

**THE PROMISE AND THE PERIL OF EQUIPPING SERVICE CHATBOTS
WITH EMOTIONS AND CHOICES**

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The Academic Faculty

By

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To my family and friends

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TABLE OF CONTENTS

| | |
|--|-----------|
| ACKNOWLEDGMENTS | IV |
| LIST OF TABLES | IX |
| LIST OF FIGURES | X |
| SUMMARY | XI |
| CHAPTER 1. INTRODUCTION | 1 |
| 1.1 ESSAY 1 | 3 |
| 1.2. ESSAY 2 | 5 |
| 1.3. ESSAY 3 | 7 |
| CHAPTER 2. BOTS WITH FEELINGS: SHOULD AI AGENTS EXPRESS POSITIVE EMOTION IN CUSTOMER SERVICE? | 10 |
| 2.1 INTRODUCTION | 10 |
| 2.2 THEORETICAL DEVELOPMENT AND HYPOTHESES | 13 |
| 2.2.1 Expressed Emotion in Customer Service | 13 |
| 2.2.2 Chatbot-Expressed Emotion | 14 |
| 2.2.3 Chatbot-Expressed Positive Emotion and Dual Pathways | 15 |
| 2.2.4 The Moderating Effect of Relationship Norm Orientation | 19 |
| 2.3 PRETEST | 22 |
| 2.3.1 Stimulus Materials | 23 |
| 2.3.2 Procedure | 24 |
| 2.3.3 Results | 25 |
| 2.3.4 Discussion | 26 |
| 2.4 STUDY 1 | 26 |
| 2.4.1 Procedure and Measures | 27 |
| 2.4.2 Results | 29 |
| 2.4.3 Discussion | 31 |
| 2.5 STUDY 2 | 31 |
| 2.5.1 Stimulus Materials, Procedure, and Measures | 31 |
| 2.5.2 Results | 32 |
| 2.5.3 Discussion | 34 |
| 2.6 STUDY 3 | 34 |
| 2.6.1 Procedure and Measures | 35 |
| 2.6.2 Results | 36 |
| 2.6.3 Discussions | 40 |
| 2.7 GENERAL DISCUSSION | 41 |
| 2.7.1 Theoretical Implications | 42 |
| 2.7.2 Practical Implications | 44 |

| | |
|--|-----------|
| 2.7.3 Limitations and Future Research | 45 |
| 2.8 CONCLUSION | 48 |
| CHAPTER 3. CHATBOT EMPATHY IN CUSTOMER SERVICE: WHEN IT WORKS AND WHEN IT BACKFIRES | 49 |
| 3.1 INTRODUCTION | 49 |
| 3.2 THEORETICAL DEVELOPMENT | 52 |
| 3.2.1 The role of expressed empathy in customer service | 52 |
| 3.2.2 Empathy-expressing chatbots in customer service | 53 |
| 3.2.3 Chatbot-expressed empathy, chatbot perception, and service evaluation | 55 |
| 3.2.4 Chatbot-expressed empathy after conversational breakdowns | 58 |
| 3.3 STUDY 1 | 60 |
| 3.3.1 Stimulus Materials | 61 |
| 3.3.2 Procedure and Measures | 62 |
| 3.3.3 Results | 64 |
| 3.3.4 Discussion | 66 |
| 3.4 STUDY 2 | 67 |
| 3.4.1 Stimulus Materials, Procedure, and Measures | 67 |
| 3.4.2 Results | 69 |
| 3.4.3 Discussion | 71 |
| 3.5 GENERAL DISCUSSION | 71 |
| 3.5.1 Theoretical Implications | 72 |
| 3.5.2 Practical Implications | 74 |
| CHAPTER 4. CHOICE-EQUIPPED CHATBOTS IN CUSTOMER SERVICE: A BLESSING OR A CURSE? | 77 |
| 4.1 INTRODUCTION | 77 |
| 4.2 THEORETICAL DEVELOPMENT AND HYPOTHESES | 80 |
| 4.2.1 The Role of Fluency in Service Interactions | 81 |
| 4.2.2 Choice Implementation After Conversational Breakdowns | 82 |
| 4.2.3 Service Task Complexity and the Comprehensiveness of Choice Set | 84 |
| 4.3 PRELIMINARY STUDY | 87 |
| 4.3.1 Stimulus Materials | 87 |
| 4.3.2 Procedure and Measures | 90 |
| 4.3.3 Results | 91 |
| 4.3.4 Discussion | 92 |
| 4.4 STUDY 1 | 93 |
| 4.4.1 Stimulus Materials | 93 |
| 4.4.2 Procedures and Measures | 96 |
| 4.4.3 Results | 97 |
| 4.4.4 Discussion | 99 |
| 4.5 STUDY 2 | 100 |
| 4.5.1 Stimulus Materials, Procedures, and Measures | 100 |

| | |
|---|------------|
| 4.5.2 Results | 102 |
| 4.5.3 Discussion | 105 |
| 4.6 GENERAL DISCUSSION | 105 |
| 4.6.1 Theoretical Implications | 106 |
| 4.6.2 Practical Implications | 108 |
| 4.6.3 Limitations and Future Research | 109 |
| APPENDIX A: CHAT SCRIPTS USED IN PRETEST OF CHAPTER 2 | 111 |
| APPENDIX B: COVER STOREIS USED IN THE EXPERIMENTS OF CHAPTER 2 | 112 |
| APPENDIX C: VARIABLES MEASURED IN THE EXPERIMENTS OF CHAPTER 2 | 114 |
| APPENDIX D: COVER STORY USED IN THE EXPERIMENTS OF CHAPTER 3 | 116 |
| APPENDIX E: VARIABLES MEASURED IN THE EXPERIMENTS OF CHAPTER 3 | 117 |
| APPENDIX F: COVER STORIES USED IN THE EXPERIMENTS OF CHAPTER 4 | 119 |
| APPENDIX G: VARIABLES MEASURED IN THE EXPERIMENTS OF CHATPER 4 | 122 |
| REFERENCES | 124 |

LIST OF TABLES

| | | |
|-----------|---|----|
| Table 2-1 | Summary of Findings | 41 |
| Table 3-1 | Predesigned chat scripts for Study 1 | 62 |
| Table 3-2 | Predesigned chat scripts for Study 2 | 68 |
| Table 4-1 | Predesigned chat scripts for the conditions from Preliminary Study | 89 |
| Table 4-2 | Predesigned chat scripts for the conversational breakdown conditions from Study 1 | 95 |

LIST OF FIGURES

| | | |
|------------|---|-----|
| Figure 2-1 | Research Framework | 22 |
| Figure 2-2 | Chat Scripts (in chatbot conditions) | 27 |
| Figure 2-3 | Agent Icons | 28 |
| Figure 2-4 | Interaction Effect of Positive Emotion and Agent Identity | 30 |
| Figure 2-5 | Moderating Effect of Relationship Norm Orientation | 34 |
| Figure 2-6 | Study 3 Moderating Effect of Relationship Norm Orientation | 37 |
| Figure 2-7 | Mediation Analysis | 39 |
| Figure 3-1 | Research Framework | 60 |
| Figure 3-2 | Study 1 Parallel-serial Mediation Analysis | 66 |
| Figure 3-3 | Study 2 Parallel-serial Mediation Analysis | 71 |
| Figure 4-1 | Summary of the research framework | 87 |
| Figure 4-2 | An example of the chat interface for the choice-present condition | 90 |
| Figure 4-3 | Interaction effect of the presence of choices and conversational breakdowns | 98 |
| Figure 4-4 | Interaction effect of the presence of choices and task complexity | 104 |

SUMMARY

With the surge of technological innovations such as machine learning and deep learning, artificial intelligence (AI) has become a major interest for researchers, practitioners, and the public. At the moment, AI has been deployed by a variety of industries to serve numerous functions. One of the business functions in which AIs have been especially prevalent is customer service, most commonly in the form of text-based chatbots. Recognizing the prevalence of service chatbots, researchers have investigated how to maximize the value of service chatbots using their unique characteristics. Yet, few research have examined the highly relevant and important characteristics (i.e., emotional capabilities and choice provision) of service chatbots. My dissertation addresses these crucial gaps in the literature and questions the assumptions about the expected benefits for deploying service chatbots by exploring how, when, and why the unique characteristics of service chatbots enhance or impair customers' service experience.

In the first essay, I investigate the effect of positive emotion expressed by chatbots on customers' service evaluations, which differs from the effect of that expressed by human employees. Drawing on the emotional contagion and the expectation-disconfirmation literature, I develop a dual-pathway model to explain how chatbot-expressed positive emotion influence customers' service evaluations through the two opposing pathways. I also suggest a boundary condition based on individual differences that impacts one of the pathways, thus moderating the effect of chatbot-expressed positive emotion on service evaluations. Results from three experimental studies provide consistent support for the proposed hypotheses. This essay challenges the assumption that chatbot-expressed

positive emotion will enhance customers' service evaluations, as it does when expressed by human employees and takes an early step of investigating the role of chatbot-expressed emotion in customer service and human-AI interactions in general. This work further provides practical implications for firms and chatbot designers who are interested in deploying emotion-expressing chatbots.

In the second essay, I focus on the expression of empathy by service chatbots and examine how and when chatbot-expressed empathy benefits or hurts customers' service evaluations. Building on the social perception literature, I propose that, when chatbots express empathy in response to customers' negative emotions because of the consumption experience, the empathy will enhance the perception of warmth (but not competence), thus enhancing service evaluations. On the other hand, when conversational breakdowns occur due to a chatbot failure, chatbot-expressed empathy may not only fail to enhance perceived warmth but also undermine perceived competence, thus hurting service evaluations. Results of two experimental studies provide a partial support for the hypotheses. This essay illuminates the two sides of chatbot-expressed empathy depending on the source of customers' negative emotions and how people apply social perceptions when evaluating chatbots. Practical implications for the deployment of chatbots with emotional capabilities are also provided.

In the third essay, I study when the implementation of chatbot-initiated choices is beneficial or counterproductive during a service interaction and why. Drawing on the fluency literature, I suggest two contextual variables that are especially relevant to the fluency of chatbot-initiated service interactions: conversational breakdowns and service task complexity. After conversational breakdowns disrupt a service process,

implementing choices can heighten customers' perception of fluency and enhance subsequent service outcomes. Meanwhile, the same set of provided choices may be perceived differently depending on the complexity of a service task, such that, for a more complex task, a choice implementation backfires, decreasing customers' perception of fluency and deteriorating service outcomes. Results of two experimental studies provide consistent evidence supporting the hypotheses. This work provides a more nuanced picture of when and why choice implementation (a unique conversational feature of a chatbot) improves or impairs service outcomes and also practical implications for firms on the deployment of choice-enabled service chatbots.

CHAPTER 1. INTRODUCTION

With the surge of technological innovations such as machine learning and deep learning, artificial intelligence (AI) has become a major interest for researchers, practitioners, and the public. About 70% of businesses will have already implemented some form of AIs by 2030 (McKinsey 2018). At the moment, AI has been deployed by a variety of industries to serve numerous functions. One of the business functions in which AIs have been especially prevalent is customer service. Because of the cost efficiency and growing capabilities of AIs in the form of chatbots or voice-based AIs, they are increasingly used to reduce the burden of human labor and often replace customer service employees (Larivière et al. 2017). In fact, Financial Digest (2017) predicted that AIs would handle 95% of customer service interactions by 2025. Also, the market size of AIs in customer service is expected to reach \$1.3 billion by 2025, and about 50% of large companies are especially interested in the investments in text-based chatbots, the most common form of AI service agents (Accenture 2018; Cognizant 2019). Recognizing the popularity and importance of using AIs in customer service, researchers have started investigating how to maximize the value of AI service agents through means such as controlling their identity disclosure or humanizing AIs through visual, auditory, and communication cues (Lucas et al. 2014; Luo et al. 2019; Schanke et al. 2021b; Yuan and Dennis 2019).

Yet, there are still some important gaps in this emerging literature. First, due to the development of emotion intelligence technology, AIs equipped with emotional capabilities are becoming popular and already prevalent in e-learning or healthcare

businesses (Guo and Goh 2015; Gwo-Dong et al. 2012; Inkster et al. 2018; Morris et al. 2018). However, how emotional capabilities of AI service agents influence customers' service experience is less examined, although several scholars have called for a greater need to investigate the role of emotionally intelligent AIs in organizational and service research (Benbya et al. 2021; Huang and Rust 2021). Moreover, given the recent debate about the emergence of a 'sentient' AI chatbot and the need to study how people react to the emotional capabilities of an AI (Cosmo 2022), more investigations are needed to explore the promise of chatbots with emotional capabilities. Because emotional capabilities of service employees have been important drivers of traditional human-to-human service interaction (Ahearne et al. 2007; Kranzbühler et al. 2020), it is essential to illuminate the effect of emotional capabilities of a new entity—service chatbots—that is increasingly replacing human employees.

Second, service chatbots are increasingly equipped to provide choices when interacting with customers in order to generate a guided conversation, thus preventing potential conversational breakdowns that might result from chatbot failures (Klopfenstein et al. 2017). Human-based service interactions tend to involve natural conversations, so providing choices in this process may be unnecessary and break the natural flow of conversations. Therefore, providing choices can be a unique characteristic of chatbot-based service interactions. Although the implementation of choices in chatbots is prevalent in the industry (Li et al. 2020), there is not much empirical evidence for its impact on service outcomes. While the popularity of choice-enabled chatbots indicates a generally favorable view of this unique feature, a choice implementation may also have unintended consequences, and its value may not be realized under certain situations.

This dissertation aims to address these important gaps and challenges the assumptions about the expected benefits for deploying service chatbots by exploring how, when, and why the unique characteristics of service chatbots enhance or impair customers' service experience.

1.1 Essay 1

In the first essay, I explore the impact of chatbot-expressed positive emotion on customers' service evaluations. While prior research has examined how several aspects of service chatbots, such as the timing of their identity disclosure and humanization through various cues, on service outcomes (Araujo 2018; Luo et al. 2019; Schanke et al. 2021b), less attention has been paid to service chatbots' expressed emotion. Emotional expression is regarded as one of the foundational attributes that define human nature (Haslam 2006). However, the recent debate about the emergence of a sentient AI chatbot gaining consciousness and feelings raises the possibility that chatbots can also possess the primary attributes of human beings, such as the ability to perceive, think, and feel (Tiku 2022b). The emerging emotional AIs, which can recognize, interpret, process, and simulate human emotions (Huang and Rust 2018, 2021), further underscore the need to investigate how people make sense of and react to the emotional capabilities of an AI. Such emotional AI technologies can be critical for the development and deployment of service chatbots because human employees' positive emotions are a key driver of customer service evaluations in firm-customer encounters (Kranzbühler et al. 2020). As service chatbots grow more popular, equipping them with the capability of expressing positive emotion (e.g., being cheerful and happy) is expected to benefit businesses and enhance customer experience.

However, equipping service chatbots with this ability should be planned and rolled out cautiously because the positive effect of human-expressed positive emotion may not apply to a chatbot (Gray and Wegner 2012). Indeed, prior studies from HCI and psychology provided conflicting evidence for the effectiveness of AIs and robots expressing emotion in non-business contexts (Creed et al. 2014; Stein and Ohler 2017). In the customer service setting, however, little research has examined the impact of chatbot-expressed emotion. I tackle this important question: specifically, how, when, and why does a service chatbot’s expression of positive emotion influence customers’ service evaluations.

Drawing on the emotional contagion and the expectation-disconfirmation literature (Hatfield et al. 1993; Oliver 1977), I develop a dual-pathway model, proposing that positive emotion expressed by a service chatbot can influence customers’ service evaluations through emotional contagion (affective, positive pathway) and expectation-disconfirmation (cognitive, negative pathway). These two pathways will cancel each other, resulting in a weakened effect of positive emotion on service evaluations when expressed by a chatbot, compared to when expressed by a human employee. I further explore individual differences in people’s norms toward their relationship with an agent—termed “relationship norm orientation”—that can be distinguished into communal-oriented and exchange-oriented relationship norms (Clark and Mils 1993). I propose that variations in these norms lead to different expectations toward a service chatbot and subsequently affect the potency of the negative pathway.

To test these hypotheses, I conduct three experimental studies in which participants engaged in a hypothetical customer service scenario and chatted with a service agent to

resolve a service-related issue. The three studies provide consistent evidence for the predictions. The theoretical model and findings provide three primary contributions to the literature on expressed emotion in customer service and human-AI interactions. First, this paper is among the first to investigate the role of emotion expressed by a service chatbot. Our findings extend the customer service literature by exploring the implications of expressed emotion when the service is provided by a chatbot rather than a human. Second, this work illuminates the effect of expressed emotion on observers in human-AI interactions, which is a nascent area of research. Third, the findings unravel the dual pathways of expressed emotion's impact and reveal a boundary condition for the cognitive pathway, deepening the understanding of a critical but understudied phenomenon.

1.2. Essay 2

In the second essay, I focus on the expression of empathy by service chatbots and examine how and when chatbot-expressed empathy benefits or hurts customers' service evaluations. The rise of emotional intelligence technology has enabled not only emotion-expressing chatbots, but also emotionally responsive chatbots. These emotionally responsive chatbots first detect and recognize users' affective states from various cues (such as facial expressions and linguistic cues), and then they can generate and express an adequate response, such as empathy (Prendinger and Ishizuka 2005). Emotionally responsive chatbots are already prevalent in domains requiring emotional support, such as e-learning or healthcare, and studies in these domains have started to look into the implications of equipping chatbots with the capability of expressing empathy (Guo and Goh 2015; Gwo-Dong et al. 2012; Inkster et al. 2018; Morris et al. 2018).

Empathy refers to one's action of understanding and sharing another person's affective states, thus having the same emotional experience as the other (de Vignemont and Singer 2006). The experience and subsequent expression of empathy can facilitate social communication and affect interpersonal outcomes (de Vignemont and Singer 2006; Duan and Hill 1996). In the traditional service industry, emotional responsiveness, especially empathy, is also an essential capability of human employees (Parasuraman et al. 1985). Thus, empathic employees are likely to lead to successful service delivery due to their tendency to engage in customer-oriented behaviors (Aggarwal et al. 2005; Ahearne et al. 2007; Iglesias et al. 2019; Stock and Hoyer 2005; Wieseke et al. 2012). The deployment of empathic chatbots is based on such premise that empathy during human-AI interactions would be similarly beneficial. However, little research has empirically tested whether the benefit indeed persists in chatbot-driven service interactions.

Thus, building on the social perception literature, I examine the impact of chatbot-expressed empathy on service evaluations. I propose that empathic responses from a chatbot can influence customers' perceptions of the chatbot's warmth and competence, which in turn influence service evaluations. More importantly, I argue that the effect of chatbot-expressed empathy depends on the source of customers' negative emotions. Specifically, when chatbots express empathy in response to customers' negative emotions because of the consumption experience, the empathy will enhance the perception of warmth (but not competence), thus enhancing service evaluations. On the other hand, when conversational breakdowns occur due to a chatbot failure, chatbot-expressed empathy may not only fail to enhance perceived warmth but also undermine perceived competence, thus hurting service evaluations.

Through two experimental studies, I find a partial support for the proposed hypotheses. The theoretical framework and findings extend the understanding of how customers perceive the emotional capabilities of a service chatbot and how such emotional capabilities ultimately affect service evaluations. This work also enhances the empathy literature by shedding light on the role of empathy expressed by a non-human entity. In addition, the findings contribute to the emerging literature on chatbot failures by questioning empathy expressions' effectiveness as a remedy for chatbot failures. This essay further contributes to the broader literature on human-AI interactions by highlighting how people perceive chatbot-expressed empathy and how people apply social perceptions when evaluating chatbots.

1.3. Essay 3

In the third essay, I examine when the implementation of chatbot-initiated choices during a service interaction is beneficial or counterproductive and why. Although chatbots are developed based on natural language processing (NLP) technologies and are capable of understanding and speaking human languages to a certain extent, such technologies are far from perfect (Ashktorab et al. 2019; Benner et al. 2021). Thus, to prevent or reduce the likelihood of breakdowns that usually happen to chatbots, firms often employ structured message templates, which typically involve implementing choices in the form of a guided conversation, during which customers can select one of the provided pre-determined options as their input message (Klopfenstein et al. 2017).

Although the implementation of choices in chatbots is prevalent in the industry (Li et al. 2020), there is not much empirical evidence for its impact on service outcomes. Human-based service interactions tend to involve natural conversations, so providing

choices in this process may be unnecessary and break the natural flow of conversations. Therefore, providing choices can be a unique characteristic of chatbot-based service interactions. While the popularity of choice-enabled chatbots indicates a generally favorable view of this unique feature, a choice implementation may also have unintended consequences, and its value may not be realized under certain situations.

Drawing on the fluency literature, I suggest two contextual variables that are especially relevant to the fluency of chatbot-initiated service interactions and thus, vary the impact of chatbots' choice provision: conversational breakdowns and service task complexity. Conversational breakdowns often occur during the interaction with chatbots due to their imperfect capability to understand users' messages (Ashktorab et al. 2019). Implementing choices after conversational breakdowns are especially beneficial because it can heighten customers' perception of fluency and enhance subsequent service outcomes. Some research suggested providing choices as one of the repair strategies after conversational breakdowns during an interaction with a chatbot (Ashktorab et al. 2019; Benner et al. 2021), but to my knowledge, there was no empirical evidence focusing exclusively on its effect. Meanwhile, the same set of provided choices may be perceived differently depending on the complexity of a service task, such that, as service task becomes more complex, a predefined set of choices would be less likely to encompass all the necessary options required by customers. In such cases, a choice implementation may backfire, decreasing customers' perception of fluency and deteriorating service outcomes.

I test these predictions using a series of experimental studies in which participants engaged in a hypothetical customer service scenario and chatted with a chatbot to resolve a service issue. The studies provide consistent evidence supporting the hypotheses. The

theoretical framework and findings contribute to the literature on chatbots' role in customer service and the broader literature on human-AI interaction. Specifically, this work provides a more nuanced picture of when and why choice implementation (a unique conversational feature of a chatbot) improves or impairs service outcomes. This research also extends customer service literature by illuminating the benefits and drawbacks of technology-induced service interactions. Finally, this essay bolsters the literature on fluency by identifying boundary conditions that can either augment or deteriorate people's perception of fluency.

CHAPTER 2. BOTS WITH FEELINGS: SHOULD AI AGENTS EXPRESS POSITIVE EMOTION IN CUSTOMER SERVICE?

2.1 Introduction

With the surge of technological innovations such as machine learning and deep learning, artificial intelligence (AI) has become a major interest for researchers, practitioners, and the public. In 2020, 56% of businesses adopted AI in at least one function, and more than 50% of the AI use cases were related to service operations (McKinsey 2021). Indeed, because of the cost efficiency and growing capabilities of AIs in the form of chatbots or voice-based AIs, they have been increasingly deployed in customer service to reduce the burden of human labor and often replace customer service employees (Larivière et al. 2017). Financial Digest (2017) predicted that AIs would handle 95% of customer service interactions by 2025. Recognizing the popularity and importance of using AIs (especially chatbots) in customer service, researchers have started exploring how to maximize the value of service chatbots through means such as controlling their identity disclosure or humanizing AIs through visual, auditory, and communication cues (Lucas et al. 2014; Luo et al. 2019; Schanke et al. 2021b; Yuan and Dennis 2019).

While prior research has examined several aspects of service chatbots and their impact on service outcomes (Araujo 2018; Luo et al. 2019; Schanke et al. 2021b), less attention has been paid to the chatbots' expressed emotion. Emotional expression is regarded as one of the foundational attributes that define human nature (Haslam 2006). However, the recent debate about the emergence of a sentient AI chatbot gaining consciousness and feelings raises the possibility that chatbots can also possess the primary attributes of

human beings, such as the ability to perceive, think, and feel (Tiku 2022a). The emerging emotional AIs, which can recognize, interpret, process, and simulate human emotions (Huang and Rust 2018, 2021), further underscore the need to investigate how people make sense of and react to the emotional capabilities of an AI. Indeed, the global affective computing market, which develops technologies for emotional AIs, is projected to reach \$100 billion by 2024 and \$200 billion by 2026 at a compounded annual growth rate of over 30% (Global Industry Analysts 2021; Reports and Data 2021). Such emotional AI technologies can be critical for the development and deployment of service chatbots because human employees' positive emotions are a key driver of customer service evaluations in firm-customer encounters (Kranzbühler et al. 2020). As service chatbots grow more popular, equipping them with the capability of expressing positive emotion (e.g., being cheerful and happy) is expected to benefit businesses and enhance customer experience.

However, equipping service chatbots with this ability should be planned and rolled out cautiously because the positive effect of human-expressed positive emotion may not apply to a service chatbot (Gray and Wegner 2012). Prior studies from HCI and psychology provided conflicting evidence for the effectiveness of AIs and robots expressing emotion in non-business contexts (Creed et al. 2014; Stein and Ohler 2017). In the customer service setting, however, little research has examined the impact of chatbot-expressed emotion. We focus on service chatbots increasingly deployed in customer service departments and explore the impact of their expressed positive emotion on service evaluations.

Our research question is the following: how, when, and why does a chatbot's expression of positive emotion influence customers' service evaluations? Our primary goal is to examine the unique impact of chatbot-expressed emotion that might be different from the impact of human-expressed emotion. Since human service employees typically display positive emotion during a service encounter, we also restrict our focus to positive emotion that is deemed appropriate as a first step toward achieving our primary goal. Drawing on emotional contagion and expectation-disconfirmation literature (Hatfield et al. 1993; Oliver 1977), we argue that positive emotion expressed by a chatbot can influence customers' service evaluations through dual pathways: one affective and the other cognitive. On the one hand, the affective pathway of emotional contagion that underlies the positive effect of human-expressed positive emotion, as repeatedly confirmed in the prior customer service literature (Pugh 2001; Tsai and Huang 2002), may also apply to a service chatbot. On the other hand, an emotion-expressing chatbot might violate a customer's expectation that it is not capable of feeling emotion (Gray et al. 2007; Haslam 2006). This negative, cognitive pathway may cancel out the positive, affective pathway of emotional contagion, resulting in a weakened effect of positive emotion on service evaluations. We further explore individual differences in people's norms toward their relationship with an agent—termed “relationship norm orientation”—that can be distinguished into communal-oriented and exchange-oriented relationship norms (Clark and Mils 1993). We propose that variations in these norms lead to different expectations toward a service chatbot and subsequently affect the potency of the negative pathway.

To test these hypotheses, we present three experimental studies in which participants engaged in a hypothetical customer service scenario and chatted with a service agent to resolve a service-related issue. We find consistent evidence for our predictions. Our theoretical framework and findings provide three primary contributions to the literature on expressed emotion in customer service and human-AI interactions. First, this paper is among the first to investigate the role of emotion expressed by a service chatbot. Our findings extend the customer service literature by exploring the implications of expressed emotion when the service is provided by a chatbot rather than a human. Second, we illuminate the effect of expressed emotion on observers in human-AI interactions, which is a nascent area of research. Third, we unravel the dual pathways of expressed emotion's impact and reveal a boundary condition for the cognitive pathway, deepening our understanding of a critical but understudied phenomenon.

2.2 Theoretical Development and Hypotheses

2.2.1 Expressed Emotion in Customer Service

In traditional customer service settings where humans are service providers, the role of their displayed emotion has been an important area of scholarly inquiry (Pugh 2001; Rafaeli and Sutton 1990). The display of positive emotion by service employees is generally desirable as it enhances service outcomes (Kranzbühler et al. 2020). For example, displaying a smile to customers can lead to higher service evaluations in both face-to-face and online interactions because of emotional contagion (Barger and Grandey 2006; Pugh 2001; Tsai and Huang 2002; Verhagen et al. 2014). Emotional contagion refers to the process in which an individual's emotional state is transferred to an observer (Hatfield et al. 1993). The means through which emotional contagion occurs is not

confined to nonverbal behaviors, such as facial, postural, or vocal expressions, and it also includes text-based computer-mediated communication (Goldenberg and Gross 2020). Thus, if a customer perceives positive emotion from a service agent, he or she can experience the same emotion and evaluate the service more positively as a result.

However, expressing positive emotion might not always be beneficial. For example, expressed emotion could backfire when it is perceived as inappropriate or inauthentic (Cheshin et al. 2018). Also, Li et al. (2018) investigated the effect of positive emotion expressed through emoticons during online service interactions and found that expressing positive emotion can enhance the perceptions of a service agent's warmth but not competence. These findings suggest a need to explore the consequences of expressing positive emotion when the service is provided by a chatbot.

2.2.2 Chatbot-Expressed Emotion

While prior studies provided extensive evidence for the effect of emotion expressed by a human service agent, little research has examined the applicability of these findings when a chatbot provides the service. AIs have been rapidly replacing human service agents in the recent decade (Oracle 2016). Moreover, we are witnessing the development of emotional AIs that are increasingly able to recognize human emotions and simulate human's emotional responses (Somers 2019). Thus, it is crucial to understand how, when, and why the positive emotion expressed by a service chatbot can influence customers' service evaluations.

As the history of developing emotional AIs is short, research on the effect of chatbot-expressed emotion is nascent. The very few studies examining the effects of AIs' simulated emotions, mostly in non-business contexts, provided mixed evidence, partly

because the contexts of the studies varied substantially. Machines displaying emotions were preferred over their neutral counterparts in certain contexts (Creed et al. 2014), but they also elicited people's negative feelings in other contexts (Kim et al. 2019; Stein and Ohler 2017). These mixed findings suggest that insights from earlier customer service studies based on humans expressing positive emotion may not apply to chatbots equipped to mimic human emotions.

