation	Natural language	Clickable buttons	FAQ strategy	
Non-task-oriented goals	General information request						
Non-task-oriented goals	Entertainment	Psycho-emotional information needs	Informality	Colloquial language	Social cues	Social reciprocity strategy	Social reciprocity strategies

### 5.3. The role of social presence

As customers engage in their conversations with the chatbot using information-seeking strategies, certain degrees of social presence emerge. The degree of social presence was found to interact with the information-seeking strategies throughout the customer-chatbot interaction, which eventually shaped the outcomes. The analysis reveals two degrees of social presence manifested in the interactions: low social presence and medium social presence.

#### 5.3.1. Low social presence

A low degree of social presence refers to the situation in which customers are aware of the chatbot's existence but they do not cognitively and emotionally become involved in a joint task. At this degree, customers recognise the co-existence of the chatbot in the conversations. However, their ability to monitor each other is not always possible as indicated. Moreover, only a minimal level of interactional involvement is established by the chatbot while resolving customers' problems. Therefore, low social presence is expressed by three sub-categories: (i) mutual awareness, (ii) limited mutual monitoring, and (iii) low level of interactional involvement.

First, mutual awareness refers to the acknowledgment of customers for the existence of the chatbot in the same virtual space and that they can interact with it and vice versa. Customers' awareness about the chatbot's existence was demonstrated by the way they got the conversation started. They were found to treat the chatbot as if it were a human agent and present in the same space with them. This can be observed by their greetings, curiosity about the chatbot and politeness towards it. The fact that customers start conversations with the chatbot, either through text-based inputs or pre-set options, and that the chatbot responds to the customers' triggers makes every interaction pertain to a certain level of mutual awareness. For example, in the interaction below, the customer acknowledges the co-existence of the chatbot by greeting it and introducing himself. He also uses formal words and a complex sentence structure to communicate with the chatbot. This behavior indicates that the customer is aware that the chatbot is collocated with him and available for interaction, which illustrates a mutual awareness between them.

Bot:	<i>Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?</i>
Customer:	<i>Hi [Chatbot name], this is [Customer name]. Can I talk to you about the power line that goes from the lamppost (at the street) and then connect</i>

*to another lamppost (down the driveway) before connecting to my house?*

Bot: *I'm sorry I couldn't be of more help. Please call us directly so we can assist further. | [phone numbers] – [attached links].*

Bot: *Would it be ok if I ask you a couple of questions so I can improve your experience with me in the future?*

Second, the analysis identified several expressions of mutual monitoring, albeit limited, between the chatbot and customers. The limited level of mutual monitoring is reflected by the constrained ability to monitor and understand the behaviours of others, including (i) the chatbot's inability to capture the intents of customers, (ii) the chatbot's misinterpretation of customers' requests, (iii) the chatbot's repeated errors, and (iv) customers' repeated requests.

The chatbot's inability to identify the intents of customers is found when the chatbot claims that it does not know how to answer a question. In the example below, although the customer clearly states his purpose, which is to investigate his power outage, the chatbot cannot understand his intentions and, therefore, establishes a limited level of mutual monitoring.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *Time expect power on [street address]*

Bot: *I don't know how to answer that I'm sorry. These are some of the things I can currently help you with. || [provided options]*

Customer: *(select a pre-set option) Outages*

Bot: *Sounds like your power may be out – I'm sorry to hear that. You can get in touch with [Company name] by phoning [phone number] ([Company name]) or at the contact details linked below. How else can I help?*

The chatbot's misinterpretation of customers' intents is exhibited when the chatbot provides irrelevant responses to customers' queries. For example, the customer in the interaction below wants to check if his mail has been delivered, however, the chatbot replies with the information about quote cancellation. This indicates that the chatbot fails to understand the customer's intentions and, therefore, manifest a limited level of mutual monitoring.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *Keen to find out if my mail has been delivered to Finance Ltd in regards to due payment from last year*

Bot: *If you have accepted the quote but decide to cancel before the work starts, there is a standard cancellation fee of \$100 (including GST). What can I help you with?*

The chatbot also makes some errors that are repeated multiple times within an interaction, which makes it difficult for customers to understand the chatbot's behaviour. The following example shows that, while helping the customer to check his address for an outage, the chatbot informs the customer that there is an error in validating his address. However, this error is not resolved afterwards but keeps being repeated several times. This repeated error hinders the customer from understanding the chatbot's intentions. Since he cannot carry on with the conversation due to the error, he leaves the chat eventually. Therefore, the repeated errors of the chatbot also establish a low level of mutual monitoring.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *(select a pre-set option) Check outages*

Bot: *I can help you check your address for an outage. What address would you like to check?*

Customer: *(input home address)*

Bot: *There was an error validating your address. Please enter the address again.*

Customer: *(input home address)*

Bot: *There was an error validating your address. Please enter the address again*

Customer: *(input home address)*

Bot: *There was an error validating your address. Please enter the address again*

Customers' repeated responses were found when they repeated their responses multiple times as they were unable to adequately monitor the chatbot's behaviour. In the following interaction, as the chatbot misinterprets the customer's intent, he repeats his request twice to restate the purpose and to re-trigger responses from the chatbot. This response repetition indicates that the customer is not certain whether the chatbot can fully understand his request and, therefore, is evidence of limited mutual monitoring.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *Where is the outage map*

Bot: *Outage Centre – The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | ['Go to Outage Centre' option]*

Bot: *How else can I help? If you'd like to give feedback, just type feedback.*

Customer: *Outage map*

Bot: *Outage Centre – The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | ['Go to Outage Centre' option]*

Bot: *What else would you like to know? If you'd like to give feedback, just type feedback.*

Third, the low level of interactional involvement was identified when little commitment is shown between the customer and the chatbot as they are involved in a joint task, i.e. addressing the customers' problems. While customers expected to have their problems solved immediately, the chatbot sometimes failed to meet those expectations by showing its disinterest in resolving the problems. The low level of interactional involvement is reflected by the chatbot (i) navigating customers to other websites, (ii) escalating customer requests, (iii) suggesting customers to seek human agent support and (iv) scripted responses to pre-set options.

The chatbot usually navigates customers to other websites where their desired information is rather than directly giving them the answers. For example, in the case below, the chatbot could have informed that customer with the outcome of the outage check. However, it directs the customer to the Outage Centre website to check it themselves. This avoidance to providing direct responses indicates a low interactional involvement of the chatbot with the customer's problem.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *(select pre-set option) Check outages*

Bot: *Outage Centre - The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | ['Go to Outage Centre' option] -*

Bot: *What else can I help you with? If you'd like to give feedback, just type feedback.*

Similarly, instead of providing adequate support right on spot, the chatbot also escalates customer requests to the human employee support despite whether it is during or after office hours. In the example below, although the chatbot can directly answer the customer's question, it keeps escalating his query to the human employee helpline, which makes the customer feel impatient and frustrated. Since this



reaction displays a lack of interest in helping the customer to address the issue, it is a demonstration of limited interaction involvement.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *[street address] - do u know why power is out?*

Bot: *Outages - Here's some handy links about outages. If your outage isn't shown on our map then you can report it to us by calling [phone number]. | ['View outage map' option] – ['Popular questions' option] – ['Contact us' option] -*

Bot: *What else can I help you with? If you'd like to give feedback, just type feedback.*

Customer: *Can't see any outage on map*

Bot: *I've found this answer for you...*

Bot: *Why isn't my outage on the map? If your outage is not shown on our outage map, please call us on [phone number] to report it to us. | ['Find out more' option] –*  
*What else can I help you with? If you'd like to give feedback, just type feedback.*

Customer: *Do u have anything at your end??*

Bot: *Outages - Here's some handy links about outages. If your outage isn't shown on our map then you can report it to us by calling [phone number]. | ['View outage map' option] – ['Popular questions' option] – ['Contact us' option] -*

The chatbot would suggest customers seeking human staff support when it could not further resolve the issues. In the following interaction, the chatbot understands that the problem cannot be addressed at its level and, therefore, recommends the customer to contact the company for further help. The suggestion is offered right after the customer states his query, indicating the chatbot's disinterest in addressing the issue and, hence, establish a low level of interactional involvement.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *Hi there I received a bill from [Company name] but I am not a client*

Bot: *I'm sorry I couldn't be of more help. Please call us directly so we can assist further.*

Bot: *How else can I help?*

The use of pre-set options will elicit adequate scripted responses from the chatbot. These scripted responses are different from those elicited by text-based inputs. With text-based inputs, the chatbot is

required to process customers' queries and identify their intentions in order to provide relevant scripted responses. On the other hand, when a pre-set option is selected, the chatbot just automatically replies with pre-programmed responses. Therefore, scripted responses to pre-set options do not require much attention of the chatbot to the intentions of the customers, demonstrating its low interest in solving customers' problems and, hence, manifesting a low level of interactional involvement. The following data illustrates an interaction with low involvement between the chatbot and its customer. When the customer selects the pre-set option to learn more about the process of getting connected to the power network of the company, the chatbot merely provides him with the scripted responses. The interaction is relatively short and shows little involvement of the chatbot in helping the customer, which establishes a low level of interactional involvement.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *(select 'Getting connected' option)*

Bot: *The process of getting connected to the Vector network has several stages:*

- 1. You make an application to Get Connected.*
- 2. We send you a quote.*
- 3. After the quote is accepted and paid, we commence work.*
- 4. The connection is built and any reinstatement work is done.*

Bot: *Would you like any more details?*

#### 5.3.2. Medium social presence

A medium degree of social presence refers to the situation in which customers and the chatbot are not only aware of the other's co-existence but also cognitively and emotionally involved in accomplishing a joint task. At this degree, a high level of interactional involvement and joint engrossment of customers are established, which indicates that the chatbot and customers can identify the intents of each other and are engaged in the conversations. Therefore, medium social presence is illustrated by two sub-categories: (i) high interactional involvement and (ii) joint engrossment.

