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Enhancing Online Customer Service: The Impact of Empathy, Active Listening, and Proactive Behavior on Customer Satisfaction

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Abstract

Today, there is an increase in online customer service interactions, and the shift from in-person to textual communication is affecting interaction patterns with less possibility for showing physical verbal and non-verbal communication cues. Moreover, efficient online encounters can lead to repeat customer contact as all customer concerns are not being handled during the initial interaction. There is extensive research on customer service, however, the effects of changes in interaction patterns due to increased online interactions are understudied. Additionally, there is a need for a better understanding of the effects of specific communication strategies on customer satisfaction in private online customer service chats. Therefore, this study aims to investigate the effects of empathy, active listening, and proactive behavior displayed by customer service employees on customer satisfaction in the context of online customer service chats. The Emotion as Social Information (EASI) theory serves as the theoretical framework for understanding the interpersonal effects of customers' displayed emotions and arousal levels in these interactions. The study employs text mining using KNIME analytics platform to analyze the impact of empathy, active listening, and proactive behavior on the Net Promoter Score (NPS). Moreover, the impact of customer negative high arousal as a potential moderation effect on the customer service interaction is accounted for. The results indicate that customers expressing negative high arousal negatively affects the NPS, while empathy, active listening, and proactive behavior exhibited by customer service employees have a positive impact on the NPS. However, the measures of active listening and proactive behavior requires improvement to provide significant results. Additionally, the moderation effect analysis reveals that empathy and customer negative high arousal interaction have a positive effect on the NPS. The findings highlight the importance of training customer service employees to respond empathetically and proactively to various customer emotions and arousal levels, thereby improving the overall customer experience. Further research is recommended to explore additional strategies for de-escalating negative high arousal and enhancing customer satisfaction in online customer service interactions.

1. Introduction

The emergence of the Internet has substantially altered customer expectations regarding business interactions, setting new standards for online engagements between customers and businesses (Misischia et al., 2022). For companies, offering online customer service can benefit them greatly as it often results in lower costs, increased efficiency, and improved customer satisfaction (Dimyadi, 2018; Olenski, 2016). However, the rapid evolution of technology and the sudden dependence on digital solutions due to the Covid-19 pandemic has raised customer expectations for online brand interactions even further (Berg et al., 2022; Jarman, 2021; Misischia et al., 2022). Thus, there is a pressing need for companies to provide exceptional online customer service to maintain their competitive edge. Chat-based customer service interactions have become a popular choice for many customers, leading to expectations of prompt and effective problem-solving (Adam et al., 2020; Charlton, 2013). Despite its many benefits, the shift from in-person to online customer-employee interactions also comes with its challenges. For example, customers misinterpreting service employees' communication efforts and "too efficient" problem-solving are potential consequences of online customer service that can lead to frustration and even lost customers (Beaujean et al., 2006; Dixon et al., 2010). Firstly, the increase in text-based communication has changed interaction patterns, as in-person communication allows for a broader exchange of verbal and non-verbal communication cues (Herhausen et al., 2023). This can significantly impact the customer experience and lead to misinterpretation as it eliminates prevalent cues in communication such as facial expressions, tone of voice, and body language (Packard & Berger, 2022). Secondly, the shift from in-person to remote customer service can lead to frustration among customers as the percentage of repeat customer contact increases due to problems not being solved during the initial service interaction (Dixon et al., 2010). Consequently, companies can potentially fail to provide a good online customer experience. As friction between customers and employees due to service failure is impossible to prevent (Joireman et al., 2013), so are negative customer emotions. Negative emotions, such as anger, make customers more likely to engage in negative behavior towards the company (Bougie et al., 2003; Gelbrich, 2010; Herhausen et al., 2019; Joireman et al., 2013; Kalamas et al., 2008; Nguyen & McColl-Kennedy, 2003; Strizhakova et al., 2012). Thus, companies should avoid this by ensuring that frontline employees (FLEs) are trained properly to make sure that online customer interactions are not misinterpreted or unappreciated by customers.

There is extensive research on different constructs that can both positively and negatively impact the customer service experience such as the role of language (Holmqvist & Grönroos, 2012), concrete language (Packard & Berger, 2021), empathy (Clark et al., 2013) and apologies (Kim, 2007). However, as customer service interactions continue to shift from in-person to text-based communication, further research is needed to better understand the impact of these changes on customer experiences and their outcomes (Packard & Berger, 2022). Van Kleef (2009) introduce the theory of Emotion as Social Information (EASI) which is based on the interpersonal effects of emotions. He suggests that displayed emotions not only influence oneself but also the behavior of the observer. This behavior can both be caused by affect (natural, immediate reaction) or inference (strategic process) and is a process that should not be overlooked as it can influence how customer service employees react to customer emotions and various levels of arousal. The way service employees respond to displayed emotions can further affect the customer experience. Therefore, knowing what type of reaction customer service employees should adopt to various customer emotion states to improve the customer experience during online interactions is important. However, the link between customer emotions and arousal, employee responses and customer satisfaction in private online customer service situations has, so far, not been explored. Two ways FLEs can strategically act to avoid negative friction and make sure that customers feel understood is by communicating empathy and attentive listening (Bahadur et al., 2018; Herhausen et al., 2023; Min et al., 2015). This can be done by carefully choosing words and phrases that affirm the customer's emotions (i.e., "I understand", "that must be difficult") and emphasizing active listening (i.e., "Can you elaborate", "I see what you mean"). Herhausen et al. (2023) explore this, by examining customer emotions and arousal levels and how the role of active listening and empathy can impact customer gratitude and de-escalate negative arousal states in social media complaint handling. They find that both constructs show significant effects in improving customer gratitude after a service failure and that empathy was most effective in de-escalating high negative arousal (Herhausen et al., 2023). While this research examines public complaint handling on social media, further investigation is needed to explore the impact of active listening and empathy on customer satisfaction in the context of private online customer service chats. It is important to consider the potential differences between public and private online communication channels, as they may have distinct effects on how customers perceive and react to online service interactions (Herhausen et al., 2023).

Another important, but somewhat overlooked, customer service behavior that can positively affect customer satisfaction is proactive customer service performance (Rank et al., 2007; Raub & Liao, 2012). Reducing customer efforts, waiting time and repeat contact with companies are some aspects that can improve the customer experience (Dixon, et al., 2010; Valentini et al., 2020). To succeed with this, Dixon, Freeman and Toman (2010) suggest that employees should "make it easy" for customers by foreseeing future obstacles and solving them before they appear. By simply asking whether there is anything else the customer needs help with, the employee initiates additional support and can prevent the interaction from feeling rushed. Moreover, FLEs can perform proactively by foreseeing potential problems that customers often experience and helping them solve them before they occur. However, there is a lack of research on whether proactivity among service employees leads to positive outcomes and satisfaction among customers. Heinonen and Pesonen (2022) emphasize that most of the literature on service quality and experiences from online customer service evolves around technical and structural service elements. Therefore, it is crucial to further explore the role of text-based communication on the customer experience. In sum, there is a need for a better understanding of how customer emotions and different customer arousal states can affect customer satisfaction by being met with various employee reactions as a direct response to their displayed emotions.

Therefore, with this study, I aim to explore how negative high customer arousal can be affected by being met with active listening, empathy, and proactive behavior from a customer service employee and how the various employee reactions can impact customer satisfaction and behavioral loyalty towards a company expressed by the net-promoter score (NPS). The research will be based on data, in the form of customer chat conversations with its associated customer assessment of the interaction, from a large telecom company in Norway. Based on the EASI theory and previous findings on the role of active listening, empathy, and employee proactivity, I will use text mining to analyze the effect of these constructs on the NPS provided by customers with various emotional arousal levels. Based on this, I hypothesize that customers who express negative high arousal generally provide a lower NPS (***H_1***). However, when customer service employees demonstrate empathy (***H_{2A}***), active listening (***H_{3A}***), and proactive behavior (***H_{4A}***) customers, in general, provide a higher NPS. This effect can further be affected when customer service employees draw strategic inferences when met with negative high arousal customers and react by moving towards the customer with empathy (***H_{2B}***), active listening (***H_{3B}***), and proactive behavior (***H_{4B}***).

2. Literature Review

2.1 Emotions as Social Information

Emotions as social information (EASI) is a social-functional approach to emotions and was officially introduced by Van Kleef (2008, 2009). Emotions can have two different roles in social settings which are called *intra*personal effects and *inter*personal effects (Van Kleef, 2009). Whereas studies on emotion within psychology have predominantly explored the intrapersonal effects of emotions, there is a lack of focus on the interpersonal effects (Van Kleef, 2009; Van Kleef & Côté, 2022; Van Kleef et al., 2010). When a person's behavior is influenced by his or her own emotions, the emotions have an intrapersonal effect (Van Kleef, 2008). However, Van Kleef (2009) argues that the effect of an individual's emotions on other individuals' behavior, or interpersonal effects of emotion, is just as important to consider when trying to understand the complexity of human emotions. Thus, the EASI theory contributes to the interpersonal perspective of emotions and suggests that each emotion portrayed by an individual is an expression of specific information for another person to interpret (Van Kleef et al., 2010). So far, most research using the EASI framework has investigated conflict and negotiation, except for some studies focusing on, for example, the role of emotion in shared decision-making in oncology (Treffers & Putora, 2020), upward impression management (Deng et al., 2019), and social media (Xu et al., 2022). However, as the theory emphasize how people's behavior is influenced by others' emotions, it is directly relatable to the realm of customer service as service employees should adapt their behaviors according to their customers' emotions. By considering the EASI framework in relation to customer emotions and which communicative strategies best fit these different emotions and arousal states, the customer service literature will gain valuable insight into how companies can further improve their customer service.

