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Three Essays on Consumer Interaction with Artificial Intelligence

par
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Three Essays on Consumer Interaction with Artificial Intelligence

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Résumé

La thèse est divisée en trois essais. Le premier essai examine comment les consommateurs réagissent différemment à un service basé sur l'IA. Plus précisément, j’examine l’influence des défaillances des services d’IA sur la propension à partager du bouche-à-oreille négatif. Trois expériences démontrent que les consommateurs sont moins disposés à partager du bouche-à-oreille négatif après une défaillance de service causée par un système de recommandation d'IA, contrairement à un employé humain, bien qu'il n'y ait aucune différence dans l'échec, le blâme de l'entreprise ou le mécontentement à l'égard du échec. Une enquête plus approfondie suggère que cet effet est motivé par la connexion perçue des consommateurs avec l'IA qui utilise leur comportement passé pour prédire leurs préférences futures. Les conclusions mettent en lumière la compréhension globale des interactions consommateur-IA.

Le deuxième essai examine les technologies basées sur l'IA dans le secteur de la vente au détail et des services (par exemple, les assistants virtuels, les objets intelligents et les robots), sur la façon dont les consommateurs les perçoivent et interagissent avec eux. Des recherches récentes suggèrent que plusieurs types de relations avec l'IA peuvent émerger à différents points de contact tout au long du parcours client. Cependant, l'impact potentiel de ces relations sur l'expérience du consommateur n'est pas clair. Dans cet article, je découvre un effet d'épée à double tranchant en examinant deux rôles relationnels prédominants (c.-à-d. Partenaire vs serviteur). À travers quatre expériences, les résultats montrent que le positionnement d'un assistant virtuel d'IA en tant que partenaire augmente l'auto-expansion des consommateurs avec l'IA par rapport au positionnement d'un

serviteur, ce qui à son tour empêche les consommateurs de faire des attributions intéressées (études 1-2). Cependant, de telles relations de partenariat ne semblent pas profiter aux évaluations de l'IA suite à une panne de service, car les utilisateurs sont moins susceptibles de l'utiliser à nouveau à l'avenir (étude 3). Une analyse plus approfondie suggère que cet effet négatif est motivé par une diminution de l'auto-efficacité perçue (étude 4).

Le troisième essai se poursuit avec l'examen de l'échec de l'interaction avec l'IA, mais met l'accent sur la manière d'atténuer son effet négatif. J'examine un type particulier d'IA, les assistants vocaux, qui sont devenus un point de contact de plus en plus populaire dans les rencontres de services infusés par l'IA. En m'inspirant du paradigme de recherche *Computers As Social Actors* (CASA) et le *Stereotype Content Model*, j'explore comment la chaleur peut atténuer les conséquences négatives de l'échec de service des assistants vocaux. Dans deux expériences utilisant à la fois des mesures physiologiques (EDA) et psychologiques, les résultats montrent que la perception de la chaleur émotionnelle améliore les réactions émotionnelles des consommateurs et augmente l'intention de re-patronage suite à un résultat d'interaction négatif. En plus, la voix optimale à utiliser en cas d'échec de service est un style de discours dynamique combiné à un contenu verbal émotionnellement expressif et chaleureux. Ces résultats contribuent aux connaissances sur l'interaction des services vocaux et fournissent des informations sur la manière d'atténuer les conséquences négatives d'une défaillance des services impliquant des assistants vocaux.

Mots clés : intelligence artificielle; échec de service; bouche-à-oreille négatif; relation; expansion de soi; attribution; auto-efficacité; assistant virtuel; chaleur émotionnelle; style d’élocution.

Méthodes de recherche : design expérimental; mesures psychophysiologiques

Abstract

The thesis is divided into three essays. The first essay looks at how consumers react differently toward an AI-based service. Specifically, I examine the influence of AI service failures on consumers' propensity to share negative word-of-mouth. Three experiments demonstrate that consumers are less willing to share negative word-of-mouth after a service failure caused by an AI recommendation system, in contrast to a human employee, despite there being no difference in the failure, firm blame, or dissatisfaction with the failure. Further investigation suggests that this effect is driven by consumers' perceived connection with the AI that uses their past behavior to predict their future preferences. The conclusions shed light on the overall understanding of consumer-AI interactions.