First, a high level of interactional involvement is reflected by the high commitment of the chatbot to resolving customers' problems. It is exhibited through the chatbot's response appropriateness, which can be observed from the chatbot's adequate responses and sufficient problem-solving attempts, such as clarifying the intents of customers, expressing its willingness to help and directly providing relevant responses to the customers' queries. The example below illustrates an interaction in which the chatbot attempts to clarify the customer's intent by asking a question about his exact purpose. These attempts

show that the chatbot is able to identify which information the customer requires and therefore, indicate a high level of interactional involvement.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *Is gas available in [street address]?*

Bot: *Would you like to connect gas or organize bottle delivery? Click one of the buttons below | [provided options] -*

Customer: *(select 'Connect to gas' option)*

Bot: *Start the connections quote process... | ['Apply now' option] -*

Bot: *What else would you like to know? If you'd like to give feedback, just type feedback.*

Second, joint engrossment refers to the emotional involvement of customers with the chatbot. Their joint engrossment is demonstrated by customers' self-disclosure and expression of engagement with the chatbot. For example, the following interaction shows the chatbot's high interactional involvement by expressing its willingness to help lighten the customer's moods. It also reveals that the customer discloses his feelings in the conversation and becomes engaged in the chatbot's jokes, i.e. asking for them twice. Therefore, joint engrossment between the customer and the chatbot is established.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *how are you?*

Bot: *I'm feeling good today. How are you today?*

Customer: *I'm feeling super dooper terrible*

Bot: *Ah - that's too bad. Can I brighten up your day?*

Customer: *Joke*

Bot: *I have a joke to share: My mother believed I'd be a good electrician. She always said "You conduit!"*  
*What else can I help you with? If you'd like to give feedback, just type feedback.*

Customer: *Tell me a joke*

Bot: *I have a joke to share: My friend told me how electricity is measured and I was like [Chatbot name]!*

Bot: *How else can I help? If you'd like to give feedback, just type feedback.*

#### 5.4. Outcomes of the interactions

Based on the analysis, four categories of interaction outcomes were discovered: (i) absolute failure, (ii) failure, (iii) subtle success, and (iv) success. These outcomes are characterised by the matching level

between the acquired and desired information and the effort that a customer expended to acquire the information (see Table 10 below), which reflected the effectiveness and efficiency of the utilisation of the chatbot for information-seeking. The following sections discuss how these outcomes were shaped by information-seeking strategies and social presence.

**Table 10.** *Different dimensions of interaction outcomes*

		Matching level between desired and acquired information	
		Matching	Not matching
Required effort	Additional effort	Subtle success	Absolute failure
	Minimal effort	Success	Failure

#### 5.4.1. Absolute failure

Absolute failure refers to the situation in which the acquired information does not match the desired information after a customer expended significant efforts to interact with the chatbot. This type of outcome takes up 17% of total interactions. Due to the failure to obtain the desired information from the chatbot, customers had to either make a phone call to the company, self-search for information in other websites, or repeat their queries to clarify their intents. For example, the customer in the interaction below has to self-search his desired information by navigating to the suggested webpage while the chatbot could have helped the customer with the search directly. Eventually, due to not receiving the desired information, the customer felt unsatisfied and complained about the inadequate support:

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *(select 'Getting connected' option)*

Bot: *The process of getting connected to the Vector network has several stages:*  
*1. You make an application to Get Connected.*  
*2. We send you a quote.*  
*3. After the quote is accepted and paid, we commence work.*  
*4. The connection is built, and any reinstatement work is done.*

Bot: *Would you like to know more?*

Customer: *Apply now*

Bot: *Start the connections quote process... / ['Apply now' option] -*

Bot: *What else would you like to know? If you'd like to give feedback, just type feedback.*

Customer: *Feedback*

Bot: *We'd really appreciate your feedback.*

On a scale of 1 - 7 how would you rate your experience with me today?  
With 1 being very difficult and 7 being very easy.

Customer: 1

Bot: I'm sorry to hear that. Can you tell me why you choose that rating? Then I can send on your feedback.

Customer: I still can't get my query addressed

Bot: Thank you for your feedback. How else can I help?

In another case, while the customer requested for technicians to come to check for a gas leak, the chatbot kept misinterpreting the query, which left the customer frustrated. In such a situation, the customer's safety was likely to be at risk, but the chatbot did not seem to understand the seriousness of the situation and failed to show the intention to address the problem urgently. Instead, it constantly directed the customer to other information sources. Since no information was acquired while more effort was required than expected, the customer ended the conversation by an insult to the chatbot.

Bot: Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?

Customer: Gas safety

Bot: Outage Centre - The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | ['Go to Outage Centre' option] -

Bot: We are committed to keeping the public, our people, our customers and suppliers safe around our networks. For more details about how to stay safe around electricity check out our website: Vector Safety | ['Find out more' option] -

Bot: How else can I help? If you'd like to give feedback, just type feedback.

Customer: I smell gas. What should I do

Bot: In an emergency, please call 111.

Bot: What else would you like to know? If you'd like to give feedback, just type feedback.

Customer: Can I get a technician to check out my connection?

Bot: What do you need connected?

Customer: Gas

Bot: Would you like to connect gas or organise bottle delivery? Click one of the buttons below. [provided options]

Customer: Neither you muppet. I want someone to inspect whether or not I have a gas leak

Bot: Would you like to connect gas or organise bottle delivery? Click one of the buttons below.

The analysis reveals that absolute failures are shaped by the interaction between information interrogation strategies and low social presence. Particularly, the interplay of the keyword search strategy and the FAQ strategy with limited mutual monitoring shapes an absolute failure interaction. For instance, in the following interaction, the customer applies the keyword search strategy to look for his desired information. However, the chatbot fails to understand the customer's intention and, therefore, establishes a limited level of mutual monitoring. To re-trigger the chatbot's response, the customer re-rephrases his search term, i.e. additional efforts, but still cannot receive his desired information, i.e. no matches between acquired and desired information. Hence, the interaction between the keyword search strategy and limited mutual monitoring has led the interaction to an absolute failure outcome.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: Tree management

Bot: *I don't know how to answer that I'm sorry. These are some of the things I can currently help you with. || [provided options]*

Customer: *vegetation information*

Bot: *I don't know how to answer that I'm sorry. These are some of the things I can currently help you with. || [provided options]*

Additionally, the analysis also identifies that the interaction between the fragmented strategy and low social presence, either limited mutual monitoring or low interactional involvement, will lead to absolute failure interactions. In the example below, the customer uses the fragmented strategy to search for his desired information. The chatbot first misinterprets and then fails to identify the customer's intents, manifesting a limited level of mutual monitoring. Moreover, it also asks if the customer would like to seek human staff support. This behaviour shows its lack of interactional involvement in solving the customer's problem. Since the customer is requested to repeat his query but still cannot acquire the desired information, the interaction in this case is an absolute failure. This absolute failure outcome is shaped by the interplay of fragmented strategy with both limited mutual monitoring and low interactional involvement.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: Hi, I logged a fault, but our power just came back on

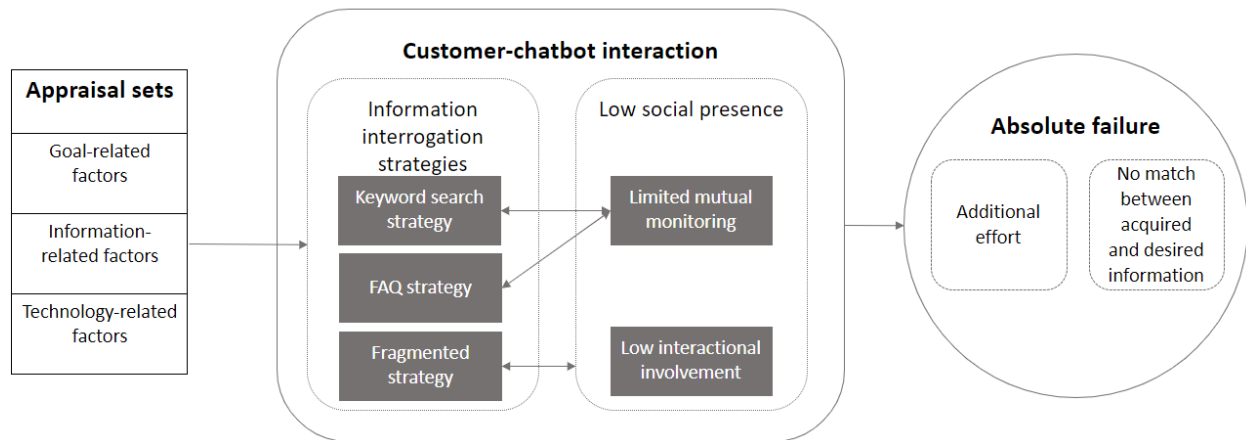
Bot: *Outage Centre - The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | ['Go to Outage Centre' option] -*

Bot: *What else can I help you with? If you'd like to give feedback, just type feedback.*

Customer: *how do I cancel?*

Bot: *I'm just a chatbot - try telling me what you want in the simplest way possible.*  
*Would you like to try again, or talk to a person?*

Figure 3 below illustrates how an absolute failure outcome is shaped by the appraisal sets, information interrogation strategies and low social presence degree.