The EASI theory specifies two processes that can potentially influence observers of emotions, namely affective reactions, and inferential processing, and then introduces two moderating variables, namely information processing and social context, that can influence the predictive strength of these mechanisms (Van

Kleef et al., 2011). An affective reaction can be evoked relatively automatically by another individual's expressed emotion, it can be both reciprocal and complementary reactions (Van Kleef & Côté, 2022). For instance, this can happen through emotional contagion, where an observer "catches" the other person's emotion (Van Kleef et al., 2011). It can also happen through complementary emotional experiences, where anger can illicit fear and sadness can illicit compassion from the observer (Van Kleef et al., 2011). Inferential processing is more deliberate and includes cognitive responses where observers make inferences or assumptions about the expressed emotions and act based on these inferences (Van Kleef & Côté, 2022). For example, an observer might perceive anger as an expression of a person feeling injustice and from this change their behavior to whether the anger is directed towards them or a specific situation (Van Doorn et al., 2015; Van Kleef et al., 2011). Furthermore, the interpersonal effects of emotion can be moderated by the observer's motivation and ability to comprehend the information from an emotion. When observers' information processing is profound, the predictive power of the inferential process is increased (Van Kleef, 2009; Van Kleef et al., 2011). Social context is the second moderator and can be explained by, for example, social and cultural norms, appropriateness of the emotion, the relative status of the expresser, the interpersonal relationship, and way of expression (Van Kleef, 2009, 2010; Van Kleef et al., 2011). Thus, Van Kleef et al. (2011) propose that the inferential process of emotion is more powerful when the emotion expressed is perceived as appropriate, and when the emotion is perceived as inappropriate, affective reactions become more predictive.

Van Kleef and Côté (2022) predict that the EASI theory can give successful predictions regardless of how emotions are communicated. This also includes textual cues and symbolic cues which are the prominent social cues in text-based communication, for instance for online customer service. Moreover, they argue that when the senders are highly emotionally expressive and the observers have a high emotional perception, the encoding and decoding of this social information is increasingly facilitated and will therefore have stronger effects (Van Kleef & Côté, 2022). This is highly relevant when considering customer service chats as customer service employees are hired to properly understand and make inferences regarding customer emotions, wants and needs (Okeke, 2017). Further, Hillebrandt and Barclay (2017) use EASI to investigate emotions in communicating strategic information. They differ between integral and incidental emotions and emphasize the importance of acknowledging the type and target of an emotion. The authors argue that a person showing emotion can have various goals for showing this emotion, and this goal can directly influence to what extent an observer will attribute the emotion to his or her own behavior (Hillebrandt & Barclay, 2017). In their study, they mostly focus on inferential processes and situations of negotiation. This can be considered the most relevant process for customer service purposes as well, as customers sometimes exaggerate the situation to make the employee feel that they need urgent help and special attention (Baker & Kim, 2019; Harris et al., 2016; Spillane, 2012). If customer service employees are successfully dissecting the emotions of the customer and know how to best react to their emotional state, they have the potential to increase customer satisfaction. To develop this theory further, I have decided to focus on the outcome that happens after the service respondents' action, namely the customer providing an NPS to indicate their satisfaction with the response of the service employee. Thus, specific employee reactions will be evaluated as (mainly) strategic inferences that could lead to an improved online customer experience.

2.2 Online Customer Service

Successful customer service encounters are crucial to the overall customer experience, and as many as 96% of customers emphasize that customer service is essential for brand loyalty (Amaresan, 2022; Morgan, 2019). Moreover, the top reason why customers decide to move to a competitive brand is due to feeling unappreciated by the brand (Morgan, 2019). With the increasing preference for encountering companies through online interactions, it is crucial for companies to understand the impact of text-based communication on the individual customer experience (Heinonen & Pesonen, 2022; Jarman, 2021; Misischia et al., 2022). As writing involves deliberation and may make people express fewer emotions (Berger et al., 2022), it is important that customer service employees improve their understanding of individual customer needs and further adapt their communication to avoid misinterpretations and improve customer-employee relations. Qin et al. (2022) accentuate that the perceived quality of online customer service has a positive effect on purchase intentions. Therefore, there is a need for more research that can build on the extensive research on physical customer service encounters to further understand the effects and maximize the potential of online customer service.

Beaujean et al. (2006) emphasize that what is usually missing to achieve a successful customer service experience is the spark between the FLE and the customer. As customer experiences are subjective, it is crucial to understand which communication efforts can efficiently improve the overall customer experience. Previous research suggests that customized service strategies directed towards different segments (Lee & Lee, 2020; Narayana & Durga, 2017; Rust & Lemon, 2001), and offering customer compensation (Kim, 2007) can lead to increased customer satisfaction and loyalty towards the company. Whereas the use of emoticons gave both positive and negative effects as the service employees were considered to have more warmth by some customers, but they were also perceived as less competent by others (Li et al., 2019). As customers are emotionally invested in the service interactions, employees need to instinctively put the emotional needs of the customers in front of the agendas of the company and the service employee (Beaujean et al., 2006). Heinonen and Pesonen (2022) underlines that a great customer experience demands personalized and effective communication. This emphasizes that the various emotions customers experience is crucial for the FLE to correctly interpret and understand during the service interaction. However, most research within the realm of customer service does not consider customer emotions, especially not its associated level of arousal, as a variable that can affect the customer experience. A potential strategy companies can adopt to ensure better online customer handling is through investing in proper training of the customer service staff. Training FLEs to improve their interpersonal skills (i.e., showing courtesy and empathy) (Dagger et al., 2013) and provide interactional justice (Tax et al., 1998) can positively affect the customers' perception of the service quality and strengthen customer relationships. Most research on online customer service focuses on customer complaints and not necessarily on general customer interactions for help and advice. However, customer service interactions can also be used to prevent service failures. Therefore, it is crucial to get a better understanding of how this preliminary step to a potential service failure or customer complaint can be successfully handled in private online service interactions.

2.3 Customer Emotions and Arousal States

Service failures are impossible to prevent completely (Joireman et al., 2013). Consequently, companies cannot avert customers experiencing negative emotions from bad customer experiences. The customer experience can be affected by the positive or negative emotions and level of arousal the customer experiences before, during, and after a company interaction. These emotions can further develop during the service interaction where the service employee's actions can lead to escalation or de-escalation of the arousal state the customer is experiencing related to the emotional valence. A customer can experience negative emotions such as frustration or disappointment (i.e., towards a service or product, or from negative experiences when contacting the firm) before the customer service interaction, which can affect the experience of the customer-employee interaction (Kalamas et al., 2008). Negative emotions can also develop during the interaction, for instance, if the customer does not feel heard or is dissatisfied with how the service employee is acting, which can develop into the customer experiencing increased arousal (Tax et al., 1998). Lastly, these negative emotions can further elevate the arousal state after the customer service interaction due to unresolved issues, which can develop over time and lead to negative high arousal (Nguyen & McColl-Kennedy, 2003; Surachartkumtonkun et al., 2014). When a customer is experiencing negative high-arousal such as anger and rage, they are more likely to engage in further negative behavior directed towards the company, such as negative word-of-mouth (WOM), complaining on social media, and even switching to a competitive company (Bougie et al., 2003; Gelbrich, 2010; Herhausen et al., 2019; Joireman et al., 2013; Kalamas et al., 2008; Nguyen & McColl-Kennedy, 2003; Strizhakova et al., 2012). When service employees are unsuccessful in de-escalating negative high arousal, they usually fail to recover the service experience (De Pelsmacker et al., 2007, p. 443; Herhausen et al., 2023; Kalamas et al., 2008). As customer retention is less costly than acquiring new customers (Beaujean et al., 2006) it is crucial for companies to focus on how to train customer service employees to handle negative emotions.

Herhausen et al. (2023) emphasize that there is a lack of differentiation between high and low negative customer arousal. A contribution to the customer emotion literature is made by Villarroel Ordenes et al. (2017) who divides customer emotions into four categories. Namely positive vs. negative customer valence and high vs. low emotional activation (Villarroel Ordenes et al., 2017). Further, the research of Herhausen et al. (2019) and Herhausen et al. (2023) builds on this classification which relates high negative arousal to anxiety, anger, and disgust, and low negative arousal to sadness and disappointment. In physical customer-employee interactions, positive customer emotions (i.e., joy, delight) and negative emotions (i.e., anxiety, anger) can be identified based on physical cues such as facial expressions, tone of voice, and body language in addition to the language used by the customer (Menon & Dubé, 2000). Moreover, when customers for instance are experiencing negative high arousal, the physical cues can be even more prevalent for the FLE to identify. However, in text-based communication, physical cues are eliminated, and customer emotions and levels of arousal need to be identified based on different cues such as the use of punctuation, emoticons, and various emotionally loaded words (Herhausen et al., 2023). One way to determine these emotions is through text mining. Herhausen et al. (2023) did this by using dictionaries to identify high vs. low and negative vs. positive arousal and identified the percentage of the various words in customer complaints.