The second essay examines AI-powered technologies in the retail and service sector (e.g., virtual assistants, smart objects, and robots), on how consumers perceive and interact with them. Recent research suggests that several types of relationship with AI can emerge at various touchpoints along the customer journey. However, the potential impact of these relationships on consumer experience is unclear. In the second article, I uncover a double-edged sword effect by examining two prevalent relationship roles (i.e., partner vs. servant). Through four experiments, the findings show that positioning an AI virtual assistant as a partner increases consumers' self-expansion with the AI compared to a servant positioning, which in turn constrains consumers from making self-serving attributions (Studies 1-2). However, such partner relationship does not seem to benefit AI evaluations following a service failure, since consumers are less likely to use it again in

the future (Study 3). Further analysis suggests that this negative effect is driven by a decrease in perceived self-efficacy (Study 4).

Essay 3 continues with the examination of interaction failure with AI, but shifts the focus on how to mitigate its negative effect. We look at one particular type of AI, namely voice assistants, which have become an increasingly popular touchpoint in AI-infused service encounters. Drawing from the Computers As Social Actors (CASA) research paradigm and the Stereotype Content Model, I explore how warmth can mitigate the negative consequences of service failure by voice assistants. In two experiments using both physiological (EDA) and psychological measures, we show that the perception of warmth improves consumers' emotional reactions and increases re-patronage intention following a negative interaction outcome. We also found that the optimal voice to be used in service failure is a dynamic speech style combined with emotionally expressive and warm verbal content. These findings contribute to the knowledge on voice-based service interaction and provide insight for how to mitigate negative consequences of service failure involving voice assistants.

Keywords : artificial intelligence; service failure; negative word-of-mouth; relationship; self-expansion; attribution; self-efficacy; virtual assistant; warmth; speaking style.

Research methods : experimental design; psychophysiological measures

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For the sweet future, that is yet to come.

Acknowledgements

A funny fact you might not know: my given name is 博 (Bo), in Chinese it literally means abundant and vast, with an extended meaning of a doctoral degree. When I was a kid, people always made fun of me: *Ah, you will be a "PhD" when you grow up!* Well, jokes on them, I really am one now.

It almost seems surreal looking back at this journey. I would be lying to say that the past 4 years was easy. It wasn't. But I count myself lucky. I am lucky that I studied at HEC Montreal, an institution that I proudly feel a part of; I am lucky that I have the two best PhD supervisors that one can hope for; I am lucky that I have my dearest and most supportive friends along the road; I am lucky that I realized the rules of game early enough to steer to the right direction.

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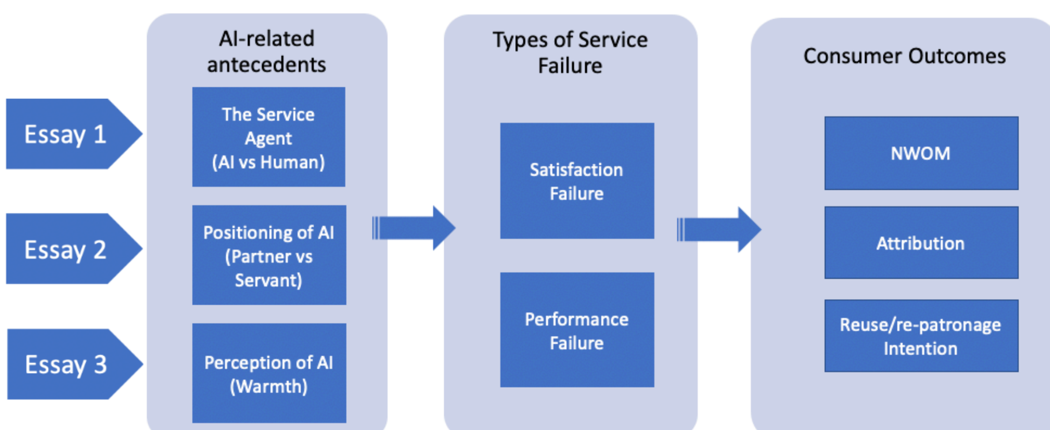
Introduction

Today's service landscape has been increasingly shaped by emerging technologies led by artificial intelligence (AI). This AI infusion creates novel consumer interactions with a variety of non-human entities such as algorithms, service robots, and virtual assistants along the customer journey. As those AI-powered technologies become a routine element in service encounters and even partially (or completely for certain industries) replace human frontline employees, the traditional view of service encounter (i.e., the dyadic interaction between a customer and a service provider) has been expanded to interspecific service encounters (human-to-AI), and even inter-AI service encounters (AI-to-AI). Such service revolution calls for an entire research paradigm shift to consumer-AI interactions. Against this backdrop, in three essays, the thesis contributes to the literature by exploring service encounters involving AI from three interrelated topics (Figure A).