**Figure 3.** The influence of the appraisal sets, information interrogation strategies, and the degree of social presence on the absolute failure outcomes

#### 5.4.2. Failure

Failure refers to the situation in which the acquired information does not match the desired information but a customer did not have to expend significant effort to interact with the chatbot. Failure interactions take up the smallest percentage (7%) of the total interactions. Unlike customers in absolute failure interactions, those in failure interactions tend to leave the conversations and save their efforts rather than leaving negative comments or insults to the chatbot. For instance, the conversation below ends immediately when the customer realises that the chatbot is unable to provide him with his desired information, no additional efforts are expended.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *Hi [chatbot name], we're building in [street address] and we'd like to know about gas connection. [customer name]*

Bot: *It looks like you've entered an address. Did you want to check for outages, get a new connection or organise a disconnection? | [provided options]*

Failure interactions were revealed to be shaped by the reciprocal relationship between the complete-sentence strategy and limited mutual monitoring. For example, in the following interaction, the customer applies the complete-sentence strategy as his approach to extract information from the chatbot. Although the customer's intent is clearly stated, the chatbot still misinterprets it, which establishes a limited level of mutual monitoring. Due to the failure to obtain the desired information, the customer leaves the chat right after. The example interaction demonstrates how the complete-sentence strategy and limited mutual monitoring interact with each other in shaping failure outcomes.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *Hi, wish to know if gas line available on [street address]*

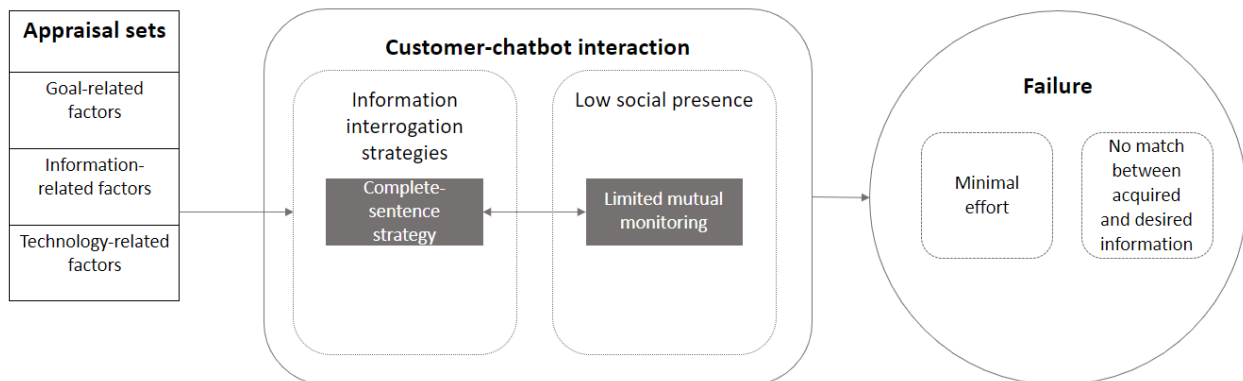
Bot: *In an emergency, please call 111.*

Bot: *What else would you like to know? If you'd like to give feedback, just type feedback.*

Customer: *Nope*

Bot: *I'm sorry, I didn't understand that.  
These are some of the things I can currently help you with. | [provided options]*

Figure 4 presents the influence of the appraisal set, the complete-sentence query strategy and low social presence on the failure outcomes.



**Figure 4.** The influence of the appraisal sets, information interrogation strategies, and the degree of social presence on the failure outcomes.

#### 5.4.3. Subtle success

Subtle success refers to a type of interaction outcomes, in which the information acquired from the chatbot matched the desired information, but customers are required to expend additional effort to obtain more information from other sources to complete their goals. These other sources may include



making phone calls, navigating to other websites, and repeating the same queries. Subtle success is the most common outcome, which takes up around 54% of total interactions. The example below presents a typical subtle success interaction. In the example, the customer has to self-search his desired information by navigating to the suggested websites. However, different from the previous types of outcome, the chatbot understands the customer's queries and directs him to the relevant websites.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *I want to report an outage*

Bot: *Outage Centre - The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre | ['Outage Centre' link]*

Bot: *What else would you like to know? If you'd like to give feedback, just type feedback.*

Customer: *Can I get an LPG bottle delivered*

Bot: *If you would like to order gas bottles delivered to your home, visit the [company name] website.  
Order LPG | ['Order now' options]*

Bot: *What else can I help you with? If you'd like to give feedback, just type feedback.*

The analysis reveals that the reciprocal relationship of information interrogation strategies and low social presence shapes the subtle success outcome. Particularly, the interplay of the complete-sentence strategy and the keyword search strategy with low level of interactional involvement leads an interaction to subtle success. For example, in the interaction below, the keyword search strategy is used by the customer to interact with the chatbot. Although the chatbot can identify the customer's intent, it does not address the query directly and navigate the customer to another website. This is an expression of low interactional involvement as it demonstrates the chatbot's lack of interest in helping the customer. In order to acquire the desired information, the customer needs to follow the suggested website and self-search for the information, i.e. additional efforts. This example indicates that the interaction between the keyword search strategy and the low interactional involvement results in subtle success interactions.

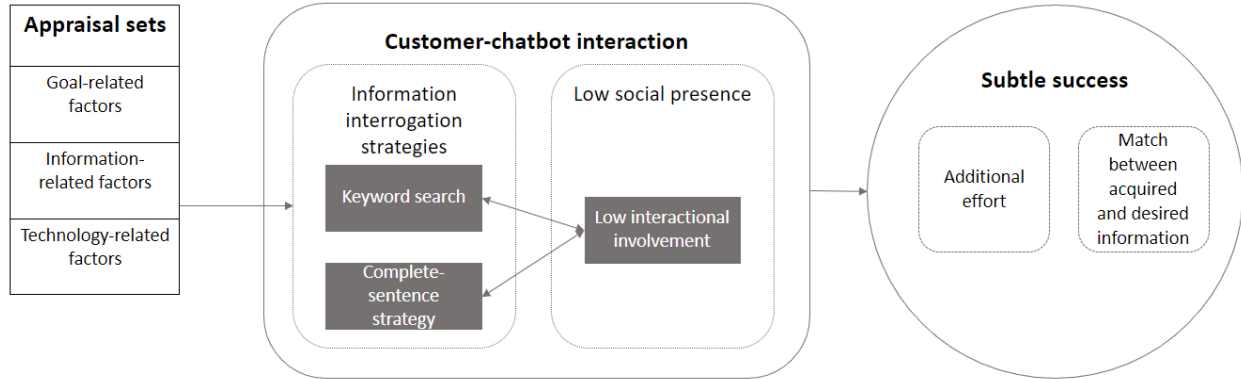
Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *Direct credit claim*

Bot: *To make a claim or talk to us about claims, please call us on [phone number]. For more info on our Service Standards, please see the brochure below.*

Bot: *Service Standards | ['More info' option] - What else would you like to know? If you'd like to give feedback, just type feedback.*

Figure 5 presents how complete-sentence and keyword search strategies interact with low level of interactional involvement to shape subtle success outcomes.