Most research on online customer-employee interactions focuses on service recovery and public interactions (i.e., Gelbrich, 2010; Herhausen et al., 2023; Valentini et al., 2020), and not on private customer chats. Surachartkumtonkun et al. (2014) find that rage as a negative high arousal most often is not the immediate reaction to a service failure but develops over time if the service failure is not resolved. Thus, resolving customer issues early and meeting them with the proper communication is crucial to avoid negative high arousal. Additionally, Grégoire et al. (2018) suggest that companies can successfully de-escalate customer revenge due to negative high arousal if they "nip it in the bud". As more and more customers are now utilizing companies' customer service chats to seek information and help (Adam et al., 2020), training service employees to detect negative emotions and negative high arousal early and understanding how to properly handle these customers is crucial. Moreover, Menon and Dubé (2000) emphasize that customer satisfaction is formed not only by the observed salesperson response but also by the normative expectations of the employee response. This is important to consider as giving a drastically different response than what customers usually expect from a service encounter can have an impact on the customer experience, both negatively and positively. Consequently, further understanding of negative emotions, their levels of arousal, as well as the appropriate and expected employee reactions could lead to avoidance of potential service failures and negative customer actions. In general, there is a lack of research on text-based customer interactions as most research on customer-employee interactions is based on in-person interactions and physical cues such as tone-of-voice and body language (i.e., Menon & Dubé, 2000; Nguyen & McColl-Kennedy, 2003; Surachartkumtonkun et al., 2014). Thus, understanding how customer service employees best can respond and act towards customers in various arousal states in online service interactions is important to avoid potential service failures and public customer complaints. Based on this, I hypothesize that customers demonstrating negative high arousal emotions are less satisfied with the customer service experience.

***H_1*: Customers who demonstrate high negative arousal will provide a lower NPS.**

2.4 Empathy

Empathy can be defined as the ability to recognize and understand another person's feelings, thoughts, and position without experiencing these emotions oneself (Futrell, 2011, p. 161; Hoffman, 2008, p. 440; Wieseke et al., 2012;). In textual communication, empathy is related to the content of a message, such as using empathetic words, words of validation, or affirmation (Herhausen et al., 2023). There is extensive research emphasizing that employee empathy is crucial to satisfy customer needs and improving the customer experience (Bahadur et al., 2018; Clark et al., 2012; Gorry & Westbrook, 2011; Wieseke et al., 2012). Moreover, Itani and Inyang (2015) found that empathetic behavior from employees is an important means to achieve successful service encounters which further can lead to long-lasting customer relationships and increased customer satisfaction. A lack of empathy among employees in customer interactions has also been shown to lead to dissatisfaction among customers (Bahadur et al., 2018) which emphasizes the importance of employees' ability to show empathy. Additionally, Belanche et al. (2020) found that consumers attribute more responsibility and have higher expectations towards FLEs than towards service robots. Thus, it is evident that employee empathy is key to improving the customer service experience as lack thereof can lead to customer dissatisfaction.

Recent research by Herhausen et al. (2023) finds evidence that empathy by a firm can increase customer gratitude and minimize high-arousal emotions of complaining customers when handling social media complaints. Moreover, they found that empathy was even more effective in improving customer gratitude relative to active listening (Herhausen, 2023). Gorry and Westbrook (2011) emphasize how companies' efforts to save cost by implementing technology in customer service have led to customer frustration and inadequate customer service. It has become harder for employees to empathize with the customers as digitalization decreases customers' ability to share their experiences properly. However, they emphasize that using technology does not necessarily have to be responsible for the loss of empathy if used correctly in a customer-centric way (Gorry & Westbrook, 2011). Empathy is mostly linked to affective reactions as complementary emotional experiences (Duan & Hill, 1996; Eisenberg & Strayer, 1987, p.3). However, in a customer service situation, it can also be used strategically as an inferential action as service employees usually are aware of the importance of empathetic behavior on customer satisfaction, especially when customers experience high negative arousal (Herhausen et al. 2023). Based on this, I hypothesize that employee empathy increases customer satisfaction. Moreover, when a customer experiences high negative arousal, employee empathy will increase customer satisfaction.

H_{2A}: Customers provide a higher NPS when the FLE is empathetic.

H_{2B}: Customers who demonstrate high negative arousal will be more satisfied when being met with employees who react with empathy.

2.5 Active Listening

Active listening can be defined as attentively listening to what a customer says before verbally acknowledging the customer by, for instance, repetition, paraphrasing, mimicking, or adapting the language towards a customer (de Ruyter & Wetzels, 2000; Herhausen et al., 2023; Min et al., 2021; Ramsey & Sohi, 1997). As for text-based communication, active listening needs to be identified by the style of the employee response (i.e., matching the customers' communication style) (Herhausen et al., 2023) or the validation (i.e., a response that confirms understanding and evaluation of the message) (Min et al., 2015; Ramsey & Sohi, 1997). Ireland & Henderson (2014) and Gonzales et al., (2010) both suggest that matching the language style of a communication partner is a way for people to show that they are actively listening to this partner. Further, Collins (2022) emphasizes that expressing verbal cues is the most effective way to signal active listening. There is substantial evidence that employees who demonstrate that they are attentively listening to the customers result in increased satisfaction and trust towards the service assistant (Gruber, 2011; Nguyen & McColl-Kennedy, 2003; Ramsey & Sohi, 1997; van Baaren, 2005). And whereas Nguyen and McColl-Kennedy (2003) found that active listening could reduce negative high arousal such as customer anger in service recovery, Dickinger & Bauernfeind (2009) found evidence that active listening also increased customer satisfaction in online text-based communication.

Active listening has been shown to have positive effects on customer satisfaction but can also have diminished effects under certain conditions. Min et al. (2021) are looking more specifically into the joint role of listening and apologizing. In their first study, they found that active listening led to higher customer satisfaction as well as higher intentions to tip employees (Min et al., 2021). Moreover, they found that satisfaction was higher among customers who perceived they were receiving preferential treatment (Min et al., 2021). However, this effect was decreased when the customers were offered a complimentary service, as the feeling of receiving preferential treatment diminished (Min et al., 2021). Furthermore, Herhausen et al. (2023) found that active listening had a significant and positive effect on customer gratitude as well as it could decrease the arousal level of high-aroused customers. Interestingly, they also found that an increase in active listening resulted in a diminished effect among low-arousal customers. Thus, this could indicate that active listening is not necessarily crucial in all customer-employee interactions.

van Baaren (2005) found that waitresses received larger tips from customers by solely repeating or paraphrasing customer orders. In his research, the form of mimicry was named the Parrot Effect and was found to give the customers a sense of reassurance of simply being heard (van Baaren, 2005). His research is based on a similar effect, which was introduced by Chartrand & Bargh (1999), namely the Chameleon Effect. The Chameleon Effect of mimicking behaviors such as facial expressions and posture was found to increase cohesion and liking within the group (Chartrand & Bargh, 1999). As active listening by repeating words can be seen as a part of the Chameleon Effect and Parrot Effect, there is reason to believe that active listening will increase a customer's feeling of being heard and, therefore, increase the overall customer experience. Moreover, Collins (2022) suggests that those who are best at listening are those who express this verbally.

Additionally, actively listening to someone can improve well-being across domains (Collins, 2022). Thus, providing customers with verbal cues to make them feel heard could be more important than showing non-verbal cues and could lead to an improved customer experience. In relation to the EASI theory, this type of response can be performed nonconscious (Lakin & Chartrand, 2003) as an affective behavior, or conscious as a strategy to make the customer feel heard and understood and to de-escalate high negative arousal. Therefore, I hypothesize that active listening by employees results in a higher NPS, and when a customer experiences high negative arousal, customer service employees can improve the customer experience by strategically performing active listening.

***H_{3A}*: Customers provide a higher NPS when the FLE performs active listening.**

***H_{3B}*: Customers who demonstrate high negative arousal will be more satisfied when being met with employees who react with active listening.**

2.6 Proactive Customer Service Performance

Proactive customer service performance can be defined as employees that are willing and able to work in an active and forward-thinking manner, to improve and positively impact the customer experience without being told to do so (Crant, 2000; Grant and Ashford, 2008; Rank et al., 2007; Raub & Liao, 2012). This type of behavior distinguishes itself from task performance as employees are initiating actions beyond their job description and standard procedures (Rank et al., 2007; Raub & Liao, 2012). In an online customer service setting, FLEs can demonstrate proactivity by foreseeing potential issues customers might encounter in the future connected to previous experiences, or simply by asking whether the customer needs assistance with anything else than their initial inquiry. In this way, the customer can get the impression that the employee is attentive and willing to do their best to provide proper customer service. Dixon, Freeman and Toman (2010) addressed how various aspects of customer service result in customer loyalty. Interestingly, they found that trying too hard to delight customers did not lead to loyalty, whereas reducing customer efforts did (Dixon et al., 2010). Further, they emphasize that the main cause of excessive customer effort is having to contact the company again after initial contact (Dixon et al., 2010), and one efficient way to solve this could be through the service employee acting proactively in the initial service interaction. Further, Delana et al. (2021) explored proactive customer service and conclude that it leads to reduced waiting time. This can potentially also lead to evoking positive customer emotions (Valentini et al., 2020), and further improve the customer experience.

Proactive employee behavior usually leads to higher job performance. (Crant, 2000; Thompson, 2005). However, proactive behavior should feel natural to the service employee as pressure from the organization could lead to stress (Bolino et al., 2010) and initiatives such as reward systems could have the opposite effect on this behavior (Lau et al., 2017). Therefore, finding the right personality type to match the ambitions of proactive service employees is crucial. Sok et al. (2018) found that to improve service performance, service employees had to have high levels of both creativity and attention to detail behaviors. Moreover, Rank et al.