2.2.3 Chatbot-Expressed Positive Emotion and Dual Pathways

First, we believe that the impact of a service agent's expressed positive emotion in service encounters depends on the agent's identity as a human or a chatbot. A possible reason is that emotion-related capabilities are deemed unique capabilities of humans, such as experiencing and expressing one's own emotions as well as sharing others' emotions (i.e., empathy) (Haslam 2006). Thus, customers should have different expectations about these capabilities from a human versus a chatbot. As explained in more depth later, a chatbot is less expected to express positive emotion than a human employee because machines are generally believed to lack consciousness or feelings (Gray et al. 2007; The Economist 2022). A violation of this expectation in the case of a chatbot should weaken the positive impact of expressed positive emotion revealed in prior literature studying human agents. Thus, we propose the following:

H1: The positive effect of positive emotion expressed by an agent on service evaluations depends on the agent's identity, such that the effect is greater for a human agent than for a chatbot.

Because the focus of our paper is positive emotion expressed by *chatbots*, we limit our attention in the rest of theory development to *chatbot*-expressed positive emotion and

discuss how it influences service evaluations through dual, opposing processes: one affective and the other cognitive. First, one's expressed emotion can lead an observer to feel the same emotion through emotional contagion (Hatfield et al. 1993). Prior literature in customer service showed that the display of a human employee's positive emotion provokes the positive affect of a customer, thus enhancing service evaluations (Pugh 2001). In addition, the likelihood and extent of emotional contagion may depend on various factors, such as the expresser's characteristics, the expresser-perceiver relationship, and the perceiver's susceptibility to others' emotions (Doherty 1997; van der Schalk et al. 2011).

Emotional contagion might be weakened when the expresser is a chatbot rather than a human agent. However, we argue that the affective process of emotional contagion can still underlie the impact of chatbot-expressed positive emotion. After observing another person's emotional expression, one's affective states can be automatically and subconsciously evoked without involving any cognitive resources and often, even without being aware of the origin (Neumann and Strack 2000). Moreover, prior literature on computer-mediated communication suggested that textual cues suffice for eliciting emotional contagion because affective words prime an observer with the emotion conveyed in those words (Cheshin et al. 2011; Hancock et al. 2008). This finding also implies that emotional contagion may occur through IT artifacts in digital environments that lack human presence, such as on social media (Ferrara and Yang 2015; Kramer et al. 2014).

In our context, if a service chatbot expresses positive emotion during a service interaction, the textual cues of positive emotion can prime a customer with the same

emotion, thus automatically triggering positive emotion of the customer before they form any cognitive judgment towards the agent's identity. The triggered positive emotion will then serve as information for judging the service encounter. According to affect-as-information theory, one's affective states provide information about an event he or she is involved in (Schwarz and Clore 1983). Specifically, affective valence can be attributed to the value judgment of an event, such that positive (negative) emotion leads to a perception that the event is pleasant (unpleasant) (Clore et al. 2001). Thus, a customer's positive emotion triggered by emotional contagion will lead to a positive evaluation of a service encounter (Pugh 2001). Taken together, we propose that a customer's felt positive emotion can mediate the impact of chatbot-expressed positive emotion.

H2a (positive mediation through emotional contagion): A chatbot's expressed positive emotion increases a customer's positive emotion, which in turn enhances service evaluations.

In addition to the affective pathway of emotional contagion, we also propose a cognitive pathway such that chatbot-expressed positive emotion increases the magnitude of expectation-disconfirmation, which refers to the extent to which an individual's prior expectation does not align with the actual experience (Oliver 1977). Expectation-disconfirmation is known to influence various consumer behaviors, such as product or service evaluations, post-purchase behavior, and continuous use of information systems (Bhattacharjee 2001; Oliver 1993). During a service interaction, customers compare their expectations and the actual service experience when evaluating a service (Oliver 1993; Parasuraman et al. 1985). The impact of expectation is especially salient for interpersonal communication that involves emotion, as individuals have strong expectations toward

others' emotional expressions (Burgoon 1993). Beyond interpersonal communication, an expectation has also been revealed to play an important role in the context of communication through technological artifacts (Jensen et al. 2013; Jin 2012; Kalman and Rafaeli 2011; Ramirez and Wang 2008). Overall, when the expectation is violated, especially if the observed behavior is inferior to the expected behavior (i.e., negative violation), the resulting disconfirmation and cognitive dissonance often lead people to develop negative attitudes or behaviors (Festinger 1957).

While several factors can determine the impact of expectation, one factor is a communicator's characteristics (Burgoon 1993), and we focus on the identity of a service agent as such a characteristic in our context. For a chatbot, customers should have prior expectations regarding its capability of feeling (and subsequently expressing) emotion, which should be different from that of a human agent. One of the core characteristics that define human nature and differentiate humans from machines is related to emotion, such as emotionality (i.e., experiencing or expressing one's own emotions) and emotional responsiveness (i.e., understanding or sharing others' emotions and responding accordingly) (Haslam 2006). Different from humans, machines are commonly believed to lack the mental capability of feeling various emotions (e.g., joy, fear, rage) (Gray et al. 2007; Gray and Wegner 2012), which is a necessary step before emotional display. Due to this fundamental difference in emotional capabilities between humans and machines, customers should have different expectations for the agent's emotional display, such that a human agent can and should express (supposedly positive) emotion, while a chatbot cannot. Thus, when a chatbot expresses emotion during an actual interaction, customers' expectations about its emotional expression should be disconfirmed.

While the violation of expectation can be either positive or negative, we argue that an emotion-expressing chatbot will result in a negative violation because emotionally capable machines can evoke a sense of threat to human uniqueness and lead to strong eeriness and aversion toward the machines (Stein and Ohler 2017). Such a negative violation of expectation will lead to lower service evaluations (Brady and Cronin 2001; Oliver 1993). Thus, expectation-disconfirmation can also mediate the impact of a chatbot's expressed positive emotion on service evaluations.

H2b (negative mediation through expectation-disconfirmation): *A chatbot's expressed positive emotion increases the extent of expectation-disconfirmation, which in turn reduces service evaluations.*

Accordingly, when a chatbot expresses positive emotion, the negative indirect effect through expectation-disconfirmation may cancel out the positive indirect effect through emotional contagion. The co-occurrence of these two opposing processes may explain the weaker effect of a chatbot's expressed positive emotion compared to a human agent's expressed positive emotion, as proposed in H1. Meanwhile, the two proposed pathways may be interdependent due to the intertwining of affect and cognition (Izard 2011; Phelps 2006). While we acknowledge that the two processes can be mutually influential, we still treat the two pathways as distinct processes because a) such a model is more parsimonious and b) this treatment is consistent with similar theories such as the emotions as social information theory (Van Kleef 2009) and dual-process theories (Evans 2003; Petty and Cacioppo 1986).

2.2.4 The Moderating Effect of Relationship Norm Orientation

While two opposing processes might underlie the impact of chatbot-expressed positive emotion, the pathway of expectation-disconfirmation may vary based on an individual's exact expectation. We suggest relationship norm orientation as an individual difference variable to capture the natural variation in customers' expectations. Relationship norm is used in social psychology to explain people's varying norms about two distinct types of relationships—exchange and communal—based on economic and social factors (Clark and Mils 1993). An exchange relationship is a quid pro quo relationship of exchanging a similar level of benefits. In communal relationships, however, such quid pro quo is not obligatory. Instead, benefits are given in response to a person's need or to demonstrate a general concern for another. Because this distinction is based on a rule or a norm about giving and receiving benefits, the two relationships generate different norms of behavior which, in turn, influence expectations toward another's behavior in an interpersonal relationship (Clark and Taraban 1991). Thus, the same behavior might lead to different interpersonal outcomes depending on the observer's relationship norm orientation.

Relationship norm orientation has been found to be influential beyond interpersonal relationships. For example, customers tend to form different expectations toward a brand depending on their relationship norm orientation, ultimately influencing their evaluations of the brand or its product (Aggarwal 2004; Liu and Gal 2011). These studies provide converging evidence that violating the relationship norm leads to a negative evaluation because of cognitive dissonance between expectations and actual observations. Similarly, customers' relationship norm orientation may influence how they interpret certain cues

from a service agent during a service encounter (Scott et al. 2013), which in turn can alter the subsequent likelihood of expectation-disconfirmation.

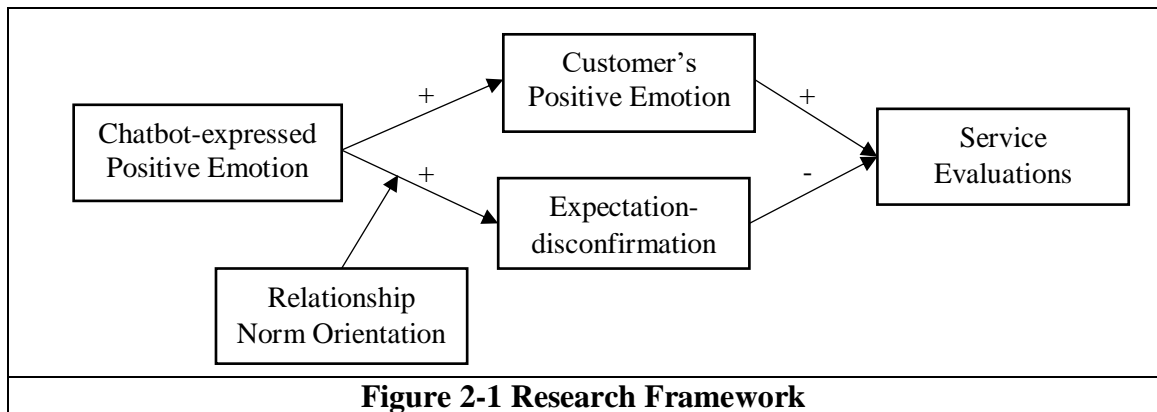
In our context, customers can evaluate chatbots' expression of positive emotion differently depending on their relationship norm orientation. Customers with a communal relationship norm—communal-oriented customers—will expect a service agent to show a genuine concern and care like a friend or a family member (Scott et al. 2013). Because the expression of positive emotion insinuates such care and attention, it will confirm communal-oriented customers' expectations derived from their relationship norm, even if the source is a chatbot. Thus, the positive effect of chatbot-expressed positive emotion on expectation-disconfirmation will be weaker for communal-oriented customers.

In contrast, customers with an exchange relationship norm—exchange-oriented customers—will expect a service agent to be more transaction-focused, providing a professional and exact service (Scott et al. 2013). Because the expression of positive emotion does not satisfy such a transaction-focused norm, it will not confirm exchange-oriented customers' expectations derived from their relationship norm. As exchange-oriented customers are more likely to treat a chatbot as a machine (which is not supposed to have emotion) than a friend or family member, the positive effect of chatbot-expressed positive emotion on expectation-disconfirmation should be greater for them than for communal-oriented customers. Taken together, a chatbot's expression of positive emotion should enhance the service evaluations when the customers are communal-oriented (because of emotional contagion and weaker expectation-disconfirmation), but this effect should weaken or even reverse when the customers are exchange-oriented (because of emotional contagion and expectation-disconfirmation operating in opposite

directions). We propose our last hypothesis below. Figure 2-1 depicts the complete research framework.

H3 (moderation by relationship norm orientation): *For communal-oriented customers, a chatbot’s expressed positive emotion has a positive effect on service evaluations, but for exchange-oriented customers, such an effect is non-existent or even reversed.*

To test these hypotheses, we conducted three laboratory experiments in which participants were asked to interact with a customer service agent in a hypothetical scenario. In the first study, we tested H1 by manipulating the agent’s (human vs. chatbot) identity and the presence of positive emotional expression during the interaction. In Study 2, we focused only on the chatbot and explored the moderating role of participants’ relationship norm orientations as proposed in H3. In the final study, we tested H3 as well as the underlying mechanisms as proposed in H2a and H2b.



2.3 Pretest

Before the main experiments, we conducted a pretest to verify the effectiveness and validity of our key emotion manipulation in a customer service context. To achieve this goal, we varied a chatbot’s expressed positive emotion at multiple levels in a between-

subjects design and kept all other aspects of the interaction identical across conditions. We focused only on the chatbot in this pretest because our primary interest is the effectiveness of chatbots expressing emotion. During the study, participants took part in a hypothetical customer service task and interacted with a chatbot via virtual chat to resolve a service-related issue. After the chat, participants evaluated the expressed emotion of the chatbot.

2.3.1 Stimulus Materials

To ensure that participants across conditions receive the same messages from the chatbot during the chat except for the level of expressed emotion, we used a predesigned script. The script included four messages from the agent, with two to four sentences within each message. The script was devised based on examples of best practices and canned responses for live chat from livechat.com, a popular platform that provides live chat software. Messages at the beginning (for greetings) and end of the chat followed the exact examples from the platform. The rest of the messages also followed the best practice examples from the platform but were slightly modified to fit our setting.

We manipulated expressed positive emotion at three levels by selecting one sentence from each message and varying the presence of emotional adjectives or exclamation marks in the sentence. We focused only on the positive emotion to avoid the possible confound of valence. For the low emotion condition, there were neither emotional adjectives nor exclamation marks throughout the interaction. For the intermediate emotion condition, following Yin et al. (2017), we added exclamation marks and emotional adjectives to every manipulated sentence. For the high emotion condition, we added both exclamation marks and emotional adjectives to every manipulated sentence.

Furthermore, to strengthen participants' belief that they are interacting with a chatbot, we showed an introductory message of "being connected to a bot created by the customer service department" before the chat started. We also inserted a robot icon under the introductory message and next to each message from the agent. The three versions of the entire script can be found in Appendix A.

2.3.2 Procedure

One hundred and five subjects from Amazon Mechanical Turk (53 female) participated in the pretest. Participants were randomly assigned to one of the three conditions with different levels of expressed positive emotion. The cover story involved a hypothetical but realistic scenario that described a service-related issue. We chose the online retail industry as the setting because virtual chat is commonly deployed to communicate with customers, and this industry is at the forefront of rapidly replacing human agents with chatbots. For the service-related issue, we used one of the most common complaints in the online retail industry: a missing item from a delivery. The scenario described a recent delivery in which one of the items was missing. Participants were asked to chat with a service agent and request delivery of the missing item (see Appendix B for details). Then participants saw the introductory message that they were being connected to a customer service bot, and the chat started on a new screen.

When the chat started, the first message was displayed. Participants had to type in their response below the first message before moving on to the next screen and seeing the agent's next message. Participants were instructed to provide a response to the agent based on the cover story. Furthermore, on each screen, we provided a reminder of the facts from the cover story that pertained to the agent's question so that the chat would not

go off topic, and the subsequent message from the agent would appear logical. On each screen, participants could also see the chat history up to that point. To further enhance the live chat experience, each of the agent's messages was presented with a slight delay.

To verify the effectiveness of our affect intensity manipulation (Jensen et al. 2013), we asked the participants to rate the intensity of the agent's expressed emotion after the chat concluded. Emotional intensity was measured using three items from Puntoni et al. (2008) (e.g., "very little emotion / a great deal of emotion"). We also asked participants to report the appropriateness of expressed emotion to ensure that they are similarly appropriate across conditions (Van Kleef and Côté 2007). Emotion appropriateness was measured using four items from Cheshin et al. (2018) (e.g., "The emotions the service agent expressed were appropriate."). All these questions were measured on a seven-point semantic differential scale. To identify outliers and ensure subject quality, we also asked participants to answer two attention check questions about the content of the service issue and the solution provided by the agent. All measurement items are listed in Appendix C.

2.3.3 Results

Out of 105 subjects, 84 subjects passed both attention check questions and were used in our analysis. We first conducted a manipulation check for the perceived intensity of the agent's expressed emotion. Analysis revealed that participants perceived the emotional intensity of the agent differently across the three conditions ($F(2, 81) = 17.324$, $p < .001$). According to a Tukey post-hoc test, the low emotion agent was perceived as less emotionally intense than the intermediate emotion agent ($M_{low} = 2.36$ vs. $M_{intermediate} = 4.01$, $SDs = 1.43$ and 1.53 , $p < .001$) or high emotion agent ($M_{high} = 4.48$, $SD_{high} = 1.22$, $p < .001$). However, the intermediate emotion agent and the high emotion agent were not

perceived differently in terms of emotional intensity ($p = .4$). Thus, our manipulations indeed varied emotional intensity successfully between low and higher levels but not between intermediate and high levels.

Next, we evaluated the appropriateness of expressed emotion to rule out this possible confound. Results revealed that subjects did not evaluate the appropriateness of emotion differently across conditions ($F(2, 81) = .878, p = .4$). The pairwise comparisons further confirmed that the participants did not perceive a difference in emotional appropriateness between low versus intermediate ($p = .4$), low versus high ($p = .6$), or intermediate versus high ($p = 1$) emotion conditions.

2.3.4 Discussion

This pretest manipulated the level of emotion expressed by a service agent and validated this key manipulation. Among the three levels, we picked the low and high levels for use in the main studies for two reasons. First, the perceived intensity of the agent's expressed emotion was the lowest in the low emotion condition and the highest in the high emotion condition, and this difference was significant. We did not choose the intermediate level of expressed emotion because we intended to strengthen the manipulation as much as possible. Second, we verified that perceived appropriateness did not differ across intensity levels. For simplicity, we will refer to the low and high levels as "emotion-absent" and "emotion-present," and the presence of positive emotion as "positive emotion" henceforth.

2.4 Study 1

In Study 1, we investigated whether the effect of expressed positive emotion depends on the service agent's identity, as suggested in H1. To do so, we varied both the presence

of the expressed positive emotion and the agent’s (human versus chatbot) identity in a between-subjects design.

2.4.1 Procedure and Measures

Our stimulus materials were based on the low and high emotional intensity scripts verified in the pretest (see Figure 2-2). To manipulate the agent’s identity, we varied the icons that appeared next to each of the agent’s messages (see Figure 2-3). For those assigned to the human condition, the employee was either male or female (randomly determined) to reduce a possible gender effect.

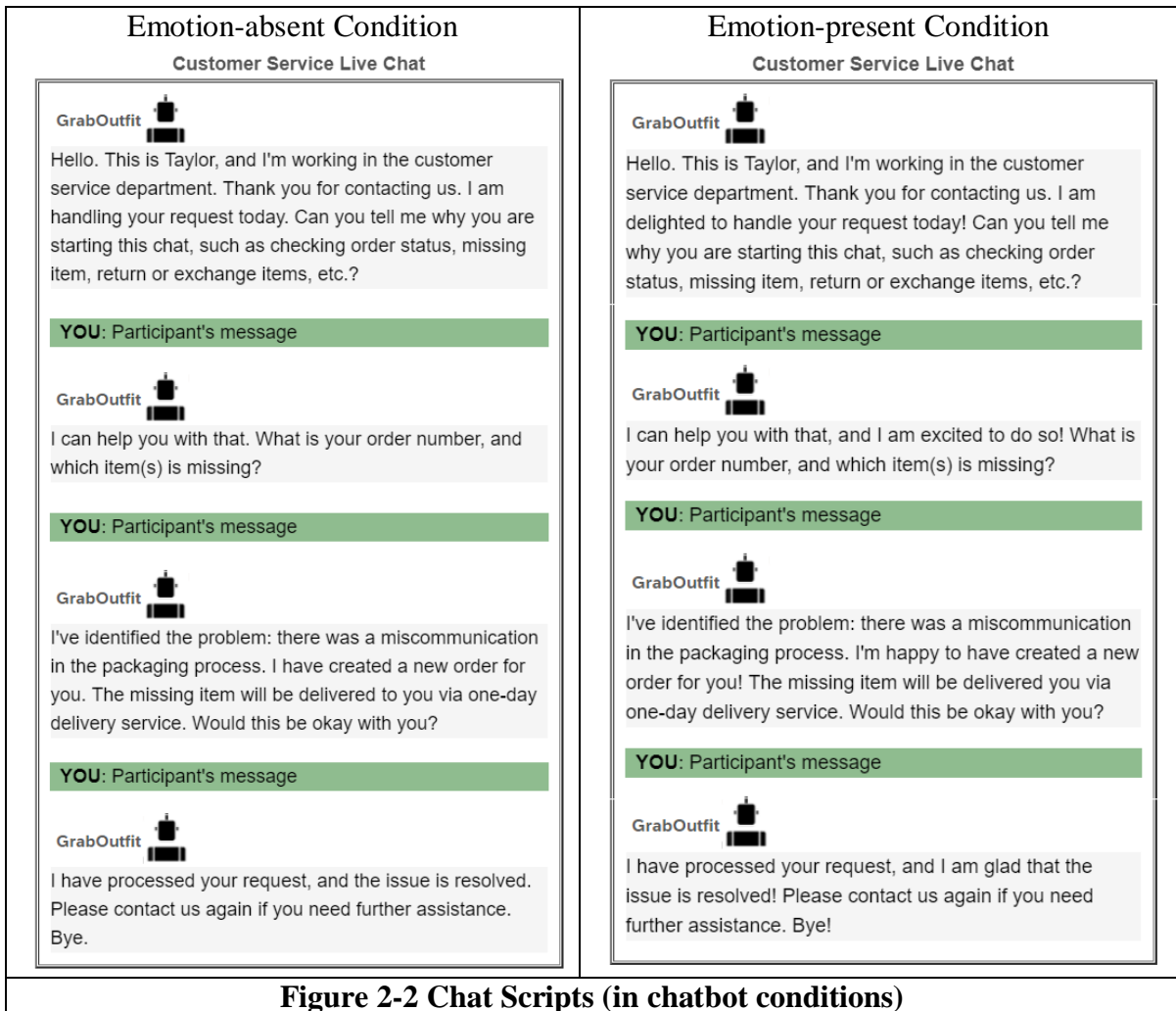
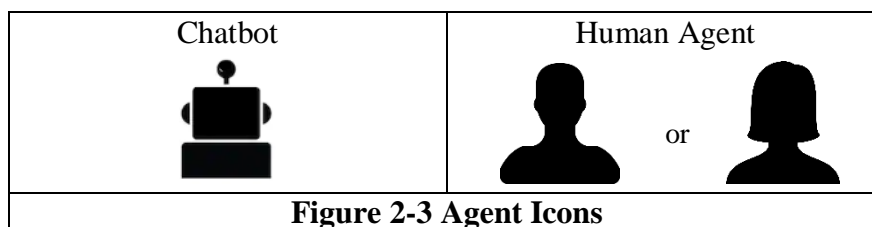


Figure 2-2 Chat Scripts (in chatbot conditions)



One hundred and fifty-eight undergraduate students (86 female) from a U.S. university participated in the study in exchange for course credit. Participants were randomly assigned to one of the four treatment conditions. The cover story and procedure were identical to that of the pretest, except that we asked the outcome variables right after participants finished their chat with the agent.

We focused on two important service evaluation outcomes: perceived service quality and satisfaction with the service. Perceived service quality is an overall evaluation of the service outcome and interaction, and it is associated with key organizational outcomes such as customer loyalty, market share, and purchase intention (Brady and Cronin 2001). Satisfaction with the service is another essential evaluation metric, as it is a key predictor of customers' intention to continue using the service (Oliva et al. 1992). Although the two have been revealed to jointly influence more downstream consequences (Cronin et al. 2000; Gotlieb et al. 1994), they are distinct constructs at the theoretical level (Anderson and Sullivan 1993; Cronin et al. 2000; Taylor and Baker 1994). To measure perceived service quality and satisfaction with the service, we adapted existing scales from the customer service literature (Cronin et al. 2000). Perceived service quality was measured using three items (e.g., "poor / excellent"). Satisfaction with the service was measured using three questions (e.g., "Overall, how satisfied or dissatisfied did your

experience with the service agent leave you feeling?”, “extremely dissatisfied / extremely satisfied”).

After the measures for service evaluations, we asked two attention check questions as in the pretest, followed by the manipulation check questions. As a manipulation check for the presence of emotion, we used the same measure of emotional intensity from the pretest. As a manipulation check for the agent’s identity, we measured the perceived human-likeness of the agent on a seven-point, semantic differential scale, using three items from MacDorman (2006) and Lankton et al. (2015) (e.g., “very mechanical / very humanlike”). All measurement items of this study and the later studies are listed in Appendix C.

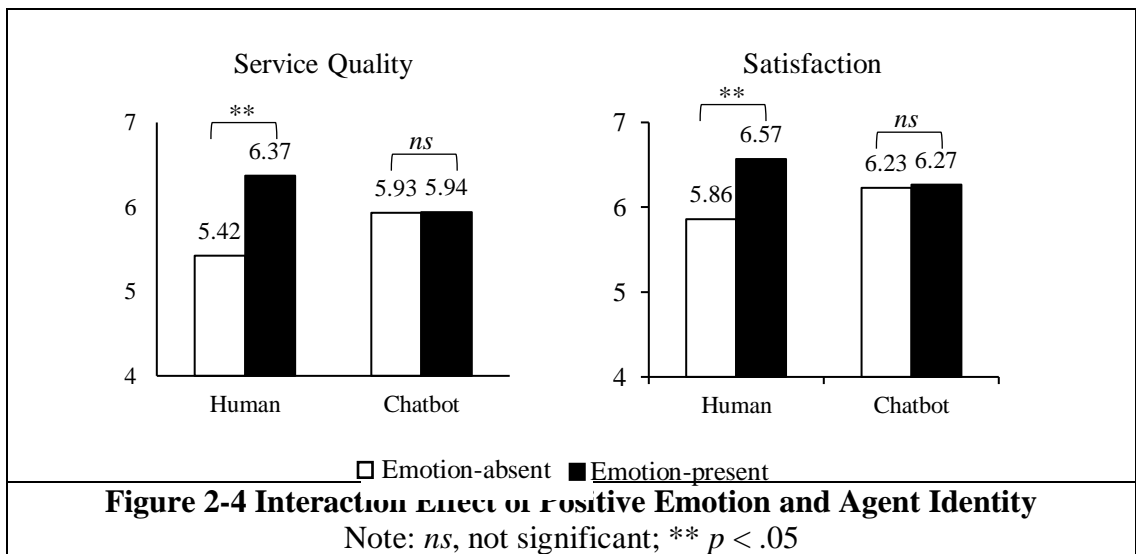
2.4.2 Results

We used 155 subjects who passed attention checks. The analysis of the manipulation checks revealed that participants perceived the emotion-present agent as more emotionally intense than the emotion-absent agent ($M_{present} = 4.04$ vs. $M_{absent} = 2.52$, $SDs = 1.35$ and 1.47 , $t(153) = 6.703$, $p < .001$). Also, participants perceived the human agent as more human-like than the chatbot ($M_{human} = 3.23$ vs. $M_{chatbot} = 2.68$, $SDs = 1.79$ and 1.27 , $t(153) = 2.208$, $p = .029$). Therefore, both of our manipulations were deemed successful.

To test H1, we conducted a two-way ANCOVA with positive emotion and the agent’s identity as between-subjects factors and gender as a covariate. We used gender as a covariate because of the prior literature indicating gender differences in emotion recognition and perception (Brody and Hall 2008; Fischer et al. 2018). Results revealed a main effect of positive emotion, such that overall, expressing positive emotion led to a

more positive evaluation of service quality ($M_{absent} = 5.67$ vs. $M_{present} = 6.13$, $SDs = 1.45$ and 1.07 , $F(1, 150) = 5.650$, $p = .019$) and greater satisfaction ($M_{absent} = 6.04$ vs. $M_{present} = 6.41$, $SDs = 1.21$ and $.94$, $F(1, 150) = 4.601$, $p = .034$). However, the main effect of agent identity was not observed ($ps = .8$), nor the main effect of gender ($ps = .2$ and $.6$).

Most importantly, agent identity significantly moderated the positive effect of positive emotion on perceived service quality ($F(1, 150) = 5.451$, $p = .021$) and on satisfaction ($F(1, 150) = 3.606$, $p = .059$). Pairwise comparisons showed that positive emotion from a human agent significantly increased perceived service quality ($M_{human_absent} = 5.42$ vs. $M_{human_present} = 6.37$, $SDs = 1.25$ and 1.29 , $t(75) = 3.282$, $p = .001$) and satisfaction ($M_{human_absent} = 5.86$ vs. $M_{human_present} = 6.57$, $SDs = 1.06$ and 1.11 , $t(75) = 2.871$, $p = .005$). In the case of a chatbot, however, the effects of positive emotion did not reach significance for service quality ($M_{chatbot_absent} = 5.94$ vs. $M_{chatbot_present} = 5.93$, $SDs = 1.25$, $t(76) = .035$, $p = 1$) or satisfaction ($M_{chatbot_absent} = 6.27$ vs. $M_{chatbot_present} = 6.23$, $SDs = 1.06$, $t(76) = .167$, $p = .9$) (see Figure 2-4). These results confirmed H1.



2.4.3 Discussion

This study provides direct evidence that positive emotion expressed by a human agent can increase perceived service quality and satisfaction with the service, but such effects are absent when the emotion is expressed by a chatbot. As discussed before, prior literature on customer service has shown that positive emotional expressions by a human service agent positively influence customers' service evaluations (Kranzbühler et al. 2020). However, this study suggests that the positive impact of human's positive emotional displays is not directly applicable when chatbots replace human agents.

A reason for this lack of effect in the case of a chatbot might be that customers differ in perceived norms regarding their relationships with the chatbot and thus have different expectations toward the chatbot's expressed emotion. Such different expectations may lead to different reactions, as we proposed in H3. Thus, we focused only on chatbots in the next study and tested this hypothesis.

2.5 Study 2

The goal of Study 2 was to investigate whether the effect of chatbot-expressed positive emotion is dependent on customers' individual differences in their relationship norm orientation as proposed in H3. Because we shifted our focus to only the chatbot, we varied the presence of positive emotion as a single between-subjects factor and measured participants' relationship norm orientation.

2.5.1 Stimulus Materials, Procedure, and Measures

We changed our predesigned script by switching to a different service-related issue and extending the length of the conversation. We asked participants to request an exchange for a textbook they had already ordered, as this scenario is more relevant to

student subjects. We also added one more message to the conversation to enhance participant engagement. This additional message, which was inserted after the greetings message, asked why a participant wanted an exchange. Manipulation of emotional intensity was also implemented in this additional message and all other messages as in the first study.

Ninety-two undergraduate students (49 female) from a U.S. university participated in this study in exchange for course credit. Participants were randomly assigned to either the emotion-absent or the emotion-present condition. The cover story and procedure were identical to those of Study 1. In addition to the measures used in Study 1, we added a new scale measuring participants' individual differences in relationship norm orientation. We used a seven-point, semantic differential scale with three items, describing the kind of relationship a participant would want with an online customer service agent (e.g., "strictly for business / bonded like family and friends") (Aggarwal 2004; Li et al. 2018).