**Figure 5.** The influence of the appraisal sets, information interrogation strategies, and the degree of social presence on the subtle success outcomes

#### 5.4.4. Success

Success refers to those interactions in which customers obtain their desired information from their interactions with the chatbot without the need to acquire information from additional sources. In other words, the chatbot provides direct answers and adequate assistance to address the customers' problems. Success interactions take up 22% of total interactions. For instance, the data below demonstrates a successful interaction triggered by the FAQ strategy. As the customer wants to check the address for outages, the chatbot asks for supporting information to address the customer's request. The fact that additional information is required is not identified as an extra effort because the customer does not have to acquire his desired information himself but, by giving supporting information to the chatbot, gets the desired information immediately without it being escalated or navigated to other information sources. In the following example, the customer is eventually informed that the outage was not planned, and he is suggested to report it to the outage centre. This interaction, therefore, was considered a successful one, in which the customer received the desired information with minimal efforts.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *(select a pre-set option) Outages – Check my address*

Bot: *I can help you check your address for an outage. You can type or send me your location (don't forget to click 'Allow'). What is your street address?*

Customer: *(input home address)*

Bot: *Thanks. Is [home address] the correct location?*

Customer: *Yes*

Bot: *We are not aware of an outage in your area. Please report it to us via the link below so we can investigate. | [attached links]*

Successful interactions also took place in another different context. In another interaction, the customer applies the social reciprocity strategy to communicate with the chatbot. The chatbot not only could understand the customer's intention but also expressed its willingness to get emotionally involved with the customer by offering to share jokes. The fact that the customer requested the chatbot to share jokes twice revealed that he is truly engaged with the conversation.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *How are you?*

Bot: *I'm feeling good today. How are you today?*

Customer: *I'm feeling super doper terrible.*

Bot: *Ah – That's too bad. Can I brighten up your day?*

Customer: *Joke*

Bot: *I have a joke to share: My mother believed I'd be a good electrician. She always said, "You conduit!". What else can I help you with? If you'd like to give feedback, just type feedback.*

Customer: *Tell me a joke*

Bot: *I have a joke to share:  
My friend told me how electricity is measured, and I was like [Chatbot name]!*

Bot: *What else can I help you with? If you'd like to give feedback, just type feedback.*

Successful interactions are found to be shaped by the interaction of either information interrogation strategies and low social presence or social reciprocity strategies and medium social presence. First, the analysis shows that the FAQ strategy interacts with the low interactional involvement in shaping successful outcomes. The data below illustrates a successful interaction that is carried out by using the FAQ strategy. In the interaction, the customer wants to acquire information about the company's contact details from the chatbot by selecting the pre-set option. The chatbot automatically replies with scripted responses. The chatbot's scripted response to the pre-set option is an expression of low interactional

involvement because it demonstrates a lack of concentration on the customer's query. Eventually, the customer receives his desired information without expending additional efforts. This example shows that the interaction between the FAQ strategy and low interactional involvement shapes the outcome for success.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *(select a pre-set option) Contact [company name]*

Bot: *You can get in touch with Vector by phoning [phone number] or at the contact details linked below. | [attached links]*

Bot: *What else would you like to know? If you'd like to give feedback, just type feedback.*

Second, the analysis reveals that success outcomes are also shaped by the interaction between the social reciprocity strategy and medium social presence, including high level of interactional involvement and joint engrossment. For instance, the successful interaction below is carried out by the social reciprocity strategy. As requested by the customer, the chatbot shares some jokes to lighten his mood, indicating the chatbot's high interactional involvement. Furthermore, the customer not only confides his feelings but also gets engaged in the conversation as he asks the chatbot for jokes twice, which reveals the customer's joint engrossment with the chatbot. The customer, eventually, acquires his desired information with minimal efforts required. This example, therefore, indicates that the interplay of the social reciprocity with either high interactional involvement or joint engrossment shapes the outcome for success.

Bot: *Hi, I'm [Chatbot name] from [Company name]. I can help you check for an outage at your address, find information you may need or chat about who [Company name] is and what we do. How can I help?*

Customer: *How are you?*

Bot: *I'm feeling good today. How are you today?*

Customer: *Bad*

Bot: *Ah – That's too bad. Can I brighten up your day?*

Customer: *Joke*

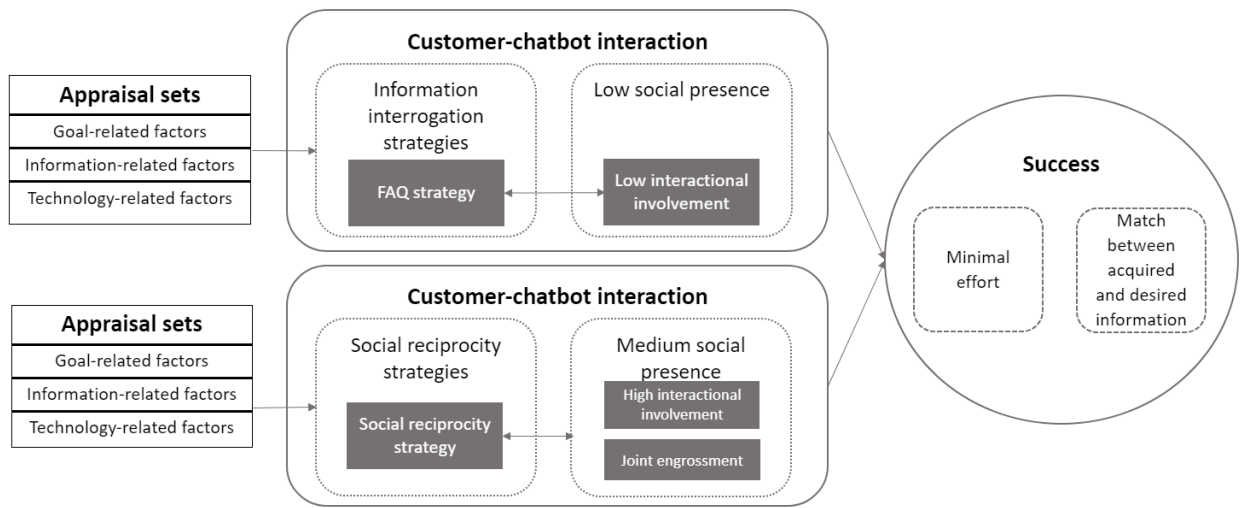
Bot: *I finally managed to get rid of that nasty electrical charge I've been carrying. I'm ex-static!*

Customer: *Tell me a joke*

Bot: *I have a joke to share, I finally managed to get rid of that nasty electrical charge I've been carrying. I'm ex-static!*

Bot: *What else can I help you with? If you'd like to give feedback, just type feedback.*

Figure 6 depicts how the appraisal sets, information interrogation strategies, social reciprocity strategies, and the social presence interact to shape the outcome for success.



**Figure 6.** The influence of the appraisal sets, information interrogation strategies, social reciprocity strategies, and the degree of social presence on the success outcomes.

See Table 11 below for a summary of the mutual impact of information-seeking strategies and social presence on the outcome of interactions between customers and the chatbot.

**Table 11.** Summary of the interplay between information-seeking strategies and social presence

Outcomes	Information-seeking strategies		Degree of social presence	
<b>Absolute failure</b>	<i>Information interrogation strategies</i>	Fragmented strategy	<i>Low social presence</i>	Limited mutual monitoring
		Keyword search strategy	<i>Low social presence</i>	Low interactional involvement
		FAQ strategy	<i>Low social presence</i>	Limited mutual monitoring
		FAQ strategy	<i>Low social presence</i>	Limited mutual monitoring
<b>Failure</b>	<i>Information interrogation strategies</i>	Complete-sentence strategy	<i>Low social presence</i>	Limited mutual monitoring
<b>Subtle success</b>	<i>Information interrogation strategies</i>	Complete-sentence strategy	<i>Low social presence</i>	Low interactional involvement
		Keyword search strategy	<i>Low social presence</i>	Low interactional involvement
<b>Success</b>	<i>Information interrogation strategies</i>	FAQ strategy	<i>Low social presence</i>	Low interactional involvement
	<i>Social reciprocity strategies</i>	Social reciprocity strategy	<i>Medium social presence</i>	High interactional involvement
				Joint engrossment

## 6. DISCUSSION

In recent years, various organisations have jumped on the bandwagon and implemented CAs to facilitate different customer service functions. Despite the benefits that CAs promise to bring, many CA implementation projects have failed to meet the high expectations of the organisations. This high failure rate in implementing CAs indicates the gap between the organisations' understanding of the human-CA interaction and the actual performance of CAs. To address this gap, this study was devoted to examining how customer-CA interactions take place and why many of them fail. In doing so, this study took a closer look at the information-seeking strategies that customers usually use to search for information and the social presence manifested through their interactions with CAs.

Guided by two theoretical lenses, the social information-seeking model (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019), this study was conducted to address the research question, "How do information-seeking strategies and social presence shape the outcome of interactions between customers and conversational agents?" The analysis was conducted on the interaction logs of 507 interactions between customers and a chatbot implemented into the website of an electricity provider. By taking an abductive qualitative research approach and adopting a configurational thinking, the researcher identified (i) multiple factors that influence different information-seeking strategies and (ii) the interplay of the information-seeking strategies and social presence in shaping distinct interaction outcomes.