(2007) attempt to expand the research on proactive employee behavior to the realm of customer service and identify predictors of service employees' proactive behavior. Individual variables such as trait personal initiative and the attitudinal variable affective organizational commitment were found to be positively associated with proactive employee behavior (Rank et al., 2007). Lau et al., (2017) emphasize that work climate also can affect the extent to which employees exert proactive customer service behavior. Further, Raub and Liao (2012) emphasize that proactive customer service performance is affected by factors on an individual level and organizational level. Additionally, they find that this combination of an "initiative climate" and individual factors ultimately can contribute to customer satisfaction (Raub & Liao, 2012). Despite plenty of research on proactive employee behavior, there is a lack of research on how proactive service employees affect the online customer service experience (Rank et al., 2007; Raub & Liao, 2012). Proactive customer service performance can be the result of inferential processing as employees strategically act to meet future customer needs before they appear. Based on this, I hypothesize that proactive service performance can lead to improved customer experiences. Moreover, when a customer experiences high negative arousal, proactive customer service performance will increase customer satisfaction.

***H$_{4A}$*: Customers provide a higher NPS when the FLE is behaving proactively.**

***H$_{4B}$*: Customers who demonstrate high negative arousal will be more satisfied when being met with proactive service employees.**

3. Research Method

3.1 Data Description

To investigate my hypotheses, I will conduct an analysis based on data gathered from a large telecom company in Norway. The dataset consists of online customer-employee chat conversations, where some chats were solely between a human agent and customers, and the rest were conversations that initially started with a chatbot before the customers were handed over to human agents. After the customer service interaction, customers received a survey where they were asked to rate to what extent they were willing to recommend the company from a scale of 0-10. This rating indicates their satisfaction with the service interaction and is usually referred to as a Net-promoter-score (NPS). The company uses the scale to differentiate between those who have given a score between 0 and 6 as detractors, between 7 and 8 as passive, and a score of 9 to 10 as promoters. Detractors are seen as unsatisfied customers who can potentially impede growth, passives are the customers who are satisfied but not enthusiastic about the company, and promoters are the loyal customers who are enthusiastic and can potentially spread positive WOM and generate growth (Qualtrics, *n.d.*). The data was gathered between January and December 2021 and was sent as text files (.txt). The files were cleaned using KNIME analytics platform before it was translated from Norwegian to English using the Google Translator Node. The chat conversations that started directly with a human agent were correctly transferred from the initial data to the text files. However, the handover data did not successfully transfer to the text files, thus, the correct sender of each chat message (FLE vs. customer) was not identified. As a result, each chat message in the handover data had to be manually defined as either a customer or as an FLE. As the data set is substantially large, the manual coding was divided between me and a fellow student, and we each coded approximately 43.000 chat lines. The manual coding resulted in a total of 5.870 chat conversations. Whereas the human agent-only data included 5.262 chat conversations. With an additional handover data set that was coded by another MSc student last year, the total data set includes 11.132 customer-employee chats.

3.2 Measurements

Both the independent variables (empathy, active listening, and proactivity) and the moderating variables (high vs. low, positive vs. negative emotional arousal) will be measured based on existing measures from pre-made dictionaries and new measures from self-made dictionaries. The NPS indicating customer satisfaction is the dependent variable and is already included as a scale measurement from 0-10.

3.2.1 Customer Emotion and Arousal State

As valence and activation have been measured to indicate customer emotional state in previous studies (Herhausen et al., 2023; Villarroel Ordenes et al., 2017), I will use the dictionaries created by Villarroel Ordenes et al. (2017) to measure negative valence and high activation. The dictionary consists of 429 words that relate to high negative arousal such as “fool”, “fuming”, and “lousy”.

3.2.2 Empathy

To measure empathy, I will use the pre-existing dictionary developed by Herhausen et al. (2023). However, as I am measuring active listening based on a dictionary and not based on Linguistic Style Matching (LSM), as was done by Herhausen et al. (2023), I have made some changes to the word list. Firstly, I included some additional words (“relate” and “regret”) and removed some phrases (i.e., “you’re right”, “your position”). The phrases were removed because they were perceived to better measure and reflect active listening than empathy. After revising the dictionary, it ended up including 107 words and phrases aimed to measure the level of employee empathy.

3.2.3 Active Listening

To measure active listening, I have composed a dictionary with words and phrases that typically indicate that someone is paying attention and listening attentively to another person. In this case, I have included 57 words and phrases such as “elaborate”, “explain”, “give me more details”, and “I see”. The words and phrases in the dictionary were based on the relevant literature that has been reviewed for this study as well as additional words and phrases I saw as important and appropriate based on my insight from manually coding 43.000 chat lines and 10 years of work experience within customer service.

3.2.4 Proactive Customer Service Performance

Lastly, a dictionary for proactive customer service performance was also made. It is comprised of 61 words and phrases such as “anything else”, “do for you”, “help you”, and “have you considered”. Most of the phrases were based on the insight I gained from the manual coding of the handover data, as most conversations included the customer service employee offering additional help after the first customer inquiry was resolved.

3.3 Modelling

Firstly, the two different datasets (human only and handover) were imported and given a constant value to indicate whether the initial service conversation was handled by a chatbot before the tables were concatenated (handover from bot =1, human only = 0). After implementing basic nodes for data preparation (e.g., filtering columns, correcting column types and removing missing values), the data set was sent through a group loop. This organized the order of each chat line so that the FLE and customer had every second chatline, and indicated how many turns every chat conversation had between customer and employee. This can measure whether the chat inquiry was long or short which could indicate the circumstance of the content of the conversation. Further, pre-existing, and new dictionaries were implemented and tagged related to sentiment. Empathy was tagged as “very positive”, active listening as “neutral”, proactive behavior as “positive”, and negative high arousal as “very negative”. To differentiate between the measures of customers and employees, as I intended to measure customer negative high arousal and employee actions, I included a pivot node. Moreover, missing values that did not detect active listening, empathy, proactive behavior, or negative high arousal, were set to 0, as they would not be measured otherwise. Further, I created math formulas to measure whether customer arousal in combination with the various employee actions had a moderating effect. Lastly, I created two regression models one for the “baseline” independent variables (customer arousal, empathy, active listening, and proactive behavior) together with the control variables (chat turns and bot vs no bot), and one model with all variables. The full model included the moderating variables (customer arousal interaction) and control variables.

4. Results

Both the baseline model and full model included significant and non-significant results. The adjusted R^2 were low in both models (baseline = 0.0102, full = 0.0107), with a slightly higher result in the full model. The adjusted R^2 measures the model’s goodness-of-fit which indicates how well the independent variables accurately explain the variance in the dependent variables (Bhandari, 2020). Even though the adjusted R^2 measures were low, which indicates that the independent variables do not account for a high percentage of the variance in the NPS, there were still some interesting results. Since the full model had a slightly higher accuracy than the baseline model (Appendix, Table 2), I will continue to discuss these results. Firstly, customers who demonstrated negative high arousal had a negative effect on the NPS (β = -0.153, p = 4.91E – 6), which confirms ***H₁***, the results were also significant. Further, the control variables turns and bot, (β = 0.2117, p = 3.88E – 10 / β = - 0.2464, p = 0.0001) and FLE empathy (β = 0.1542, p = 4.60E – 6) variable all gave statistical, significant results at a 99% and 95% confidence level. Thus, $\boldsymbol{H_{2A}}$ can also be confirmed. FLE proactive behavior is almost significant at a 90% confidence level (β = 0.0538, p = 0.1143). However, when being specific, the p-value at 11% is slightly higher than what is required to confirm $\boldsymbol{H_{4A}}$ with 90% confidence. Thus, at a 90% confidence level and up, $\boldsymbol{H_{4A}}$ is rejected. FLE empathy has a positive impact on the NPS, and employee proactivity also had a slightly positive impact on the NPS. $\boldsymbol{H_{3A}}$ is rejected as FLE active listening (β = -0.0131, p = 0.7037) did not give significant results in the regression. As for the control variables, a higher number of turns in a chat conversation also had a positive effect on the NPS, whereas if the conversation was started with a chatbot this negatively affected the customer satisfaction. Moreover, only one moderation effect was significant at a 95% confidence level, namely customer negative high arousal and empathy interaction (β = 0.1132, p = 0.0111). This effect also had a positive effect on the NPS, and therefore, $\boldsymbol{H_{2B}}$ is accepted whereas $\boldsymbol{H_{3B}}$ and $\boldsymbol{H_{4B}}$ are rejected.

Variable	**Coeff.**	**Std. Err.**	**t-value**	**P > | t |**
CUS Neg. High Arousal	-0.153	0.0335	-4.571	4.91E – 6
Turns (max)	0.2117	0.0338	6.2654	3.88E – 10
Bot	-0.2464	0.065	-3.793	0.0001
FLE Empathy	0.1542	0.0336	4.5848	4.60E – 6
FLE Active Listening	-0.0131	0.0346	-0.3804	0.7037
FLE Proactive Behavior	0.0538	0.0341	1.5792	0.1143
Empathy Interaction	0.1132	0.0445	2.5427	0.0111
Active Listening Interaction	0.0132	0.0259	0.5096	0.6103
Proactive Behavior Interaction	0.0175	0.0245	0.7137	0.4754
Intercept	8.4793	0.047	180.4054	0.0

Table 1. Results Linear Regression Full Model

5. Discussion

The results from the linear regression give prominent indications for what customer service employees should prioritize during online customer service encounters. Firstly, the NPS is negatively impacted by customers who demonstrate negative high arousal, which, empirically, makes sense as angry or distressed customers most often judge their customer service encounters to be less positive (Tax et al., 1998). The positive impact on the NPS, when FLEs demonstrate empathy and proactive behavior, indicates that customers appreciate present and empathetic service employees, which is often harder to demonstrate through online communication. Moreover, the positive but insignificant result of the active listening variable emphasizes that this new measure should be improved or measured in a different way than with a dictionary. As active listening is difficult to demonstrate in words, other ways to measure active listening could be through LSM. The p-value of FLE proactive behavior also indicates that this new measure can be further improved to measure proactivity more accurately among customer service employees. These measures also have an impact on the moderation effects, where only the empathy and customer high negative arousal interaction is significant. Importantly, we can see that this moderation effect is positive, which further should be explored to see whether being empathetic towards customers with negative high arousal continues to have a positive impact on the outcome of the customer-employee interaction. Moreover, improving the measurements for active listening and proactive employee behavior could also affect the moderation further and, perhaps, improve the significance of the results.