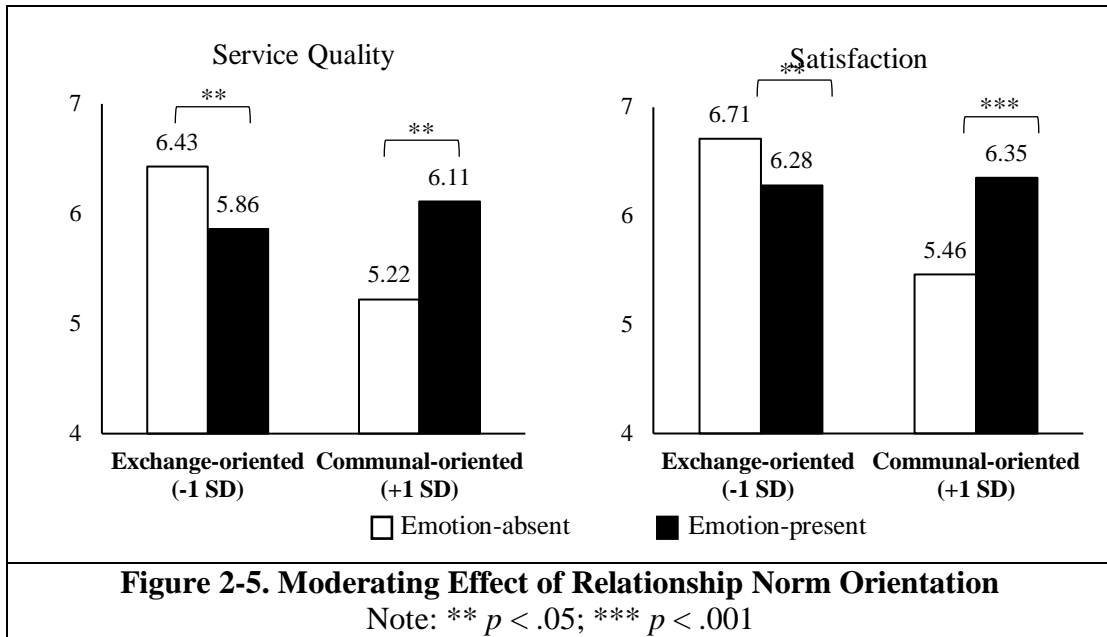
2.5.2 Results

We used the responses from 88 subjects who passed both attention checks. Analysis of the manipulation check for emotional intensity revealed that participants perceived the emotion-present chatbot as more emotionally intense than the emotion-absent chatbot ($M_{present} = 4.22$ vs. $M_{absent} = 2.86$, $SDs = 1.27$ and 1.39 , $t(86) = 4.791$, $p < .001$). Therefore, this manipulation was deemed successful.

To test the moderation effect proposed in H3, we conducted a one-way ANCOVA with positive emotion as a between-subjects factor, relationship norm orientation as a continuous moderator, and gender as a covariate. First, replicating the chatbot-related findings from Study 1, we did not find any significant main effect of positive emotion on

perceived service quality ($M_{absent} = 5.98$ versus $M_{present} = 6.02$, $SDs = .93$ and $.94$, $F(1, 83) = .667$, $p = .4$) or satisfaction ($M_{absent} = 6.25$ versus $M_{present} = 6.33$, $SDs = .96$ and $.73$, $F(1, 83) = 1.836$, $p = .2$). Meanwhile, we observed a significant effect of gender on satisfaction, such that females tended to be more satisfied with the service than males ($F(1, 83) = 6.140$, $p = .015$), but not on service quality ($F(1, 83) = 1.426$, $p = .2$).

Most importantly, we discovered that relationship norm orientation significantly moderated the effect of positive emotion on perceived service quality ($F(1, 83) = 12.744$, $p = .001$) and on satisfaction ($F(1, 83) = 14.066$, $p < .001$). In order to probe the pattern of the interaction, we conducted a simple slope analysis and examined the marginal effect of positive emotion at one standard deviation above and below the mean of relationship norm orientation. For exchange-oriented individuals (relationship norm orientation = 1.10, 1 SD below the mean), chatbot-expressed positive emotion has a significant, negative effect on perceived service quality ($\beta = -.57$, $t(86) = -2.12$, $p = .037$) and satisfaction ($\beta = -.44$, $t(86) = -1.88$, $p = .06$). On the other hand, for communal-oriented individuals (relationship norm orientation = 3.95, 1 SD above the mean), chatbot-expressed positive emotion had a significant, positive effect on perceived service quality ($\beta = .89$, $t(86) = 3.04$, $p = .003$) and satisfaction ($\beta = .89$, $t(86) = 3.52$, $p < .001$). Figure 2-5 illustrates the simple slope analyses. Taken together, these results indicate that the effect of positive emotion from a chatbot on service evaluations depends on an individual's relationship norm orientation, thus confirming H3.



2.5.3 Discussion

Study 2 extends our previous findings by revealing the moderating role of a theoretically relevant individual difference variable, relationship norm orientation. Individuals with a communal-oriented norm evaluated a chatbot’s service more positively when the agent expressed positive emotion than when it did not. Conversely, individuals with an exchange-oriented norm evaluated a chatbot’s service more negatively when the agent expressed positive emotion than when it did not. Despite the revelation of the moderating role of relationship norm orientation in this study, we have not explored the underlying mechanisms, which we turn to in the final study.

2.6 Study 3

In Study 3, we delved into the mechanisms proposed in H2a and H2b. Similar to Study 2, we focused only on chatbots and manipulated the presence of positive emotion as a single between-subjects factor. To test the proposed mechanisms, we added new

measures for the subject's felt positive emotion and the extent of expectation-disconfirmation to capture the opposing pathways.

2.6.1 Procedure and Measures

One hundred and eighty-six undergraduate students (93 female) from a U.S. university participated in this study in exchange for course credit. Similar to Study 2, participants were randomly assigned to either the emotion-absent or the emotion-present condition. We used the same predesigned script from Study 1 to vary the presence of positive emotion. The cover story and procedure were similar to those of prior studies. After interacting with the chatbot, participants reported service evaluations, followed by attention checks, mechanism measures, manipulation checks, and individual difference measures of relationship norm orientation.

To measure the mechanisms, we asked participants' felt positive emotions to quantify emotional contagion because measuring one's emotion right after an emotion-invoking stimulus can capture affective transfer (Hasford et al. 2015). We used five items from Pham (1998) to measure participants' felt emotions (e.g., "sad / joyful"). We also measured the extent to which participants confirmed their expectations toward the service agent, using three items from Bhattacharjee (2001). We modified the original items to tailor to our need to capture the specific expectations about the level of emotion expressed by the service agent (e.g., "The level of the chatbot's emotional display was exactly what I expected"). In data analysis, we reversed these items' scores to represent expectation-disconfirmation.

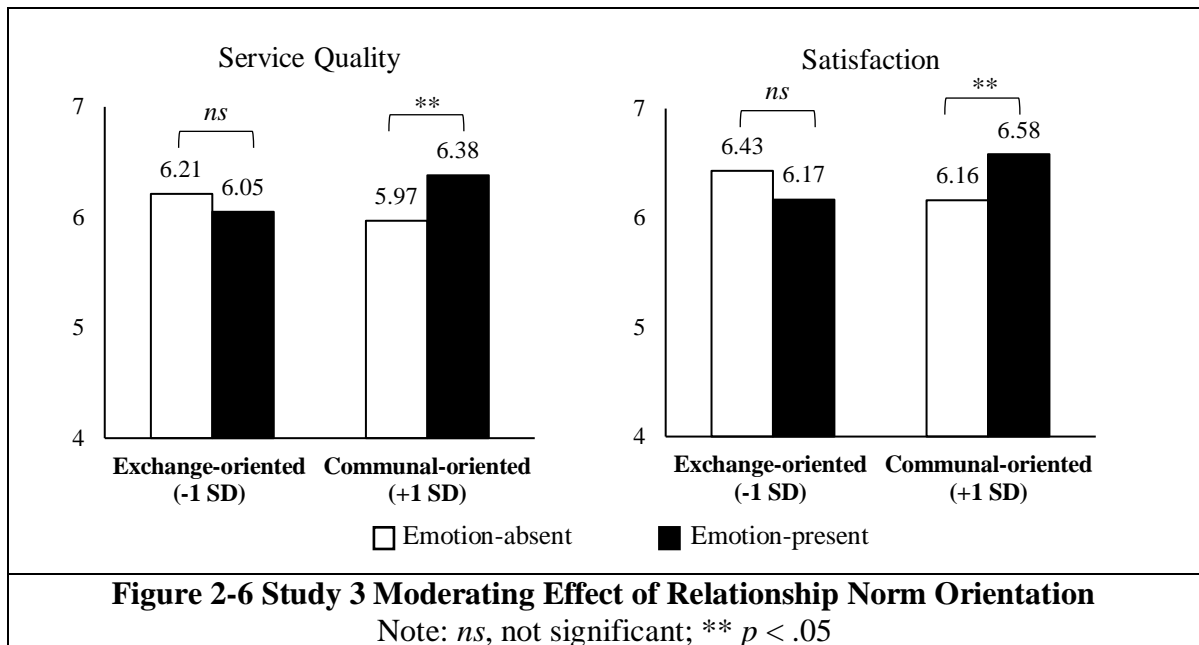
2.6.2 Results

One hundred and seventy-seven subjects passed the attention checks and thus were used in the following analyses. We first analyzed the perceived emotional intensity of the service chatbot as a manipulation check. We found that participants perceived the emotion-present chatbot as more emotionally intense than the emotion-absent chatbot ($M_{absent} = 3.11$ vs. $M_{present} = 5.19$, $SDs = 1.25$ and 1.22 , $t(175) = 11.194$, $p < .001$), indicating that our manipulation of the presence of positive emotions was successful.

Next, we conducted a one-way ANCOVA to replicate prior findings, with positive emotion included as a between-subjects factor, relationship norm orientation as a continuous moderator, and gender as a covariate. Results revealed that AI-expressed positive emotion did not significantly influence perceived service quality ($M_{absent} = 6.13$ vs. $M_{present} = 6.26$, $SDs = 1.02$ and $.82$, $F(1, 172) = .726$, $p = .4$) or satisfaction with the service ($M_{absent} = 6.33$ vs. $M_{present} = 6.44$, $SDs = .93$ and $.75$, $F(1, 172) = .404$, $p = .5$). We did not find any significant effect of gender on service evaluations ($ps = .4$ and $.9$). These results replicated the lack of effect of chatbot-expressed positive emotion in the earlier studies.

We also discovered a significant moderation by relationship norm orientation for the effect of positive emotion on perceived service quality ($F(1, 172) = 3.738$, $p = .055$) and on satisfaction ($F(1, 172) = 6.683$, $p = .011$). Simple slope analysis showed that, for communal-oriented individuals (relationship norm orientation = 4.54, 1 SD above the mean), AI-expressed positive emotion significantly increased perceived service quality ($\beta = .41$, $t(172) = 1.99$, $p = .049$) and satisfaction ($\beta = .43$, $t(172) = 2.30$, $p = .023$). However, for exchange-oriented individuals (relationship norm orientation = 1.67, 1 SD

below the mean), positive emotion did not have any effect on perceived service quality ($\beta = -.16, t(172) = -.76, p = .45$) or on satisfaction ($\beta = -.26, t(172) = -1.37, p = .17$). Figure 2-6 illustrates the simple slope analyses. These results, once again, confirmed H3.

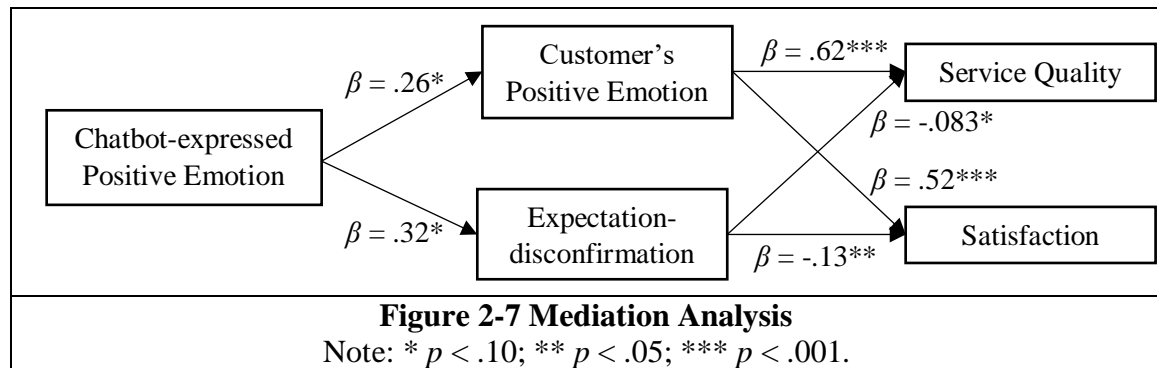


To determine if the effect of chatbot-expressed positive emotion on service evaluations is mediated by emotional contagion and expectation-disconfirmation, we used PROCESS Model 4 (parallel mediation model) with gender as a covariate and a bootstrapped sample of 5,000 (Hayes 2013). Results revealed the lack of total effects and direct effects of chatbot-expressed positive emotion on perceived service quality ($ps = .3$ and 1) and satisfaction ($ps = .4$ and $.9$). However, chatbot-expressed positive emotion increased customers' positive emotions ($\beta = .26, t(175) = 1.737, p = .084$), implying emotional contagion. An increase in felt positive emotion further led to greater perceived service quality ($\beta = .62, t(173) = 11.498, p < .001$) and greater satisfaction ($\beta = .52,$

$t(173) = 10.362, p < .001$). The test of indirect effects revealed a marginally significant, positive indirect effect of chatbot-expressed positive emotion through participants' felt positive emotion on perceived service quality ($\beta = .16, SE = .097, 90\% CI = [.006, .332]$) and on satisfaction ($\beta = .14, SE = .082, 90\% CI = [.007, .277]$). These results provide suggestive evidence for the positive, affective pathway of emotional contagion as hypothesized in H2a.

On the other hand, positive emotion increased expectation-disconfirmation ($\beta = .32, t(175) = 1.859, p = .065$), which further reduced perceived service quality ($\beta = -.083, t(173) = -1.759, p = .080$) and satisfaction ($\beta = -.13, t(173) = -3.074, p = .003$). The test of indirect effects confirmed a marginally significant, negative indirect effect of chatbot-expressed positive emotion through expectation-disconfirmation on satisfaction ($\beta = -.043, SE = .033, 90\% CI = [-.106, -.002]$), but not on perceived service quality ($\beta = -.026, SE = .023, 90\% CI = [-.074, .001]$). These results partially support the negative, cognitive pathway of expectation-disconfirmation proposed in H2b. Overall, our results suggest that the two opposing pathways may explain the lack of total effects of chatbot-

expressed positive emotion on service evaluations.¹ Figure 2-7 shows the summary of the mediation model along with the results.²



¹ We tested an additional model that accounts for the interdependencies of the two mediating processes. We believe that expectation-disconfirmation influencing a customer's felt positive emotion is more likely than vice versa. Expectation-disconfirmation is derived from a cognitive evaluation of comparing the expected and the actual experiences (Oliver 1980). This indicates that the process of expectation-disconfirmation is unlikely to be driven by emotion. On the other hand, expectation-disconfirmation can influence affective judgment (Oliver 1977), and thus may affect positive emotion. After adding a path from expectation-disconfirmation to felt positive emotion, we found this additional path to be significant. However, our findings regarding the parallel model still held. We also tested whether expectation-disconfirmation moderates the effect of chatbot-expressed positive emotion on felt positive emotion, but we did not find any evidence. These findings indicate the robustness of treating the two paths as dual processes and mitigate the concerns of their potential interdependencies.

² We also tested whether relationship norm orientation moderates the two pathways proposed in our hypotheses. We found a significant interaction effect between the presence of positive emotion and relationship norm orientation on expectation-disconfirmation ($F(1,173) = 8.823, p = .003$), such that, for exchange-oriented individuals, the presence of positive emotion significantly increased the extent of expectation-disconfirmation ($M_{absent} = 1.98$ versus $M_{present} = 2.81, F(1, 172) = 10.757, p = .001$), whereas for communal-oriented individuals, such an effect was not observed ($M_{absent} = 2.58$ versus $M_{present} = 2.35, F(1, 172) = .833, p = .4$). These findings suggested a potential reason for the moderating role of relationship norm orientation revealed in Study 2 and Study 3. Meanwhile, we did not find any significant interaction effect on customer's positive emotion.

2.6.3 *Discussions*

Study 3 unraveled how individuals might react to chatbot's expressed positive emotion affectively and cognitively, thus illuminating the potential reasons for the lack of effect of chatbot-expressed positive emotion on service evaluations. Although positive emotion expressed by a chatbot could be transferred to customers through emotional contagion, it violated the customers' expectations toward the chatbot (e.g., machines are not supposed to have emotions). Therefore, the positive affective pathway and negative cognitive pathway may have canceled out each other's effects.

However, our hypotheses regarding the indirect effects obtained only marginal statistical support, as the effects of chatbot-expressed positive emotion on the two mediators were marginally significant. First, the marginally significant indirect effect through expectation disconfirmation is not unexpected. The reason is that based on findings from Studies 2-3, the impact of positive emotion on expectation disconfirmation was revealed to depend on participants' relationship norm orientation. In addition, as revealed in footnote 2, the indirect effect through expectation-disconfirmation was present and significant for exchange-oriented individuals, but such an indirect effect was absent for communal-oriented individuals, exactly as we expected. Thus, the overall indirect effect through expectation disconfirmation is expected to be weak if we disregard this interaction in a pure-mediation model. Second, the marginal support for the indirect effect through emotional contagion may arise from different reasons, including the relatively subtle manipulation of expressed positive emotion, our focus on measuring the valence (but not other aspects) of felt emotion, and the presence of other mechanisms not captured in our dual-pathway model.

2.7 General Discussion

Extending the concept of expectation-disconfirmation (Oliver 1977), we propose that positive emotional expressions of service chatbots may not be as effective as those of human service employees in enhancing customers' service evaluations. Despite customers' increased positive feelings triggered by emotional contagion, there is also a risk of emotion-expressing service chatbots violating customers' expectations, thus weakening the positive effect of positive emotion. We further propose relationship norm orientation as a moderator because it might influence the likelihood of customers' expectation-disconfirmation as customers hold different norms regarding their relationship with service agents. Three experimental studies provided converging evidence for our predictions. Table 2-1 summarizes our findings.

| Table 2-1. Summary of Findings | | | |
|--|-----------|-----------|---------------------|
| | Study 1 | Study 2 | Study 3 |
| H1: <i>The positive effect of positive emotion expressed by an agent on service evaluations depends on the agent's identity, such that the effect is greater for a human agent than for a chatbot.</i> | Supported | - | - |
| H2a (positive mediation through emotional contagion): <i>A chatbot's expressed positive emotion increases a customer's positive emotion, which in turn enhances service evaluations.</i> | - | - | Supported |
| H2b (negative mediation through expectation-disconfirmation): <i>A chatbot's expressed positive emotion increases the extent of expectation-disconfirmation, which in turn reduces service evaluations.</i> | - | - | Partially supported |
| H3 (moderation by relationship norm orientation): <i>For communal-oriented customers, a chatbot's expressed positive emotion has a positive effect on service evaluations, but for exchange-oriented customers, such an effect is non-existent or even reversed.</i> | - | Supported | Supported |
| Note: "-" indicates that the hypothesis was not explored in that study. | | | |

2.7.1 Theoretical Implications

Prior investigations of the effect of emotional expressions by a customer service agent have focused entirely on human employees (Barger and Grandey 2006; Cheshin et al. 2018; Kranzbühler et al. 2020; Li et al. 2018). However, the rapid deployment of chatbots for handling a service encounter calls for extending the study of emotions to service chatbots. Addressing this emerging phenomenon, we discover that the commonly observed positive effect of positive emotion from human service employees is not directly applicable to service chatbots. To the best of our knowledge, this paper is the first in the customer service literature to examine the role of emotion expressed by a service chatbot, illustrating the need to study the unique impacts of chatbot-expressed emotion in service encounters.

This research also contributes to the burgeoning human-AI interaction literature, in which the exploration of interactions between emotional AIs and humans has just started to emerge (Creed et al. 2014; Melo et al. 2013; Stein and Ohler 2017). Most of the research examining factors that influence the effectiveness of human-AI interactions focused on the transparency of an AI's decision-making process and an AI's behaviors that can enhance its social presence or conformity to the norms (Amershi et al. 2019; Velez et al. 2019). On the other hand, emotional AIs have been increasingly popular in automated chatbots or conversational agents, and their expressed emotions can potentially influence various business outcomes. However, the impact of chatbot-expressed emotion, especially in business domains, has not received much attention from scholars studying human-AI interactions. Our research underscores the importance of incorporating emotional factors in future investigations of human-AI interactions.

At a broader level, we supplement the emotion literature by delving into how, when, and why emotions from a chatbot, a new entity, are perceived by the observers. Emotion has been known to serve an important role in interpersonal relationships (Van Kleef et al. 2010). Prior research has extensively documented how various aspects of emotion influence interpersonal outcomes (Lazarus 2006; van Kleef and Côté 2022). As emotion is universally considered a unique capability of human beings, emotion scholars rarely acknowledged the possibility of chatbots or machines expressing emotions. However, the latest technological innovations have enabled chatbots to mimic a human's emotion-related capabilities, raising the need to study emotions in human-AI relationships. Our study addresses this need by discovering the distinct role of emotion expressed by human vs. non-human agents. Thus, this research opens up exciting opportunities for further studies to explore the impact of emotion in novel contexts.

Furthermore, our finding that emotional expressions from a chatbot may trigger emotional contagion extends this well-documented phenomenon beyond interpersonal relationships. Although prior literature suggested various boundary conditions of emotional contagion related to the characteristics of the expresser, the perceiver, and their relationship (Doherty 1997; van der Schalk et al. 2011), we confirm the existence of emotional contagion even when the expresser is a chatbot. This finding also contributes to the information systems literature on emotional contagion by supplementing prior findings on how emotional contagion may occur through IT artifacts that lack human presence, such as on social media and via instant messaging (Cheshin et al. 2011; Ferrara and Yang 2015; Goldenberg and Gross 2020).

Finally, this paper unravels the underlying mechanisms and a boundary condition for the unique impact of chatbot-expressed positive emotion in customer service. Our findings of expectation-disconfirmation as an underlying pathway contribute to the emotion literature by highlighting the role of expectations in the social impact of emotions when the expresser is not a human. Prior literature has shown that various norms or display rules exist regarding emotional expressions (Ekman et al. 1969; Heise and Calhan 1995). Such norms are also present when communicating with others, and others' emotions are one of the key expectations that have significant impacts on interpersonal outcomes (Burgoon 1993). Our work extends these prior findings by not only providing empirical evidence for the mediating role of expectation-disconfirmation in human-AI interactions, but also suggesting relationship norm orientation as a novel boundary condition.

2.7.2 Practical Implications

This work provides valuable guidance for practitioners who are interested in deploying emotional chatbots in customer service. The argument of an AI chatbot becoming sentient has evoked a contentious debate not only about whether the argument is true, but also about the benefits and costs of deploying AIs (The Economist 2022). Service chatbots can save costs—both economic costs and emotional labor of human employees—and streamline firm-customer interactions. However, one of the primary goals of customer service is to maximize customers' service evaluations through their experience and interaction with a service agent. Our findings suggest that the positive effect of expressing positive emotion on service evaluations may not materialize when

the source of the emotion is not a human. Practitioners should be cautious about the unique impact of equipping chatbots with emotion-expressing capabilities.

In addition, our findings indicate that a chatbot expressing positive emotion is beneficial when customers expect a communal relationship, but such a beneficial effect may not exist or even backfire when they expect an exchange relationship from the interaction. Companies can design emotional chatbots in such a way that they are context-aware and express positive emotion only when the expression effectively facilitates service outcomes. For example, they may benefit from switching on or off the emotion-expressing capabilities of chatbots based on the type of customers that could be determined through past communication histories. Alternatively, companies can selectively deploy emotion-expressing chatbots based on the nature of their tasks because different tasks may activate different relationship norms. For instance, chatbots dealing with personalized tasks (activating a communal-oriented relationship norm) might benefit by expressing positive emotion, whereas chatbots dealing with more standardized tasks (activating an exchange-oriented norm) might not. Companies may also set up a more communal environment beforehand to nudge customers' expectations in such a way that can reduce their expectation disconfirmation when encountering emotional expressions of a chatbot.

2.7.3 Limitations and Future Research

Several opportunities present themselves for future research. First, our findings for the moderating role of relationship norm orientation can be extended to various avenues. For instance, researchers can examine how customers' norms toward their relationship with a brand (Aggarwal 2004) can influence the impact of chatbot-expressed emotion. A brand

that oversees close interactions with customers and holds a communal relationship (e.g., in healthcare and education markets) may benefit from chatbot-expressed emotion. However, a brand with a pure exchange relationship (e.g., in finance markets) may not witness such a beneficial impact. In addition to relationship norm orientation, future research can also explore other factors that may vary the impact of chatbot-expressed emotion on customers' expectations and norms during a service interaction, such as price, culture, etc.

Second, our manipulation of emotional intensity is restricted to emotional phrases that are expressed normally or appropriately because companies are unlikely to configure chatbots to express extremely intense emotion. Still, varying emotional intensity at a more granular level may yield interesting findings not uncovered in this research. Furthermore, emotional intensity can be manipulated through various vocal qualities (Murray and Arnott 1993). As voice-based AIs are another emerging trend in both personal lives (e.g., virtual assistants such as Apple's "Siri" and Amazon's "Alexa") and customer service interactions (during phone calls), future research can look into the impact of emotions expressed through the voice.

Third, our proposed theoretical model does not address the interdependencies of affective and cognitive processes. Due to the complex relationship between affect and cognition (Izard 2011; Phelps 2006), it is likely for our two proposed mechanisms to influence each other. Although this work provides suggestive evidence for our parallel model after accounting for possible interdependencies (see footnote 1), future research can attempt to disentangle affective and cognitive processing more clearly.

Fourth, in addition to relationship norm orientation, other boundary conditions for our proposed mechanisms are worthy of further exploration. Because the likelihood and extent of the emotional contagion process in human relationships depend on the expresser, the perceiver, and the relationship between the two, it is also possible that boundary conditions exist for emotional contagion between a chatbot and a human. For instance, emotional contagion may be stronger for those individuals who have more experience with chatbots or feel more attached to them. Furthermore, the expectation-disconfirmation process may depend on when and how expectations are formed. Whereas our studies disclosed the chatbot's identity before the interaction, a disclosure during or after the interaction may lead to different expectations toward the agent, which can, in turn, influence the extent of expectation-disconfirmation and customers' reactions to the agent's emotional expression.

Lastly, emotion is a complex concept that comprises various aspects, such as other dimensions (e.g., valence) and discrete emotions. The ability of a chatbot to express emotion has just started to emerge, and further research into other aspects of emotional expressions can provide additional insights into the best ways of deploying emotionally intelligent chatbots. For example, chatbots may empathize with customers' concerns by expressing sadness or responding to customers' anger in an apologetic manner. Delving into other emotions can help draw a comprehensive picture of the unique impact of chatbot-expressed emotions. The emotion used in our work is also fixed to be appropriate because we primarily investigate the unique impact of emotion expressed by a chatbot rather than a human. Chatbots may be prone to errors or express irrelevant emotions, so exploring the consequences of inappropriate emotional expressions can have significant

implications. Our work opens up exciting opportunities for future research to look into the role of emotion in this nascent but essential area.

2.8 Conclusion

Considering the recent trend in the rapid deployment of chatbots across various industries and the growing capabilities of emotional chatbots, this research points to the importance of studying the unique impact of chatbot-expressed emotion. Our paper provides experimental evidence that the emotional expressions of a service chatbot have a distinct impact on customers' evaluations of service outcomes compared to those of a human agent. We also reveal a novel individual-difference variable, relationship norm orientation, further enriching our theoretical framework. We believe this work represents an initial step into a nascent yet critical area of human-AI interactions. We anticipate future research to further expand our understanding of the role of a chatbot's emotional expressions in diverse contexts.

CHAPTER 3. CHATBOT EMPATHY IN CUSTOMER SERVICE: WHEN IT WORKS AND WHEN IT BACKFIRES

3.1 Introduction

The effective deployment of chatbots in customer service has been an interest of both researchers and practitioners. As artificial intelligence (AI) and natural language processing (NLP) technologies advance rapidly in the past decade, the focus of chatbot development has been to engender a natural conversation that emulates human-to-human conversations. More recently, the rise of emotional intelligence technology has enabled not only emotion-expressing chatbots, but also emotionally responsive chatbots. These emotionally responsive chatbots first detect and recognize users' affective states from various cues (such as facial expressions and linguistic cues), and then they can generate and express an adequate response, such as empathy (Prendinger and Ishizuka 2005). Emotionally responsive chatbots are already prevalent in domains requiring emotional support, such as e-learning or healthcare, and studies in these domains have started to look into the implications of equipping chatbots with the capability of expressing empathy (Guo and Goh 2015; Gwo-Dong et al. 2012; Inkster et al. 2018; Morris et al. 2018).