Figure A. Overall Conceptual Framework



The overall conceptual frame shows that in three essays, the thesis examines three AI-related antecedents and several consumer outcomes with a central focus of service failure. First, based on the characteristics of AI-based service, I differentiate two types of failure: satisfaction failure and performance failure. Essay 1 and 2 investigate satisfaction failure, which is deeply rooted in the expectancy-disconfirmation paradigm, whereby consumer satisfaction is determined by positive or negative disconfirmation between perceived service performance outcome and prior expectations. For example, a customer checks in an AI hotel (such hotels already exist in Japan and China) where services are provided by robots and virtual assistants. However, he/she is not satisfied with the experience. In this case, the service failure occurs when the service is delivered by the AI, but not to the customer's satisfaction. Such failure is similar to those caused by human employees, where the services provided yield unsatisfactory outcomes. In contrast, Essay 3 looks at a different type of failure which is referred as performance failure, where the service is not delivered due to the AI's inability. For example, a customer places an order through an AI voice ordering system at a restaurant. However, the order is not placed because the AI is unable to understand this customer. Such failure is more common in the AI context as traditional services delivered by human agents are unlikely to suffer from misunderstanding or incomprehension. However, considering its current technical limitations, performance failure is unavoidable in today's service interactions involving AI. By integrating the two types of service failure, this thesis provides a comprehensive and holistic view of the different antecedents and outcomes.

Across three essays, this thesis links several important antecedents to a variety of consumer post-failure reactions in AI-based service interactions. The research starts with a direct comparison between an AI agent versus a human employee, by investigating the benefits of replacing human with AI. Such comparison echoes with most extant research on services encounters with AI. Here, I study one of the most important outcomes following service failure – negative word-of-mouth (NWOM) behaviors. It is found that compared to a human employee, AI inhabits consumers from sharing NWOM after receiving an unsatisfactory service, especially when the AI is built to mirror the consumer's self-image, which in turn enhances their perceived connection with the AI. Essay 2 builds on this idea of self-AI connection and extends it to the concept of self-expansion. Although essay one finds that consumers feel connected to AI algorithm, such connection doesn't go further into building social relationship. Therefore, Essay 2 introduces the idea of consumer-AI relationship into this context. Another addition is that rather than comparing AI versus human (as Essay 1), in this essay I focus on the positioning of the AI. In terms of the outcomes, Essay 2 focuses on attribution (how consumers attribute the outcome) and re-use intention. Drawing on previous theorizations, I distinguish two types of relationship that consumers tend to form with an AI: partner and servant. The findings suggested that such positioning has a double-edged sword effect: on the one hand, an AI-as-partner role makes consumers more likely to incorporate the AI into themselves, and such relationship closeness leads to more gracious attribution in the case of service failure. However, it also brings down consumers' future reuse intention due to a decreased self-efficacy. Building on the first two essays, the final essay focuses specifically on one type of AI service interaction: voice AI. In addition, essay three also complements the other two essays by proposing a viable way to mitigate negative consumer outcomes after a service failure involving AI. In this essay, I also look beyond reuse intention of the AI, to re-patronage of the firm who uses AI to provide service. Such lens brings managerial insight into the findings. Specifically, in Essay 3, the findings showed that increasing a voice assistant's perceived warmth can improve consumers' emotional reactions and increase re-patronage intention. The results further suggested that from a voice point of view, the perception of warmth can be induced both verbally and vocally.

In studying consumer-AI interaction, this empirical research adopts a multi-method approach. Essay one and two use scenario-based experimental design and psychological measures (e.g., self-reported questionnaires) for data collection. Essay three incorporates a controlled laboratory experiment where participants interacted with a stimulated voice assistant. Neuroscience tool is also used to assess their physiological reactions during the interaction. Taken together, the diverse methodology used in this thesis across three essays is also a unique contribution to the emerging literature on consumer-AI interaction.

To sum up, this thesis consists of 3 essays examining various antecedents and consumer outcomes in service encounters involving AI. Building on the idea of viewing AI as a social actor, it applies theories from social psychology and marketing to empirically answer three sets of distinct research questions. The findings contribute to the extant literature on consumer-AI interaction and AI-based services, as well as provide managerial insights for firms to better implement AI in their service provision.