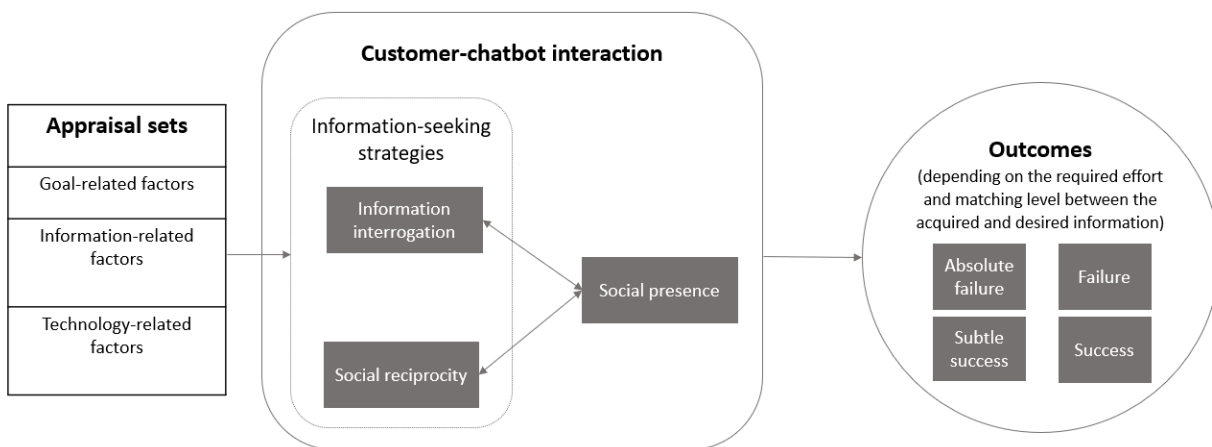
The following sections of this chapter introduce a process model that illustrates the information-seeking process taking place between the customers and the chatbot, and associated outcomes (Figure 7). The findings are then discussed in relation to previous studies in the literature. Finally, the theoretical contributions and practical implications derived from this study are presented at the end of this chapter.

### 6.1. A model of the interplay between information-seeking strategy and social presence in shaping the outcome of customer-chatbot interactions

Based on the findings derived from the analysis, this study developed a model that illustrates how customer-chatbot interactions take place under the interplay of information-seeking strategies and social presence (Figure 7 below).

The customer-chatbot interaction is initiated when customers chose to use the chatbot in seeking their desired information. Certain information-seeking strategies are selected by customers to help them acquire their desired information. There are two main classes of strategy that are applicable in this

context, which are information interrogation strategies and social reciprocity strategies. The selection of these strategies is influenced by distinct appraisal sets, each of which consists of different appraisal factors. Among the appraisal factors, those that are related to the characteristics of goals, desired information and the technology, are the main factors that play essential roles in shaping the strategy selection. Based on their consideration of the effects of these factors, customers choose an appropriate strategy to carry out the conversations with the chatbot in order to extract their desired information. Through the use of the strategies, different degrees of social presence are formed and, in return, influence how customers further use the strategies. This interaction between the information-seeking strategy and social presence eventually shapes the interaction outcomes. The outcome of the interactions reflects how much effort customers are required to put in and how the acquired information matches the desired information.



**Figure 7.** *The process model of the customer-chatbot interaction*

## 6.2. The information-seeking strategies and their appraisal sets

This study identifies two main classes of information-seeking strategy that customers use to interact with the chatbot: information interrogation strategies and social reciprocity strategies. The information interrogation strategies refer to those that involve intense information exchanges between customers and the chatbot. These strategies include the complete-sentence strategy, fragmented strategy, keyword search strategy, and FAQ strategy. Social reciprocity strategies are concerned with less intense information exchanges and more with casual conversations between the chatbot and customers. The identification of these strategies extends the work of Ramirez et al. (2002) by explicating that interactive information-seeking strategies can be expressed in multiple ways in the context of customer-chatbot interactions.



Moreover, building upon the social information-seeking model of Ramirez et al. (2002), this study also discovers the factors that influence the selection of each strategy. Four appraisals were analysed for their impact on the strategies, including (i) context-related factors, (ii) goal-related factors, (iii) information-related factors, and (iv) technology-related factors. The collective impact of these appraisals constitutes distinct appraisal sets, each of which consists of core and supporting factors. Different appraisal sets would lead to the use of different strategies. The findings of this study support previous studies by confirming the impact of various multi-dimensional factors on information-seeking strategies (Belkin, Cool, Stein, and Thiel, 1995; Han et al., 2010; Kim, 2009; Xie, 2000; 2002). The factors proposed by this study are similar to those of previous research, such as types of goal (Belkin et al., 1995; Xie, 2000), characteristics of the desired information (Belkin et al., 1995), and types of information need (Han et al., 2010; Kim, 2009). The analysis also suggested that each information-seeking strategy is influenced by a distinct set of multi-dimensional factors, which are consistent with what was found in previous studies (Han et al., 2010; Xie, 2000; 2002). Guided by the configurational approach (Fiss, 2011), the researcher considered not only the effect of these factors in their appraisal set as a whole but also their cause-effect relationship with the information-seeking strategies. Unlike previous studies in which the multi-dimensional factors were proposed to have equal impact on information-seeking strategies (Belkin et al., 1995; Han et al., 2010; Xie, 2000; 2002), this study clustered the factors into two classes based on their causal relationship with the strategies: main factors and supporting factors. In doing so, this study highlighted the patterns in which the information-seeking strategies were influenced, rather than focusing on the interactions between the appraisal factors.

It should be noted that this study found no discerning impact from the context-related factors on the strategy selection. They only play a supporting role in shaping the use of information-seeking strategies. The other factors, including goal-related, information-related and technology-related factors, are the main elements that determine which strategy will be selected. They influence the selection of a customer's strategy, and any amendments made among these factors within their appraisal sets would result in a different strategy being chosen.

### 6.3. Social presence in the customer-chatbot interaction

As customers apply an information-seeking strategy to carry out conversations with the chatbot, certain degrees of social presence are established through the manifestation of mutual awareness, limited mutual monitoring, low and high interactional involvement, and joint engrossment between the chatbot and customers. Similar to previous studies, this study confirms the manifestation of social presence in the

interaction between humans and CAs (Araujo, 2018; Diederich et al., 2019; Gnewuch et al., 2018a; Nowak and Biocca, 2003). It extends our understanding of the role of social presence in the customer and chatbot interactions by identifying two different levels of social presence: low and medium.

Low social presence can be observed from the customers' acknowledgement of the chatbot's co-presence, which was expressed by their mutual awareness, limited mutual monitoring, and low interactional involvement. Firstly, customers expressed their mutual awareness of the chatbot by showing their recognition of the existence of the chatbot (Goel et al., 2013; Riva and Mantovani, 2014). This study suggests that, by posing their queries, customers imply that they are aware of the chatbot's existence and that they can interact with it to search for information. Moreover, social responses of customers, such as politeness and curiosity about its background, indicate customers' awareness of the chatbot's co-existence during their interactions (Nowak and Biocca, 2003; Qiu and Benbasat, 2005). The findings of this study about the mutual awareness between customers and chatbot support those of Schultze and Brooks (2019). They argued that a certain level of mutual awareness exists when a customer-chatbot conversation is carried out. Secondly, a limited level of mutual monitoring between customers and the chatbot was found at a low degree of social presence. The limited mutual monitoring was exhibited by the chatbot's inability to identify the intent of customers and its misinterpretation of their requests. Moreover, response repetition of customers also reflected the limited mutual monitoring as customers could not tell whether the chatbot could understand their intentions. Finally, at the low social presence degree, a limited interactional involvement is identified. This study found different expressions of limited interactional involvement, such as the chatbot escalating requests and navigating customers to other information sources. Overall, at the low degree of social presence, customers are aware of the chatbot's existence and its availability for interaction; however, mutual monitoring is not always possible, and the chatbot is not highly committed to the interactions.

On the other hand, medium social presence illustrates a higher interactional involvement and the customers' joint engrossment. First, the high level of interactional involvement is illustrated by the chatbot's response appropriateness and its commitment to addressing customers' requests, such as providing adequate answers to customers' questions and asking for relevant details for further information required to fulfil the customers' information needs. This was similar to Diederich et al.'s (2020) findings, where it was suggested that appropriate responses would establish a higher degree of social presence between customers and CAs. Second, the medium social presence also exhibits the joint engrossment of customers to their conversations with the chatbot. It is expressed by how engaged the

customers are during their interactions, such as their reciprocal self-disclosure and their desire to keep conversations going. These findings support what was found in previous studies, confirming the positive relationship between customer engagement and the degree of social presence (Gnewuch et al., 2018b; Li and Mao, 2015). In general, the medium degree of social presence demonstrates that customers and the chatbot are cognitively and emotionally involved in accomplishing the joint task which is getting customers to access their desired information.

#### 6.4. The interaction between information-seeking strategies and social presence

Customers apply certain information-seeking strategies through their interactions with the chatbot. As the conversation is initiated, some degree of social presence is established. The interaction between the selected information-seeking strategy and the social presence determines the outcome of interactions between customers and the chatbot.

This study reveals that information interrogation strategies, including the complete-sentence strategy, fragmented strategy, keyword search strategy, and FAQ strategy, have a reciprocal relationship with low social presence. These strategies are found to be mainly concerned with task-oriented goals and exploratory information needs, which indicates highly impersonal interactions between customers and the chatbot (Walther, 1996). Due to the nature of these strategies, more scripted responses are generated, and fewer chances for social cue exchange are created (Diederich et al., 2019); therefore, they tend to establish a low degree of social presence of interaction (Schultze and Brooks, 2019). In return, the manifestation of a low degree of social presence also influences how customers use these strategies. It is suggested that at low social presence customers are more likely to switch or even quit using their strategy.