The low adjusted R^2 indicates that there are several other variables that explain the variance in the NPS. Firstly, the new measurements could be improved to obtain higher significance which could positively affect the model fit. Secondly, as there are many elements that can be measured in a customer service interaction and that can both positively and negatively affect customer satisfaction, this could be the reason for the poor model fit. Other variables such as the difference in customer inquiries and other customer emotions and arousal levels could also affect the customer experience. Additionally, other employee behaviors such as the way the FLE describes solutions and provides arguments for the situation as well as the use of, for instance, humor, slang, spelling, and emoticons are also examples of potential elements that can impact the NPS. Thirdly, the data set includes general customer-employee interactions that mostly include short interactions where customers have simple questions that can be solved quickly without problems. This could lead to an avoidance in escalated arousal among customers. As previous research has mostly focused on customer complaints, this could also explain the low adjusted R^2 and could indicate that it is more important to focus the research on complaints rather than simple customer inquiries. Ultimately, including more independent variables, improving the new measurements, and using data with solely customer complaints could improve the model fit and provide a better explanation for the NPS.

6. Conclusion and Managerial Contribution

As active listening, empathy and proactive behavior are low-cost strategies, they can all be efficient tools to improve customer service (Min et al., 2021). However, more research is needed to further investigate these communication constructs to improve reliability and validity. Even though the model had a relatively low goodness-of-fit, this study has provided some interesting contributions to the online customer service field. Firstly, negative high customer arousal is negatively affecting customer satisfaction, which accentuates that companies should work on solutions to prevent customers from reaching such an emotional state. As negative high arousal is not appearing frequently in the data this could signify that private customer service chats are an important tool to quickly resolve customer issues and de-escalate negative emotions before they evolve into high arousal levels. Furthermore, the positive impact of FLE empathy emphasizes that empathetic customer service employees are appreciated by customers. The positive effect of employee proactivity could also indicate that customers appreciate attentive and forward-thinking service employees. However, this measure should be further developed to gain significant results. The effect of customer negative high arousal is slightly moderated when the customer is met with employee empathy. As empathy showed to have positive effects on the NPS of customers who experienced negative high arousal, this could be a crucial element for FLEs to include in online customer service interactions to avoid escalation of negative arousal.

This emphasizes that companies should focus on properly training their employees to respond in an empathetic way as well as it can be beneficial to train them to become more proactive in their online customer service interactions. However, it is important to emphasize that companies also should hire customer service agents who have trait personal initiative and affective organizational commitment to ensure that proactive behavior feels natural for the employee (Rank et al., 2007) as too much pressure from training could lead to unnecessary stress (Bolino et al., 2010). Consequently, there should also be an increased focus on how customer service employees can detect negativity and high arousal among customers, and how they strategically should respond to these customers to improve the customer experience. It is crucial for customer service employees to draw strategic inferences when encountering various customer emotions and arousal levels to properly respond to the displayed emotions. The results emphasize that there is a need for further investigation to understand additional elements that affects online customer service encounters, and what should be prioritized to improve them. To be able to do this, further research should be conducted to understand additional strategies service employees can use to de-escalate negative high arousal and make customers more satisfied. This will give managers improved insight into the complexity of communication in online customer service. Ultimately, this could provide companies with cost-efficient tools that will prevent negative emotions from transitioning into high negative arousal towards the company.

7. Limitations and Further Research Directions

Studying the impact of customer negative high arousal and employee actions on customer satisfaction has led to some interesting insights that should be further investigated. This study also has its limitations, mostly technical. Firstly, there are several ways to measure the various constructs and build prediction models using KNIME analytics platform, and a higher proficiency level in KNIME could lead to different results. Moreover, the measures of active listening and proactive employee behavior were based on self-made dictionaries which could be further improved based on data annotation or be measured in a different way (i.e., measuring LSM for active listening). Previous research on proactive employee behavior has indicated that it can positively impact companies (Crant, 2000; Thompson, 2005). However, these studies are mostly concerned with proactive behavior within a company and not within the realm of customer service. As proactive customer behavior within customer service has little previous research, this is a field that should be explored further to gain better insight concerning its impact on the customer experience. Moreover, future research should be directed towards customer complaints rather than general customer service interactions to see if the model can provide better predictions. The negative high customer arousal will most likely be more prominent which also leads to higher expectations towards the service employees. This can give better predictions of how companies should train their employees to react when customers show emotion, which is especially important when these emotions increase in arousal and are negative. The EASI framework should also be explored further, as customers could have various intent of their displayed emotions, which could also affect how they react to the FLE responses. Negative high arousal and rude or inappropriate customer communication could also affect whether a FLE has an affective or inferential or affective reaction which could, ultimately, also affect the customer experience.

The negative effect of the control variable that measured handover conversations from chatbots to human agents vs conversations only with human agents is also an interesting result that could be explored further. As artificial intelligence (AI) is rapidly improved and used for customer service, the impact of using chatbots for customer service purposes on the customer experience should be further investigated. Moreover, the role of customer valence and arousal should be included in this research to see whether various customer needs and emotions should be met with various customer service solutions to further optimize the customer experience.

Lastly, to improve validity and generalizability, further research should be done using data from various industries and various markets. As this study is based on data from a Norwegian telecom company, the conversations were translated with a Google Translator node in KNIME, which could also have an impact on the results as some errors in translating the text could affect the results. Customer service interactions within telecom are also quite narrow as it usually involves industry-specific inquiries, which makes it problematic to import these results to other industries. Therefore, further research within different industries (e.g., banks, online retail), and different countries or cultures should be made. Moreover, further variables should be considered such as different employee behaviors (e.g., humor, slang, emoticons, argumentativeness) and other external variables (e.g., the variety in seriousness in inquiry, other customer emotions). These considerations can all contribute to a more developed understanding of the effects of text-based customer service interactions, and how companies can benefit from meeting their customers online.

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Appendix

Dictionaries

Empathy	admir, affection, appreciat, assur, better, care, careful, caring, challenging, comfort, commitment, confiden, considerate, contact, contented, courag, determin, devot, difficult, discourag, divin, eager, encourag, engag, entertain, enthus, excel, excit, experience, faith, favor, favour, feedback, feel, fix, forgiv, frustrat, gentle, gently, glad, gladly, gratef, grati, happen, hear, hearing, heartwarm, help, honest, honest, honor, honour, hope, hoping, imagine, improve, improving, keen, kind, know, look, "make it better," "makes me really sad," "makes me sad," "my mistake," notify, open, openness, "our mistake," patience, peace, perfect, personally, pleas, precious, promis, regret, relate, relief, reliev, resolv, respect, safe, same, satisf, save, sense, share, sharing, similar, sincer, sound, support, sympath, "tell me," thank, thoughtful, touch, true, truly, trust, understand, upset, useful, valuabl, value, valuing, welcom, wish, worthwhile
Active Listening	Agree, clarif, correct, "can you motivate", "can you repeat", elaborat, explain, explanation, geez, "get it", "give details", "give me details", "give more details", "give me more details", "go on", "got it", hear, how, "hear you", "how so", "how is it", interesting, inform, information, "I am listening", "I'm listening", "I can tell", "I see", "it sounds", "in what way", repeat, repetition, right, say, sound, tell, "that sounds", "tell me", "tell more", understand, understood, what, where, why, wow, "what you are", "what you're", "what you say", "what you explain", "you are right", "you're right", "your position", "you are totally right", "you're totally right", "you say", "you are saying", "you're saying"
Proactive Behavior	"already complete", "already completed", "already done", "already fixed", "anything else", "anything further", "anything I can", "anything I could", "another solution", "another thing", "another way", "at it", "before you go", "before you leave", "before it happens", "can be beneficial", "can be smart", "can be helpful", "can I help", "change for you", "changed for you", "change it for you", "changed it for you", check, "do for you", "do for u", "do to help", fix, "find a solution", "find it for you", "find the solution", "find solutions", "have a look", "help u" ,"help you", "have you considered", investigat, inspect, "I can", "if you want", "I notice", "I noticed", "I will", "I want to ensure", "I