Chapter 1

When AI-based Services Fail: Examining the Effect of the Self-AI Connection on Willingness to Share Negative Word-of-Mouth after Service Failures[1][2]

Context

As the first essay of the thesis, this paper draws a direct comparison between an AI versus human agent, in the context of service failure. Specifically, I look at satisfaction failure, which occurs when the service is delivered, but not to the customer's satisfaction. Such failures are very common during traditional service encounters. The outcome examined, specifically NWOM, is also one of the most important outcomes following service failures. Therefore, the extension to new AI-infused service encounters is novel and insightful. In addition, this essay focuses on how the actual provider of the service (whether it is an AI or a human agent) affects consumers NWOM sharing intentions. As the first essay, this paper opens an initial discussion on how consumers react differently toward service failures involving an AI agent.

Abstract

Recent proliferation of artificial intelligence (AI) in service encounters gives rise to questions on how consumers respond to these novel technologies. This study seeks to

[1] This article has been published in the *Service Industries Journal* (2020), 1-23.
[2] This article is co-authored with Matthew Philp (Ryerson University).

examine the influence of AI service failures on consumers' propensity to share negative word-of-mouth. Three experiments demonstrate that consumers are less willing to share negative word-of-mouth after a service failure caused by an AI recommendation system, in contrast to a human employee, despite there being no difference in the failure, firm blame, or dissatisfaction with the failure. Further investigation suggests that this effect is driven by consumers' perceived connection with the AI that uses their past behavior to predict their future preferences. The conclusions shed light on the overall understanding of consumer-AI interactions. The results also provide managerial implications for firms to implement AI effectively and carefully in their service offerings.

1.1 Introduction

In recent years, the services industry has seen a rapid transformation led by innovative technologies such as artificial intelligence (AI), big data, machine learning, and robotics (Belanche et al., 2020; Belk, 2020; Huang & Rust, 2018; Marinova et al., 2017; Wirtz et al., 2018; Van Doorn et al., 2017). In fact, many companies have integrated to various degrees AI systems into their businesses. For example, according to a recent global survey of more than 2,000 companies across various sectors, 47% of respondents said that their companies had embedded at least one AI capability in their business processes, and 71% overwhelmingly expected an increase in AI investments (2018 McKinsey & Company report). Moreover, in an industry report released by PricewaterhouseCoopers (PwC) (2018), the services industry is predicted to benefit the most from AI development with a projected economic gain of 21%, especially in retail, accommodation, food, transportation, and logistics as well as financial and professional services.

In consumer-facing services, the primary job of many frontline employees is to customize an offering to each customer's individual tastes (e.g., sales assistants, travel agents, financial advisors, etc.). Unsurprisingly, these tasks are being increasingly replaced by AI systems that are able to provide more personalized recommendation services by accurately learning from prior behaviors, purchases, and preferences. For example, companies such as Netflix, Amazon, and Google use AI to compile each consumer's prior purchasing, web browsing, and social media behaviors to make accurate assessments of who they are and what they like so as to provide personalized recommendations. As consumers become more educated and aware of the nature of these algorithms, we believe it will have impacts on how they respond to these service encounters, especially after a service failure.

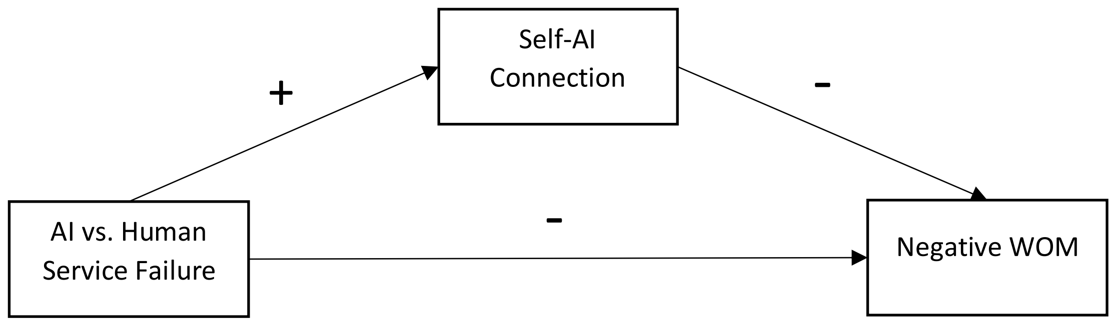
Yet, despite the growing application of AI in service encounters, academic research in this area is still in its infancy (Wirtz et al., 2018). The aim of this article is to address this theoretical gap by examining how consumers respond to AI-based service failures, especially in contexts where AI is used to provide personalized recommendations. One important research question is, compared to service failures from a human employee in a traditional service encounter, do consumers react to service failures delivered by an AI any differently? And if so, how and why? In the current study, because of its importance in the service industry (e.g., Grégoire, Tripp, & Legoux, 2009), we focus on consumers' willingness to share negative word-of-mouth (NWOM) following a service failure.