Our focus is on the impact of chatbot-expressed empathy in customer service. Empathy refers to one's action of understanding and sharing another person's affective states, thus having the same emotional experience as the other (de Vignemont and Singer 2006). As an inter-personal phenomenon, empathy not only arises from inter-personal interactions, but it can also be expressed through various cues (Håkansson and Montgomery 2003; Olson 1995). The experience and subsequent expression of empathy

can facilitate social communication and affect interpersonal outcomes (de Vignemont and Singer 2006; Duan and Hill 1996). In the traditional service industry, emotional responsiveness, especially empathy, is also an essential capability of human employees (Parasuraman et al. 1985). Thus, empathic employees are likely to lead to successful service delivery due to their tendency to engage in customer-oriented behaviors (Aggarwal et al. 2005; Ahearne et al. 2007; Iglesias et al. 2019; Stock and Hoyer 2005; Wieseke et al. 2012). Recognizing the importance of empathy during a service interaction, service practitioners have started to deploy empathic machines, especially in the hospitality industry (de Kervenoael et al. 2020). The application of empathic chatbots is likely to expand as well because of the rapid adoption of chatbots in customer service and their potential strength in forming a relationship with customers (Huang and Rust 2021).

The deployment of empathic chatbots is based on the premise that empathy during human-AI interactions would be similarly beneficial. However, little research has empirically tested whether the benefit indeed persists in chatbot-driven service interactions. Some emerging studies have started to look into the role of empathy in human-AI interactions, but their focus has been confined to customers' perceived empathy of anthropomorphized chatbots rather than the impact of chatbot-expressed empathy (de Kervenoael et al. 2020; Luo et al. 2019; Pelau et al. 2021). Or, empathic response has been merely used as one of the cues for anthropomorphizing chatbots rather than being a primary focus (Adam et al. 2021). Given the recent debate about the emergence of a 'sentient' AI chatbot and the need to study how people react to the

emotional capabilities of an AI (Cosmo 2022), more investigations are needed to explore the promise of empathic chatbots.

In this paper, we aim to examine the impact of chatbot-expressed empathy on service evaluations. Building on the social perception literature, we argue that empathic responses from a chatbot can influence customers' perceptions of the chatbot's warmth and competence, which in turn influence service evaluations. More importantly, we propose that the effect of chatbot-expressed empathy depends on the source of customers' negative emotions. Specifically, when chatbots express empathy in response to customers' negative emotions because of the consumption experience, the empathy will enhance the perception of warmth (but not competence), thus enhancing service evaluations. On the other hand, when conversational breakdowns occur due to a chatbot failure, chatbot-expressed empathy may not only fail to enhance perceived warmth but also undermine perceived competence, thus hurting service evaluations.

To test these predictions, we conduct two laboratory experiments in which participants engaged in a hypothetical scenario about customer service and interacted with a chatbot to resolve a service-related issue. We find partial supports for our proposed hypotheses. Our theoretical framework and findings provide several implications. First, this paper is among the first to investigate the impact of chatbot-expressed empathy on service evaluations. Our findings extend the impact of expressed empathy beyond human-driven service interactions. Second, we enhance the empathy literature by examining the role of empathy expressed by a non-human entity. We shed light not only on the impact of chatbot-expressed empathy, but also on a boundary condition that drives the impact in opposing directions. Third, this work contributes to the chatbot failure literature by

questioning the conventional wisdom that empathy expression can be a remedy for chatbot failures. Practical implications for the deployment of chatbots with emotional capabilities are also provided.

3.2 Theoretical Development

3.2.1 The role of expressed empathy in customer service

Due to the complicated nature of empathy, there is no consensus about its definition in prior literature. The most recent effort to conceptualize empathy defines it as an observer's affective response that can be automatically elicited and results in an affective state congruent to the observer's perception and understanding of the expresser's affective state (Cuff et al. 2016). While empathy is sometimes used interchangeably or confused with sympathy, perspective-taking, or emotional contagion, these concepts are fundamentally different from each other (de Vignemont and Singer 2006; Wispé 1986).

As the basis of human interactions, empathy can facilitate social communication and affect interpersonal outcomes (de Vignemont and Singer 2006; Duan and Hill 1996). In particular, the *expression* of empathy is a fundamental component of the entire empathic process because it enables a person who expresses his or her affective state to perceive an empathizer's empathy (Barrett-Lennard 1981). Indeed, the expression of empathy facilitates intergroup reconciliations during conflicts or negotiations, and it also begets forgiveness in victim-perpetrator interactions (Nadler and Liviatan 2006; Shnabel and Nadler 2008). Expressing empathy is especially important in counseling, nursing, and education contexts because it has critical implications for the well-being of patients and pedagogical outcomes (Elliott et al. 2011; Warren 2018).

Meanwhile, empathy has also been regarded as a crucial element during service interactions. Empathy is one of the five dimensions of service, which can drive customers' perceptions of service (Parasuraman et al. 1985; Parasuraman et al. 1991). Thus, having and expressing empathy has become an essential capability of human service employees, especially toward customers' negative emotional states that are the norm in service encounters. Indeed, empathic employees tend to perform better in service deliveries because they are more likely to address customer needs and desires, be helpful, and engage in customer-oriented behaviors (Aggarwal et al. 2005; Ahearne et al. 2007; Iglesias et al. 2019; Stock and Hoyer 2005). The expression of empathy from employees can also elicit reciprocal actions from customers, leading to mutually supportive behaviors (Wieseke et al. 2012). Accordingly, showing empathy to customers has long been advocated as a major strategy for service recovery (Bell and Zemke 1987). These beneficial consequences of service employees showing empathy toward customers pose an intriguing question: will such benefits persist if empathy is expressed by service chatbots that are increasingly replacing human employees? As customers' service evaluations are likely influenced by expressed empathy, it is crucial to uncover the impact of chatbot-expressed empathy.

3.2.2 Empathy-expressing chatbots in customer service

The prevalence of chatbots in customer service has led to the emergence of chatbot-related research in recent years. Existing research has explored how customers' perceptions of chatbots and services can be influenced by various characteristics of chatbots, such as the timing of identity disclosure (Luo et al. 2019) and anthropomorphic or social cues (Crollic et al. 2022b; Schanke et al. 2021b; Verhagen et al. 2014).

Meanwhile, despite the essential role of empathy expressions in human-driven service interactions, research on the impact of chatbot-expressed empathy is nascent. Some recent studies have examined *perceived* empathy as a mediator to explain customers' evaluations of service chatbots and service outcomes. For instance, Luo et al. (2019) showed that the disclosing chatbot identity leads to negative service outcomes because chatbots tend to be perceived as less empathetic than human employees. de Kervenoael et al. (2020) also found that customers in the hospitality industry are more receptive to empathic social robots. On the other hand, responding empathically has been used as one of several anthropomorphizing cues that can influence the perceptions of interaction quality and other downstream consequences (Castelo 2019; Pelau et al. 2021). Although these studies illustrate the importance of perceiving empathy from service chatbots or empathy's effectiveness for anthropomorphizing chatbots, we know little about how and when chatbots' explicit expression of empathy can influence service outcomes.

Empathy-expressing chatbots have been studied in non-business contexts, but the findings are mixed. Empathic chatbots could be beneficial in specific contexts where people need emotional support, such as for socially excluded people or in healthcare settings (de Gennaro et al. 2020; Liu and Sundar 2018; Meng and Dai 2021; Morris et al. 2018). However, the recognition of users' emotions and empathy expressions are often perceived as creepy and invasive due to the uncanny valley (a sudden downturn in the affinity toward an anthropomorphized nonhuman entity) and users' perceptions that they have lost autonomy or control over the machine (Andalibi and Buss 2020; Stein and Ohler 2017). These contradictory results suggest that a chatbot's ability to express

empathy may not always be desirable in non-business settings, and there is a need to elucidate its impact in business settings.

3.2.3 Chatbot-expressed empathy, chatbot perception, and service evaluation

We first explore the role of chatbot-expressed empathy during a typical service encounter, where empathy is expressed toward a customer's (usually negative) emotion that has been evoked due to service issues. To do so, we build on the warmth-competence distinction in the social perception literature. In a social relationship, people evaluate others along the two broad dimensions of warmth and competence (Fiske et al. 2007). Warmth tends to be associated with traits that portray an individual's intent (e.g., friendliness, sincerity), whereas competence tends to be associated with traits that portray an individual's ability (e.g., efficacy, capability). The perceptions of warmth and competence are regarded as the most important factors determining one's judgment of others and corresponding behavioral and relationship outcomes (Cuddy et al. 2008). Although warmth and competence perceptions have been primarily applied to human relationships, they can also be applied to the relationship between humans and machines. Computers-are-social-actors (CASA) paradigm posits that individuals' interactions with computers are fundamentally social, and they can result in social responses or behaviors such as reciprocity and the application of social norms (Nass et al. 1994). Similarly, customers interacting with a service chatbot may apply an evaluative process frequently applied to humans, namely evaluating its warmth and competence.

There has been extensive evidence about the association between empathy and warmth from the prior literature on interpersonal relationships. One's empathy conveys that he or she is understanding and supporting the other, which is a defining trait of warmth (Cuddy

et al. 2008; Davis and Oathout 1987). In customer service, empathy from a human service employee also signals care and attention towards customers (Parasuraman et al. 1991), thus enhancing customers' perception of the employee's warmth. We argue that empathy from a service chatbot can also increase customers' perception of the chatbot's warmth. Empathy is related to emotional responsiveness, which is deemed as an attribute unique to humans (Haslam 2006). Thus, enabling chatbots to express empathy can lead to anthropomorphism, which is imbuing a human characteristic to non-humans (Epley et al. 2007). Several research studies have shown that anthropomorphizing entities, such as brand, robot, and money, enhance people's perception of their warmth (Chandler and Schwarz 2010; Kim et al. 2019; Zhou et al. 2018). Similarly, a chatbot's expression of empathy, an anthropomorphic quality, can increase the perception of the chatbot's warmth.

On the other hand, a chatbot's expression of empathy is less likely to have an impact on the perception of the chatbot's competence. As mentioned before, competence captures the traits of an individual's ability. Because empathy is an essential quality of human service employees (Parasuraman et al. 1991), and, in a broader sense, empathy is regarded as a necessary skill for maintaining relationships (Davis and Oathout 1987), empathy can influence the perception of *human* employees' competence. In contrast, empathy is not an essential quality of chatbots because people do not expect machines to experience any emotion (Gray and Wegner 2012). Since customers do not deem empathy as a necessary ability for a chatbot, the chatbot's empathy expression should not influence the perception of the chatbot's competence. Therefore, we propose the following:

Hypothesis 1: *When customers are emotional because of service-related issues, a) chatbot-expressed empathy increases a customer's perception of the chatbot's warmth, but b) it has no effect on perceived competence.*

When evaluating a service, the perception of service quality is a crucial component as it provides a comprehensive summary of service outcome, interaction, and environment (Brady and Cronin 2001). Because an experience from a service interaction is the basis of customer service evaluation, the performance and attributes of a service provider contribute to the perception of service quality (Parasuraman et al. 1985). In our context, the warmth perception of a service provider (a chatbot) will contribute to the perception of service quality. Specifically, the warmth perception tends to be linked to positive attitudes toward the target (Cuddy et al. 2008). Such positive attitudes toward a service provider (a chatbot) triggered by increased warmth perception will enhance the perception of service quality.

Meanwhile, another essential evaluation metric for service is satisfaction with service (Oliva et al. 1992). The perception of service quality and satisfaction with service have been shown to jointly influence various downstream consequences (Cronin et al. 2000; Gotlieb et al. 1994). In particular, the perception of service quality can predict satisfaction with service because satisfaction is determined by the extent to which service quality meets customers' expectations (Anderson and Sullivan 1993; Gotlieb et al. 1994). Thus, the change in service quality perception will affect service satisfaction. In sum, we present the following hypothesis:

Hypothesis 2: *Greater perception of a chatbot's warmth a) enhances a customer's perception of service quality, which in turn b) leads to higher satisfaction with service.*

3.2.4 Chatbot-expressed empathy after conversational breakdowns

Based on the prior findings related to empathy-expressing chatbots in non-business settings (Andalibi and Buss 2020; Stein and Ohler 2017), chatbot-expressed empathy may not always be beneficial. For instance, when a chatbot's competence has already been undermined and thus, customers feel negative emotions in response to that, empathy expression may have a backfiring effect. The most common instance of a chatbot's competence being undermined is a conversational breakdown resulting from the chatbot's inability to understand users' messages.

Conversational breakdowns during the interaction with chatbots are a common phenomenon due to the imperfect natural language processing technology and increasing sophistication in users' requests (Ashktorab et al. 2019; Simonite 2017). One of the primary reasons for conversational breakdowns is a chatbot's failure to decipher a user's input message (Ashktorab et al. 2019). Customers will associate such failure with the chatbot's competence because fluent and efficient service delivery is regarded as a primary task of chatbots (Meuter et al. 2000).

Recognizing the prevalence and negative consequences of conversational breakdowns caused by chatbots, recent research has examined recovery strategies after the breakdowns, such as making an apology, providing explanations for the breakdowns, and admitting the chatbot's weakness (Benner et al. 2021; Choi et al. 2020). These recovery strategies fall into the category of emotional recovery, which focuses on recovering intangible resources of customers (e.g., emotion, self-esteem, sense of control) (Bitner et al. 1990). Empathy expression may also be considered as an emotional recovery strategy because the expression of empathy recognizes the suffering of a customer and aims to

mitigate the following negative emotions (Nadler and Liviatan 2006). Indeed, empathy expression has been one of the most effective recovery strategies deployed by human employees after a service failure (Wieseke et al. 2012). Due to its effectiveness in human-driven service interactions, empathy expression has also been speculated as a potential remedy for the failures in chatbot-driven service interactions (Benner et al. 2021).

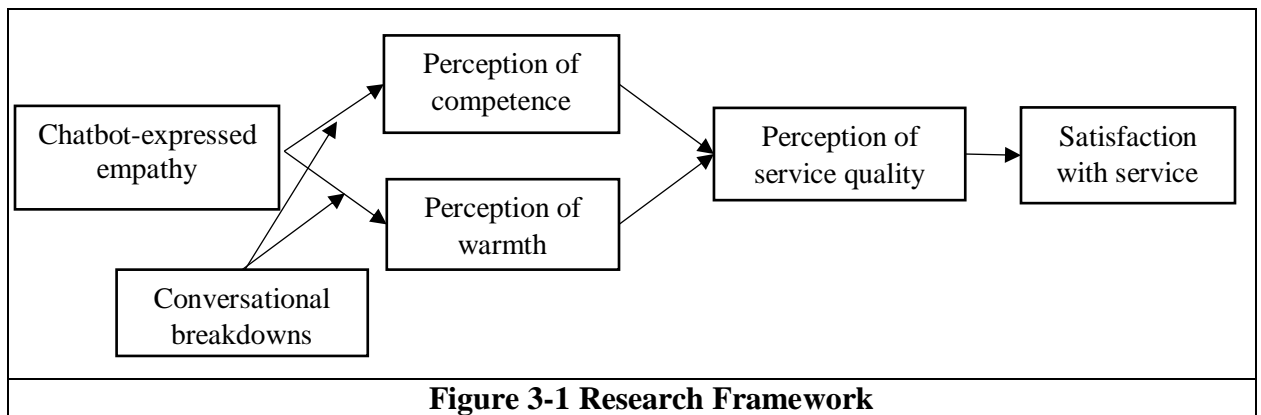
However, a chatbot's expression of empathy after conversational breakdowns can be viewed as a cover-up for its incompetence due to the enhanced perception of inauthenticity. The inauthenticity of chatbot-expressed empathy can be driven by the conventional wisdom that chatbots lack emotional capabilities (Gray and Wegner 2012). The perception of such inauthenticity will be especially high when customers doubt the real motive behind empathy expression (e.g., concealing the chatbot's incompetence). Then, the inauthenticity of empathy can be used as a piece of information when customers make inferences about the empathy expresser's attributes (Glikson et al. 2018). Accordingly, empathy expression, in this case, may not only fail to enhance perceived warmth but may also backfire by further undermining the perception of the chatbot's competence. Thus, we propose the following:

Hypothesis 3: *After conversational breakdowns, a) chatbot-expressed empathy decreases a customer's perception of the chatbot's competence, but b) it has no effect on perceived warmth.*

The judgment of competence for a service chatbot should also have direct implications for service evaluations. A decrease in perceived competence of the chatbot should be regarded as a lack of ability to resolve a service issue and further insinuate the failure of successful service delivery. Indeed, prior literature in customer service and marketing has

found consistent evidence for the impact of the perceived competence of a service employee on service evaluations (Li et al. 2018; Scott et al. 2013; Thompson and Ince 2013). Similarly, we argue that reduced perceived competence of a service chatbot will create a negative perception of the service, thus impairing the perception of service quality and subsequent satisfaction with service. Figure 3-1 summarizes our theoretical framework.

***Hypothesis 4:** Lower perception of a chatbot’s competence a) hurts a customer’s perception of service quality, which in turn b) leads to lower satisfaction with service.*



3.3 Study 1

In this study, we aim to first illuminate the effect of chatbot-expressed empathy on service evaluations during a typical service interaction where customers may get emotional because of service-related issues. To do so, we manipulated the presence of empathy expression in a between-subjects design. During the study, participants interacted with a service chatbot to resolve a hypothetical service issue and answered questions about their perceptions toward the service and the chatbot.

3.3.1 Stimulus Materials

Similar to the studies from Chapter 2, we used a predesigned script to isolate the effect of chatbot-expressed empathy and minimize the influence of potential confounding conversational elements. The predesigned script enabled participants across conditions to receive the same message from the chatbot, except for the presence of empathy expression. The messages in the script were similarly worded as in the script from the studies in Chapter 2. The final script included four chatbot messages, each including two to four sentences.

Based on the conceptualization of empathy (Cuff et al. 2016), we manipulated the presence of empathy expression by inserting several sentences in which the chatbot expresses its experience of the emotion a participant may feel (e.g., “I really feel your frustration”). Whereas those in the empathy-absent condition did not receive any message expressing empathy, those in the empathy-present condition received messages including empathy expressions. Specifically, the chatbot expressed empathy after the participants described a service issue they were encountering and after the chatbot figured out why the issue had occurred. The entire chat script can be found in Table 3-1. Furthermore, to ensure that participants know they are interacting with a chatbot, we displayed an introductory message of “being connected to a bot created by the customer service department” before the chat started. We also showed a robot icon along with the introductory message and next to each chatbot message.

| Table 3-1 Predesigned chat scripts for Study 1 | |
|---|---|
| Empathy-absent | Empathy-present |
| <p>Hello. This is Taylor, and I am a bot created by the customer service department. I am handling your request today. What brings you here?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>I can help you with that. Could you tell me your order number below?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>Alright. Please give me a moment.</p> <p>I found out that the driver who was assigned to your order did not show up. I found another driver who can pick up your food and deliver it in about thirty minutes. Would you like to proceed with your order, or cancel it and get a refund?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>I have processed your request. Please contact us again if you need further assistance. Bye.</p> | <p>Hello. This is Taylor, and I am a bot created by the customer service department. I am handling your request today. What brings you here?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>I really feel your frustration. I can help you with that. Could you tell me your order number below?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>Alright. Please give me a moment.</p> <p>I found out that the driver who was assigned to your order did not show up. I genuinely feel your disappointment. I found another driver who can pick up your food and deliver it in about thirty minutes. Would you like to proceed with your order, or cancel it and get a refund?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>I have processed your request. Please contact us again if you need further assistance. Bye.</p> |

3.3.2 Procedure and Measures

One hundred and eleven subjects (51 female) from a U.S. university participated in the study in exchange for course credit. Participants were randomly assigned to either the empathy-absent or the empathy-present condition. The cover story described a hypothetical but realistic service issue that can be encountered in online food delivery services. We chose an online food delivery service as the setting of our scenario for two reasons. First, a virtual chat with a chatbot is commonly deployed to communicate with customers about issues related to delivery services. Second, the setting enables us to easily evoke emotions (in our case, negative emotions) from the participants. A service agent's expression of empathy (even when the agent is a human) would be natural only if

a customer feels certain emotions, and then the agent shares the same emotions. Thus, we chose a setting where a service issue can naturally and easily evoke negative emotions from the participants. For the service issue, we used the most common issue that occurs in online food delivery services: delivery delay. The scenario described a situation in which the participant desperately wanted food and thus, placed a delivery order, but the food had not arrived after waiting for a long time. Participants were asked to chat with a service chatbot and resolve the delivery issue. The detailed cover story can be found in Appendix D. After the cover story, participants saw the introductory message that they were being connected to a bot created by the customer service department. The chat started on a new screen. The rest of the chat process was similar to those from Chapter 2, with only exception that participants did not go through multiple screens to chat with the chatbot. Instead, we created an automated chat interface, in which participants could interact with the chatbot in a single screen.

After the chat ended, the participants answered questions related to their perception of the service and the chatbot. To measure perceived service quality and satisfaction with service, we adapted existing scales from the prior customer service literature (Cronin et al. 2000). Perceived service quality was measured using three items (e.g., “poor / excellent”). Satisfaction with the service was measured using three questions (e.g., “Overall, how satisfied or dissatisfied did your experience with the service agent leave you feeling? extremely dissatisfied / extremely satisfied”).

Then, the participants responded to two attention check questions about the content of the service issue and the solution provided by the chatbot. The responses to these questions were later used for ensuring subject quality. To measure the participants’

perceptions of the chatbot's competence and warmth, we presented a list of common characteristics people have (six related to competence and six related to warmth) and asked the participants to evaluate the chatbot based on each characteristic (e.g., "not at all capable / extremely capable"; "not at all warm / extremely warm") (Fiske et al. 2007).

To verify the effectiveness of our empathy expression manipulation, we used three items from prior literature on the perceived empathic concern (e.g., "the chatbot understands my feeling... strongly disagree / strongly agree") (Goldstein et al. 2014; Toi and Batson 1982). All these questions were measured on seven-point scales. All measurement items are listed in Appendix E.

3.3.3 Results

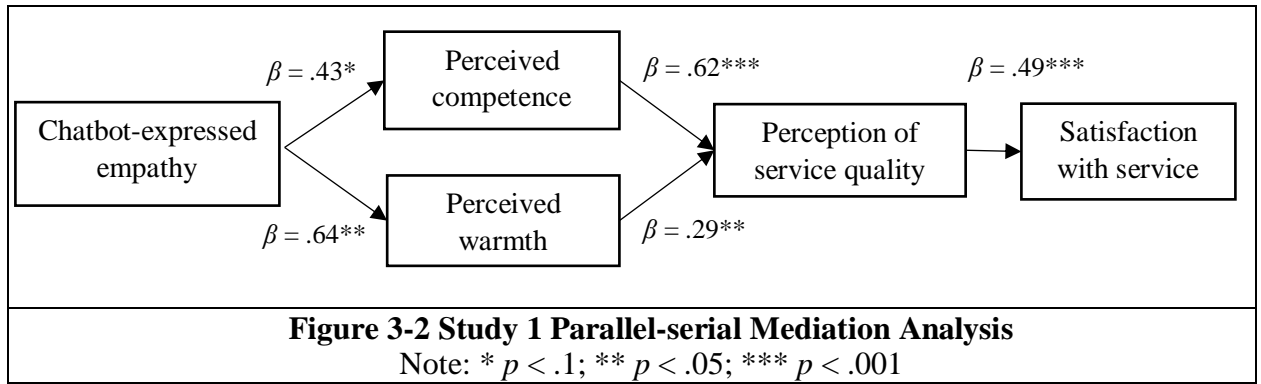
Ninety-five subjects passed the two attention checks and thus were used in the following analyses. We first confirmed the success of our manipulation by finding that the participants perceived greater empathy from the empathy-present chatbot compared to the empathy-absent chatbot ($M_{absent} = 3.33$ vs. $M_{present} = 5.41$, $SDs = 1.74$ and 1.38 , $t(93) = 6.45$, $p < .001$).

Next, to explore the main effect of chatbot-expressed empathy, we conducted a one-way ANOVA with the presence of expressed empathy included as a between-subjects factor. Results showed that chatbot-expressed empathy had a marginally significant, positive effect on perceived service quality ($M_{absent} = 5.26$ vs. $M_{present} = 5.78$, $SDs = 1.55$ and 1.22 , $F(1, 93) = 3.253$, $p = .075$) and satisfaction with the service ($M_{absent} = 5.36$ vs. $M_{present} = 5.83$, $SDs = 1.54$ and 1.15 , $F(1, 93) = 2.843$, $p = .095$).

To test if the effect of chatbot-expressed empathy on service evaluations is mediated by the perception of the chatbot's warmth, but not competence, as proposed in

Hypotheses 1 and 2, we used a custom model from PROCESS macro with a bootstrapped sample of 5,000 (Hayes 2013). The model included chatbot-expressed empathy as the independent variable, perceptions of the chatbot's competence and warmth as parallel, first-level mediators, perceived service quality as the second-level mediator, and satisfaction with service as the dependent variable. First, results revealed a significant, positive effect of chatbot-expressed empathy on the perception of the chatbot's warmth ($\beta = .64, t(94) = 2.473, p = .015$) and a marginally significant, positive effect on the perception of the chatbot's competence ($\beta = .43, t(94) = 1.761, p = .082$). These results provide support for H1a but not H1b; still, we observe a stronger effect of chatbot-expressed empathy on perceived warmth than that on perceived competence. Then, we found that increased perceptions of both competence and warmth enhanced perceived service quality ($\beta = .62, t(94) = 4.025, p < .001; \beta = .29, t(94) = 1.989, p = .050$). We also discovered that greater perceived service quality leads to higher satisfaction ($\beta = .49, t(94) = 5.911, p < .001$). These results support Hypothesis 2.

Most importantly, the test of indirect effects revealed a significant, positive indirect effect of chatbot-expressed empathy through the participants' perception of the chatbot's warmth and service quality on satisfaction ($\beta = .091, SE = .057, 95\% CI = [.005, .222]$). Meanwhile, we found a marginal support for the indirect effect through the participants' perception of the chatbot's competence and service quality on satisfaction ($\beta = .13, SE = .099, 90\% CI = [.009, .326]$). Overall, these results provide a partial support for our theorizing, such that chatbot-expressed empathy affects customers' service evaluations by enhancing their perception of the chatbot's warmth, but less so through the chatbot's competence. Figure 3-2 summarizes our findings.



3.3.4 Discussion

In this study, we examined the role of empathy expressed by a service chatbot during a general service interaction. While we observed the main, positive effect of chatbot-expressed empathy on service evaluations and the positive indirect effect through perceived warmth, confirming a part of our hypotheses, we also observed the marginally significant, positive indirect effect through perceived competence. We initially argued that displaying empathy generally is not an expected capability for chatbots (Gray et al. 2007) and thus would not necessarily enhance the perception of their competence. However, based on our findings, it is possible that displaying empathy is regarded as one of the chatbots' capabilities. This could be because, for customers having a negative consumption experience, emotional support from service agents (regardless of their identity) is deemed necessary. Thus, chatbots expressing empathy might have satisfied such a need, which enhanced the perception of competence.

However, it is possible that chatbot-expressed empathy may have a backfiring effect in certain cases where a chatbot's competence has deteriorated. For instance, when a chatbot expresses empathy after conversational breakdowns due to chatbot failures, its expression of empathy may actually backfire and reduce the competence perception because

customers may believe that the chatbot is trying to cover up its incompetence and the expressed empathy is ingenuine. We investigate this possibility in the next study.

3.4 Study 2

This study aims to examine the role of chatbot-expressed empathy when the chatbot's competence deteriorates. The most common instance of the chatbot's incompetence is a conversational breakdown due to the chatbot's inability to understand a user's message (Ashktorab et al. 2019). Thus, in this study, we presented a scenario in which conversational breakdowns occurred during the interaction with a service chatbot and manipulated the presence of empathy expression. After the interaction, participants reported their perception of the service and the chatbot.

3.4.1 Stimulus Materials, Procedure, and Measures

One hundred and twelve subjects (54 female) from a U.S. university participated in the study in exchange for course credit. Similar to Study 1, participants were randomly assigned to either the empathy-absent or the empathy-present condition. Whereas we used a similar cover story and chat script as Study 1, the major differences in this study include the existence of conversational breakdowns and the timing of empathy expression. Conversational breakdowns occurred during the interaction as the chatbot said that it did not understand the participant's message. Participants in every condition encountered a conversational breakdown twice throughout the interaction. After each instance of a conversational breakdown, the chatbot expressed empathy to those in the empathy-present condition. To those in the empathy-absent condition, the chatbot did not express empathy after the conversational breakdown. Then, the participants in both conditions had to rephrase what they had said previously to proceed. The way the chatbot

expressed empathy remained the same as in the prior study. Table 3-2 shows the complete chat script.