Similarly, a reciprocal relationship is found between social reciprocity strategy and medium social presence. As the use of the social reciprocity strategy is motivated by entertainment purposes and the chatbot's colloquial language, there are less intense information flows and more opportunities for social cue exchange. The exchange of social cues triggers a higher degree of social presence compared to information interrogation strategies. Similar to previous studies, the findings of this study reveal that human-like social cues, such as jokes and self-disclosure, can increase the degree of social presence of interactions between the customer and the chatbot (Schuetzler, Grimes, Giboney, and Nunamaker Jr., 2018; Wuenderlich and Paluch, 2017). Moreover, previous studies have found that medium social presence is positively linked with customer engagement (Gnewuch et al., 2018b; Li and Mao, 2015), which was shown by the customers expressing their desire to sustain the conversations. At this degree of social

presence, customers tend to use the same strategy throughout the interactions without making any modifications.

The findings of this study provide more insight into how customers assessed their selected strategies, which was only briefly touched on by Ramirez et al. (2002). The interplay between the information-seeking strategies and social presence reflects how effective the selected information-seeking strategies are in helping customers to acquire their desired information. This is based on the degree of social presence established during the interactions, that will later drive how customers and the chatbot interact with each other, such as limited mutual monitoring or the high level of interactional involvement. How effective the strategies are would help customers to determine whether to switch, quit or keep using the strategies.

The interrelation between information-seeking strategies and social presence shapes the outcome of interactions. Four outcomes were identified, including absolute failure, failure, subtle success and success. Each of them is characterised by the required effort and how the acquired information matches the desired information (Ramirez et al., 2002). Absolute failure outcomes refer to the situation in which customers expended additional efforts but received information that did not match their desired information. Failure outcomes are associated with interactions in which the chatbot failed to provide information that matched the desired information of customers, and minimal effort was put into the interactions. Subtle success outcomes refer to the situation in which customers were required to expend extra effort in order to acquire the information that matched their desired information. Finally, success outcomes are linked to interactions in which customers not only acquired their desired information but also did not expend any additional effort.

The interplay between information interrogation strategies and limited mutual monitoring of low social presence results in absolute failure and failure outcomes. While absolute failures are related to limited mutual monitoring during the interaction with either fragmented strategy, keyword search strategy, or FAQ strategy, failures are the results of the interplay between limited mutual monitoring and complete-sentence strategy. Since these strategies are task-oriented, the ability to monitor behaviours and to capture each other's intentions is important to carry out a successful interaction (Riva and Mantovani, 2014; Schultze and Brooks, 2019).

On the other hand, subtle success and success outcomes can be identified at both low and medium degree of social presence. At the low degree of social presence, they are shaped by the interplay of low interactional involvement with any information interrogation strategies, including the complete-sentence

strategy, keyword search strategy and FAQ strategy, except for the fragmented query strategy. Due to the task-related and impersonal nature of these strategies (Walther, 1996), cognitive and emotional involvement with the chatbot is generally not the main concern of the customers. Therefore, a low level of interactional involvement is sufficient to achieve the success of interactions. When an acceptable level of mutual monitoring between customers and the chatbot is achieved, a slight degree of interactional involvement in the interactions can lead to either subtle success or success outcomes. At the medium degree of social presence, successful interactions are shaped by the interplay between the social reciprocity strategy and either the high level of interactional involvement or joint engrossment of customers. What drives this type of interaction is the customers' desire to exchange psycho-emotional information. Therefore, the meaningfulness of the chatbot's responses and the engagement of customers in conversation with the chatbot play an important role in building a successful interaction. This finding is similar to that of Adam and Klumpe (2018), which ascertained the positive relationship between customer engagement and the success of human-CA interactions.

#### 6.5. Theoretical contributions

This study makes four main contributions to the body of knowledge. First, it offers an explanation on how customers interact with CAs for their information search on online self-service. The analysis identifies how different multi-dimensional factors collectively influence the customer-CA interaction. The findings of this study confirm the social nature of the customer-chatbot interaction and reveal different patterns of the mutual influence of information-seeking strategies and the degree of social presence on the interaction outcomes.

Second, this study extends existing work on the social information-seeking process in the computer-mediated context. It provides a nuanced understanding of the different interactive information-seeking strategies which can be used to interact with CAs for their information search. In the context of customer-chatbot interactions, these strategies are broadly classified, based on the customer's primary intention to the interaction, into information interrogation strategies and social reciprocity strategies. For the information interrogation strategies, customers may choose to interact with the chatbot using the complete-sentence strategy, fragmented strategy, keyword search strategy, and FAQ strategy. In addition, the study also discovers the appraisal factors that influence the selection of strategy, which was not fully theorised in the study done by Ramirez et al. (2002). However, differing from previous research, this study acknowledges the asymmetric impacts of these factors on the strategies, classifying them as core and supporting factors. Findings suggest that the goal-related factors, information-related factors

and technology-related factors play the main role in shaping the use of strategy, with the context-related factors playing a supporting role.

Third, this study finds the manifestation of social presence in human-CA interactions and theorises its impact on information-seeking behaviours. Different degrees of social presence were found, ranging from low to medium. By conducting empirical analysis, this study reveals the effect of the different degrees of social presence on how customers interact with the CA to acquire their desired information.

Finally, this study develops a process model that illustrates the process of a customer-CA interaction and its associated outcomes. The model was informed by the social information-seeking process (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019). It provides an integrative view on the entire interaction process, from how the strategy is selected, to how the interaction takes place and how the outcome is shaped. The model reveals the contributory elements and their interplay that influences how customers and the chatbot interact with each other. In particular, the interplay of information-seeking strategies with social presence is found to have shaped the interaction outcomes. The sub-categories of the information-seeking strategy and social presence that are involved in the interplay are proposed as the factors that contribute to the success or failure of an interaction, which is an under-explored research area.

#### 6.6. Practical implications

This study has three main practical implications. First, customers, especially those who are unfamiliar with using CAs, may find this study useful as it provides a holistic view of how they can be used to help them acquire their desired information. From the process model of the customer-chatbot interaction, customers can envision the different phases that they will experience in order to obtain the information they need. Findings also reflect how CAs can assist customers with seeking information related to their services. Moreover, this study suggests the different information-seeking strategies that are applicable in the context. Based on the characteristics of each strategy, customers would be able to determine the strategy that is best suited for their use. For example, for the aim of getting questions answered, the complete-sentence strategy, keyword search strategy and FAQ strategy are suggested; whereas, conversations with casual and random content are recommended to be conducted by using the social reciprocity strategy. Moreover, customers can also anticipate the types of outcome from their interactions with CAs, depending on the strategy and perceived level of social presence.

Second, several practical contributions are applicable to organisations that are utilising CAs to support their customer services. The process model of the customer-chatbot interaction serves as a foundation

for organisations that are studying their customer experience in leveraging CAs for seeking service-related information. It provides them with a holistic view of the interaction process that their customers might go through to acquire their desired information. Along with that, they will be well-aware of factors that contribute to successful (subtle success and success) and failed interactions (absolute failure and failure), including the appraisal sets, the selected information-seeking strategies, and the degree of social presence, which offers fruitful insights for organisations to assess the performance of their CAs. More specifically, organisations can use the process model of the customer-chatbot interaction to develop a testing framework in order to evaluate the performance and the outcomes that their chatbots have delivered. Since social presence is one of the important factors contributing to the success of the customer-chatbot interaction, organisations may want to scrutinise the level of mutual monitoring and interactional involvement that customers experience in chatbot testing.

Finally, for organisations intending to put CAs into their service operations, the findings can be used as a reference material for them to develop an implementation plan. The process model of the customer-chatbot interaction developed from this study provides them with a practical view of the interactions, presenting what a typical interaction might look. The organisations can explore the different scenarios that they may encounter and, therefore, use the feedback to improve the design of their CAs. From this empirical study, the organisations can get more hints on what benefits or challenges that CAs may bring, such as autonomous responses or awkward conversations, which helps to fine-tune their chatbots before the rollout. For example, since failed interactions (absolute failure and failure) resulted from the limited level of mutual monitoring between customers and the CA and the low level of interactional involvement, organisations may want to ensure that their chatbots have the ability to identify customers' intents, to provide meaningful responses and to deliver an engaging experience.

## 7. CONCLUSION

Several organisations have implemented CAs to facilitate customer service experience. Chatbots have many potential benefits because they can provide autonomous responses, quick issue resolution and converse with customers without human customer service involvement. However, they also pose some challenges, such as the awkwardness in communication and trusting issues. Despite the high expectation that organisations have for their CAs, there has been a high failure rate in their implementation, indicating a knowledge gap in our understanding about the nature of the interaction between customers and CAs and factors that contribute to the outcome of the interaction. Therefore, in order to reduce the failure rate, it is essential to understand how customers actually interact with their CAs and why some

interactions are successful while others have failed. In doing so, this study examines the influence of information-seeking strategies and social presence on the customer-CA interaction.