Extant research on service failures suggests that dissatisfaction and firm blame are primary drivers of sharing NWOM (Albrecht, Walsh, & Beatty, 2017; Bechwati & Morrin, 2003; Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Wangenheim & Bayon, 2004; Wangenheim, 2005; Wetzer, Zeelenberg, & Pieters, 2007). These prior studies, however, assume the dyadic commercial exchange that leads to NWOM to be between a consumer and a human service employee. But what if the service exchange is between a consumer and an AI?

On the one hand, AI recommendation systems serve the interests of a firm and can therefore be considered conceptually as an agent or "employee" of the firm. Consequently, any service encounter with an AI should be similarly treated as an extension of the firm. The likely result would be consistent with existing research on firm blame, dissatisfaction, and NWOM, in which a consumer would be upset with the agent (in this case, the AI system), blame the firm, and be motivated to share NWOM. On the other hand, consumers share their personal data with AI recommendation systems in order to get personalized solutions and suggestions. It is possible that such behavior could potentially make consumers perceive the AI as a "virtual self" (i.e., a representation of the self in relation to a certain consumption domain in digital form). Such a possibility, as we argue, suggests that a consumer can develop a closer personal connection with the AI than they would typically with a human agent. We refer to this as a *self-AI connection*. From this perspective, sharing NWOM about the AI system may portray a negative self-image, essentially sharing NWOM about oneself. Therefore, if consumers are reluctant to portray something connected to the self in a negative light through NWOM, it is possible that despite their dissatisfaction, NWOM following an AI service failure will be less than the NWOM following the same service failure from a human agent. This study seeks to clarify this discrepancy and examine how NWOM can differ depending on whether the service failure is caused by a human or an AI.

Our research makes several contributions. First, we add to the service failure literature by examining service failures caused by an AI, extending beyond traditional failure episodes led by firms and their employees. As AI is increasingly present in the service sector, a better understanding of consumer-AI interactions is needed. In this research, by examining failures of a widely utilized AI form, namely an AI recommendation system, we demonstrate that consumers respond quite differently in terms of willingness to share NWOM, in contrast to traditional employee-led service failures. Specifically, we present evidence that demonstrates consumers are less willing to share NWOM following an AI-, compared to employee-, led service failure. Second, an extensive body of literature suggests that consumers tend to form close connections with a variety of objects, such as possessions and brands (e.g., Belk, 1988; 2013; Fournier, 1998; Escalas & Bettman, 2005; Cheng, White, & Chaplin, 2012; Weiss & Johar, 2013; 2016). The current research extends these findings to AI recommendation systems utilized in the service sector. Specifically, as with possessions and brands, consumers can also form a self-connection with an AI system that collects and uses their behavioral data to provide personalized solutions. We suggest that consumers recognize this personalization and feel more connected to the AI because of it. Finally, while the extant literature on NWOM suggests that firm blame and dissatisfaction are primary drivers to sharing NWOM (Albrecht et al., 2017; Bechwati & Morrin, 2003; Hennig-Thurau et al., 2004; Wetzer et al., 2007), our research highlights that in the context of AI service failures that a felt self-AI connection can influence consumers' willingness to share NWOM. This is a novel concept that we propose by building on and integrating concepts from the brand relationship, human-computer interaction, and service failure literature. We present evidence that consumers may feel personally connected with an AI when it uses past behaviors to provide personalized solutions. We further demonstrate that this self-AI connection diminishes NWOM, despite no difference in firm blame and felt dissatisfaction (see figure 1.1 for the conceptual framework).