After the chat ended, the participants reported their perception of service quality, satisfaction with service, perceptions of the chatbot’s competence and warmth, and perceived empathy as in the prior study.

| Table 3-2 Predesigned chat scripts for Study 2 | |
|--|---|
| Empathy-absent | Empathy-present |
| <p>Hello. This is Taylor, and I am a bot created by the customer service department. I am handling your request today. What brings you here?</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>I do not understand what you said. Can you please try again?</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>I can help you with that. First, could you tell me your order number?</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>Got it. Please allow me few seconds for pulling up your order.</p> <p>I checked your order. There has been a system error, and no driver was assigned to your order. We found a nearest driver, and your food can be picked up within five minutes. What would you like to do next? We can proceed with your order or cancel it.</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>I cannot figure out what your message means. Could you respond to the question again?</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>I will process your request. Please hold on for a moment.</p> <p style="text-align: center;">[Slight delay]</p> | <p>Hello. This is Taylor, and I am a bot created by the customer service department. I am handling your request today. What brings you here?</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>I do not understand what you said. I really feel your frustration for this. Can you please try again?</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>I can help you with that. First, could you tell me your order number?</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>Got it. Please allow me few seconds for pulling up your order.</p> <p>I checked your order. There has been a system error, and no driver was assigned to your order. We found a nearest driver, and your food can be picked up within five minutes. What would you like to do next? We can proceed with your order or cancel it.</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>I cannot figure out what your message means. I feel your irritation because of this. Could you respond to the question again?</p> <p style="text-align: right;"><i>Participant’s message</i></p> <p>I will process your request. Please hold on for a moment.</p> <p style="text-align: center;">[Slight delay]</p> |

| | |
|---|---|
| I have processed your request. Please contact us again if you need further assistance. Bye. | I have processed your request. Please contact us again if you need further assistance. Bye. |
|---|---|

3.4.2 Results

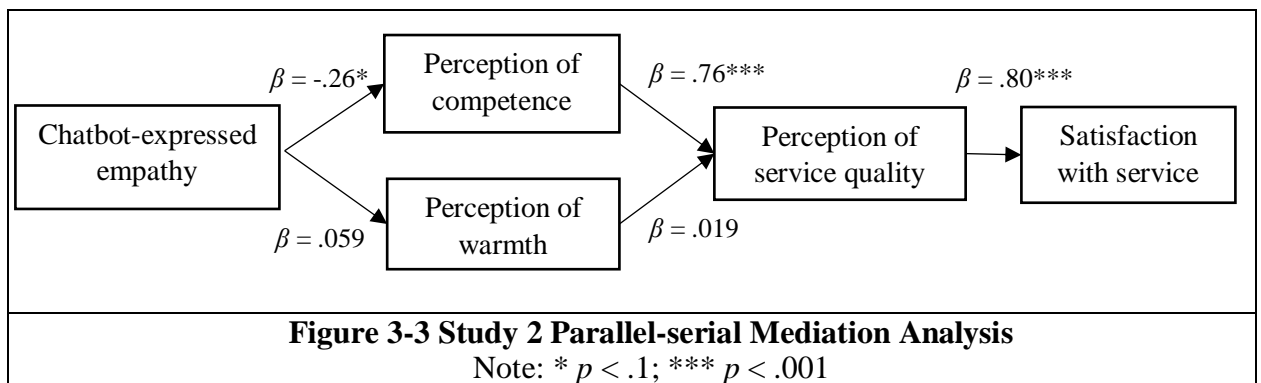
After filtering based on the two attention checks, we obtained a usable sample of 98 subjects. With this sample, we first conducted the manipulation check. We found that those interacting with the empathy-expressing chatbot perceived greater empathy than those interacting with the chatbot that did not express any empathy ($M_{absent} = 2.93$ vs. $M_{present} = 3.54$, $SDs = 1.45$ and 1.73 , $t(96) = 1.90$, $p = .060$). The difference was marginally significant, indicating that our manipulation may not be as strong as we hoped, but it also implies a more conservative test of the hypotheses.

To examine the main effect of chatbot-expressed empathy, we conducted a one-way ANOVA with the presence of expressed empathy included as a between-subjects factor. Contrary to Study 1, results revealed a marginally significant, negative effect of chatbot-expressed empathy on perceived service quality ($M_{absent} = 3.66$ vs. $M_{present} = 3.09$, $SDs = 1.49$ and 1.59 , $F(1, 96) = 3.334$, $p = .071$) and satisfaction with service ($M_{absent} = 4.18$ vs. $M_{present} = 3.65$, $SDs = 1.41$ and 1.66 , $F(1, 96) = 2.843$, $p = .095$).

Hypotheses 3 and 4 argued that the effect of chatbot-expressed empathy on service evaluations is mediated by the perception of the chatbot's competence, but not warmth. To test these hypotheses, we used a custom model from PROCESS macro with a bootstrapped sample of 5,000 (Hayes 2013). We used a similar model as in Study 1. We first discovered a marginally significant negative effect of chatbot-expressed empathy on the perception of the chatbot's competence ($\beta = -.26$, $t(96) = -1.922$, $p = .058$), but no effect on the perception of the chatbot's warmth ($\beta = .059$, $t(96) = .455$, $p = .7$). These

findings confirm Hypothesis 3 by revealing how chatbot-expressed empathy further worsens the perception of the chatbot’s competence, but it does not necessarily enhance the perception of warmth. Then, we found that reduced perception of competence led to lower perception of service quality ($\beta = .76, t(96) = 5.998, p < .001$), which in turn resulted in lower satisfaction ($\beta = .80, t(96) = 11.903, p < .001$). However, we did not find any effect of perceived warmth on perceived service quality ($\beta = .019, t(96) = .137, p = .9$). Thus, Hypothesis 4 is supported.

The test of indirect effects further supplements our findings by showing a marginally significant, negative indirect effect of chatbot-expressed empathy through the participants’ perception of the chatbot’s competence and service quality on satisfaction ($\beta = -.16, SE = .088, 90\% \text{ CI} = [-.318, -.0255]$). In contrast, we did not observe any indirect effect through the participants’ perception of the chatbot’s warmth and service quality on satisfaction ($\beta = .0009, SE = .011, 90\% \text{ CI} = [-.0197, .170]$). The findings altogether substantiate our claim that, when a chatbot expresses empathy after a conversational breakdown, it backfires and decreases the perception of its competence, ultimately hurting service evaluations. Figure 3-3 provides a summary of our findings.



3.4.3 Discussion

This study investigated the impact of chatbot-expressed empathy after conversational breakdowns. We showed that chatbot-expressed empathy hurts service evaluations because it reduces the perception of the chatbot's competence. According to Study 1, the expression of empathy is supposedly beneficial for the perception of the chatbot's warmth. But in the case where the chatbot's competence has already deteriorated to a certain extent, chatbot-expressed empathy no longer influenced the perception of warmth but backfired by further hurting the perception of competence. As argued before, this might be because when the chatbot's competence is in question, customers' perception that a chatbot cannot empathize with them becomes salient, and its empathy expression is deemed to be inauthentic and viewed merely as a cover-up for its incompetence.

3.5 General Discussion

Based on the social perception literature (Fiske et al. 2007), we proposed that chatbot-expressed empathy may be beneficial or harmful depending on service contexts. During a typical service interaction where customers had a negative consumption experience, the chatbot's expression of empathy will enhance not only the perception of the chatbot's warmth, but also the perception of competence. Thus, increased perceived warmth and competence will lead to greater service evaluations. On the other hand, when conversational breakdowns occur due to chatbot failures, the inauthenticity of chatbot-expressed empathy may become salient and give customers the impression that empathy is expressed to cover up its incompetence. This will further undermine the perception of the chatbot's competence, hurting service evaluations. Two experimental studies provide supportive evidence for our hypotheses.

3.5.1 Theoretical Implications

Prior literature on the role of empathy in customer service has been largely confined to human-expressed empathy (Aggarwal et al. 2005; Ahearne et al. 2007; Iglesias et al. 2019; Stock and Hoyer 2005; Wieseke et al. 2012). However, as technology advances have enabled emotionally responsive chatbots, empathy-expressing chatbots are becoming ever relevant. Whereas few research investigated the role of empathy in chatbot-driven service interactions by treating perceived empathy as a mediator or emotional responsiveness as one of the anthropomorphizing cues, we focus on a chatbot's empathy expression and how it may have varying impacts depending on a service context. Our study extends our understanding of how customers perceive the emotional capabilities of a service chatbot and how such emotional capabilities ultimately affect service evaluations.

Our work also enhances the empathy literature by shedding light on the role of empathy expressed by a non-human entity. Empathy is considered an important quality in maintaining social relationships, not only in customer service but also in interpersonal relationships in general (Davis and Oathout 1987). Because empathy is viewed as a unique capability of human beings (Haslam 2006), scholars have rarely acknowledged the possibility of non-human entities expressing empathy. However, the recent rise of emotionally intelligent AIs urges the need to examine the implications of the related technologies equipped with emotional capabilities. We address this need by showing how chatbots' empathy expression in a specific service context can be beneficial, as in the case of human employees, by increasing the perception of warmth. Such findings indicate the applicability of our understanding of the role of empathy expression beyond

interpersonal relationships. Meanwhile, our findings that chatbot-expressed empathy may also backfire after conversational breakdowns, insinuating that boundary conditions may exist for the impact of empathy expressed by chatbots. Overall, this research opens up exciting opportunities for further studies to explore the impact of empathy expressions in novel contexts.

We also contribute to the emerging literature on chatbot failures (Choi et al. 2020; Leo and Huh 2020; Sheehan et al. 2020). Conversational breakdowns resulting from chatbot failures have rapidly become a prevalent problem since the advent of chatbot technologies. Because of the uncertainty of a service environment, the technology cannot perfectly avoid potential failures, and thus, conversational breakdowns are inevitable. Some literature proposed empathy expressions as a remedy for conversational breakdowns due to the potential of empathy expressions for emotional and social recovery (Benner et al. 2021). However, we question empathy expressions' effectiveness by revealing their backfiring effect. This finding implicates how a recovery strategy commonly used by human employees may not materialize its effect on chatbot-driven service interactions.

At a broader level, this paper contributes to the burgeoning literature on human-AI interaction. Acknowledging the relevance and the potential of emotional AIs, researchers have been exploring the interactions between emotional AIs and humans (Creed et al. 2014; Melo et al. 2013; Stein and Ohler 2017). While prior research produced mixed findings on the impact of chatbot-expressed empathy, our study adds to the ongoing debate and illuminates the contexts in which the impact of chatbot-expressed empathy might vary. By further disclosing how customers evaluate empathy-expressing chatbots

based on social perceptions, we also reveal the application of warmth and competence perception, primarily related to humans, for evaluating chatbots.

3.5.2 Practical Implications

Our work provides valuable guidance for customer service practitioners interested in deploying emotionally responsive chatbots. Numerous businesses have been deploying chatbots to save both economic costs and emotional labor costs for human employees and facilitate service outcomes. More recently, emotionally responsive chatbots have been the focus of interest, with the hope of engendering interactions that resemble human-to-human interactions. Indeed, based on our findings, the expression of empathy by chatbots in a typical service interaction can enhance service evaluations, which confirms the expected effect of deploying empathy-expressing chatbots. However, our findings also suggest that empathy expressions may backfire when empathy is expressed after an incidence in which chatbots' competence is undermined. Thus, practitioners should not haphazardly equip chatbots with empathy-expressing capabilities and avoid deploying such chatbots in instances in which chatbots' competence is questionable or unreliable.

Moreover, our findings warn practitioners who utilize empathy-expressing capabilities to remedy conversational breakdowns due to chatbot failures. Empathy expression might be a viable strategy for mitigating negative customer responses after conversational breakdowns. Instead, empathy expressed by chatbots may backfire and incur even higher costs by further undermining the perception of the chatbot's competence. We urge firms to acknowledge the likelihood of negative consequences of chatbot-expressed empathy after conversational breakdowns and carefully weigh its potential costs against benefits before adopting empathy-expressing chatbots. If practitioners want to realize the benefit

of empathy expressions but avoid the potential negative consequences, they may design emotionally responsive chatbots that are context-aware and express empathy only when appropriate and in the absence of competence-undermining instances. Companies can selectively deploy empathy-expressing capabilities for expressing empathy towards customers' negative experience that is beyond chatbots' control.

3.5.3 Limitations and Future Research

This paper provides a basis for several future research opportunities. First, we showed only a single example of competence-undermining instances in which the effect of chatbot-expressed empathy may backfire. Even for conversational breakdowns, there may be various reasons other than chatbots' non-understanding of the message, such as misinterpreting a message, making nonsensical responses, and not adhering to conversational norms. Besides conversational breakdowns, chatbots' competence may be undermined when service delivery is slow, chatbots provide inappropriate resolutions to a service issue, and so on. Since these instances are different in various aspects, our findings for the role of chatbot-expressed empathy as a recovery strategy may not transpire. Thus, examining the impact of chatbots' empathy expressions in diverse instances will provide a more comprehensive picture for the role of empathy expressions in service interactions.

In addition, our study focused on the expression of empathy, especially toward negative emotional states. While negative empathy is the most common form of customer emotions during service interactions, examining the role of positive empathy may provide additional insight. As recent psychology scholars raised the need to study positive empathy more often (Morelli et al. 2015), investigating how the valence of chatbot-

expressed empathy affects customers' perceptions of chatbots and service will further advance our understanding of this phenomenon. In addition to the valence, the intensity of expressed empathy can be another area of future research interest. Because emotional intensity influences the perceiver's judgment of inappropriateness or inauthenticity of emotion (Cheshin et al. 2018), the intensity of expressed empathy can also affect the extent to which the perceiver thinks empathy is inappropriate or inauthentic. Research on these complex and various aspects of empathy from chatbots will enrich both the chatbot-related and empathy literature.

CHAPTER 4. CHOICE-EQUIPPED CHATBOTS IN CUSTOMER SERVICE: A BLESSING OR A CURSE?

4.1 Introduction

Firms are increasingly adopting artificial intelligence (AI) powered applications to streamline various business processes thanks to continuous technological advances. As one of the most widely adopted AI-powered applications, the chatbot—a text-based conversational agent—is projected to reach a global market size of over \$100 billion by 2026 (Mordor Intelligence 2022). Chatbots have been vastly used in customer service, where chatbots interact with customers to provide a wide range of service tasks, from answering simple questions to giving recommendations and advice (Markets and Markets 2019). The implementation of service chatbots increases the efficiency of service delivery processes, and it also reduces the costs of both physical and emotional labor for frontline employees. Thus, the role of chatbots in customer service, especially the way they communicate with customers, has been vital for both researchers and practitioners (Crolic et al. 2022a; Fotheringham and Wiles 2022; Huang and Rust 2021; Luo et al. 2019).

Although chatbots are developed based on natural language processing (NLP) technologies and are capable of understanding and speaking human languages to a certain extent, such technologies are far from perfect (Ashktorab et al. 2019; Benner et al. 2021). When customers interact with a conversational agent such as a chatbot, they often expect the technology-induced service to provide a smooth and seamless experience (Ostrom et al. 2021). To prevent or reduce the likelihood of breakdowns that usually happen to chatbots, firms often employ structured message templates. These structured templates typically involve implementing choices in the form of a guided conversation, during

which customers can select one of the provided pre-determined options as their input message (Klopfenstein et al. 2017). Implementing chatbot-provided choices during a service interaction is deemed especially suitable for routine and standardized service tasks (Huang and Rust 2021; Li et al. 2020).

Despite the prevalence of choice-implemented chatbots in the industry (Li et al. 2020), there is not much empirical evidence for its impact on service outcomes. Human-based service interactions tend to involve natural conversations, so providing choices in this process may be unnecessary and break the natural flow of conversations. Therefore, providing choices can be a unique characteristic of chatbot-based service interactions. While the popularity of choice-enabled chatbots indicates a generally favorable view of this unique feature, a choice implementation may also have unintended consequences, and its value may not be realized under certain situations.

To shed light on the impact of this crucial practice, we examine when the implementation of chatbot-initiated choices during a service interaction is beneficial or counterproductive and why. The primary reason for implementing choices in practice is to enhance the fluency of a service process, where fluency is defined as the ease of processing ongoing tasks or information (Oppenheimer 2008). Because customers' perception of fluency influences service outcomes (Fernández-Sabiote and López-López 2020), we focus on two contextual variables that are especially relevant to the fluency of chatbot-initiated service interactions: conversational breakdowns and service task complexity. Conversational breakdowns often occur during the interaction with chatbots due to their imperfect capability to understand users' messages (Ashktorab et al. 2019). The benefit of implementing choices might not materialize in a service interaction that is

already fluent. In contrast, after conversational breakdowns disrupt a service process, implementing choices can heighten customers' perception of fluency and enhance subsequent service outcomes. Some research suggested providing choices as one of the repair strategies after conversational breakdowns during an interaction with a chatbot (Ashktorab et al. 2019; Benner et al. 2021), but to our knowledge, there was no empirical evidence focusing exclusively on its effect. In addition, the same set of provided choices may be perceived differently depending on the complexity of a service task, as task complexity affects customers' assessment of information presentation formats (Jiang and Benbasat 2007). Specifically, as service task becomes more complex, a predefined set of choices would be less likely to encompass all the necessary options required by customers. In such cases, a choice implementation may backfire, decreasing customers' perception of fluency and deteriorating service outcomes.

We tested these predictions using a series of experimental studies in which participants engaged in a hypothetical customer service scenario and chatted with a chatbot to resolve a service issue. The studies provided consistent evidence supporting our hypotheses. Our theoretical framework and findings contribute to the literature on chatbots' role in customer service and the broader literature on human-AI interaction. Specifically, this work provides a more nuanced picture of when and why choice implementation (a unique conversational feature of a chatbot) improves or impairs service outcomes. Our research also extends customer service literature by illuminating the benefits and drawbacks of technology-induced service interactions. Finally, we bolster the literature on fluency by identifying boundary conditions that can either

augment or deteriorate people's perception of fluency. We also provide practical implications for firms on the deployment of choice-enabled service chatbots.

4.2 Theoretical Development and Hypotheses

As chatbots' capabilities advance, they are increasingly deployed for various tasks, from providing simple information to engaging in intimate conversations with users. Many firms adopt chatbots to be at the frontline of interacting with customers. To facilitate a social and interpersonal environment for such customer-chatbot interactions, recent research has emphasized the need for equipping chatbots with the ability to have natural and human-like conversations (Fotheringham and Wiles 2022; Huang and Rust 2021; Schanke et al. 2021a). However, using natural language processing (NLP) technologies to emulate human often backfires due to inauthenticity, reduced perception of control over a chatbot, and uncanniness (Fotheringham and Wiles 2022; Kim et al. 2019; Nguyen et al. 2022). Moreover, during technology-based service encounters, customers tend to seek quick, efficient, and task-oriented interactions (Meuter et al. 2000). For efficiency and speed purposes, practitioners often adopt structured message templates to generate a guided conversation (Klopfenstein et al. 2017). These structured templates commonly incorporate menu-based interfaces, allowing users to choose options provided by the chatbot. This feature is deployed by various businesses to deal with routine, systematic tasks without incurring much cost of applying a more advanced technology (Klopfenstein et al. 2017; Li et al. 2020).

A chatbot's provision of choices indeed enables users to make a quick response, and it has the benefits of saving time, increasing efficiency, and minimizing the risk of errors. Moreover, the provision of choices reduces a user's cognitive load and increases the

perception of autonomy by allowing the user to select his or her own action, as often achieved through menu-based interfaces of a traditional website (Nguyen et al. 2022). While these advantages are recognized by practitioners, there are not much empirical evidence on the impact of a chatbot providing choices. The advantages of providing choices are undoubted, but it is possible that such advantages are only realized in certain situations. Furthermore, providing choices may be counterproductive depending on how it is presented. Thus, we aim to explore the impact of providing choices and illuminate the potential boundary conditions for such an impact.

4.2.1 The Role of Fluency in Service Interactions

A primary reason for implementing choices in a service chatbot is to achieve frictionless interaction with customers. Also, technology-induced service encounters are typically expected to provide seamless interaction from both a firm's and a customer's perspectives (Bitner et al. 2000; Voorhees et al. 2017). Processing fluency, which refers to a subjective experience of how information or a task is easily processed, is known to significantly impact people's judgments and decision-making (Alter and Oppenheimer 2009; Schwarz 2004). Frequently, an individual's judgment based on certain stimuli is determined by how quickly and easily the stimuli are processed rather than the stimuli themselves (Schwarz et al. 1991).

Prior literature on customer service has also acknowledged the importance of fluency for crucial business outcomes, such as brand evaluation, service evaluation, and customers' emotions (Fernández-Sabiote and López-López 2020; Orth and Wirtz 2014; Shen et al. 2018; Sirianni et al. 2013). While fluency examined in the customer service literature and the general fluency literature takes various forms (e.g., visual, linguistic,

semantic), the underlying notion is that the perception of fluency is driven by the ease and the speed of processing stimuli (Alter and Oppenheimer 2009; Reber et al. 2004). A chatbot's provision of choices can facilitate fluency as it allows customers to respond quickly and enhance the ease of proceeding with the ongoing interaction and the service task.

However, the supposed positive effect of choice provision may not always materialize because the perception of fluency may vary based on situational factors, such as when and how choices are presented. Therefore, we focus on two relevant boundary conditions for the impact of choices: conversational breakdowns and service task complexity. First, during a service interaction that is already flowing well, the effect of choices on the perception of fluency might not emerge. Instead, the value of choices is more likely to be recognized during an interaction experiencing disruptions. A common disruption in our context is a conversational breakdown due to chatbot failures (Ashktorab et al. 2019). Thus, when a conversational breakdown occurs, providing choices may restore the lost fluency. Second, how choices are structured can also influence their impact on fluency, similar to the role of choice architecture in rational decision-making (Thaler and Sunstein 2008). For instance, if the provided choices do not include everything related to what a customer needs or requests (e.g., when a customer is making a complicated or unique request), providing choices may undermine fluency. Next, we explain each of these boundary conditions and present our hypotheses.

4.2.2 Choice Implementation After Conversational Breakdowns

While we have observed chatbots' ever-increasing intelligence and capability, the technology is not mature yet. Due to the imperfect NLP technology and increasing

sophistication in users' requests, high failure rates are expected and often observed (Ashktorab et al. 2019; Simonite 2017). Acknowledging the imperfection of AI technologies, several studies have investigated the impact of AI failures, but they provided mixed evidence. While some showed a negative impact of a service robot failure on responsibility attribution (Leo and Huh 2020), adoption intent (Sheehan et al. 2020), and service evaluation (Choi et al. 2020; Lee et al. 2010), others found that errors made by an AI can, in fact, humanize the AI and increase the perception of warmth and liking (Bluvstein et al. 2019; Mirnig et al. 2017).

One of the most prevalent failures of a chatbot is its inability to understand a user's input message (Ashktorab et al. 2019). Such failures can be technical errors due to an inherent problem with the chatbot's system or interaction failures due to "incomprehensible" user messages beyond the chatbot's capability. As malfunctioning of an IT system may disrupt an individual's flow of work (Addas and Pinsonneault 2015), service chatbot failures will incur a conversational breakdown, disrupting the flow of the communication and, ultimately, the service delivery process. When humans communicate with each other orally, speech disfluency is usually triggered by minor interruptions, such as pauses, delays, and utterances (Shriberg 2001). Errors made during a traditional human-delivered service create interruptions to the service flow and inhibit the fluent service delivery process (Froehle and White 2014; Sampson and Froehle 2006; Seshadri and Shapira 2001; Stewart and Chase 1999). For a chatbot, a prominent source of communication disfluency comes from its inability to understand a message from humans. Such a breakdown can trigger a customer to anticipate a potential service failure, consequently impairing the perception of fluent service delivery.

We argue that the provision of choices is more likely to be beneficial for service outcomes when conversational breakdowns occur. Because providing choices can guide customers back to a structured conversation, it can repair the disruption caused by conversational breakdowns. Specifically, when conversational breakdowns occur and cause a salient disruption to a service process, the provision of choices can prevent future disruptions and improve the perception of fluency. Increased fluency can then prompt the customers to form positive perceptions toward an entire service experience (Alter and Oppenheimer 2009). In contrast, when breakdowns are absent, the value of choice provision may not be recognized by consumers. In this research, we focus on customers' perceptions of a service encounter because of their implications for designing and managing the service experience, which is directly linked to various business outcomes (Heskett et al. 1994; Zomerdijk and Voss 2010). In sum, we propose the following:

Hypothesis 1: *When there are conversational breakdowns, the provision of choices by a chatbot enhances service evaluations. In contrast, such an effect disappears when there are no conversational breakdowns.*

Hypothesis 2: *When there are conversational breakdowns, the positive effect of chatbot-provided choices is driven by a customer's increased perception of fluency of the service interaction.*

4.2.3 Service Task Complexity and the Comprehensiveness of Choice Set

During rational decision-making, the structure of a choice set plays a significant role in people's decisions. The design of a choice set structure is also known as choice architecture, which is a vital driving force that can nudge a decision maker's behavior (Thaler and Sunstein 2008). Several elements compose choice architecture, such as the

number of choices provided, the description of each choice in a choice set, and the presentation format of choices (Johnson et al. 2012). The impact of these elements is often not one-directional, and it may depend on various contextual and individual differences (Scheibehenne et al. 2010; Sunstein 2017).

In customer service, one factor that generates contextual differences and would be relevant to customers' perceptions of choice structure is a service's task type. One of the ways to characterize a task is its complexity. Task complexity refers to the amount of sophistication involved in completing a task (Wood 1986). Task complexity tends to have a crucial impact on goal-setting, performance strategy, and task performance (Campbell 1988). Furthermore, task complexity can also drive how customers evaluate information presentation formats and react to the platform in which information is presented (Jiang and Benbasat 2007). Similarly, the complexity of a service task may influence how customers process and react to choices provided by a chatbot.

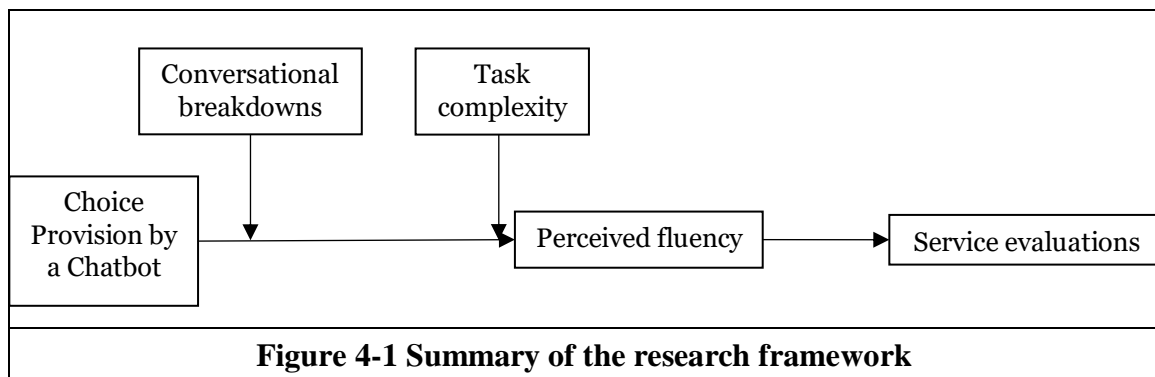
When choices are implemented, they are predefined in a system before an interaction begins and are usually not flexible enough to be changed during the interaction. Thus, from a practitioner's standpoint, it is essential to design choices that can satisfy every customer. However, it is unlikely that a predefined choice set with a limited number of options can encompass every potential request. In particular, if a service task is very complex (e.g., when potential customers' demand is ambiguous and uncertain), there is a higher chance that a customer does not find a satisfying option from the predefined choice set. A task with high complexity often requires service technologies to personalize and be aware of specific demands (Xu et al. 2014), but inflexible, predefined choices will not be able to accommodate every personal need. Such incomprehensiveness of a choice

set driven by task complexity will deter the perception of fluency by causing difficulty in decision-making and increasing customers' cognitive loads (Alter and Oppenheimer 2009).

Moreover, how fluently an individual decides his or her subsequent action depends on the alignment of that action and any stimuli provided right before deciding and committing to that action (Chambon and Haggard 2012). Similarly, the extent to which a customer's anticipated action aligns with the provided choices may drive the fluency of the choice process. An incomprehensive choice set will deter fluency because none of the choices align with a customer's expected action. Such deterrence of fluency will drive a negative perception of an entire service experience (Alter and Oppenheimer 2009). Thus, we present the next set of hypotheses below. Figure 4-1 summarizes our research framework.

Hypothesis 3: *When a service task is complex (leading a choice set to be incomprehensive), the provision of choices by a chatbot hurts service evaluations. In contrast, such an effect disappears when the service task is less complex.*

Hypothesis 4: *When a service task is complex (leading a choice set to be incomprehensive), the negative effect of chatbot-provided choices is driven by a customer's decreased perception of fluency of the service interaction.*



4.3 Preliminary Study

This preliminary study was conducted to explore the effect of providing choices on service evaluations during an “ideal” service interaction situation. As discussed before, the provision of choices tends to be desirable due to its efficiency and contribution to fluency (Klopfenstein et al. 2017). However, we are unsure whether the effect of choices is salient enough during an already fluent interaction. To shed light on this matter, we utilized a between-subjects design, manipulating the presence of choices during the interaction with a service chatbot and keeping all other aspects of the interaction identical. During the study, participants interacted with a service chatbot via virtual chat to resolve a hypothetical service issue. After the chat, participants evaluated the service provided by the chatbot and answered other questions.

4.3.1 Stimulus Materials

We used a predesigned script for the chatbot’s messages to ensure that every aspect of the interaction remains identical, except for the presence of choice. The script included five messages from the chatbot, with two to four sentences within each message. The messages were similar to those used in the studies from Chapter 2 and 3, while slightly modified to fit the current setting.