	want to make sure", "I'll check", "let me", "look at it", offer, "of course", "on it", solution, "something else", "take a look", "taking a look", "would you like", "you need", "you might be interested", "you might need", "you might want", "you will need"
Negative High Arousal	afraid, beaten, crap, crappy, critical, cut, devil, distraught, emotional, envious, fear, feared, fearing, fears, fool, fought, frightened, fuck, fucks, fuming, fury, harm, harmed, harmful, harming, harms, hate, hated, hates, hating, hatred, hell, hellish, helplessness, horribly, hysterical, jerk, jerked, jerks, junk, kidding, lame, lied, lies, loath, loathing, loser, lousy, lying, mad, maddening, madder, maddest, mess, misleading, mock, mocked, mocking, mocks, mofo, mortification, motherfucker, motherfucking, nastiness, nasty, nausea, nauseating, nauseous, nerd, nervousness, nigger, nightmar, nix, nonsense, numbing, obses, odd, offended, offensive, opbsurd, overwhelming, pained, paining, pains, pathetic, perver, pettiest, pissed, pointless, ponderous, prejudiced, preposterous, protest, protested, protesting, pussy, queer, raging, rancid, rant, raping, rat, rediculious, redundant, reek, repugnance, repugnant, repulse, repulsion, repulsive, resentful, revolt, revulse, revulsion, ridiculed, ridiculous, ripoff, rip-off, rotten, rudeness, ruder, rudest, sarcasm, sarcastic, scandal, scared, scaring, scary, scorn, shaky, shallow, shameful, shitty, shook, sick, sickening, sickness, sinister, sloppy, sluggish, slut, sluttish, slutty, sonofa, stank, steal, stench, stink, stressful, stunk, stunned, stuns, suck, sucked, sucks, sucky, sufferer, suffering, superficial, suspense, suspicion, suspicious, tasteless, tedious, temper, tempers, tensing, terrible, terrified, terrifies, terrify, terrifying, thief, thieve, threatening, tick, ticked, toobad, torment, torture, tortured, trash, trauma, trouble, turmoil, ugh, uglier, ugliest, ugly, unattractive, uneasiness, uneasy, unkind, unreasonable, unsatisfying, unsavory, upsetting, useless, vapid, vexed, vexing, vile, violate, violence, vulgar, vulnerable, wanker, wannabe, war, warred, warring, wars, wimp, worried, worries, worrisome, worry, worrying, worst, wrath, wtf, yikes, yuck, disrespect, disrespectfully, disrespectful, alarm, anguish, anxi, apprehens, asham, aversi, avoid, awkward, confus, craz, desperate, discomfort, distract, distress, disturb, doubt, dread, dwell, embarrass, fearful, frantic, fright, guilt, hesita, horr, humiliat, impatien, indecis, inhib, insecur, irrational, irrita, miser, nervous, neurotic, obsess, panic, petrif, phobi, pressur, reluctan, repress, restless, rigid, risk, scare, shake, shaki, shame, shy, sicken, startl, strain, stress, struggl, suspicion, tense, tension, terror, timid, trembl, uncertain, uncomfortabl, uncontrol, uneas, unsure, upset, uptight,

	vulnerab, worr, abuse, abusi, aggravat, aggress, agitat, anger, angr, annoy, antagoni, argh, argu, arrogan, assault, asshole, attack, bastard, battl, bitch, bitter, blam, bother, brutal, cheat, confront, contempt, contradic, critici, crude, cruel, cunt, cynic, damn, danger, defenc, defens, despis, destroy, destruct, disgust, distrust, domina, dumb, dump, enemie, enemy, enrage, envie, envy, evil, feroc, feud, fiery, fight, foe, frustrat, fucked, fucker, fuckin, fume, furious, goddam, greed, grouch, grr, harass, hateful, hater, heartless, hostil, humiliat, idiot, insult, interrup, intimidat, jealous, kill, liar, lous, ludicrous, maniac, mocker, molest, moron, murder, nag, nast, obnoxious, offence, offend, offens, outrag, paranoi, pettie, petty, piss, poison, prejudic, prick, punish, rage, rape, rapist, rebel, resent, revenge, ridicul, rude, sarcas, savage, sceptic, screw, shit, skeptic, smother, snob, spite, stubborn, stupid, sucker, tantrum, teas, threat, tortur, trick, ugl, vicious, victim, villain, violat, violent, warfare, weapon, wicked

Table 2 – Results Linear Regression Baseline Model

Variable	Coeff.	Std. Err.	t-value	P > | t |
Cus Neg. High Arousal	-0.1382	0.0327	-4.2304	2.35E – 5
Turns (max)	0.2119	0.0338	6.2698	3.77E – 10
Bot	-0.2435	0.065	-3.7481	0.0002
FLE Empathy	0.1482	0.0336	4.4156	1.02E – 5
FLE Active Listening	-0.0084	0.0333	-0.251	0.8018
FLE Proactive Behavior	0.06	0.0335	1.7897	0.0735
Intercept	8.4789	0.047	180.2885	0.0

Table 2. Results Linear Regression Baseline Model

Summary

Introduction

The nature of customer service interactions has substantially changed over the past years due to the digitalization of consumers' everyday lives. This has further affected customer expectations towards companies' service quality (Misischia et al., 2022). For many consumers, online customer service chats have become the preferred way of interacting with companies (Adam et al., 2020; Charlton, 2013). This has provided many opportunities for companies as customer service chats are efficient and cost-effective (Dimyadi, 2018; Olenski, 2016). Thus, companies can benefit both in terms of increased customer satisfaction as well as decreased operating costs. However, the shift from in-person customer service to text-based customer service has resulted in a change in interaction patterns as communication cues such as tone of voice, body language, and facial expressions are eliminated from the conversation (Herhausen et al., 2023). This can lead to misunderstanding and, consequently, negatively impact the customer experience. As friction between customers and employees due to service failure is impossible to prevent (Joireman et al., 2013), so are negative customer emotions. Customers who experience negative emotions are more likely to behave negatively towards the company after a service failure (Bougie et al., 2003; Gelbrich, 2010; Herhausen et al., 2019; Joireman et al., 2013; Kalamas et al., 2008; Nguyen & McColl-Kennedy, 2003; Strizhakova et al., 2012). Based on this, it is crucial for companies to properly train their employees to act strategically to ensure that customer interactions are not misinterpreted.

Decades of research on customer service and customer experience have resulted in research on various constructs that can affect customer-employee interactions. However, with the tremendous changes in customer service interactions from in-person to online and mostly text-based, there is a need for more research within the field of online customer service. One theory that is not particularly investigated within the realm of customer service, and especially online customer service, is the theory of Emotion as Social Information (EASI). The EASI theory was introduced by Van Kleef (2009) and suggests that, in addition to an *intra*personal effect, emotions also have an *inter*personal effect, where displayed emotions affect the behavior of the observer. The affected behavior can be caused by affect (natural, immediate reaction) or inference (strategic process) and is important to be aware of for customer service employees as their reaction to a customer behavior further can affect the customer experience. Dagger et al. (2013) emphasize the importance of properly training service employees to improve their interpersonal skills (i.e., increased courtesy and empathy) as it can improve the customer experience in more ways than solely the customer-employee interaction. Thus, being aware of the importance of displayed customer emotions and how this can be used in the training of frontline employees can be crucial to maximize customer service efforts.

Herhausen et al. (2023) explore customer emotions and how active listening and empathy can impact customer gratitude and de-escalate negative emotions during social media complaint handling. The research specifically looks at text-based communication and finds that both empathy and active listening have a positive effect on customer gratitude and can also de-escalate negative high arousal among customers (Herhausen et al., 2023). However, as this research is based on public online interactions, further investigation is needed to properly understand whether these effects also apply in private online customer-employee interactions. A public vs. private customer service interaction may have distinct effects on how customers perceive and react to the communication from a customer service employee and could therefore not give the same results (Herhausen et al., 2023).

A different, and somewhat neglected, customer service behavior that can potentially have a positive effect on the customer experience is proactive customer service performance (Rank et al., 2007; Raub & Liao, 2012). Proactive customer service employees can contribute to both reducing customer effort and waiting time, which can improve customer satisfaction (Dixon et al., 2010; Valentini et al., 2020). However, there is little knowledge of how and when the role of proactive service employees can positively affect the customer experience in various contexts. In sum, there is a need for more research that combines various elements of the customer experience (i.e., customer emotions, employee reactions, and customer satisfaction) to get a better picture of how frontline service employees can better navigate during customer-employee service interactions to improve customer satisfaction.

This study aims to examine how active listening, empathy, and proactive behavior from customer service employees affect customer satisfaction and loyalty expressed by the Net Promoter Score (NPS) and whether negative high arousal customer emotions affect this relationship. This will be done by using data in the form of private customer service chat interactions gathered from a large Norwegian telecom company. Based on the EASI theory and previous findings on the role of active listening, empathy, and employee proactivity, I will use text mining to analyze the effect of these constructs on the NPS provided by customers with various emotional arousal levels. Based on this, I hypothesize that customers who express negative high arousal generally provide a lower NPS (***H_1***). However, when customer service employees demonstrate active listening (***H_{2A}***), empathy (***H_{3A}***), and proactive behavior (***H_{4A}***) customers, in general, provide a higher NPS. This effect can further be affected when customer service employees draw strategic inferences when met with negative high arousal customers and react by moving towards the customer with active listening (***H_{2B}***), empathy (***H_{3B}***), and proactive behavior (***H_{4B}***).

EASI

The Emotions as Social Information (EASI) theory focuses on the social aspects of emotions and was introduced by Van Kleef (2008, 2009). It distinguishes between the *intra*personal effects (emotions influencing one's own behavior) and the *inter*personal effects (emotions influencing others) of emotions. While research within psychology has predominantly focused on the intrapersonal effects, there is a lack of focus on the interpersonal effects of emotions (Van Kleef, 2009; Van Kleef & Côté, 2022; Van Kleef et al., 2010). The EASI theory suggests that each emotion portrayed by an individual is an expression of specific information for others to interpret (Van Kleef et al., 2010). Most research applying the EASI framework to date has focused on contexts within conflict, negotiation, and shared decision-making. However, the theory is also relevant to the realm of customer service, as service employees constantly need to adapt their behavior based on customers' emotions. By considering the EASI framework in relation to customer emotions and which communicative strategies best fit these different emotions, the customer service literature will gain valuable insight into how companies can further improve their customer service.