Figure 1.1: Conceptual Framework



1.2 Theoretical Background

AI Applications in Services

Various definitions of AI exist in the literature. A notable definition was proposed by Bellman (1978), who defines AI as "the automation of activities that we associate with human thinking, activities such as decision-making, problem-solving, and learning." In addition, some popular media define AI from a more behavioral perspective. For example, Kurzweil (1990) defines AI as "the act of creating machines that perform functions that require intelligence when performed by people." During the course if its development, the field of AI has undergone significant advancements in terms of its capabilities and applications. Synthesizing from both the AI and services literature, Huang and Rust (2018) propose four types of AIs across various service sectors according to their historical development: mechanical, analytical, intuitive, and empathetic. In this current paper, we focus on analytical AI, which is being increasingly utilized across many service offerings. Compared to other types of AI, we believe that studying analytical AI provides the most relevance and importance to both consumers and companies. According to Huang, Rust, and Maksimovic (2019, p. 43), this type of AI requires thinking intelligence, which is the "capability to analyze and make decisions rationally (or boundedly rationally) and involves learning and adapting systematically from data autonomously".

In the service industry, an important application of analytical AI is when an AI system learns from a consumer's own interests, preferences, and behaviors to give highly personalized recommendations (i.e., an AI recommendation system). With a combination of big data and deep learning, an increasing number of AI algorithms can provide personalized recommendations for music, movies, food, and even financial services. For example, harnessing the power of AI and machine learning, Netflix's recommender system is based on a personalized video ranker (PVR) algorithm (Gomez-Uribe & Hunt, 2016). This AI system orders, filters, and recommends the best-matching videos from the entire catalog for each member profile in a personalized way, based on the consumer's prior behaviors and ratings. Amazon.com uses similar recommendation systems to suggest products. Airbnb.com employs these kinds of AI systems to suggest accommodations and experiences that are expected to arouse the most interest from specific users. The same procedures have also been extended into the food service industry, with companies like Forkable.com or Halla.io which use prior behaviors to predict and automatically deliver personalized food orders. Given the rise and adoption of such AI applications across services, and the importance of word-of-mouth in the service sector, we develop predictions for how consumers will respond (i.e., share NWOM) when AI recommendation services fail to deliver satisfactory outcomes (i.e., a service failure).

Service Failure and NWOM

Consumers frequently talk to others about their consumption experiences, and often the bad ones. Drawing from attribution theory (Weiner, 1985; 2000), previous research consistently demonstrates that service failures tend to lead to external attributions directed towards the firm, especially following highly controllable service failures caused by the firm (Van Vaerenbergh et al., 2014; Suri, Huang & Sénécal, 2019). Another important outcome of service failure is dissatisfaction, as most service failures are usually the result of a firm's poor performance in falling below consumer expectations (McCollough, Berry, & Yadav, 2000; Smith & Bolton, 1998). This is deeply rooted in the expectancy-disconfirmation paradigm (Oliver,1980; Oliver & Bearden, 1985; Oliver & Burke, 1999), whereby customer satisfaction is determined by positive or negative disconfirmation between perceived service performance outcome and prior expectations.

Researchers have found that both firm blame and dissatisfaction following service failure lead to retaliatory behavior, such as vindictive complaining, third-party complaining, and sharing NWOM (Bechwati & Morrin, 2003; Betsy & Beatty, 2003; Grégoire & Fisher, 2008; Mattila & Ro, 2008; Mattila & Wirtz, 2004; Ward & Ostrom, 2006). In this research, we focus on NWOM, which is a common behavior that consumers exhibit following a service failure. NWOM is the sharing of bad consumer experiences with other people, either on a smaller (e.g., talking about it to a friend) or larger (e.g., leaving a negative review online) scale. The extant literature in this area broadly suggests two primary motives for spreading NWOM. First, consumers share NWOM to "get revenge," as negative publicity is evidently harmful to the firm (Grégoire et al., 2018). Second, NWOM is shared to help and warn other customers avoid a similarly bad experience (Wetzer et al., 2007; Hennig-Thurau et al., 2004). Unlike positive word-of-mouth, which works to benefit firms, NWOM is detrimental because prospective customers tend to anchor more heavily on negative than positive information when making decisions (Ahluwalia, 2002; Ito, Larsen, Smith, & Cacioppo, 1998).

We note that previous research on service failure and NWOM, however, was mainly conducted in service contexts where the focus was on “dyadic, human and role-driven interactions between customers and employees” (Larivière et al., 2018, p. 239). What remains relatively underexplored is consumer reactions when the interaction is with a non-human agent AI recommendation system. In a contextually similar domain, however, some past research has examined service failures with self-service technologies (SSTs) (e.g., ATMs, self-checkouts, airport kiosks). When dealing with SSTs, prior research has demonstrated that following a failure, consumers tend to blame the firm (Lee & Cranage, 2018) and the SST system (Dabholkar & Spaid, 2012) more than themselves. Consumer are also likely to share NWOM, complain, and avoid future usage following an SST failure (Meuter, Ostrom, Roundtree, & Bitner, 2000).