We manipulated the presence of choices by varying whether participants freely type in their messages or click and choose one of the options provided by the chatbot in their messages. For instance, when the chatbot asked participants to describe a service issue, those in the choice-absent condition would type in their response and then see the subsequent message from the chatbot. To those in the choice-present condition, the chatbot provided three options: ‘Missing item,’ ‘Check order status,’ and ‘Return/exchange item(s).’ The participants could see the subsequent message from the chatbot only after they chose one of the options. Table 4-1 shows the predesigned scripts for the two conditions. Figure 4-2 shows an example of how the choices were presented in the chat interface we used.

| Table 4-1 Predesigned chat scripts for the conditions from Preliminary Study | |
|--|--|
| Choice-absent | Choice-present |
| <p>Hello. This is Taylor, and I am a bot created by the customer service department. I am handling your request today. What brings you here?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>I can help you with that. First, could you tell me why you need to replace or return this textbook?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>Got it. Could you input your order number below?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>Alright. I will process your request. Please give me a moment.</p> <p style="text-align: center;">[Slight delay]</p> <p>The 3rd edition is currently in stock. For your information, you need to pay \$50 more for the newer edition. Would you still like to exchange the book?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>Alright. I'll process your request. Please give me a moment.</p> <p style="text-align: center;">[Slight delay]</p> <p>I have processed your request. The issue is resolved. Please contact us again if you need further assistance. Bye.</p> | <p>Hello. This is Taylor, and I am a bot created by the customer service department. I am handling your request today. What brings you here?</p> <ul style="list-style-type: none"> • Missing item • Check order status • Return/ exchange items <p style="text-align: right;"><i>Participant's choice</i></p> <p>I can help you with that. First, could you tell me why you need to replace or return this textbook?</p> <ul style="list-style-type: none"> • Damage in the item • Need a different version or edition • Incorrect item delivered <p style="text-align: right;"><i>Participant's choice</i></p> <p>Got it. Could you input your order number below?</p> <p style="text-align: right;"><i>Participant's message</i></p> <p>Alright. I will process your request. Please give me a moment.</p> <p style="text-align: center;">[Slight delay]</p> <p>The 3rd edition is currently in stock. For your information, you need to pay \$50 more for the newer edition. Would you still like to exchange the book?</p> <ul style="list-style-type: none"> • Yes, I would like an exchange. • No, I don't want an exchange. <p style="text-align: right;"><i>Participant's choice</i></p> <p>Alright. I'll process your request. Please give me a moment.</p> <p style="text-align: center;">[Slight delay]</p> <p>I have processed your request. The issue is resolved. Please contact us again if you need further assistance. Bye.</p> |

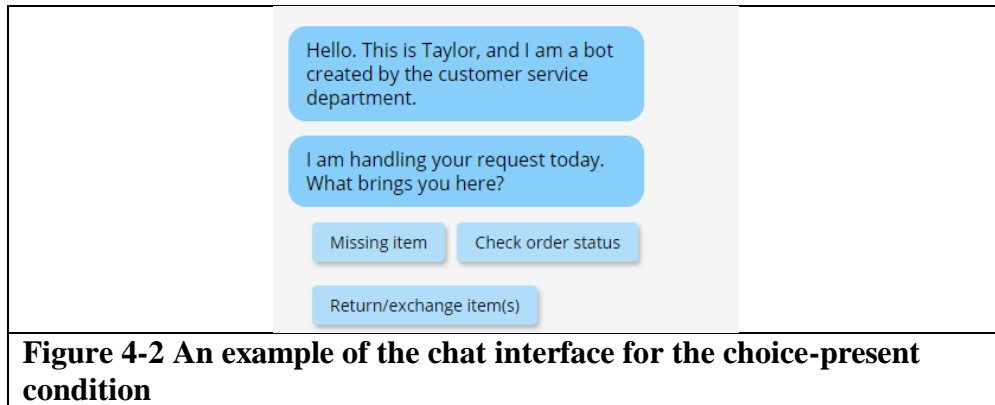


Figure 4-2 An example of the chat interface for the choice-present condition

4.3.2 Procedure and Measures

One hundred and sixty-eight undergraduate students (92 female) from a U.S. university participated in the study in exchange for course credit. Participants were randomly assigned to either the choice-absent or the choice-present condition.

The cover story was similar to the one used in Chapter 2. The cover story was about exchanging an item in the online retail industry. We chose such a standardized service task for practical and design reasons: first, most chatbots are deployed to handle standardized service tasks in practice, and second, using such a standardized task reduces the risk of a chatbot making inconsistent responses to participants and ensures procedure equivalence across conditions. The scenario described a recent order of a textbook, which needed to be exchanged for a newer edition. The detailed cover story can be found in Appendix F. After the cover story, participants saw an introductory message that they were connected to a bot created by the customer service department. The chat started on a new screen. The rest of the chat process was similar to that from Chapter 2 and 3.

After the chat, participants evaluated the chatbot-provided service by reporting their perception of service quality and satisfaction with the service, two important service evaluation outcomes (Cronin et al. 2000). Customers' perception of service quality is

critical for service providers because it is an overall evaluation of service outcome, interaction, and environment associated with vital organizational outcomes, such as customer loyalty, market share, and purchase intention (Brady and Cronin 2001). Perceived service quality was measured using three items (e.g., “poor / excellent”). Customers’ satisfaction with the service is also essential as it is a key predictor of their intention to continue using the service (Oliva et al. 1992). Satisfaction was measured using three questions (e.g., “how satisfied or dissatisfied did your experience with the service agent leave you feeling?”). Both were measured on a seven-point semantic differential scale and adapted from Brady and Cronin (2001). Participants also answered two attention check questions, which were later used to ensure subject quality. As a manipulation check, participants were asked how often they clicked and chose from options provided during the chat on a five-point scale (‘never’ equals 1; ‘always’ equals 5).

4.3.3 Results

Out of 168 subjects, 149 subjects passed both attention check questions and were used in our analysis. We first conducted a manipulation check for the presence of choices. Analysis revealed that participants in the choice-present condition perceived that they had to choose options more often than those in the choice-absent condition ($M_{present} = 4.03$ vs. $M_{absent} = 1.12$, $SDs = 1.02$ and $.50$, $t(147) = 22.004$, $p < .001$). Therefore, our manipulation was deemed successful.

Next, we conducted a one-way ANOVA with the presence of choices as a between-subjects factor to test its effect on perceived service quality and satisfaction with the service. Results revealed no significant effect of choices on either the perception of

service quality ($M_{absent} = 5.97$ vs. $M_{present} = 6.19$, $SDs = 1.11$ and $.98$, $F(1, 147) = 1.596$, $p = .21$) or satisfaction with the service ($M_{absent} = 6.31$ vs. $M_{present} = 6.45$, $SDs = .94$ and $.76$, $F(1, 147) = 1.030$, $p = .31$).

4.3.4 Discussion

This study explored whether a chatbot's provision of choices would have an impact when a service interaction is already fluent, and we did not find any evidence for such an effect. While firms often implement a choice-equipped chatbot to standardize service interactions and increase the speed of a service process, the choice provision might not necessarily enhance customers' service evaluations. On the other hand, firms are increasingly utilizing NLP to emulate a service interaction with a human employee, and they may be concerned that a chatbot simply providing choices will result in a less social or interactive environment. However, we did not find any evidence that providing choices would impair service experience either. In summary, a lack of effect of chatbot-provided choices in this preliminary study refutes the conventional wisdom that providing choices will enhance customer service experience by streamlining the service process, and it also alleviates the concern that choices alone can hurt service outcomes.

Although we did not find any evidence for the effect of a chatbot providing choices, it is possible that the provision of choices might be beneficial or harmful in certain situations. For instance, the choice provision might signal the restoration of fluency and work as a remedy when a customer experiences a disruption during an otherwise fluent service interaction (e.g., conversational breakdowns). Alternatively, providing choices might harm the fluency of service interaction when the provided choice set is incomplete. Thus, in the subsequent studies, we focused on two moderators commonly associated

with a service chatbot and examined how those moderators influence the effect of choices on service evaluations.

4.4 Study 1

The goal of Study 1 was to investigate whether a conversational breakdown moderates the impact of a chatbot's choice provision on service evaluations as well as the role of customers' perception of fluency, as proposed in Hypotheses 1 and 2. To do so, we manipulated the presence of choices and also the presence of conversational breakdowns in a between-subjects design. As in the Preliminary Study, participants were engaged in a hypothetical task of using a service chatbot to resolve a service-related issue and then answered several questions.

4.4.1 Stimulus Materials

While we used a similar predesigned script for the chatbot's messages from the Preliminary Study, we switched to a different service issue to extend the generalizability. Participants were asked to request the delivery of a missing item from a recent order by interacting with a service chatbot. We also modified the script by manipulating the presence of conversational breakdowns. To manipulate the presence of conversational breakdowns, we inserted error messages that the chatbot could not understand the participant's response. We used such error messages because misunderstanding a customer's input message is one of the most common pitfalls of a chatbot that disrupts conversational flow (Benner et al. 2021). While those in the conversational breakdown conditions encountered several error messages throughout the chat, those in the no-breakdown conditions did not encounter any error messages. We slightly varied each of the inserted error messages, but overall, these error messages asked participants to

rephrase what they had said right before. Then, the chat continued as in the no-breakdown conditions.

We manipulated the presence of choices as in the preliminary study. The two no-breakdown conditions were similar to the choice-present and the choice-absent conditions from the preliminary study. In the breakdown, choice-present condition, choices were provided only after the conversational breakdown occurred. In the breakdown, choice-absent condition, the chatbot did not provide any choices after a breakdown, and participants had to respond after the breakdown by typing in their messages. Table 4-2 shows the predesigned scripts for the two breakdown conditions.

| Table 4-2 Predesigned chat scripts for the conversational breakdown conditions from Study 1 | |
|---|--|
| Choice-absent | Choice-present |
| <p>Hello. This is Taylor, and I am a bot created by the customer service department. I am handling your request today. What brings you here? <i>Participant's message</i></p> <p>I do not understand what you said. Can you try again? <i>Participant's message</i></p> <p>I can help you with that. First, could you tell me your order number? <i>Participant's message</i></p> <p>Got it. Please allow me few seconds for pulling up your order. [Slight delay] Which item(s) is missing? <i>Participant's message</i></p> <p>I don't quite get what you're saying. Please repeat. <i>Participant's message</i></p> <p>Can you describe conditions of the rest of the items? <i>Participant's message</i></p> <p>I can't process your message. Please type again. <i>Participant's message</i></p> <p>Thank you for telling me. Meanwhile, I've identified the problem: there was a miscommunication in the packaging process. I can create a new order that will be delivered within a day, or I can refund for the missing item. What would you prefer? <i>Participant's message</i></p> | <p>Hello. This is Taylor, and I am a bot created by the customer service department. I am handling your request today. What brings you here? <i>Participant's message</i></p> <p>I do not understand what you said. Can you choose one of the options below?</p> <ul style="list-style-type: none"> • Missing item • Check order status • Return/ exchange items <p><i>Participant's message</i></p> <p>I can help you with that. First, could you tell me your order number? <i>Participant's message</i></p> <p>Got it. Please allow me few seconds for pulling up your order. [Slight delay] Which item(s) is missing? <i>Participant's message</i></p> <p>I don't quite get what you're saying. Please choose an option below.</p> <ul style="list-style-type: none"> • Sweater • Jeans • Baseball cap <p><i>Participant's message</i></p> <p>Can you describe conditions of the rest of the items? <i>Participant's message</i></p> <p>I can't process your message. Please select one.</p> <ul style="list-style-type: none"> • In a good condition • Not in a good condition <p><i>Participant's message</i></p> <p>Thank you for telling me. Meanwhile, I've identified the problem: there was a miscommunication in the packaging process. I can create a new order that will be delivered within a day, or I can refund for the missing item. What would you prefer? <i>Participant's message</i></p> <p>I cannot understand. Can you choose from below?</p> |

| | |
|---|--|
| <p>I cannot understand. Can you repeat? <i>Participant's message</i></p> <p>Alright. I'll process your request. Please give me a moment. [Slight delay]</p> <p>I have processed your request. The issue is resolved. Please contact us again if you need further assistance. Bye.</p> | <ul style="list-style-type: none"> • Create a new order • Refund the item <p style="text-align: right;"><i>Participant's message</i></p> <p>Alright. I'll process your request. Please give me a moment. [Slight delay]</p> <p>I have processed your request. The issue is resolved. Please contact us again if you need further assistance. Bye.</p> |
|---|--|

4.4.2 Procedures and Measures

Three hundred and thirty-nine undergraduate students (188 female) from a U.S. university participated in the study in exchange for course credit. Participants were randomly assigned to one of the four conditions: breakdown or no-breakdown and choice-present or choice-absent.

Participants first encountered the cover story now involving a different service issue from that in the Preliminary Study. The scenario described a recent delivery from an online clothing store in which one of the items was missing. The detailed cover story can be found in Appendix F.

After the cover story, participants followed the same procedure and answered a similar set of questions as in the Preliminary Study. In addition, we measured participants' perception of fluency of their service experience using six items (e.g., "flowing very unwell / flowing very well;" "very disfluent / very fluent") on a seven-point semantic differential scale (Graf et al. 2018). As a manipulation check for the presence of conversational breakdowns, participants were asked how often they thought their encounter with the chatbot was interrupted on a five-point scale ('never' equals 1; 'always' equals 5) (Speier et al. 1999).

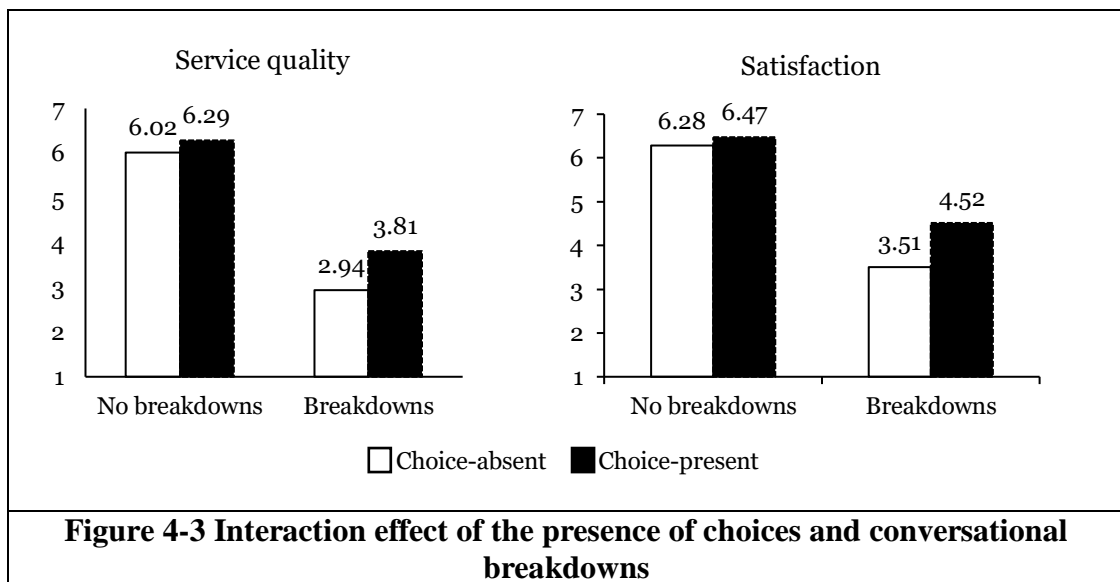
4.4.3 Results

In our analyses, we used the responses from 303 subjects who passed the two attention checks. Analysis of the manipulation check for the presence of choices confirmed that participants in the choice-present conditions perceived that they had to choose options more often than those in the choice-absent conditions ($M_{present} = 4.24$ vs. $M_{absent} = 1.56$, $SDs = .94$ and $.96$, $t(301) = 24.660$, $p < .001$). The manipulation check for the presence of conversational breakdowns revealed that participants in the breakdown conditions perceived the conversational breakdowns to have occurred more frequently than those in the no-breakdown conditions ($M_{breakdown} = 2.31$ vs. $M_{no-breakdown} = 1.22$, $SDs = 1.25$ and $.69$, $t(301) = 9.433$, $p < .001$). Thus, we found both of our manipulations to be successful.

Next, to test our first hypothesis about the moderating impact of conversational breakdowns, we conducted a two-way ANOVA with the presence of choices and the presence of conversational breakdowns as two between-subjects factors, and perceived service quality and satisfaction with the service as two outcome variables. We observed significant main effects of both factors, such that overall, the provision of choices led to greater perception of service quality ($M_{present} = 5.05$ vs. $M_{absent} = 4.48$, $F(1,299) = 14.261$, $p < .001$) and satisfaction ($M_{present} = 5.49$ vs. $M_{absent} = 4.89$, $F(1,299) = 19.035$, $p < .001$), while the presence of conversational breakdowns led to lower perception of service quality ($M_{breakdown} = 3.37$ vs. $M_{no-breakdown} = 6.16$, $F(1,299) = 341.654$, $p < .001$) and satisfaction ($M_{breakdown} = 4.01$ vs. $M_{no-breakdown} = 6.37$, $F(1,299) = 294.128$, $p < .001$).

Most importantly, we found a significant interaction effect of choices and conversational breakdowns on perceived service quality ($F(1,299) = 3.987$, $p = .047$) and

on satisfaction ($F(1,299) = 8.803, p = .003$). Pairwise comparisons further showed that when there were no conversational breakdowns, providing choices did not have any significant effect on either perceived service quality ($M_{present} = 6.29$ vs. $M_{absent} = 6.02, F(1,299) = 1.600, p = .2$) or satisfaction ($M_{present} = 6.47$ vs. $M_{absent} = 6.28, F(1,299) = .984, p = .3$), just as what we observed in the preliminary study. On the other hand, when there were conversational breakdowns, providing choices significantly enhanced the perception of service quality ($M_{present} = 3.81$ vs. $M_{absent} = 2.94, F(1,299) = 16.495, p < .001$) and satisfaction ($M_{present} = 4.52$ vs. $M_{absent} = 3.51, F(1,299) = 26.592, p < .001$). These findings indicate that a chatbot’s provision of choices benefits customers’ service experience only after conversational breakdowns, thus confirming Hypothesis 1. Figure 4-3 depicts the interactions.



To examine the underlying mechanism for the observed interaction, we first tested the moderating role of conversational breakdowns for the impact of the choice provision on perceived fluency. We found a positive main effect of providing choices on perceived

fluency ($M_{present} = 5.11$ vs. $M_{absent} = 4.64$, $F(1,299) = 14.007$, $p < .001$) and a negative main effect of conversational breakdowns ($M_{no-breakdown} = 5.99$ vs. $M_{breakdown} = 3.75$, $F(1,299) = 320.047$, $p < .001$). In addition, we confirmed a significant interaction effect of the two on the perception of fluency ($F(1,299) = 8.250$, $p = .004$). Pairwise comparisons revealed that providing choices significantly increased the perception of fluency only when there were conversational breakdowns ($M_{present} = 4.17$ vs. $M_{absent} = 3.34$, $F(1,299) = 21.656$, $p < .001$). When there were no conversational breakdowns, providing choices did not have any impact on perceived fluency ($M_{present} = 6.04$ vs. $M_{absent} = 5.94$, $F(1,299) = .383$, $p = .5$). These results were in line with Hypothesis 2.

We also conducted a mediated moderation analysis using a PROCESS Model 8 with a bootstrapping approach and the two service evaluation variables as the dependent variables (Hayes 2013). The analysis showed that, when there were conversational breakdowns, the presence of choices significantly increased the perception of fluency, which led to higher perception of service quality (indirect effect = .70; 95% CI = [.37, 1.05]) and satisfaction (indirect effect = .61; 95% CI = [.32, .90]). However, when there were no conversational breakdowns, the indirect effects disappeared for both service quality (indirect effect = .09; 95% CI = [-.16, .36]) and satisfaction (indirect effect = .08; 95% CI = [-.14, .32]). Overall, these results confirmed Hypothesis 2 and provided concrete evidence for the mediated moderation.

4.4.4 Discussion

Study 1 delved into a boundary condition for the impact of providing choices: conversational breakdowns. While finding evidence for the moderating effect of conversational breakdowns, the study also revealed the role of perceived fluency as a

driving force for such moderating effect. In sum, providing choices enhances service evaluations only when they are provided after conversational breakdowns because the choices can amplify a customer's perception of fluency that might have been disrupted due to a conversational breakdown.

While we discovered a boundary condition in which providing choices has a positive impact, it is also possible that the presence of choices engenders a negative impact by hurting the perception of fluency. This can happen, for instance, when a service task is complex, such that a given choice set is not comprehensive. We focus on this boundary condition in the subsequent study.

4.5 Study 2

This study aimed to examine the moderating role of task complexity for the impact of providing choices on service evaluations, as proposed in Hypothesis 3. Similar to Study 1, we also study whether the perception of fluency serves as an underlying mechanism for the moderation effect, as proposed in Hypothesis 4. Thus, in addition to the presence of choices, we manipulated the complexity of a service task in a between-subjects design. As in prior studies, participants interacted with a service chatbot to resolve a hypothetical service-related issue and then answered several questions.

4.5.1 Stimulus Materials, Procedures, and Measures

Two hundred and seventy-four undergraduate students (154 female) from a U.S. university participated in the study in exchange for course credit. Participants were randomly assigned to one of the four conditions: choice-present or choice-absent and high task complexity (leading to an incomprehensive choice set) or low task complexity (leading to a comprehensive choice set).

We used a similar predesigned script for the chatbot's messages and the cover story from the Preliminary Study as a starting point because they enabled us to create a variation in the task complexity more efficiently. While we maintained the manipulation of choice provision, we showed different cover stories before interacting with the chatbot to manipulate the task complexity. Because task complexity is primarily determined by the amount of information relevant to a specific task (Wood 1986), we varied the number of requests to be made by participants to the service chatbot. In the low task complexity condition, participants read that they needed to request an exchange for a newer edition of the textbook they recently ordered. In the high task complexity condition, participants were asked to take on an additional task, requesting a free shipping label for sending the older edition back. Because a choice set is predefined and can only include a limited number of options, there is a higher chance that the additional task is not compatible with the existing options.

During a chat, the chatbot first proceeded to process the exchange as in the Preliminary Study. Then, at the end, the chatbot asked: "Is there anything else you need?" Those in the choice-absent conditions could freely type their response. Those in the choice-present conditions were provided with three options: 1) express shipping (\$15), 2) access to an e-book version, and 3) none. Those in the low task complexity conditions could choose option 3) because their task (i.e., requesting an exchange for a newer edition) was already finished, and they did not need to request for anything else. In contrast, those in the high task complexity conditions were not able to choose any because none of the options included their additional task of requesting a free shipping label, making the choice set incomprehensive. Except for these later messages, all other

messages and the manipulation of choice provision remained the same as those in the Preliminary Study.

Along with the measures used in the prior studies, we measured participants' perception of task complexity using three items (e.g., "not at all complicated / very complicated") as a manipulation check for task complexity (Campbell 1988). We also measured participants' perception of choice comprehensiveness using three items (e.g., "sufficient for completing the task"; "Strongly disagree / Strongly agree") (Yang et al. 2005). The perception of choice comprehensiveness was measured only for those who were assigned to the two choice-present conditions. Both items were measured on a seven-point semantic differential scale.

4.5.2 Results

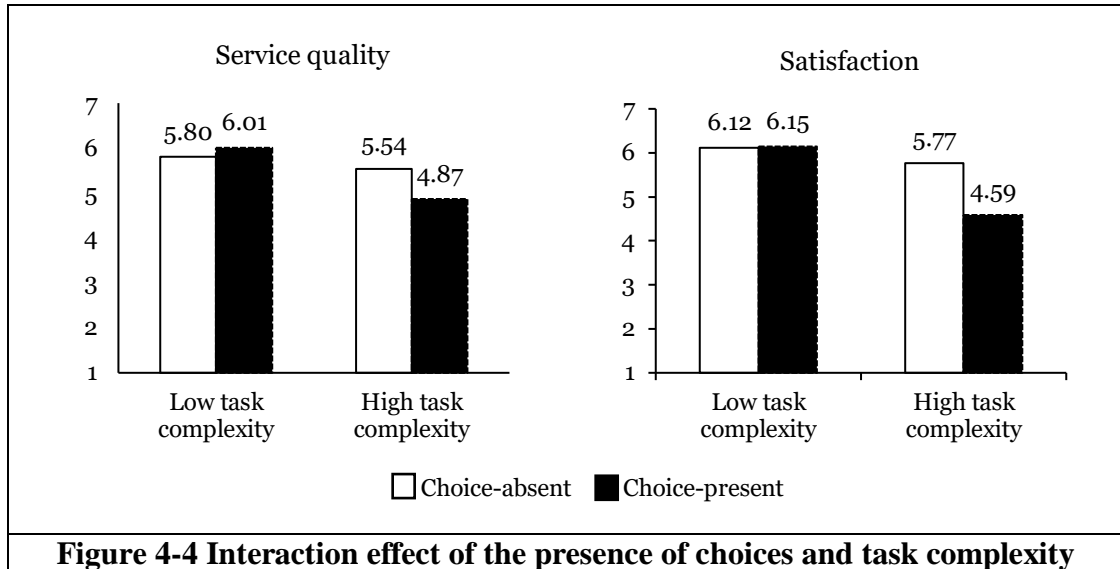
Two hundred and thirty-three subjects passed both attention checks and were used in the analyses. We first confirmed that the manipulation check of choice was successful by finding that participants in the choice-present conditions perceived that they encountered choices more frequently than those in the choice-absent conditions ($M_{present} = 4.10$ vs. $M_{absent} = 1.21$, $SDs = .91$ and $.55$, $t(231) = 29.656$, $p < .001$). Next, we checked the manipulation of choice comprehensiveness by examining the perceptions of both task complexity and choice comprehensiveness. We found that those in the high task complexity conditions perceived their task to be more complex than those in the low task complexity conditions ($M_{high} = 3.03$ vs. $M_{low} = 2.67$, $SDs = 1.32$ and 1.42 , $t(231) = 1.984$, $p = .048$). We also discovered that, among those who encountered choices during the interaction, those in high task complexity condition perceived the choices provided to be more incomprehensible than those in low task complexity condition ($M_{high} = 4.42$ vs. M_{low}

= 6.05, $SDs = 1.61$ and $.92$, $t(111) = 6.476$, $p < .001$). These results verify that our indirect manipulation of choice comprehensiveness through the manipulation of task complexity was successful.

To test our third hypothesis about the moderating effect of task complexity, we conducted a two-way ANOVA with the presence of choices and task complexity as two between-subjects factors, and two service evaluation variables as the dependent variables. We observed a significant main effect of task complexity, such that overall, more complex task led to lower perception of service quality ($M_{high} = 5.20$ vs. $M_{low} = 5.90$, $F(1,229) = 16.507$, $p < .001$) and satisfaction ($M_{high} = 5.18$ vs. $M_{low} = 6.13$, $F(1,229) = 27.993$, $p < .001$). Meanwhile, the positive main effect of choice was observed only on satisfaction ($M_{absent} = 5.37$ vs. $M_{present} = 5.94$, $F(1,229) = 10.160$, $p = .002$), but not perceived service quality ($M_{present} = 5.44$ vs. $M_{absent} = 5.67$, $F(1,229) = 1.804$, $p = .181$).

Moreover, we found a significant interaction effect of choice provision and task complexity on perceived service quality ($F(1,229) = 6.368$, $p = .012$) and on satisfaction ($F(1,229) = 11.494$, $p = .001$). Pairwise comparisons revealed that, when task complexity was low (thus choices were comprehensive), choice provision did not have any impact on either perceived service quality ($M_{present} = 6.01$ vs. $M_{absent} = 5.80$, $F(1,229) = .697$, $p = .4$) or satisfaction ($M_{present} = 6.15$ vs. $M_{absent} = 6.12$, $F(1,229) = .021$, $p = .9$). However, when task complexity was high (thus choices were incomprehensive), choice provision hurt the perception of service quality ($M_{present} = 4.87$ vs. $M_{absent} = 5.54$, $F(1,229) = 7.472$, $p = .007$) and satisfaction ($M_{present} = 4.59$ vs. $M_{absent} = 5.77$, $F(1,229) = 21.624$, $p < .001$). These results confirm Hypothesis 3 by revealing a negative impact of a chatbot's

provision of choices for complex tasks, which might lead to an incomprehensive choice set. Figure 4-4 illustrates the results.



Next, we investigated the moderating role of task complexity for the impact of choice provision on perceived fluency, our proposed mediator. Overall, providing choices did not have any effect on the perception of fluency ($M_{present} = 5.62$ vs. $M_{absent} = 5.84$, $F(1,229) = 2.318$, $p = .13$), and task complexity had a negative effect ($M_{high} = 5.47$ vs. $M_{low} = 5.99$, $F(1,229) = 12.142$, $p = .001$). Moreover, there was a significant interaction effect ($F(1,229) = 3.872$, $p = .05$), such that providing choices significantly reduced the perception of fluency only when task complexity was high ($M_{present} = 5.21$ vs. $M_{absent} = 5.73$, $F(1,229) = 6.087$, $p = .014$). When task complexity was low, providing choices did not influence perceived fluency ($M_{present} = 6.02$ vs. $M_{absent} = 5.95$, $F(1,229) = .099$, $p = .8$).

To test the full mediated moderation, we used a PROCESS Model 8 with a bootstrapping approach and the two service evaluation variables as the dependent variables (Hayes 2013). The analysis revealed that, when task complexity was high, providing choices significantly decreased the perception of fluency, which led to lower perception of service quality (Indirect effect = $-.41$; 95% CI = $[-.78, -.03]$) and satisfaction (Indirect effect = $-.40$; 95% CI = $[-.76, -.04]$). For a less complex task, such effects were not observed for either service quality (Indirect effect = $.05$; 95% CI = $[-.21, .33]$) or satisfaction (Indirect effect = $.05$; 95% CI = $[-.20, .32]$). These findings altogether confirm Hypothesis 4.

4.5.3 Discussion

In Study 2, we examined another boundary condition for the impact of providing choices: task complexity. The findings supported our hypotheses by illuminating the negative impact of providing choices on service evaluations for a more complex task, and such a negative impact is due to reduced perception of fluency. Indeed, because chatbots are programmed to provide a predefined set of choices, it is very likely that they cannot flexibly incorporate more complex customer requests. Facing a choice set that does not include the desired request, customers may feel interrupted, and the service process to be disfluent. This study, along with Study 1, underscores the role of fluency during a service interaction and how the contextual variables related to fluency can serve as boundary conditions for the impact of a service chatbot's provision of choices.

4.6 General Discussion

This research investigated the role of a chatbot's provision of choices during a service interaction. Based on the notion of fluency (Alter and Oppenheimer 2009), we proposed

two boundary conditions—conversational breakdowns and task complexity—for the impact of a chatbot providing choices on service evaluations. We hypothesized that the two boundary conditions moderate the impact of a chatbot’s choice provision by altering customers’ perception of the fluency of a service experience. We proposed that providing choices can enhance fluency and service outcomes only when conversational breakdowns occur. We further argued that providing choices may backfire when the complexity of a service task is high, enhancing the likelihood of a choice set to be perceived as incomprehensible. We conducted a series of experimental studies and found support for these hypotheses.

4.6.1 Theoretical Implications

Although prevalent in practice, the implementation of choices on a service chatbot has not been studied extensively. Prior studies on a service chatbot have focused mostly on the impact of incorporating social factors, such as anthropomorphism and conversational behaviors that emulate interpersonal interaction (Crollic et al. 2022a; Kim et al. 2019; Schanke et al. 2021a). In contrast, choice provision is a conversational characteristic unique to a chatbot and may affect customers’ perception of a chatbot and its performance. Such an implementation of choices has been suggested as one of the repair strategies after chatbot failures (Ashktorab et al. 2019; Benner et al. 2021), but we are not aware of any empirical efforts investigating its effects. By exploring the impact of choice implementation and its boundary conditions, we provide a more complete picture of when and why implementing choices can be a boon or a bane. More importantly, we question the conventional wisdom that implementing choices is always better, thus

extending the understanding of a prevalent conversational behavior of a service chatbot and its impact on users' assessment of a chatbot's performance.