The EASI theory specifies two processes that influence observers of emotions, namely affective reactions, and inferential processing. Affective reactions can be automatic and reciprocal or complementary responses to another person's expressed emotion (Van Kleef & Côté, 2022). Inferential processing, on the other hand, involves deliberate cognitive responses. Observers make inferences or assumptions about the expressed emotions and adjust their behavior accordingly (Van Kleef & Côté, 2022). The effectiveness of these processes is influenced by two moderating variables: information processing and social context. Van Kleef et al. (2011) propose that the inferential process of emotion is more powerful when the emotion expressed is perceived as appropriate, and when the emotion is perceived as inappropriate, affective reactions become more predictive.

Van Kleef and Côté (2022) propose that the EASI theory can be successfully applied to various communication modes, including text-based interactions such as online customer service. They argue that when senders are highly emotionally expressive and observers have high emotion perception, the encoding and decoding of social information are facilitated, leading to stronger effects (Van Kleef & Côté, 2022). The EASI theory becomes highly relevant in customer service chats as employees need to understand and infer customer emotions (Okeke, 2017). By accurately interpreting and responding to customer emotions, service employees can increase customer satisfaction. To advance the theory, I have decided to focus on the outcome of customer service interactions, particularly customers' NPS as an indicator of satisfaction with the service employees' response. Thus, specific employee reactions will be evaluated as (mainly) strategic inferences that could lead to an improved online customer experience.

Online customer service

Successful customer service encounters are vital for overall customer satisfaction and brand loyalty, with 96% of customers emphasizing the importance of customer service (Amaresan, 2022; Morgan, 2019). As online interactions with companies are increasingly preferred, understanding the impact of text-based communication on the customer experience is crucial (Heinonen & Pesonen, 2022; Jarman, 2021; Misischia et al., 2022). Writing in text-based communication may lead to reduced emotional expression, so customer service employees must understand individual customer needs and adapt communication to avoid misinterpretations and improve customer-employee relations (Berger et al., 2022). The perceived quality of online customer service positively influences purchase intentions (Qin et al., 2022). Further research is needed to leverage the extensive knowledge from physical customer service encounters and maximize the potential of online customer service.

Creating a spark between frontline employees (FLEs) and customers is crucial for successful customer service experiences (Beaujean et al., 2006). Customized service strategies targeting different customer segments and offering compensation can enhance satisfaction and loyalty (Kim, 2007; Lee & Lee, 2020; Narayana & Durga, 2017; Rust & Lemon, 2001). A great customer experience requires personalized and effective communication, understanding and interpreting customer emotions, and considering the level of arousal (Heinonen & Pesonen, 2022). However, customer emotions are often neglected in research on customer service experiences. Proper training of customer service staff, including interpersonal skills and interactional justice, can enhance perceived service quality and strengthen customer relationships (Dagger et al., 2013; Tax et al., 1998). While most research focuses on customer complaints, customer service interactions can also be used to prevent service failures, highlighting the importance of handling pre-emptive interactions effectively in private online service interactions.

Arousal states and emotions

Service failures are inevitable, and customers may experience negative emotions as a result (Joireman et al., 2013). The customer experience is influenced by the emotions and arousal levels customers feel before, during, and after interactions with a company. Negative emotions that evolve over time can potentially result in negative behaviors such as negative word-of-mouth, social media complaints, and switching to a competitor (Bougie et al., 2003; Gelbrich, 2010; Herhausen et al., 2019; Joireman et al., 2013; Kalamas et al., 2008; Nguyen & McColl-Kennedy, 2003; Strizhakova et al., 2012). Failing to de-escalate negative high arousal can lead to a failure in service recovery (Herhausen et al., 2023; Kalamas et al., 2008). Therefore, companies should focus on training customer service employees to handle negative emotions and arousal to improve customer retention.

Villarroel Ordenes et al. (2017) classified customer emotions into four categories based on valence and emotional activation. Herhausen et al. (2019) and Herhausen et al. (2023) built upon this classification, linking high negative arousal to anxiety, anger, and disgust, and low negative arousal to sadness and disappointment. Physical cues such as facial expressions, tone of voice, and body language can help identify positive and negative emotions in face-to-face interactions, but in text-based communication, cues like punctuation, emoticons, and emotionally loaded words become important (Herhausen et al., 2023). Text mining using dictionaries can aid in identifying these emotions in customer complaints, but there is still a lack of research on how different negative and positive arousal states affect private online customer service interactions.

Most research on online customer-employee interactions focuses on service recovery and public interactions, neglecting private customer chats and general inquiries (Gelbrich, 2010; Herhausen et al., 2023; Valentini et al., 2020). Rage as a negative high arousal emotion typically develops over time if service failures are not resolved promptly (Surachartkumtonkun et al., 2014). Detecting and handling negative emotions and high arousal early on is crucial in avoiding negative customer reactions. Companies can effectively de-escalate customer revenge by addressing issues promptly (Grégoire et al., 2018). With more customers using customer service chats for information and assistance, training service employees to detect and handle negative emotions and high arousal in online interactions is crucial. The normative expectations of employee responses also play a role in customer satisfaction (Menon & Dubé, 2000). Understanding negative emotions, arousal levels, and appropriate employee reactions can help prevent service failures and negative customer actions. However, research on text-based customer interactions is limited compared to in-person interactions that rely on physical cues (Menon & Dubé, 2000; Nguyen & McColl-Kennedy, 2003; Surachartkumtonkun et al., 2014). Therefore, understanding how customer service employees should respond to customers in various arousal states during online interactions is important in avoiding service failures and public complaints. Based on this, I hypothesize that customers demonstrating negative high arousal emotions are less satisfied with the customer service experience.

H_1: Customers who demonstrate high negative arousal will provide a lower NPS.

Empathy

Empathy refers to the ability to understand and recognize another person's feelings and thoughts without experiencing them personally (Futrell, 2011; Hoffman, 2008; Wieseke et al., 2012). In text-based communication, empathy is related to using empathetic words, validation, and affirmation (Herhausen et al., 2023). Extensive research highlights the importance of employee empathy in satisfying customer needs and improving the customer experience (Bahadur et al., 2018; Clark et al., 2012; Gorry & Westbrook, 2011; Wieseke et al., 2012). Itani and Inyang (2015) found that empathetic behavior from employees is crucial for successful service encounters, leading to long-lasting customer relationships and increased satisfaction. A lack of empathy in customer interactions can result in customer dissatisfaction (Bahadur et al., 2018), emphasizing the significance of employee empathy. Additionally, Belanche et al. (2020) found that consumers have higher expectations and attribute more responsibility to human frontline employees (FLEs) compared to service robots, underscoring the importance of employee empathy in enhancing the customer service experience.

Recent research by Herhausen et al. (2023) demonstrates that empathy exhibited by a firm can increase customer gratitude and reduce high-arousal emotions among complaining customers in social media interactions. Empathy was found to be more effective in enhancing customer gratitude compared to active listening (Herhausen et al., 2023). Gorry and Westbrook (2011) emphasize that companies' efforts to cut costs by implementing technology in customer service have resulted in customer frustration and inadequate service. The digitalization of customer interactions has made it challenging for employees to empathize with customers as their ability to express experiences is limited. However, if used correctly in a customer-centric manner, technology does not necessarily lead to a loss of empathy (Gorry & Westbrook, 2011). In a customer service context, empathy can be used strategically as an inferential action, as service employees are aware of its importance in customer satisfaction, particularly when customers experience high negative arousal (Herhausen et al., 2023). Based on this, I hypothesize that when a customer experiences high negative arousal, being met with employee empathy will increase customer satisfaction

***H$_{2A}$*: Customers provide a higher NPS when the FLE is empathetic.**

***H$_{2B}$*: Customers who demonstrate high negative arousal will be more satisfied when being met with employees who react with empathy.**

Active listening

Active listening involves attentively listening to customers and verbally acknowledging them through techniques like repetition, paraphrasing, mimicking, or adapting language (de Ruyter & Wetzels, 2000; Herhausen et al., 2023; Min et al., 2021; Ramsey & Sohi, 1997). In text-based communication, active listening can be identified by matching the customer's communication style or providing validation (Herhausen et al., 2023; Min et al., 2015; Ramsey & Sohi, 1997). Matching the language style of the communication partner demonstrates active listening (Ireland & Henderson, 2014; Gonzales et al., 2010), and expressing verbal cues is an effective way to signal active listening (Collins, 2022). Studies have shown that employees who demonstrate active listening skills experience increased customer satisfaction and trust (Gruber, 2011; Nguyen & McColl-Kennedy, 2003; Ramsey & Sohi, 1997; van Baaren, 2005). Active listening can reduce negative emotions such as customer anger in service recovery (Nguyen & McColl-Kennedy, 2003) and increase customer satisfaction in online text-based communication (Dickinger & Bauernfeind, 2009).

Active listening, including repeating words, can be seen as part of these effects, suggesting that it enhances a customer's feeling of being heard and improves the overall customer experience. Collins (2022) suggests that expressing active listening verbally is important, as it can improve well-being and customer experiences. Based on the EASI theory, active listening can be performed non-consciously as an affective behavior or consciously as a strategy to make the customer feel heard, understood, and de-escalate high negative arousal (Lakin & Chartrand, 2003). Therefore, I hypothesize that active listening by employees results in a higher NPS, and when a customer experiences high negative arousal, customer service employees can improve the customer experience by strategically performing active listening.