While this prior research has examined consumer responses to service failures with non-human systems, the introduction of AI services is different from SSTs in two important ways. We argue that these differences will also result in alternative predictions for how a consumer is likely to respond to an AI service failure than what the SST failure literature would predict. First, the level of customer participation between the two varies. When using SSTs, consumers are actively engaged in value co-creation, either by serving themselves or cooperating with service providers (Dong, Evans, & Zou, 2008). However, as discussed earlier, AI-powered services such as AI recommendation systems aim at minimizing consumer efforts, by automatically giving personalized and optimized solutions. Therefore, in terms of customer participation, AI recommendation systems are closer to the participation required when interacting with a human service agent than they are to SSTs. Second, AI recommendation systems are personalized based on prior behavior, purchases, and preferences, whereas traditional SSTs are not. This, as we argue below, will influence how consumers respond to failure. Despite these variations, it is also crucial to note that AI-powered services have a much higher degree of technology infusion than SST-based services according to De Keyser (2018)'s Frontline Service Technology infusion archetypes. Furthermore, with the exponential growth of AI, SSTs are increasingly augmented with emerging smart and connected AI technologies. Therefore, as AI technology advances, traditional SSTs and AI services will become more entwined, which makes investigations into how consumers respond to AI service failures all the more relevant, as prior SST research did not consider AI capabilities. Specifically, we investigate here how the tendency to spread NWOM is likely to be affected by the fact that consumers may be personally connected with an AI system because of the nature of its personalization algorithm. We discuss this possibility next.

Self-AI Connection

We suggest that one of the important implications when interacting with an AI recommendation system is that consumers will feel more connected to the AI system than they would with a human employee providing the same service. We argue that this will occur because AI recommendation systems typically use consumers' past behaviors to provide them with personalized recommendations that predict their interests and preferences. In other words, because the AI is designed to personally reflect who the consumer is, what they need, and what they will enjoy, consumers will feel connected to the AI. It is important to note that this is based on the notion that consumers are aware of the nature of AI algorithms in collecting and using their data to personalize recommendations. In fact, today not only are firms transparent about the source of AI recommendation systems in their communications (e.g., "because you bought this, you might also like…", "top picks just for you"), consumers are also increasingly aware and willing to share more of their personal data. For example, a recent market survey showed that 73% consumers said they're willing to share more in exchange for personalized products and services and 87% saying it's important to buy from a brand or retailer that "understands the real me." (Accenture, 2019)

To demonstrate the possible psychological connection between a consumer and an AI, we refer to research on brand relationships and human-computer interactions (HCI). In these fields, researchers have extensively shown that people tend to feel connected with and even extend themselves into a variety of objects, such as possessions, brands, and even robots (Belk, 1988; 2013; Fournier, 1998; Groom, Takayama, Ochi, & Nass, 2009). Consumers are likely to feel connected with a brand when there is a high level of self-brand congruity (i.e., similarity between the self and the brand). When individuals identify with a brand, they tend to incorporate it into their self-concept, which is often referred as "self-brand connection" (Escalas, 2004). Specifically, consumers are known to form personal connections between themselves and a brand when the brand itself is somehow closely associated with their self-concept, such as user characteristics, personality traits, and personal experiences (Escalas, 2004; Escalas & Bettman, 2005). Overall, extensive studies have shown that consumers feel highly connected to brands that are symbolically representative of who they believe they are, or who they want to be (Chaplin & John, 2005; Cheng et al., 2012; Ferraro, Kirmani, & Matherly, 2013; Fournier, 1998; Moore & Homer, 2008).

In a similar vein, HCI researchers consistently provide evidence that people can incorporate both physical robots and virtual avatars into their self-concept. For example, in a lab experiment, Groom et al. (2009) found that participants perceived a non-humanoid robot (i.e., a robotic car) to be more like themselves when it was built by the participants themselves, and they demonstrated greater personality trait overlap with the robot. They also felt more attached to the robot and reported that they would feel worse if their robot was destroyed. Similarly, when interacting with robots similar to themselves, especially in the moment of interaction, people feel like the robot is part of themselves (Takayama, 2012). Similarly, in the virtual world, past research has shown that when operating a virtual avatar, users feel more personally connected and perceive the avatar to be more relevant to the self when they share physical and behavioral similarities, such as body image, gender, personality, and emotions (Ducheneaut, Wen, Yee, & Wadley, 2019; Ratan & Dawson, 2016; Suh, Kim, & Suh, 2011).