Our research also contributes to customer service literature, specifically to the stream about technology-induced service interactions (Barrett et al. 2015). The unique boundary conditions have emerged due to the advent of AI technologies. Because of the uncertainty of a service environment, the technology at the moment cannot perfectly avoid potential failures, and thus, conversational breakdowns are inevitable (Honig and Oron-Gilad 2018). Also, because chatbots and a predefined set of choices are not flexible enough to satisfy a complex request, always providing a comprehensive list of choices is challenging to achieve. Thus, it is crucial to understand how the implementation of choices interacts with these boundary conditions and why. In addition to revealing the interactions, we illuminated that the impacts of these moderations on service outcomes occur because of the perception on the fluency of a service delivery process. These findings altogether add to the nascent literature on failures during a service encounter with AIs (Choi et al. 2020; Leo and Huh 2020; Sheehan et al. 2020) and expand the literature on the role of task complexity in customer service to its role in technology-induced service interactions (Xu et al. 2014).

Broadly, our research bolsters the literature on fluency. While cues for fluency can take various forms, from visual to linguistic to semantic (Alter and Oppenheimer 2009), we present novel cues for fluency unique to the service context. Through the findings related to the interaction of choice implementation and the two contextual variables, we identify boundary conditions that can either augment or deteriorate people's perception of fluency. Furthermore, by revealing the mediated moderating role of fluency on service

evaluations, we highlight how the perception of fluency influences people's judgments of their service experience.

4.6.2 Practical Implications

Our work presents valuable guidance for practitioners who have deployed or are considering deploying service chatbots. While intuition suggests that choice implementation streamlines a service delivery process and helps deliver a satisfactory service experience, it does not necessarily provide any value for customers during an 'ideal' service interaction. Its value is only recognized and achieved when the perception of fluency is impaired (e.g., conversational breakdowns). Choice implementation can, in fact, be treated as a recovery strategy to reduce the potential negative consequences of chatbot failures in general. From a firm's perspective, providing choices not only alleviates the negative impact of conversational breakdowns but also leads to a more structured conversation and prevents further failures. Thus, unlike other recovery strategies studied in prior literature, such as making an apology or providing explanations (Choi et al. 2020), choice implementation can be a cost-efficient solution that provides a higher chance of getting the conversation back to track and complete the service process satisfactorily.

On the other hand, our findings alarm practitioners by highlighting how a chatbot's provision of choices can be counterproductive for a service task with high complexity. Providing choices has a limitation because a chatbot cannot accurately anticipate every request of customers and has to rely on a predefined, limited set of choices. Due to the likelihood of a choice set being incomprehensive, choice implementation can backfire when a customer wants to make a complicated or unique request, thus disrupting service

delivery. This implies that firms should not haphazardly implement choices to realize the potential value of mitigating the negative consequences of conversational breakdowns. Overall, we urge firms to carefully assess the right timing and occasion for providing choices to enhance the benefits while weighing its potential costs before implementing choices during a chatbot-initiated service interaction.

4.6.3 Limitations and Future Research

Our work opens up several opportunities for future research. First, various factors related to a choice structure could affect the impact of choices. In this research, we focus only on the complexity of service tasks that can influence the perceived comprehensiveness of a choice set. However, there has been an extensive stream of research about how various aspects of choice architecture, such as presentation formats, the number of choices, and the categorization of choices, can influence people's decision-making (Thaler and Sunstein 2008). Future research can examine how these other characteristics of choices can affect customers' perception of a chatbot providing choices and the overall service evaluations.

Second, although our studies manipulated conversational breakdowns based on the most common form of chatbot failures (i.e., not understanding input messages), there may be other types of failures, such as misinterpreting a message, making nonsensical responses, not adhering to conversational norms, and so on (Benner et al. 2021). Conversational breakdowns caused by different types of errors may be processed differently by customers and may not have the same moderating effect as observed in this research. For instance, the choice may not be effective when a conversational breakdown is caused by social errors, such as violating conversational norms. Future studies can


categorize conversational breakdowns based on their causes (for example, technical errors versus social errors) and examine if the impact of choice implementation depends on the type of conversational breakdowns.

Lastly, while we only examined the moderating role of task complexity, other task-relevant characteristics may constitute additional boundary conditions. For example, choice implementation can benefit a standardized, routine task, while it may be counterproductive for a less common, unstandardized task. Or, in a broader sense, industry-relevant characteristics can be crucial moderators. For instance, in an industry that focuses on customer relationships and prioritizes social factors, such as healthcare or education, a chatbot simply providing choices may lack a human touch, leading to negative consequences. On the other hand, an industry that deals with functional, utilitarian tasks, such as banking, may realize the benefit of a chatbot that implements choices during an interaction with customers. Scholars can look into these other factors and how they influence customers' perception of choice and the performance of a chatbot.


APPENDIX A: CHAT SCRIPTS USED IN PRETEST OF CHAPTER 2

I. Low emotion


Customer Service Live Chat

GrabOutfit 
Hello. This is Taylor, and I'm working in the customer service department. Thank you for contacting us. I am handling your request today. Can you tell me why you are starting this chat, such as checking order status, missing item, return or exchange items, etc.?


YOU: Participant's message

GrabOutfit 
I can help you with that. What is your order number, and which item(s) is missing?

YOU: Participant's message


GrabOutfit 
I've identified the problem: there was a miscommunication in the packaging process. I have created a new order for you. The missing item will be delivered to you via one-day delivery service. Would this be okay with you?

YOU: Participant's message


GrabOutfit 
I have processed your request, and the issue is resolved. Please contact us again if you need further assistance. Bye.

II. Intermediate emotion


Customer Service Live Chat

GrabOutfit 
Hello. This is Taylor, and I'm working in the customer service department. Thank you for contacting us. I am delighted to handle your request today! Can you tell me why you are starting this chat, such as checking order status, missing item, return or exchange items, etc.?


YOU: Participant's message

GrabOutfit 
I can help you with that! What is your order number, and which item(s) is missing?

YOU: Participant's message


GrabOutfit 
I've identified the problem: there was a miscommunication in the packaging process. I have created a new order for you! The missing item will be delivered you via one-day delivery service. Would this be okay with you?

YOU: Participant's message


GrabOutfit 
I have processed your request, and I am glad that the issue is resolved! Please contact us again if you need further assistance. Bye!

III. High emotion


Customer Service Live Chat

GrabOutfit 
Hello. This is Taylor, and I'm working in the customer service department. Thank you for contacting us. I am delighted to handle your request today! Can you tell me why you are starting this chat, such as checking order status, missing item, return or exchange items, etc.?


YOU: Participant's message

GrabOutfit 
I can help you with that, and I am excited to do so! What is your order number, and which item(s) is missing?

YOU: Participant's message

GrabOutfit 
I've identified the problem: there was a miscommunication in the packaging process. I'm happy to have created a new order for you! The missing item will be delivered you via one-day delivery service. Would this be okay with you?

YOU: Participant's message

GrabOutfit 
I have processed your request, and I am glad that the issue is resolved! Please contact us again if you need further assistance. Bye!

APPENDIX B: COVER STORES USED IN THE EXPERIMENTS OF CHAPTER 2

Pretest, Study 1, and Study 3

Internet has changed how customers contact a company for questions related to the company's products. Thanks to Internet, customers can simply use their electronic devices to communicate with a customer service agent. The most popular form of such communications is an online live chat. Through a live chat with a customer service agent, customers can inquire about product and shipping issues, and the customer service agent may help address those issues.

In particular, online live chat is widely used in the retail industry. Your task in this study is to resolve an issue about a recent order by communicating with a service agent via a live chat.

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Imagine the following:

Two weeks ago, you ordered a pair of jeans, a navy sweater, and a baseball cap through an online apparel store that you have used often. Your order number was 6322, and your order was delivered three days ago. However, you found that although the jeans and the sweater were delivered, the baseball cap was missing. When you checked your bill, you saw that you already paid for everything, including the baseball cap. You would like to get the baseball cap delivered as soon as possible.

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So you decided to contact their customer service department. You open the store's website and notice a chat window (named "Contact Us via Live Chat") at the bottom right of the webpage. You decide to try this method to get in contact with a customer service agent.

On the following screens, you will chat with a customer service agent from the apparel store.

- In each screen, you will see a message from the agent and then type your response. Your responses should be based on the scenario that you read just now. Please make sure you read all the available information on the page before you type your response.
- As you communicate with the agent, please treat it as if it is actually happening. Simply read and respond to the agent as you would normally do.

Study 2

Internet has changed how customers contact a company for questions related to the company's products. Thanks to Internet, customers can simply use their electronic devices to communicate with a customer service agent. The most popular form of such communications is an online live chat. Through a live chat with a customer service agent, customers can inquire about product and shipping issues, and the customer service agent may help address those issues.

In particular, online live chat is widely used in the retail industry. Your task in this study is to resolve an issue about a recent order by communicating with a service agent via a live chat.

-----Page break-----

Imagine the following:

You are enrolled in a class that requires a textbook. The professor has required you to buy the latest edition (3rd edition) of the book. However, when you visit your usual online secondhand bookstore, you notice that there is a 2nd edition, which is \$50 cheaper than the 3rd edition. So you decide to buy the 2nd edition instead. You have your order number, G2029.

However, during the first week of class, you realize that the 2nd edition does not have some of the materials from the 3rd edition, which are needed for your first quiz. You decide to contact the bookstore to see if you can exchange for the 3rd edition (by paying \$50 more) with a free shipping or get a refund (in case the 3rd edition is not in stock). In either case, you would also want to find out whether you can get a free shipping label to send your 2nd edition back.

-----Page break-----

You open the bookstore's website and notice a chat window (named "Contact Us via Live Chat") at the bottom right of the webpage. You decide to try this method to get in contact with a customer service agent.

On the following screens, you will chat with a customer service agent from the bookstore.

- In each screen, you will see a message from the agent and then type your response. Your responses should be based on the scenario that you read just now. Please make sure you read all the available information on the page before you type your response.
- As you communicate with the agent, please treat it as if it is actually happening. Simply read and respond to the agent as you would normally do.

APPENDIX C: VARIABLES MEASURED IN THE EXPERIMENTS OF CHAPTER 2

Service Quality (7-point scale): (Cronin et al. 2000)

Please rate the service provided by the customer service agent in each of the following items below.

- Poor / excellent
- Inferior / superior
- Low standards / high standards

Satisfaction (7-point scale): (Cronin et al. 2000)

- Overall, how satisfied or dissatisfied did your experience with the customer service agent leave you feeling? (extremely dissatisfied / extremely satisfied)
- How well did this service experience with the customer service agent meet your needs? (extremely poor / extremely well)
- To what extent do you agree or disagree that overall, you are satisfied with the experience of interacting with the customer service agent? (strongly disagree / strongly agree)

Human-likeness (7-point scale): (Lankton et al. 2015; MacDorman 2006)

Using the following scale, how would you evaluate the customer service agent?

- Very humanlike / very mechanical
- Has many more human qualities / has many more techno qualities
- Very person-like / very machine-like

Emotional intensity (7-point scale): (Puntoni et al. 2008)

In your opinion, how much emotion was expressed by the customer service agent during your conversation?

- Very little emotion / a great deal of emotion
- Very few feelings / a lot of feelings
- Expressed very few sentiments / expressed many sentiments

Relationship norm orientation (7-point scale): (Aggarwal 2004; Li et al. 2018)

If you were to interact with an online customer service agent in general, you would want the relationship with the customer service agent to be...

- Strictly for business / bonded like family and friends
- Formal and professional / informal and friendly
- Purely transactional / based on friendship

Participants' felt emotion (7-point scale): (Pham 1998)

Please indicate how you felt right after your interaction with the service chatbot.

- Depressed / cheerful
- Sad / joyful
- Annoyed / pleased
- Unhappy / happy
- In a bad mood / in a good mood

Expectation-confirmation (7-point scale; reversed in the analyses to measure expectation-disconfirmation): (Bhattacharjee 2001)

Below are statements dealing with your perception of the chatbot you've just interacted with. Please indicate to what extent you agree or disagree with each statement.

- The level of the chatbot's expressed emotion is how you would expect most chatbots to behave.
- The level of the chatbot's emotional display was exactly what I expected.
- Overall, most of my expectations regarding the level of the chatbot's expressed emotion were confirmed.

APPENDIX D: COVER STORY USED IN THE EXPERIMENTS OF CHAPTER 3

Many companies have been investing in their customer service departments to enhance their relationship with customers. Due to the rise of online platforms, many companies have started to provide customer service online and even deploy a customer service chatbot. Through an online live chat with a customer service chatbot, customers can inquire about product and services, and the customer service chatbot may help address those issues.

Your task in this study is to resolve a service issue by communicating with a service chatbot via a live chat.

====Page break=====

Imagine the following:

Today, you just finished your final exam. You pulled an all-nighter to study for the last exam and even skipped lunch. Now is the dinner time, and you are extremely starving, but you have nothing to eat at your home. Because you are so tired, you do not want to go out for dinner. Still, you want to celebrate the end of the exam, so you decide to place a delivery order from your favorite restaurant. Because the restaurant does not deliver food by themselves, you place an order through a third-party online food delivery app. You have your order number, 6322.

====Page break=====

However, even after an hour, the food still has not arrived. You check your delivery status, and it says that the food has been ready for thirty minutes, but no one has picked up. So, you decide to contact a customer service center of the app to figure out what happened and resolve the delivery issue.

====Page break=====

You open the app and notice a chat window (named “Contact Us via Live Chat”) at the bottom right. You decide to try this method to get in contact with a customer service agent.

On the following screen, you will chat with a customer service agent from the app.

- You will engage in conversations with the customer service agent and type your responses to the agent's questions. Your responses should be based on the scenario that you read just now.
- As you communicate with the agent, please treat it as if it is actually happening. Simply read and respond to the agent as you would normally do.

APPENDIX E: VARIABLES MEASURED IN THE EXPERIMENTS OF CHAPTER 3

Service Quality (7-point scale): (Cronin et al. 2000)

Please rate the service provided by the customer service agent in each of the following items below.

- Poor / excellent
- Inferior / superior
- Low standards / high standards

Satisfaction with Service (7-point scale): (Cronin et al. 2000)

- Overall, how satisfied or dissatisfied did your experience with the customer service agent leave you feeling? (extremely dissatisfied / extremely satisfied)
- How well did this service experience with the customer service agent meet your needs? (extremely poor / extremely well)
- To what extent do you agree or disagree that overall, you are satisfied with the experience of interacting with the customer service agent? (strongly disagree / strongly agree)

Perceived Competence and Warmth (7-point scale): (Fiske et al. 2007)

Below are common characteristics people have. Based on your interaction, please specify the extent to which you think the customer service agent you've interacted with possesses each characteristic.

Competence

- Not at all capable / extremely capable
- Not at all confident / extremely confident
- Not at all efficient / extremely efficient
- Not at all intelligent / extremely intelligent
- Not at all competent / extremely competent
- Not at all skillful / extremely skillful

Warmth

- Not at all trustworthy / extremely trustworthy
- Not at all good-natured / extremely good-natured
- Not at all warm / extremely warm
- Not at all sincere / extremely sincere
- Not at all well-intentioned / extremely well-intentioned
- Not at all friendly / extremely friendly

Perceived Empathic Concern (7-point scale): (Goldstein et al. 2014; Toi and Batson 1982)

Please specify to what extent you agree or disagree to each statement. During your interaction with the chatbot, to what extent did the chatbot expressed that it...

- Understands your feeling
- Is concerned about you
- Empathizes with you

APPENDIX F: COVER STORIES USED IN THE EXPERIMENTS OF CHAPTER 4

Preliminary Study:

Internet has changed how customers contact a company for questions related to the company's products. Thanks to Internet, customers can simply use their electronic devices to communicate with a customer service agent. The most popular form of such communications is an online live chat. Through a live chat with a customer service agent, customers can inquire about product and shipping issues, and the customer service agent may help address those issues.

In particular, online live chat is widely used in the retail industry. Your task in this study is to resolve an issue about a recent order by communicating with a service agent via a live chat.

-----Page Break-----

Imagine the following:

You are enrolled in a class that requires a textbook. The professor has required you to buy the latest edition (3rd edition) of the book. However, when you visit your usual online secondhand bookstore, you notice that there is a 2nd edition, which is \$50 cheaper than the 3rd edition. So you decide to buy the 2nd edition instead. You have your order number, G2029.

However, during the first week of class, you realize that the 2nd edition does not have some of the materials from the 3rd edition, which are needed for your first quiz. You decide to contact the bookstore **to see if you can exchange for the 3rd edition (by paying \$50 more)** .

Study 1:

Internet has changed how customers contact a company for questions related to the company's products. Thanks to Internet, customers can simply use their electronic devices to communicate with a customer service agent. The most popular form of such communications is an online live chat. Through a live chat with a customer service agent, customers can inquire about product and shipping issues, and the customer service agent may help address those issues.

In particular, online live chat is widely used in the retail industry. Your task in this study is to resolve an issue about a recent order by communicating with a service agent via a live chat.

-----Page Break-----

Imagine the following:

Two weeks ago, you ordered a pair of jeans, a navy sweater, and a baseball cap through an online apparel store that you have used often. Your order number was 712, and your order was delivered three days ago. However, you found that although the jeans and the sweater were delivered and in good conditions, the baseball cap was missing. When you checked your bill, you saw that you already paid for everything, including the baseball cap. You would like to get the baseball cap delivered as soon as possible.

-----Page Break-----

So you decided to contact their customer service department. You open the store's website and notice a chat window (named "Contact Us via Live Chat") at the bottom right of the webpage. You decide to try this method to get in contact with a customer service agent.

On the following screen, you will chat with a customer service agent from the bookstore.

- You will engage in conversations with the customer service agent and type your responses to the agent's questions. Your responses should be based on the scenario that you read just now.
- As you communicate with the agent, please treat it as if it is actually happening. Simply read and respond to the agent as you would normally do.

Please click below when you are ready to begin.

Study 2:

High task complexity:

Imagine the following:

You are enrolled in a class that requires a textbook. The professor has required you to buy the latest edition (3rd edition) of the book. However, when you visit your usual online secondhand bookstore, you notice that there is a 2nd edition, which is \$50 cheaper than the 3rd edition. So you decide to buy the 2nd edition instead. You have your order number, G2029.

However, during the first week of class, you realize that the 2nd edition does not have some of the materials from the 3rd edition, which are needed for your first quiz. You decide to contact the bookstore **to see if you can exchange for the 3rd edition (by paying \$50 more) or get a refund (in case the 3rd edition is not in stock)**. In either case, you would also want to find out **whether you can get a free shipping label** to send your 2nd edition back.

Low task complexity:

Imagine the following:

You are enrolled in a class that requires a textbook. The professor has required you to buy the latest edition (3rd edition) of the book. However, when you visit your usual online secondhand bookstore, you notice that there is a 2nd edition, which is \$50 cheaper than the 3rd edition. So you decide to buy the 2nd edition instead. You have your order number, G2029.

However, during the first week of class, you realize that the 2nd edition does not have some of the materials from the 3rd edition, which are needed for your first quiz. You decide to contact the bookstore **to see if you can exchange for the 3rd edition (by paying \$50 more)**.

APPENDIX G: VARIABLES MEASURED IN THE EXPERIMENTS OF CHAPTER 4

Service Quality (7-point scale): (Cronin et al. 2000)

Please rate the service provided by the customer service agent in each of the following items below.

- Poor / excellent
- Inferior / superior
- Low standards / high standards

Satisfaction (7-point scale): (Cronin et al. 2000)

- Overall, how satisfied or dissatisfied did your experience with the customer service agent leave you feeling? (extremely dissatisfied / extremely satisfied)
- How well did this service experience with the customer service agent meet your needs? (extremely poor / extremely well)
- To what extent do you agree or disagree that overall, you are satisfied with the experience of interacting with the customer service agent? (strongly disagree / strongly agree)

Perception of Fluency (7-point scale): (Graf et al. 2018)

How would you describe your experience communicating with the service agent?

- Very difficult / very easy
- Very unclear / very clear
- Very disfluent / very fluent
- Very effortless / very effortful
- Very incomprehensible / very comprehensible
- Flowing very unwell / flowing very well

Frequency of Interruption (5-point scale): (Speier et al. 1999)

How often do you think your encounter with the service agent earlier was interrupted?

- Never / always

Frequency of Choice (5-point scale)

During the chat, how often did the service agent provide different options for you to click and choose?

- Never / always

Perception of task complexity (7-point scale): (Campbell 1988)

How would you describe the service task described at the beginning of the study?

- Not at all complex / very complex
- Not at all sophisticated / very sophisticated
- Not at all complicated / very complicated

Perception of choice comprehensiveness (7-point scale): (Yang et al. 2005)

Please specify to what extent you agree or disagree to each statement. **The choices provided during the chat was...**

- Appropriate for completing the task
- Sufficient for completing the task
- Complete enough to finish the task

REFERENCES

- Accenture. 2018. "Chatbots Are Here to Stay: So What Are You Waiting For?."
- Adam, M., Wessel, M., and Benlian, A. 2021. "Ai-Based Chatbots in Customer Service and Their Effects on User Compliance," *Electronic Markets* (31:2), pp. 427-445.
- Addas, S., and Pinsonneault, A. 2015. "The Many Faces of Information Technology Interruptions: A Taxonomy and Preliminary Investigation of Their Performance Effects," *Information Systems Journal* (25:3), pp. 231-273.
- Aggarwal, P. 2004. "The Effects of Brand Relationship Norms on Consumer Attitudes and Behavior," *Journal of Consumer Research* (31:1), pp. 87-101.
- Aggarwal, P., Castleberry, S. B., Ridnour, R., and Shepherd, C. D. 2005. "Salesperson Empathy and Listening: Impact on Relationship Outcomes," *Journal of Marketing Theory and Practice* (13:3), pp. 16-31.
- Ahearne, M., Jelinek, R., and Jones, E. 2007. "Examining the Effect of Salesperson Service Behavior in a Competitive Context," *Journal of the Academy of Marketing Science* (35), pp. 603-616.
- Alter, A. L., and Oppenheimer, D. M. 2009. "Uniting the Tribes of Fluency to Form a Metacognitive Nation," *Personality and Social Psychology Review* (13:3), pp. 219-235.
- Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., and Horvitz, E. 2019. "Guidelines for Human-Ai Interaction," in: *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. Glasgow, Scotland Uk: Association for Computing Machinery, p. Paper 3.
- Andalibi, N., and Buss, J. 2020. "The Human in Emotion Recognition on Social Media: Attitudes, Outcomes, Risks," in *Proceedings of the 2020 Chi Conference on Human Factors in Computing Systems*. Association for Computing Machinery, pp. 1-16.
- Anderson, E. W., and Sullivan, M. W. 1993. "The Antecedents and Consequences of Customer Satisfaction for Firms," *Marketing Science* (12:2), pp. 125-143.
- Araujo, T. 2018. "Living up to the Chatbot Hype: The Influence of Anthropomorphic Design Cues and Communicative Agency Framing on Conversational Agent and Company Perceptions," *Computers in Human Behavior* (85), pp. 183-189.

- Ashktorab, Z., Jain, M., Liao, Q. V., and Weisz, J. D. 2019. "Resilient Chatbots: Repair Strategy Preferences for Conversational Breakdowns," in: *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. Glasgow, Scotland Uk: Association for Computing Machinery, p. Paper 254.
- Barger, P. B., and Grandey, A. A. 2006. "Service with a Smile and Encounter Satisfaction: Emotional Contagion and Appraisal Mechanisms," *Academy of Management Journal* (49:6), pp. 1229-1238.
- Barrett-Lennard, G. T. 1981. "The Empathy Cycle: Refinement of a Nuclear Concept," *Journal of Counseling Psychology* (28:2), pp. 91-100.
- Barrett, M., Davidson, E., Prabhu, J., and Vargo, S. L. 2015. "Service Innovation in the Digital Age: Key Contributions and Future Directions," *MIS Quarterly* (39:1), pp. 135-154.
- Bell, C. R., and Zemke, R. E. 1987. "Service Breakdown: The Road to Recovery," *Management Review* (76:10), p. 32.
- Benbya, H., Pachidi, S., and Jarvenpaa, S. 2021. "Artificial Intelligence in Organizations: Implications for Information Systems Research,").
- Benner, D., Elshan, E., Schöbel, S., and Janson, A. 2021. "What Do You Mean? A Review on Recovery Strategies to Overcome Conversational Breakdowns of Conversational Agents," *ICIS 2021*.
- Bhattacharjee, A. 2001. "Understanding Information Systems Continuance: An Expectation-Confirmation Model," *MIS Quarterly* (25:3), pp. 351-370.
- Bitner, M. J., Booms, B. H., and Tetreault, M. S. 1990. "The Service Encounter: Diagnosing Favorable and Unfavorable Incidents," *Journal of Marketing* (54:1), pp. 71-84.
- Bitner, M. J., Brown, S. W., and Meuter, M. L. 2000. "Technology Infusion in Service Encounters," *Journal of the Academy of Marketing Science* (28:1), pp. 138-149.
- Bluvstein, S., Zhao, X., Barasch, A., and Schroeder, J. 2019. "'Hello! How May I Helo You?': How (Corrected) Errors Humanize a Communicator."
- Brady, M. K., and Cronin, J. J. 2001. "Some New Thoughts on Conceptualizing Perceived Service Quality: A Hierarchical Approach," *Journal of Marketing* (65:3), pp. 34-49.
- Brody, L. R., and Hall, J. A. 2008. "Gender and Emotion in Context," in *Handbook of Eotions*. The Guilford Press, pp. 395-408.

- Burgoon, J. K. 1993. "Interpersonal Expectations, Expectancy Violations, and Emotional Communication," *Journal of Language and Social Psychology* (12:1-2), pp. 30-48.
- Campbell, D. J. 1988. "Task Complexity: A Review and Analysis," *Academy of Management Review* (13:1), pp. 40-52.
- Castelo, N. 2019. "Blurring the Line between Human and Machine: Marketing Artificial Intelligence." Ann Arbor: Columbia University, p. 164.
- Chambon, V., and Haggard, P. 2012. "Sense of Control Depends on Fluency of Action Selection, Not Motor Performance," *Cognition* (125:3), pp. 441-451.
- Chandler, J., and Schwarz, N. 2010. "Use Does Not Wear Ragged the Fabric of Friendship: Thinking of Objects as Alive Makes People Less Willing to Replace Them," *Journal of Consumer Psychology* (20:2), pp. 138-145.
- Cheshin, A., Amit, A., and Van Kleef, G. A. 2018. "The Interpersonal Effects of Emotion Intensity in Customer Service: Perceived Appropriateness and Authenticity of Attendants' Emotional Displays Shape Customer Trust and Satisfaction," *Organizational Behavior and Human Decision Processes* (144), pp. 97-111.
- Cheshin, A., Rafaeli, A., and Bos, N. 2011. "Anger and Happiness in Virtual Teams: Emotional Influences of Text and Behavior on Others' Affect in the Absence of Non-Verbal Cues," *Organizational Behavior and Human Decision Processes* (116:1), pp. 2-16.
- Choi, S., Mattila, A. S., and Bolton, L. E. 2020. "To Err Is Human(-Oid): How Do Consumers React to Robot Service Failure and Recovery?," *Journal of Service Research*, p. 1094670520978798.
- Clark, M. S., and Mills, J. 1993. "The Difference between Communal and Exchange Relationships: What It Is and Is Not," *Personality and Social Psychology Bulletin* (19:6), pp. 684-691.
- Clark, M. S., and Taraban, C. 1991. "Reactions to and Willingness to Express Emotion in Communal and Exchange Relationships," *Journal of Experimental Social Psychology* (27:4), pp. 324-336.
- Clore, G. L., Gasper, K., and Garvin, E. 2001. "Affect as Information," in *Handbook of Affect and Social Cognition*. pp. 121-144.
- Cognizant. 2019. "The Future of Chatbots in Insurance."
- Cosmo, L. D. 2022. "Google Engineer Claims Ai Chatbot Is Sentient: Why That Matters," in: *Scientific American*.

- Creed, C., Beale, R., and Cowan, B. 2014. "The Impact of an Embodied Agent's Emotional Expressions over Multiple Interactions," *Interacting with Computers* (27:2), pp. 172-188.
- Crolic, C., Thomaz, F., Hadi, R., and Stephen, A. T. 2022a. "Blame the Bot: Anthropomorphism and Anger in Customer–Chatbot Interactions," *Journal of Marketing* (86:1), pp. 132-148.
- Crolic, C., Thomaz, F., Hadi, R., and Stephen, A. T. 2022b. "Blame the Bot: Anthropomorphism and Anger in Customer–Chatbot Interactions," (86:1), pp. 132-148.
- Cronin, J. J., Brady, M. K., and Hult, G. T. M. 2000. "Assessing the Effects of Quality, Value, and Customer Satisfaction on Consumer Behavioral Intentions in Service Environments," *Journal of Retailing* (76:2), pp. 193-218.
- Cuddy, A. J. C., Fiske, S. T., and Glick, P. 2008. "Warmth and Competence as Universal Dimensions of Social Perception: The Stereotype Content Model and the Bias Map," in *Advances in Experimental Social Psychology*. Academic Press, pp. 61-149.
- Cuff, B. M. P., Brown, S. J., Taylor, L., and Howat, D. J. 2016. "Empathy: A Review of the Concept," *Emotion review* (8:2), pp. 144-153.
- Davis, M. H., and Oathout, H. A. 1987. "Maintenance of Satisfaction in Romantic Relationships: Empathy and Relational Competence," *Journal of Personality and Social Psychology* (53:2), pp. 397-410.
- De Gennaro, M., Krumhuber, E. G., and Lucas, G. 2020. "Effectiveness of an Empathic Chatbot in Combating Adverse Effects of Social Exclusion on Mood," *Frontiers in Psychology* (10:3061).
- De Kervenoael, R., Hasan, R., Schwob, A., and Goh, E. 2020. "Leveraging Human-Robot Interaction in Hospitality Services: Incorporating the Role of Perceived Value, Empathy, and Information Sharing into Visitors' Intentions to Use Social Robots," *Tourism Management* (78), p. 104042.
- De Vignemont, F., and Singer, T. 2006. "The Empathic Brain: How, When and Why?," *Trends in Cognitive Sciences* (10:10), pp. 435-441.
- Doherty, R. W. 1997. "The Emotional Contagion Scale: A Measure of Individual Differences," *Journal of Nonverbal Behavior* (21:2), pp. 131-154.
- Duan, C., and Hill, C. E. 1996. "The Current State of Empathy Research," *Journal of Counseling Psychology* (43:3), pp. 261-274.
- Ekman, P., Sorenson, E. R., and Friesen, W. V. 1969. "Pan-Cultural Elements in Facial Displays of Emotion," *Science* (164:3875), pp. 86-88.