By addressing the research question, “How do information-seeking strategies and social presence shape the outcome of interactions between customers and conversational agents?” this study is intended to close the knowledge gap in the nature of the customer-CA interaction and factors that lead to the success and failure. Building on the social information-seeking model (Ramirez et al., 2002) and the concept of social presence (Schultze and Brooks, 2019), this study develops a model to explain how information-seeking strategies and social presence shape the outcome of the customer-CA interaction. The research was conducted by scrutinising the interaction logs that entail real conversations between customers and a chatbot that was implemented to the website of an electricity company. Guided by an abductive qualitative approach, the analysis of 507 customer-chatbot interactions reveals five distinct information-seeking strategies used to interact with the CA: complete-sentence strategy, fragmented strategy, keyword search strategy, FAQ strategy, and social reciprocity strategy. The selection of each strategy is influenced by the interrelation of three main appraisal factors, including goal-related factors, information-related factors, and technology-related factors. This study also found that the reciprocal relationship between the information-seeking strategies and social presence that was manifested during the interactions had shaped the outcome of those interactions.

All elements and their interrelations that are involved in the customer-chatbot interaction are condensed into a process model of the customer-chatbot interaction. First, the process model illustrates how distinct appraisal sets influence information-seeking strategies. Each appraisal set consists of three key appraisal factors that shape the use of the strategies, including goal-related factors, information-related factors, and technology-related factors. The interplay between these appraisal factors results in two main classes of information-seeking strategies: information interrogation strategies and social reciprocity strategies. Second, the process model demonstrates the reciprocal relationship of the information-seeking strategies and social presence in shaping the outcome of the customer-chatbot interaction. The outcomes were classified based on the efforts that customers expended to acquire desired information and on the matching level between the acquired and desired information.

This study provides a fine-grained understanding of how the interaction between customers and CAs take place and which factors contribute to the success and failure of the interaction. Findings of this study offer several theoretical contributions to the body of knowledge by confirming and extending existing work in



previous research. Moreover, this study contributes to theory a process model that illustrates how the process of the customer-CA interaction. This research also provides some practical implications for customers who are interested in using chatbots and organisations who are currently using or intend to implement CAs. In particular, organisations can use the findings of this study to inform their development and testing of their chatbots in order to improve their performance before the rollout.

### 7.1. Limitations

This study has some limitations that need to be acknowledged. First, the study did not collect data directly from customers. Although customers are the focal actors of the interactions, the data set did not significantly reflect their emotions or feedback. Their emotional experience might also have played an important role in determining the success or failure of an interaction. Therefore, more details about how customers perceive their interactions with CAs would provide additional insights into the influence of the emotion on the customer-chatbot interaction and associated outcomes.

Second, the communicator-related factors – an appraisal that reflects the information-seeker's characteristics that might influence the selection of information-seeking strategies (Ramirez et al., 2002), were not reflected by the data set. Despite the effort of the researcher, it was difficult to identify these factors as the identity of the customers could not be traced due to their information privacy. Communicator-related factors refer to the background information, characteristics and skills of customers in using the CA for seeking information. Because of the privacy concerns and the practical limitations in obtaining this data, this study cannot assess the role of communicator-related factors in customer-chatbot interactions. Future research may consider obtaining data on customers to theorise the influence of communicator-related factors.

Third, the interaction log poses another limitation as it was not possible to trace customers' post-interaction responses. In other words, it is not possible to observe the usefulness of the chatbot's recommendations. In this study, we infer that the interaction was a success when the recommendations matched the information that customers needed. However, such assumptions would need to be validated with data from customers.

### 7.2. Avenues for future research

This study offers many opportunities for future research. First, researchers can use the process model as a foundation to study the impact of other types of CAs (such as embodied CAs) on customer experience. Moreover, future research may want to examine the interaction process between customers and chatbots

in another context, such as in a different industry. Second, as this study focused more on the impacts of the CA on the outcome of interactions, future researchers may want to follow other sources of data such as in-person interviews, to further investigate the nature of the interactions from a customer's perspective. These may reveal new patterns of information-seeking strategies used, appraisal factors, social presence, and outcomes. Third, future research can extend the work of this study by looking into the feedback or tracing post-interaction responses of customers that were not reflected in this study. Doing so would allow researchers to potentially identify other effects, which may also shed more light on how customers actually feel and evaluate their experience with the CA.

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## APPENDICES

### Appendix A – Construction of the categories with supporting data

Raw Data			Open codes	Sub-categories	Categories
Source	Message text	Timestamps	After-hours inquiries	Staff support unavailability	Context-related factors
Customer	Get started	19/11/2018 01:22:20am			
Bot	Hi, I'm [chatbot name] from [company name].	19/11/2018 01:22:22am			
Source	Message text	Timestamps	Office-hour inquiries	Staff support availability	
Customer	Get started	11/11/2019 3:56:22 pm			
Bot	Hi, I'm [chatbot name] from [company name].	11/11/2019 3:56:22 pm			
Source	Message text	Timestamps	Problem-solving	Task-oriented goals	Goal-related factors
Customer	A car crashed onto the pole	23/10/2019 1:41:49 am			
Source	Message text	Timestamps	Incident investigation		
Customer	Power outage in [street address] – How long will it take?	21/08/2018 11:37:27 am			

<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Information confirmation		
Customer	(select 'Check outages' option)	5/08/2019 7:33:23 am			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Entertainment	Non-task-oriented goals	
Customer	Tell me a joke	16/06/2019 2:33:12 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	General information request		
Customer	When is the next dividend due?	23/10/2019 1:41:51 am			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Construction information	Broadly-defined information needs	Information-related factors
Customer	Report an outage	7/06/2019 8:07:31 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Orientation information		
Customer	Is gas available in [street address]?	11/12/2018 8:54:20 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Re-orientation information need	Narrowly-defined information needs	

Customer	Is there still a planned outage for my area today?	13/08/2018 9:00:50 pm			Navigational information needs
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Chatbot-related information		
Customer	Are you a robot?	6/11/2018 12:17:40 am			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Company-related information		
Customer	What is [Company name]?	26/07/2018 9:59:50 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Information location		
Customer	Where is the outage map?	29/01/2019 3:02:47 am			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Procedural information		
Customer	(select 'Getting connected' option)	18/07/2018 11:16:44 pm			
Bot	The process of getting connected to the Vector network has several stages: ...	18/07/2018 11:16:44 pm			

<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Information importance	High-priority information needs		
Customer	We are at [home address]. When are we going to get power back?	8/06/2019 5:25:28 am				
Bot	It looks like you've entered an address. Did you want to check for outages, get a new connection or organise a disconnection?	8/06/2019 5:25:29 am				
Customer	It's a Restaurant and can't do business on one of the busiest evenings of the week	8/06/2019 5:26:06 am				
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Information urgency			
Customer	Gas safety	27/04/2019 7:19:49 am				
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Information informality	Psycho-emotional information needs		
Customer	I'm angry	25/07/2018 9:38:51 pm				
Bot	Ah – That's too bad	25/07/2018 9:38:54 pm				



<div><div>Source</div><div>Customer</div></div>	<div><div>Message text</div><div>What can you do?</div></div>	<div><div>Timestamps</div><div>26/03/2019 2:02:55 am</div></div>	Open-domain question answering ability	Natural language	Technology-related factors
<div><div>Source</div><div>Customer</div></div>	<div><div>Message text</div><div>(select ‘Contact [Company name]’ option)</div></div>	<div><div>Timestamps</div><div>13/09/2019 10:02:52 pm</div></div>	Clickable buttons		
<div><div>Source</div><div>Customer</div></div>	<div><div>Message text</div><div>Tell me a joke</div></div>	<div><div>Timestamps</div><div>22/04/2019 1:23:54 pm</div></div>	Social cues	Colloquial language	
<div><div>Source</div><div>Bot</div></div>	<div><div>Message text</div><div>I have a joke to share: ...</div></div>	<div><div>Timestamps</div><div>22/04/2019 1:23:57 pm</div></div>			
<div><div>Source</div><div>Customer</div></div>	<div><div>Message text</div><div>When is the next light event?</div></div>	<div><div>Timestamps</div><div>27/02/2019 8:47:56 pm</div></div>	Complete-sentence strategy	Information interrogation strategies	Interactive strategies
<div><div>Source</div><div>Customer</div></div>	<div><div>Message text</div><div>There was an outage</div></div>	<div><div>Timestamps</div><div>16/06/2019 11:31:33 pm</div></div>	Fragmented strategy		

Bot	Outage Centre – The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre.   [attached links]. How else can I help? If you'd like to give feedback, just type feedback.	16/06/2019 11:31:36 pm			
Customer	During the weekend	16/06/2019 11:31:39 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Keyword search strategy		
Customer	Disconnect	22/07/2018 9:06:56 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	FAQ strategy		
Customer	(select 'Check outages' option)	31/05/2019 11:42:08 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Social reciprocity strategy	Social reciprocity strategies	
Customer	How are you?	22/04/2019 1:23:36 pm			

Bot	I'm feeling good today. How are you today?	22/04/2019 1:23:39 pm			
Customer	I'm feeling super-duper terrible	22/04/2019 1:23:41 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Customer	Hi there	3/12/2018 7:10:40 pm	Greeting the chatbot		
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Customer	Who built you?	30/07/2019 3:33:51 am	Curiosity about the chatbot		
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Customer	Hi when will the [an app name] become available for use again for commercial users? Kind regards [customer name]	8/09/2018 7:09:22 pm	Politeness towards the chatbot	Mutual awareness	Low social presence
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Customer	Why are you here?	18/07/2018 11:16:31 pm	Chatbot's inability to capture customer's intents	Limited mutual monitoring	