***H$_{3A}$*: Customers provide a higher NPS when the FLE performs active listening.**

***H$_{3B}$*: Customers who demonstrate high negative arousal will be more satisfied when being met with employees who react with active listening.**

Proactive Customer Service Performance

Proactive customer service performance refers to employees who actively and forwardly work to improve the customer experience without explicit instructions (Crant, 2000; Grant & Ashford, 2008; Rank et al., 2007; Raub & Liao, 2012). This behavior goes beyond typical job responsibilities and standard procedures

(Rank et al., 2007; Raub & Liao, 2012). In an online customer service setting, frontline employees (FLEs) can demonstrate proactivity by anticipating potential customer issues based on previous experiences or by offering assistance beyond the initial inquiry, creating a sense of attentiveness and dedication to providing excellent customer service. Research by Dixon, Freeman, and Toman (2010) found that excessive efforts to delight customers did not result in loyalty, but reducing customer effort did. One effective way to achieve this is through proactive behavior by service employees during the initial interaction. Delana et al. (2021) explored proactive customer service and found that it leads to reduced waiting time, potentially evoking positive customer emotions and enhancing the overall customer experience.

Proactive employee behavior is typically associated with higher job performance (Crant, 2000; Thompson, 2005). However, it is essential for proactive behavior to feel natural to service employees as organizational pressure can lead to stress, and reward systems may have unintended consequences (Bolino et al., 2010; Lau et al., 2017). Rank et al. (2007) explored predictors of proactive employee behavior in customer service and identified individual variables such as trait personal initiative and affective organizational commitment as positively associated with proactive behavior. Thus, matching the right personality type to the ambition of proactive service employees is crucial.

Despite extensive research on proactive employee behavior, there is a lack of research on how proactive service employees impact the online customer service experience (Rank et al., 2007; Raub & Liao, 2012). Proactive customer service performance can be considered an inferential process where customers strategically anticipate future customer needs. Based on this, I hypothesize that proactive service performance can lead to improved customer experiences. Moreover, when a customer experiences high negative arousal, proactive customer service performance will increase customer satisfaction.

***H_{4A}*: Customers provide a higher NPS when the FLE is behaving proactively.**

***H_{4B}*: Customers who demonstrate high negative arousal will be more satisfied when being met with proactive service employees.**

Method

Data Description

The study aims to investigate the hypotheses using data collected from a large telecom company in Norway. The dataset comprises online chat conversations between customers and employees. Some chats involved only human agents, while others began with a chatbot before transitioning to human agents. After the customer service interaction, customers received a survey asking them to rate their willingness to recommend the company on a scale of 0-10, known as a Net Promoter Score (NPS). The NPS categorizes scores as detractors (0-6), passives (7-8), and promoters (9-10), representing unsatisfied customers, satisfied but unenthusiastic customers, and loyal and enthusiastic customers, respectively.

Data collection occurred between January and December 2021, and the data was stored as text files (.txt). The files underwent cleaning using the KNIME analytics platform and were translated from Norwegian to English using the Google Translator Node. While chat conversations starting directly with human agents were accurately transferred to the text files, the handover data did not transfer correctly, resulting in the inability to identify the correct sender (employee or customer) for each chat message. Thus, manual coding was performed to assign each chat message as either customer or frontline employee (FLE). Due to the large dataset, the manual coding was divided between the author and a fellow student, with each coding approximately 43,000 chat lines. This manual coding process resulted in a total of 5,870 chat conversations, including 5,262 conversations involving human agents only. In addition, an additional handover dataset, coded by another MSc student in the previous year, was included, bringing the total number of customer-employee chats to 11,132.

Measurements

Both the independent variables (empathy, active listening, and proactivity) and the moderating variables (high vs. low, positive vs. negative emotional arousal) will be measured based on existing measures from pre-made dictionaries and new measures from self-made dictionaries. The NPS indicating customer satisfaction is the dependent variable and is already included as a scale measurement from 0-10.

Modelling

Firstly, the two different datasets (human only and handover) were imported, and after implementing basic nodes for data preparation (e.g., filtering columns, correcting column types and removing missing values), the data set was sent through a group loop. This organized the order of each chat line and indicated how many turns every chat conversation had between customer and employee. Further, pre-existing, and new dictionaries were implemented and tagged related to sentiment. To differentiate between the measures of customers and employees, as I intended to measure customer negative high arousal and employee actions, I included a pivot node. Moreover, missing values that did not detect active listening, empathy, proactive behavior, or negative high arousal, were set to 0, as they would not be measured otherwise. Further, I created math formulas to measure whether customer arousal in combination with the various employee actions had a moderating effect. Lastly, I created two regression models one for the "baseline" independent variables (customer arousal, empathy, active listening, and proactive behavior) together with the control variables (chat turns and bot vs no bot), and one model with all variables. The full model included the moderating variables (customer arousal interaction) and control variables.

Results

There were both significant and insignificant results in the baseline and full model. In both models, the adjusted R^2 were low (baseline = 0.0102, full = 0.0107). However, the model still gave some interesting results.

First, customers who demonstrated negative high arousal were likely to give a lower NPS, confirming $\boldsymbol{H_1}$. FLE empathy had a positive impact on the NPS, which confirmed $\boldsymbol{H_{2A}}$. FLE Active Listening and Proactive Behavior did not give significant results. Nevertheless, Active listening had a slight negative effect, and Proactive Behavior had a positive effect on the NPS. Thus, $\boldsymbol{H_{3A}}$ and $\boldsymbol{H_{4A}}$ are rejected. Moreover, only one moderation effect was significant, namely customer negative high arousal and empathy interaction. This effect also had a positive effect on the NPS, and therefore, $\boldsymbol{H_{2B}}$ is accepted whereas $\boldsymbol{H_{3B}}$ and $\boldsymbol{H_{4B}}$ are rejected.

Discussion

The results from the linear regression give prominent indications for what customer service employees should prioritize during online customer service encounters. Firstly, the NPS is negatively impacted by customers who demonstrate negative high arousal, which, empirically, makes sense as angry or distressed customers most often judge their customer service encounters to be less positive (Tax et al., 1998). The positive impact on the NPS, when FLE demonstrate empathy and proactive behavior, indicates that customers appreciate present and empathetic service employees, which is often harder to demonstrate through online communication. The insignificant results of the FLE Active Listening and Proactive Behavior variables emphasize that these new measures should be further improved or measured in a different way. These measures also have an impact on the moderation effects, where only the empathy and customer high negative arousal interaction is significant. Importantly, we can see that this moderation effect is positive, which further should be explored to see whether being empathetic towards customers with negative high arousal continues to have a positive impact on the outcome of the customer-employee interaction.

The low adjusted R2 indicates that other variables account for the variance in the NPS. Firstly, improving the measurements used in the study could increase their significance and subsequently improve the model fit. Secondly, considering the numerous factors that can influence customer satisfaction in a service interaction, the limited model fit may be due to other unmeasured variables. Factors like differences in customer inquiries, various customer emotions, and arousal levels may also affect the customer experience. Additionally, other employee behaviors, such as the way solutions are described, and the use of humor, slang, spelling, and emoticons, could impact the NPS. Thirdly, the dataset primarily consists of general customer-employee interactions involving simple and quickly resolved inquiries. As previous research has primarily focused on customer complaints, this may explain the low adjusted R2 and suggest the importance of concentrating on complaints rather than simple inquiries in future studies. Ultimately, incorporating more independent variables, refining the measurements, and using data solely from customer complaints could enhance the model fit and provide a more comprehensive explanation of the NPS.

Conclusion and Managerial Contribution

Even though the model had a relatively low goodness-of-fit, this study has provided some interesting insight. Negative high customer arousal is negatively affecting customer satisfaction, which accentuates that companies should work on solutions to avoid customers ending up in this emotional state. The positive effect of FLE Empathy on the NPS both directly and with the moderating variable (negative high customer arousal) emphasizes that attentive and empathetic customer service employees are appreciated by customers. It is, therefore, crucial for FLEs to be able to draw strategic inferences when encountering various customer emotions and arousal levels. As active listening, empathy and proactive behavior are low-cost strategies, they can all be efficient tools to improve customer service (Min et al, 2021). As empathy showed to have positive effects on the NPS of customers who experienced negative high arousal, this could be a crucial element to include to avoid de-escalation of negative emotions. Thus, companies should invest in further research to gain more insight into the complexity of communication in online customer service. Ultimately, this could provide companies with cost-efficient tools that will prevent negative emotions from transitioning into high negative arousal towards the company.

Limitations and Further Research Directions

This study has its limitations. Firstly, there are several ways to measure the various constructs and build prediction models using KNIME analytics platform, and a higher proficiency level in KNIME could lead to different results. Moreover, the measures of active listening and proactive employee behavior were based on self-made dictionaries which could be further improved based on data annotation or be measured in a different way (i.e., measuring LSM for active listening). As proactive customer behavior within customer service has little previous research, this is a field that should be explored further to gain better insight concerning its impact on the customer experience. Moreover, future research should be directed towards customer complaints rather than general customer service interactions to see if the model can provide better predictions. The negative high customer arousal will most likely be more prominent which also leads to higher expectations towards the service employees. This can give better predictions of how companies should train their employees to react when customers show emotion, which is especially important when these emotions increase in arousal and are negative. The negative effect of the control variable that measured handover conversations from chatbots to human agents vs conversations only with human agents is also an interesting result that could be explored further. As artificial intelligence (AI) is rapidly improved and used for customer service, the impact of using chatbots for customer service purposes on the customer experience should be further investigated. Moreover, the role of customer valence and arousal should be included in this research to see whether various customer needs and emotions should be met with various customer service solutions to further optimize the customer experience. Lastly, to improve validity and generalizability, further research should be done using data from various industries and various markets. Translation errors could impact the results, as could the interaction within the telecom industry as customer inquiries are specific to the industry. Moreover, further variables should be considered such as different employee behaviors (e.g., humor, slang, emoticons, argumentativeness) and other external variables (e.g., the variety in seriousness in inquiry, other customer emotions). These considerations can all contribute to a more developed understanding of the effects of text-based customer service interactions, and how companies can benefit from meeting their customers online.