- Elliott, R., Bohart, A. C., Watson, J. C., and Greenberg, L. S. 2011. "Empathy," *Psychotherapy* (48:1), pp. 43-49.
- Epley, N., Waytz, A., and Cacioppo, J. 2007. "On Seeing Human: A Three-Factor Theory of Anthropomorphism," *Psychological review* (114), pp. 864-886.
- Evans, J. S. B. T. 2003. "In Two Minds: Dual-Process Accounts of Reasoning," *Trends in Cognitive Sciences* (7:10), pp. 454-459.
- Fernández-Sabiote, E., and López-López, I. 2020. "Discovering Call Interaction Fluency: A Way to Improve Experiences with Call Centres," *Service Science* (12:1), pp. 26-42.
- Ferrara, E., and Yang, Z. 2015. "Measuring Emotional Contagion in Social Media," *PLOS ONE* (10:11), p. e0142390.
- Festinger, L. 1957. *A Theory of Cognitive Dissonance*. Stanford university press.
- Financial Digest. 2017. "Ai Will Power 95% of Customer Interactions by 2025." from <https://www.financedigest.com/ai-will-power-95-of-customer-interactions-by-2025.html>
- Fischer, A. H., Kret, M. E., and Broekens, J. 2018. "Gender Differences in Emotion Perception and Self-Reported Emotional Intelligence: A Test of the Emotion Sensitivity Hypothesis," *PLOS ONE* (13:1), p. e0190712.
- Fiske, S. T., Cuddy, A. J. C., and Glick, P. 2007. "Universal Dimensions of Social Cognition: Warmth and Competence," *Trends in Cognitive Sciences* (11:2), pp. 77-83.
- Fotheringham, D., and Wiles, M. A. 2022. "The Effect of Implementing Chatbot Customer Service on Stock Returns: An Event Study Analysis," *Journal of the Academy of Marketing Science*.
- Froehle, C. M., and White, D. L. 2014. "Interruption and Forgetting in Knowledge-Intensive Service Environments," *Production and Operations Management* (23:4), pp. 704-722.
- Glikson, E., Cheshin, A., and Kleef, G. a. V. 2018. "The Dark Side of a Smiley: Effects of Smiling Emoticons on Virtual First Impressions," *Social Psychological and Personality Science* (9:5), pp. 614-625.
- Global Industry Analysts. 2021. "Affective Computing: Global Market Trajectory & Analytics."
- Goldenberg, A., and Gross, J. J. 2020. "Digital Emotion Contagion," *Trends in Cognitive Sciences* (24:4), pp. 316-328.

- Goldstein, N. J., Vezich, I. S., and Shapiro, J. R. 2014. "Perceived Perspective Taking: When Others Walk in Our Shoes," *Journal of Personality and Social Psychology* (106:6), pp. 941-960.
- Gotlieb, J. B., Grewal, D., and Brown, S. W. 1994. "Consumer Satisfaction and Perceived Quality: Complementary or Divergent Constructs?," *Journal of Applied Psychology* (79:6), pp. 875-885.
- Graf, L. K. M., Mayer, S., and Landwehr, J. R. 2018. "Measuring Processing Fluency: One Versus Five Items," *Journal of Consumer Psychology* (28:3), pp. 393-411.
- Gray, H. M., Gray, K., and Wegner, D. M. 2007. "Dimensions of Mind Perception," *Science* (315:5812), pp. 619-619.
- Gray, K., and Wegner, D. M. 2012. "Feeling Robots and Human Zombies: Mind Perception and the Uncanny Valley," *Cognition* (125:1), pp. 125-130.
- Guo, Y. R., and Goh, D. H.-L. 2015. "Affect in Embodied Pedagogical Agents: Meta-Analytic Review," *Journal of Educational Computing Research* (53:1), pp. 124-149.
- Gwo-Dong, C., Jih-Hsien, L., Chin-Yeh, W., Po-Yao, C., Liang-Yi, L., and Tzung-Yi, L. 2012. "An Empathic Avatar in a Computer-Aided Learning Program to Encourage and Persuade Learners," *Journal of Educational Technology & Society* (15:2), pp. 62-72.
- Håkansson, J., and Montgomery, H. 2003. "Empathy as an Interpersonal Phenomenon," *Journal of Social and Personal Relationships* (20:3), pp. 267-284.
- Hancock, J. T., Gee, K., Ciaccio, K., and Lin, J. M.-H. 2008. "I'm Sad You're Sad: Emotional Contagion in Cmc," in: *Proceedings of the 2008 ACM conference on Computer supported cooperative work*. San Diego, CA, USA: Association for Computing Machinery, pp. 295–298.
- Hasford, J., Hardesty, D. M., and Kidwell, B. 2015. "More Than a Feeling: Emotional Contagion Effects in Persuasive Communication," *Journal of Marketing Research* (52:6), pp. 836-847.
- Haslam, N. 2006. "Dehumanization: An Integrative Review," *Personality and Social Psychology Review* (10:3), pp. 252-264.
- Hatfield, E., Cacioppo, J. T., and Rapson, R. L. 1993. "Emotional Contagion," *Current Directions in Psychological Science* (2:3), pp. 96-100.
- Hayes, A. F. 2013. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. New York, NY, US: Guilford Press.

- Heise, D. R., and Calhan, C. 1995. "Emotion Norms in Interpersonal Events," *Social Psychology Quarterly* (58:4), pp. 223-240.
- Heskett, J. L., Jones, T. O., Loveman, G. W., Sasser, W. E., and Schlesinger, L. A. 1994. "Putting the Service Profit Chain to Work," in: *Harvard Business Review*. pp. 164-174.
- Honig, S., and Oron-Gilad, T. 2018. "Understanding and Resolving Failures in Human-Robot Interaction: Literature Review and Model Development," *Frontiers in Psychology* (9).
- Huang, M.-H., and Rust, R. T. 2018. "Artificial Intelligence in Service," *Journal of Service Research* (21:2), pp. 155-172.
- Huang, M.-H., and Rust, R. T. 2021. "Engaged to a Robot? The Role of Ai in Service," *Journal of Service Research* (24:1), pp. 30-41.
- Iglesias, O., Markovic, S., and Rialp, J. 2019. "How Does Sensory Brand Experience Influence Brand Equity? Considering the Roles of Customer Satisfaction, Customer Affective Commitment, and Employee Empathy," *Journal of Business Research* (96), pp. 343-354.
- Inkster, B., Sarda, S., and Subramanian, V. 2018. "An Empathy-Driven, Conversational Artificial Intelligence Agent (Wysa) for Digital Mental Well-Being: Real-World Data Evaluation Mixed-Methods Study," *JMIR Mhealth Uhealth* (6:11), p. e12106.
- Izard, C. E. 2011. "Forms and Functions of Emotions: Matters of Emotion–Cognition Interactions," (3:4), pp. 371-378.
- Jensen, M. L., Averbeck, J. M., Zhang, Z., and Wright, K. B. 2013. "Credibility of Anonymous Online Product Reviews: A Language Expectancy Perspective," *Journal of Management Information Systems* (30:1), pp. 293-324.
- Jiang, Z., and Benbasat, I. 2007. "The Effects of Presentation Formats and Task Complexity on Online Consumers' Product Understanding," *MIS Quarterly* (31:3), pp. 475-500.
- Jin, S.-a. A. 2012. "The Virtual Malleable Self and the Virtual Identity Discrepancy Model: Investigative Frameworks for Virtual Possible Selves and Others in Avatar-Based Identity Construction and Social Interaction," *Computers in Human Behavior* (28:6), pp. 2160-2168.
- Johnson, E. J., Shu, S. B., Dellaert, B. G. C., Fox, C., Goldstein, D. G., Häubl, G., Larrick, R. P., Payne, J. W., Peters, E., Schkade, D., Wansink, B., and Weber, E. U. 2012. "Beyond Nudges: Tools of a Choice Architecture," *Marketing Letters* (23:2), pp. 487-504.

- Kalman, Y. M., and Rafaeli, S. 2011. "Online Pauses and Silence: Chronemic Expectancy Violations in Written Computer-Mediated Communication," (38:1), pp. 54-69.
- Kim, S. Y., Schmitt, B. H., and Thalmann, N. M. 2019. "Eliza in the Uncanny Valley: Anthropomorphizing Consumer Robots Increases Their Perceived Warmth but Decreases Liking," *Marketing Letters* (30:1), pp. 1-12.
- Klopfenstein, L. C., Delpriori, S., Malatini, S., and Bogliolo, A. 2017. "The Rise of Bots: A Survey of Conversational Interfaces, Patterns, and Paradigms," in: *Proceedings of the 2017 Conference on Designing Interactive Systems*. Edinburgh, United Kingdom: Association for Computing Machinery, pp. 555–565.
- Kramer, A. D. I., Guillory, J. E., and Hancock, J. T. 2014. "Experimental Evidence of Massive-Scale Emotional Contagion through Social Networks," *Proceedings of the National Academy of Sciences* (111:24), pp. 8788-8790.
- Kranzbühler, A.-M., Zerres, A., Kleijnen, M. H. P., and Verlegh, P. W. J. 2020. "Beyond Valence: A Meta-Analysis of Discrete Emotions in Firm-Customer Encounters," *Journal of the Academy of Marketing Science* (48:3), pp. 478-498.
- Lankton, N., Mcknight, D., and Tripp, J. 2015. "Technology, Humanness, and Trust: Rethinking Trust in Technology," *Journal of the Association for Information Systems* (16), pp. 880-918.
- Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., Wunderlich, N. V., and De Keyser, A. 2017. "'Service Encounter 2.0': An Investigation into the Roles of Technology, Employees and Customers," *Journal of Business Research* (79), pp. 238-246.
- Lazarus, R. S. 2006. "Emotions and Interpersonal Relationships: Toward a Person-Centered Conceptualization of Emotions and Coping," *Journal of Personality* (74:1), pp. 9-46.
- Lee, M. K., Kiesler, S., Forlizzi, J., Srinivasa, S., and Rybski, P. 2010. "Gracefully Mitigating Breakdowns in Robotic Services," *2010 5th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pp. 203-210.
- Leo, X., and Huh, Y. E. 2020. "Who Gets the Blame for Service Failures? Attribution of Responsibility toward Robot Versus Human Service Providers and Service Firms," *Computers in Human Behavior* (113), p. 106520.
- Li, C.-H., Yeh, S.-F., Chang, T.-J., Tsai, M.-H., Chen, K., and Chang, Y.-J. 2020. "A Conversation Analysis of Non-Progress and Coping Strategies with a Banking Task-Oriented Chatbot," in *Proceedings of the 2020 Chi Conference on Human Factors in Computing Systems*. Association for Computing Machinery, pp. 1–12.

- Li, X., Chan, K. W., and Kim, S. 2018. "Service with Emoticons: How Customers Interpret Employee Use of Emoticons in Online Service Encounters," *Journal of Consumer Research* (45:5), pp. 973-987.
- Liu, B., and Sundar, S. S. 2018. "Should Machines Express Sympathy and Empathy? Experiments with a Health Advice Chatbot," *Cyberpsychology, Behavior, and Social Networking* (21:10), pp. 625-636.
- Liu, W., and Gal, D. 2011. "Bringing Us Together or Driving Us Apart: The Effect of Soliciting Consumer Input on Consumers' Propensity to Transact with an Organization," *Journal of Consumer Research* (38:2), pp. 242-259.
- Lucas, G. M., Gratch, J., King, A., and Morency, L.-P. 2014. "It's Only a Computer: Virtual Humans Increase Willingness to Disclose," *Computers in Human Behavior* (37), pp. 94-100.
- Luo, X., Tong, S., Fang, Z., and Qu, Z. 2019. "Frontiers: Machines Vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases," *Marketing Science* (38:6), pp. 937-947.
- Macdorman, K. 2006. "Subjective Ratings of Robot Video Clips for Human Likeness, Familiarity, and Eeriness: An Exploration of the Uncanny Valley," *ICCS/CogSci-2006 Long Symposium: Toward Social Mechanisms of Android Science*.
- Markets and Markets. 2019. "Chatbot Market by Component (Solutions and Services), Usage (Websites and Contact Centers), Technology, Deployment Model, Application (Customer Support and Personal Assistant), Organization Size, Vertical, and Region - Global Forecast to 2024."
- Mckinsey. 2018. "Notes from the Ai Frontier: Modeling the Impact of Ai on the World Economy." from <https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-AI-frontier-modeling-the-impact-of-ai-on-the-world-economy#>
- Mckinsey. 2021. "The State of Ai in 2021." from <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2021>
- Melo, C. M. D., Gratch, J., and Carnevale, P. J. 2013. "The Effect of Agency on the Impact of Emotion Expressions on People's Decision Making," *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, pp. 546-551.
- Meng, J., and Dai, Y. 2021. "Emotional Support from Ai Chatbots: Should a Supportive Partner Self-Disclose or Not?," *Journal of Computer-Mediated Communication* (26:4), pp. 207-222.

- Meuter, M. L., Ostrom, A. L., Roundtree, R. I., and Bitner, M. J. 2000. "Self-Service Technologies: Understanding Customer Satisfaction with Technology-Based Service Encounters," *Journal of Marketing* (64:3), pp. 50-64.
- Mirnig, N., Stollnberger, G., Miksch, M., Stadler, S., Giuliani, M., and Tscheligi, M. 2017. "To Err Is Robot: How Humans Assess and Act toward an Erroneous Social Robot," *Frontiers in Robotics and AI* (4:21).
- Mordor Intelligence. 2022. "Chatbot Market-Growth, Trends, Covid-19 Impact, and Forecasts (2022-2027)."
- Morelli, S. A., Lieberman, M. D., and Zaki, J. 2015. "The Emerging Study of Positive Empathy," *Social and Personality Psychology Compass* (9:2), pp. 57-68.
- Morris, R. R., Kouddous, K., Kshirsagar, R., and Schueller, S. M. 2018. "Towards an Artificially Empathic Conversational Agent for Mental Health Applications: System Design and User Perceptions," *J Med Internet Res* (20:6), p. e10148.
- Murray, I. R., and Arnott, J. L. 1993. "Toward the Simulation of Emotion in Synthetic Speech: A Review of the Literature on Human Vocal Emotion," *The Journal of the Acoustical Society of America* (93:2), pp. 1097-1108.
- Nadler, A., and Liviatan, I. 2006. "Intergroup Reconciliation: Effects of Adversary's Expressions of Empathy, Responsibility, and Recipients' Trust," *Personality and Social Psychology Bulletin* (32:4), pp. 459-470.
- Nass, C., Steuer, J., and Tauber, E. R. 1994. "Computers Are Social Actors," in: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Boston, Massachusetts, USA: Association for Computing Machinery, pp. 72-78.
- Neumann, R., and Strack, F. 2000. "'Mood Contagion': The Automatic Transfer of Mood between Persons," *Journal of Personality and Social Psychology* (79:2), pp. 211-223.
- Nguyen, Q. N., Sidorova, A., and Torres, R. 2022. "User Interactions with Chatbot Interfaces Vs. Menu-Based Interfaces: An Empirical Study," *Computers in Human Behavior* (128), p. 107093.
- Oliva, T. A., Oliver, R. L., and Macmillan, I. C. 1992. "A Catastrophe Model for Developing Service Satisfaction Strategies," *Journal of Marketing* (56:3), pp. 83-95.
- Oliver, R. L. 1977. "Effect of Expectation and Disconfirmation on Postexposure Product Evaluations: An Alternative Interpretation," *Journal of Applied Psychology* (62:4), pp. 480-486.

- Oliver, R. L. 1980. "A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions," (17:4), pp. 460-469.
- Oliver, R. L. 1993. "Cognitive, Affective, and Attribute Bases of the Satisfaction Response," *Journal of Consumer Research* (20:3), pp. 418-430.
- Olson, J. K. 1995. "Relationships between Nurse-Expressed Empathy, Patient-Perceived Empathy and Patient Distress," *Journal of Nursing Scholarship* (27:4), pp. 317-322.
- Oppenheimer, D. M. 2008. "The Secret Life of Fluency," *Trends in Cognitive Sciences* (12:6), pp. 237-241.
- Oracle. 2016. "Can Virtual Experiences Replace Reality?" Retrieved 06/23, 2020, from https://www.oracle.com/webfolder/s/delivery_production/docs/FY16h1/doc35/CXResearchVirtualExperiences.pdf
- Orth, U. R., and Wirtz, J. 2014. "Consumer Processing of Interior Service Environments: The Interplay among Visual Complexity, Processing Fluency, and Attractiveness," *Journal of Service Research* (17:3), pp. 296-309.
- Ostrom, A. L., Field, J. M., Fotheringham, D., Subramony, M., Gustafsson, A., Lemon, K. N., Huang, M.-H., and Mccoll-Kennedy, J. R. 2021. "Service Research Priorities: Managing and Delivering Service in Turbulent Times," *Journal of Service Research* (24:3), pp. 329-353.
- Parasuraman, A., Zeithaml, V. A., and Berry, L. L. 1985. "A Conceptual Model of Service Quality and Its Implications for Future Research," *Journal of Marketing* (49:4), pp. 41-50.
- Parasuraman, A. P., Berry, L., and Zeithaml, V. 1991. "Understanding Customer Expectations of Service," *Sloan Management Review* (32), pp. 39-48.
- Pelau, C., Dabija, D.-C., and Ene, I. 2021. "What Makes an Ai Device Human-Like? The Role of Interaction Quality, Empathy and Perceived Psychological Anthropomorphic Characteristics in the Acceptance of Artificial Intelligence in the Service Industry," *Computers in Human Behavior* (122), p. 106855.
- Petty, R. E., and Cacioppo, J. T. 1986. "The Elaboration Likelihood Model of Persuasion," in *Communication and Persuasion: Central and Peripheral Routes to Attitude Change*. New York, NY: Springer New York, pp. 1-24.
- Pham, M. T. 1998. "Representativeness, Relevance, and the Use of Feelings in Decision Making," *Journal of Consumer Research* (25:2), pp. 144-159.
- Phelps, E. A. 2006. "Emotion and Cognition: Insights from Studies of the Human Amygdala," (57:1), pp. 27-53.

- Prendinger, H., and Ishizuka, M. 2005. "The Empathic Companion: A Character-Based Interface That Addresses Users' Affective States," *Applied Artificial Intelligence* (19:3-4), pp. 267-285.
- Pugh, S. D. 2001. "Service with a Smile: Emotional Contagion in the Service Encounter," *Academy of Management Journal* (44:5), pp. 1018-1027.
- Puntoni, S., De Langhe, B., and Van Osselaer, S. M. J. 2008. "Bilingualism and the Emotional Intensity of Advertising Language," *Journal of Consumer Research* (35:6), pp. 1012-1025.
- Rafaeli, A., and Sutton, R. I. 1990. "Busy Stores and Demanding Customers: How Do They Affect the Display of Positive Emotion?," *Academy of Management Journal* (33:3), pp. 623-637.
- Ramirez, A., Jr, and Wang, Z. 2008. "When Online Meets Offline: An Expectancy Violations Theory Perspective on Modality Switching," *Journal of Communication* (58:1), pp. 20-39.
- Reber, R., Wurtz, P., and Zimmermann, T. D. 2004. "Exploring "Fringe" Consciousness: The Subjective Experience of Perceptual Fluency and Its Objective Bases," *Consciousness and Cognition* (13:1), pp. 47-60.
- Reports and Data. 2021. "Affective Computing Market."
- Sampson, S. E., and Froehle, C. M. 2006. "Foundations and Implications of a Proposed Unified Services Theory," *Production and Operations Management* (15:2), pp. 329-343.
- Schanke, S., Burtch, G., and Ray, G. 2021a. "Estimating the Impact of "Humanizing" Customer Service Chatbots," *Information Systems Research* (32:3), pp. 736-751.
- Schanke, S., Burtch, G., and Ray, G. 2021b. "Estimating the Impact of "Humanizing" Customer Service Chatbots," *Information Systems Research* (0:0), p. null.
- Scheibehenne, B., Greifeneder, R., and Todd, P. M. 2010. "Can There Ever Be Too Many Options? A Meta-Analytic Review of Choice Overload," *Journal of Consumer Research* (37:3), pp. 409-425.
- Schwarz, N. 2004. "Metacognitive Experiences in Consumer Judgment and Decision Making," *Journal of Consumer Psychology* (14:4), pp. 332-348.
- Schwarz, N., Bless, H., Strack, F., Klumpp, G., Rittenauer-Schatka, H., and Simons, A. 1991. "Ease of Retrieval as Information: Another Look at the Availability Heuristic," *Journal of Personality and Social Psychology* (61:2), pp. 195-202.

- Schwarz, N., and Clore, G. L. 1983. "Mood, Misattribution, and Judgments of Well-Being: Informative and Directive Functions of Affective States," *Journal of Personality and Social Psychology* (45:3), pp. 513-523.
- Scott, M. L., Mende, M., and Bolton, L. E. 2013. "Judging the Book by Its Cover? How Consumers Decode Conspicuous Consumption Cues in Buyer–Seller Relationships," *Journal of Marketing Research* (50:3), pp. 334-347.
- Seshadri, S., and Shapira, Z. 2001. "Managerial Allocation of Time and Effort: The Effects of Interruptions," *Management Science* (47:5), pp. 647-662.
- Sheehan, B., Jin, H. S., and Gottlieb, U. 2020. "Customer Service Chatbots: Anthropomorphism and Adoption," *Journal of Business Research* (115), pp. 14-24.
- Shen, X.-L., Li, Y.-J., Sun, Y., and Wang, N. 2018. "Channel Integration Quality, Perceived Fluency and Omnichannel Service Usage: The Moderating Roles of Internal and External Usage Experience," *Decision Support Systems* (109), pp. 61-73.
- Shnabel, N., and Nadler, A. 2008. "A Needs-Based Model of Reconciliation: Satisfying the Differential Emotional Needs of Victim and Perpetrator as a Key to Promoting Reconciliation," *Journal of Personality and Social Psychology* (94:1), pp. 116-132.
- Shriberg, E. 2001. "To 'Errrr' Is Human: Ecology and Acoustics of Speech Disfluencies," *Journal of the International Phonetic Association* (31:1), pp. 153-169.
- Simonite, T. 2017. "Facebook's Perfect, Impossible Chatbot," in: *MIT Technology Review*.
- Sirianni, N. J., Bitner, M. J., Brown, S. W., and Mandel, N. 2013. "Branded Service Encounters: Strategically Aligning Employee Behavior with the Brand Positioning," *Journal of Marketing* (77:6), pp. 108-123.
- Somers, M. 2019. "Emotion Ai, Explained." from <https://mitsloan.mit.edu/ideas-made-to-matter/emotion-ai-explained>
- Speier, C., Valacich, J. S., and Vessey, I. 1999. "The Influence of Task Interruption on Individual Decision Making: An Information Overload Perspective," *Decision Sciences* (30:2), pp. 337-360.
- Stein, J.-P., and Ohler, P. 2017. "Venturing into the Uncanny Valley of Mind—the Influence of Mind Attribution on the Acceptance of Human-Like Characters in a Virtual Reality Setting," *Cognition* (160), pp. 43-50.
- Stewart, D. M., and Chase, R. B. 1999. "The Impact of Human Error on Delivering Service Quality," *Production and Operations Management* (8:3), pp. 240-263.

- Stock, R. M., and Hoyer, W. D. 2005. "An Attitude-Behavior Model of Salespeople's Customer Orientation," *Journal of the Academy of Marketing Science* (33:4), pp. 536-552.
- Sunstein, C. R. 2017. "Default Rules Are Better Than Active Choosing (Often)," *Trends in Cognitive Sciences* (21:8), pp. 600-606.
- Taylor, S. A., and Baker, T. L. 1994. "An Assessment of the Relationship between Service Quality and Customer Satisfaction in the Formation of Consumers' Purchase Intentions," *Journal of Retailing* (70:2), pp. 163-178.
- Thaler, R. H., and Sunstein, C. R. 2008. *Nudge: Improving Decisions About Health, Wealth, and Happiness*. Yale University Press.
- The Economist. 2022. "Could Artificial Intelligence Become Sentient?," in: *The Economist*.
- Thompson, D. V., and Ince, E. C. 2013. "When Disfluency Signals Competence: The Effect of Processing Difficulty on Perceptions of Service Agents," *Journal of Marketing Research* (50:2), pp. 228-240.
- Tiku, N. 2022a. "The Google Engineer Who Thinks the Company's Ai Has Come to Life," in: *The Washington Post*.
- Tiku, N. 2022b. "The Google Engineer Who Thinks the Company's Ai Has Come to Life," in: *The Washington Post*.
- Toi, M., and Batson, C. D. 1982. "More Evidence That Empathy Is a Source of Altruistic Motivation," *Journal of Personality and Social Psychology* (43:2), pp. 281-292.
- Tsai, W. C., and Huang, Y. M. 2002. "Mechanisms Linking Employee Affective Delivery and Customer Behavioral Intentions," *J Appl Psychol* (87:5), pp. 1001-1008.
- Van Der Schalk, J., Fischer, A., Doosje, B., Wigboldus, D., Hawk, S., Rotteveel, M., and Hess, U. 2011. "Convergent and Divergent Responses to Emotional Displays of Ingroup and Outgroup," *Emotion* (11:2), pp. 286-298.
- Van Kleef, G. A. 2009. "How Emotions Regulate Social Life: The Emotions as Social Information (Easi) Model," *Current Directions in Psychological Science* (18:3), pp. 184-188.
- Van Kleef, G. A., and Côté, S. 2007. "Expressing Anger in Conflict: When It Helps and When It Hurts," *Journal of Applied Psychology* (92:6), pp. 1557-1569.
- Van Kleef, G. A., and Côté, S. 2022. "The Social Effects of Emotions," *Annual Review of Psychology* (73), pp. 629-658.

- Van Kleef, G. A., De Dreu, C. K. W., and Manstead, A. S. R. 2010. "Chapter 2 - an Interpersonal Approach to Emotion in Social Decision Making: The Emotions as Social Information Model," in *Advances in Experimental Social Psychology*. Academic Press, pp. 45-96.
- Velez, J. A., Loof, T., Smith, C. A., Jordan, J. M., Villarreal, J. A., and Ewoldsen, D. R. 2019. "Switching Schemas: Do Effects of Mindless Interactions with Agents Carry over to Humans and Vice Versa?," *Journal of Computer-Mediated Communication* (24:6), pp. 335-352.
- Verhagen, T., Van Nes, J., Feldberg, F., and Van Dolen, W. 2014. "Virtual Customer Service Agents: Using Social Presence and Personalization to Shape Online Service Encounters*," *Journal of Computer-Mediated Communication* (19:3), pp. 529-545.
- Voorhees, C. M., Fombelle, P. W., Gregoire, Y., Bone, S., Gustafsson, A., Sousa, R., and Walkowiak, T. 2017. "Service Encounters, Experiences and the Customer Journey: Defining the Field and a Call to Expand Our Lens," *Journal of Business Research* (79), pp. 269-280.
- Warren, C. A. 2018. "Empathy, Teacher Dispositions, and Preparation for Culturally Responsive Pedagogy," *Journal of Teacher Education* (69:2), pp. 169-183.
- Wieseke, J., Geigenmüller, A., and Kraus, F. 2012. "On the Role of Empathy in Customer-Employee Interactions," *Journal of Service Research* (15:3), pp. 316-331.
- Wispé, L. 1986. "The Distinction between Sympathy and Empathy: To Call Forth a Concept, a Word Is Needed," *Journal of Personality and Social Psychology* (50:2), pp. 314-321.
- Wood, R. E. 1986. "Task Complexity: Definition of the Construct," *Organizational Behavior and Human Decision Processes* (37:1), pp. 60-82.
- Xu, J., Benbasat, I., and Cenfetelli, R. T. 2014. "Research Note—the Influences of Online Service Technologies and Task Complexity on Efficiency and Personalization," *Information Systems Research* (25:2), pp. 420-436.
- Yang, Z., Cai, S., Zhou, Z., and Zhou, N. 2005. "Development and Validation of an Instrument to Measure User Perceived Service Quality of Information Presenting Web Portals," *Information & Management* (42:4), pp. 575-589.
- Yin, D., Bond, S. D., and Zhang, H. 2017. "Keep Your Cool or Let It Out: Nonlinear Effects of Expressed Arousal on Perceptions of Consumer Reviews," *Journal of Marketing Research* (54:3), pp. 447-463.

- Yuan, L., and Dennis, A. R. 2019. "Acting Like Humans? Anthropomorphism and Consumer's Willingness to Pay in Electronic Commerce," *Journal of Management Information Systems* (36:2), pp. 450-477.
- Zhou, X., Kim, S., and Wang, L. 2018. "Money Helps When Money Feels: Money Anthropomorphism Increases Charitable Giving," *Journal of Consumer Research* (45:5), pp. 953-972.
- Zomerdijk, L. G., and Voss, C. A. 2010. "Service Design for Experience-Centric Services," *Journal of Service Research* (13:1), pp. 67-82.