Bot	I don't know how to answer that I'm sorry.	18/07/2018 11:16:36 pm																
<table><tr><th>Source</th><th>Message text</th><th>Timestamps</th></tr><tr><td>Customer</td><td>How long until power on?</td><td>22/06/2019 12:46:54 pm</td></tr><tr><td>Bot</td><td>I can help you check your address for an outage. What address would you like to check?...</td><td>22/06/2019 12:46:56 pm</td></tr></table>	Source	Message text	Timestamps	Customer	How long until power on?	22/06/2019 12:46:54 pm	Bot	I can help you check your address for an outage. What address would you like to check?...	22/06/2019 12:46:56 pm		Chatbot's misinterpretation of customer's requests							
Source	Message text	Timestamps																
Customer	How long until power on?	22/06/2019 12:46:54 pm																
Bot	I can help you check your address for an outage. What address would you like to check?...	22/06/2019 12:46:56 pm																
<table><tr><th>Source</th><th>Message text</th><th>Timestamps</th></tr><tr><td>Customer</td><td>(input home address)</td><td>24/06/2019 10:04:59 pm</td></tr><tr><td>Bot</td><td>There was an error validating your address.</td><td>24/06/2019 10:05:02 pm</td></tr><tr><td>Customer</td><td>(input home address)</td><td>24/06/2019 10:05:31 pm</td></tr><tr><td>Bot</td><td>There was an error validating your address.</td><td>24/06/2019 10:05:32 pm</td></tr></table>	Source	Message text	Timestamps	Customer	(input home address)	24/06/2019 10:04:59 pm	Bot	There was an error validating your address.	24/06/2019 10:05:02 pm	Customer	(input home address)	24/06/2019 10:05:31 pm	Bot	There was an error validating your address.	24/06/2019 10:05:32 pm		Chabot's repeated errors	
Source	Message text	Timestamps																
Customer	(input home address)	24/06/2019 10:04:59 pm																
Bot	There was an error validating your address.	24/06/2019 10:05:02 pm																
Customer	(input home address)	24/06/2019 10:05:31 pm																
Bot	There was an error validating your address.	24/06/2019 10:05:32 pm																

<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Customer's repeated requests		
Customer	The Physical Risks from Climate Change Report of Findings for [Company name] Limited (November 2017)	29/11/2018 8:04:35 pm			
Bot	I'm sorry, I didn't understand that. These are some the things I can currently help you with.   [provided options]	29/11/2018 8:04:36 pm			
Customer	The Physical Risks from Climate Change Report of Findings for [Company name] Limited (November 2017)	29/11/2018 8:04:42 pm			
Bot	I'm sorry, I didn't understand that. These are some the things I can currently help you with.   [provided options]	29/11/2018 8:04:46 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Navigating customers to other websites	Low level of interactional involvement	
Bot	The easiest way to get information on current outages is to	27/07/2018 7:53:53 pm			

	contact us or check our website.				
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Bot	You can get in touch with Vector by phoning [phone number] or at the contact details linked below.	26/07/2018 10:59:26 pm	Escalating customer requests		
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Bot	I'm sorry I couldn't be of more help. Please call us directly so we can assist further.	18/12/2018 6:36:23 am	Suggesting customers to seek human agent support		
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Customer	(select 'Getting connected' option)	18/07/2018 11:16:44 pm			
Bot	The process of getting connected to the Vector network has several stages: ...	18/07/2018 11:16:44 pm	Scripted responses to pre-set options		

<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Chatbot’s adequate problem-solving attempts	High level of interactional involvement	Medium social presence
Customer	my power is out in [home address]	27/06/2019 2:44:21 pm			
Bot	I can help you check your address for an outage. Is [home address] the correct location?	27/06/2019 2:44:24 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Customer	(select ‘Contact [company name]’ option)	30/10/2019 9:00:56 pm	Chatbot’s adequate responses		
Bot	You can get in touch with Vector by phoning [phone number] or at the contact details linked below.	30/10/2019 9:00:56 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Chatbot’s willingness to help		
Customer	Can I brighten up your day?	14/08/2019 4:48:41 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Reciprocal self-disclosure	Joint engrossment	
Customer	How are you?	22/04/2019 1:23:36 pm			

Bot	I'm feeling good today. How are you today?	22/04/2019 1:23:39 pm			
Customer	I'm feeling super doper terrible	22/04/2019 1:23:41 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Customer	Gas	27/04/2019 7:20:50 am			
Bot	Would you like to connect gas or organise bottle delivery? Click one of the buttons below. [provided options]	27/04/2019 7:20:54 am	Acquired information not matching desired information and requiring additional effort	Absolute failure	
Customer	Neither, you muppet. I want someone to inspect whether or not I have a gas leak	27/04/2019 7:21:31 am			Interaction outcomes
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>			
Customer	Hi, wish to know if gas line available on [street address]	6/04/2019 2:05:15 am	Acquire information not matching desired information and requiring minimal effort	Failure	
Bot	In an emergency, please call 111.	6/04/2019 2:05:20 am			



<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Acquired information matching desired information and required additional effort	Subtle success	
Customer	I want to report an outage	2/05/2019 1:39:25 pm			
Bot	Outage Centre - The fastest and easiest way to report an outage or check your address is now online at our new Outage Centre   ['Outage Centre' link]	2/05/2019 1:39:31 pm			
<b>Source</b>	<b>Message text</b>	<b>Timestamps</b>	Acquired information matching desired information and required minimal effort	Success	
Customer	(select 'Contact [company name]' option)	30/10/2019 9:00:56 pm			
Bot	You can get in touch with Vector by phoning [phone number] or at the contact details linked below.	30/10/2019 9:00:56 pm			

## Appendix B – Strategies and their appraisal sets

Appraisals					Information-seeking strategies	
Core-supporting conditions	Goal-related factors	Context-related factors	Information-related factors	Technology-related factors		
Core	–	<ul style="list-style-type: none"> <li>• Problem-solving</li> <li>• Incident investigation</li> </ul>	<ul style="list-style-type: none"> <li>• Construction</li> <li>• Orientation</li> </ul>	<ul style="list-style-type: none"> <li>• Open-domain question answering ability</li> </ul>	Complete-sentence strategy	Information interrogation strategies
Supporting	<ul style="list-style-type: none"> <li>• After-hours inquiries</li> <li>• Office-hour inquiries</li> </ul>	<ul style="list-style-type: none"> <li>• General information request</li> </ul>	<ul style="list-style-type: none"> <li>• Re-orientation</li> <li>• Urgency</li> <li>• Chatbot-related information</li> <li>• Company-related information</li> <li>• Procedural information</li> </ul>	–		
Core	–	<ul style="list-style-type: none"> <li>• Problem-solving</li> </ul>	<ul style="list-style-type: none"> <li>• Construction</li> <li>• Orientation</li> </ul>	<ul style="list-style-type: none"> <li>• Open-domain question answering ability</li> </ul>		
Supporting	<ul style="list-style-type: none"> <li>• After-hours inquiries</li> <li>• Office-hour inquiries</li> </ul>	<ul style="list-style-type: none"> <li>• Incident investigation</li> </ul>	<ul style="list-style-type: none"> <li>• Importance</li> <li>• Information location</li> </ul>	–		
Core	–	<ul style="list-style-type: none"> <li>• Problem-solving</li> <li>• General information request</li> </ul>	<ul style="list-style-type: none"> <li>• Construction</li> <li>• Orientation</li> </ul>	<ul style="list-style-type: none"> <li>• Open-domain question answering ability</li> </ul>		
					Fragmented strategy	
					Keyword search strategy	

Supporting	<ul style="list-style-type: none"><li>• After-hours inquiries</li><li>• Office-hour inquiries</li></ul>	–	<ul style="list-style-type: none"><li>• Procedural information</li><li>• Information location</li></ul>	–		
Core	–	<ul style="list-style-type: none"><li>• Information confirmation</li><li>• General information request</li></ul>	<ul style="list-style-type: none"><li>• Orientation</li></ul>	<ul style="list-style-type: none"><li>• Clickable buttons</li></ul>	FAQ strategy	
Supporting	<ul style="list-style-type: none"><li>• After-hours inquiries</li><li>• Office-hour inquiries</li></ul>	–	<ul style="list-style-type: none"><li>• Procedural information</li><li>• Information location</li></ul>	–		
Core	–	<ul style="list-style-type: none"><li>• Entertainment</li></ul>	<ul style="list-style-type: none"><li>• Informality</li></ul>	<ul style="list-style-type: none"><li>• Social cues</li></ul>	Social reciprocity strategy	Social reciprocity strategies
Supporting	<ul style="list-style-type: none"><li>• After-hours inquiries</li><li>• Office-hour inquiries</li></ul>	–	–	<ul style="list-style-type: none"><li>• Open-domain question answering ability</li></ul>		

## Appendix C – AUTC approval letter