Overall, these past findings suggest that people can feel personally connected to a variety of objects, from the brands they use to physical robots and virtual avatars they interact with. And that this effect is amplified when these objects reflect and represent the individual consumers' personal characteristics and identity. Taken together, we suggest that when interacting with an AI recommendation system, consumers will perceive a personal connection between themselves and the AI service (i.e., a self-AI connection). We argue that this will be the case because of the nature of AI recommendation algorithms, which gather personal behavioral level data in order to make personalized recommendations. Given that AI recommendation systems typically use prior behaviors to emulate and predict individual preferences, it is likely that consumers will see these AI systems as closely associated with themselves. However, how might this influence their propensity to share NWOM when such AI services fail? This is discussed next.

Impression Management and its Effect on NWOM

From the above discussion, we predict that consumers will feel personally connected with an AI recommendation system when its algorithm is personalized on the basis of their own behaviors. Because of this self-AI connection, we postulate that the willingness to share NWOM will be lower following an AI-caused, compared to a human-caused, service failure. This prediction is supported by past research on impression management and word-of-mouth.

One of the fundamental reasons why consumers share word-of-mouth is to shape the impressions others have of them (e.g., Berger, 2014). Prior word-of-mouth research suggests that consumers are more inclined to share experiences that self-enhance (Eisingerich et al., 2015; Hennig-Thurau et al., 2004; Sundaram, Mitra, &, Webster, 1998) and avoids self-implication (Philp, Pyle, & Ashworth, 2018). For example, De Angelis et al. (2012) demonstrated that self-enhancement is a key motive for customers to generate more positive word-of-mouth, such as sharing information about their own successful and positive consumption experiences. In fact, extensive research shows that individuals have a general tendency to protect, maintain, or enhance a positive self-concept (e.g., Leary, Tambor, Terdal, & Downs, 1995).

Consistent with this logic, consumers are also less willing to share NWOM when the self is significantly involved in the negative consumption experience (Dunn & Dahl, 2012), as it is considered "admitting failure as a consumer" (Richins, 1984, p. 699). In a similar vein, Philp et al. (2018) found that individuals who feel more self-competent in general are less willing to share NWOM because having negative consumption experiences and talking about them with others portrays a contradictory self-view. Furthermore, Cheng et al. (2011) found that consumers with high self-brand connections respond to brand failures as they do to personal failures — experiencing a threat to their positive self-view, which diminishes willingness to share NWOM. Similar image concerns related to negative consumption experiences has been found to increase consumer lying behaviors (Argo, White, & Dahl, 2006) as well as discarding products prematurely (Philp & Nepomuceno, 2020).

On the basis of the above discussions, we predict that service failures caused by an AI rather than a human agent should result in less NWOM. This, as we argue, will be driven by an impression management motive, where consumers are reluctant to share negative information about anything associated with themselves, in this case, an AI system that they feel personally connected to. Therefore, consumers will be less inclined to share NWOM following an AI-, compared to a human employee-led service failure to avoid the possibility of negative self-presentation. Formally put, we propose the following hypotheses:

H1: The willingness to share NWOM is lower when the service failure is caused by an AI system than by a human employee.

H2: Consumers' perceived self-AI connection with the AI system will mediate this relationship.

1.3 Methodology

Overview of Studies

We conducted five experiments across three studies to test these hypotheses. In each study we examine the effect of a service failure from an AI-based service on the willingness to share NWOM about the experience. Study 1 tests consumers' willingness to share NWOM following a service failure when the service was initially provided by an AI versus Human-Agent. In demonstrating the robustness of this effect, the difference in AI versus Human-Agent service failures on NWOM is examined across three common service contexts that are being influenced by AI; travel agents (Study 1a), financial planners (Study 1b), and food delivery (Study 1c). Study 2 extends these findings by ruling out the possibility that variations in dissatisfaction and firm blame could be explaining the effects from Study 1. Finally, Study 3 provides mediation evidence through a moderation-of-process design, examining the role of self-AI connection. Each study relied on participants reading hypothetical scenarios and experimentally varying our independent variable of interest. This method is effective in ruling out confounds and context-dependent effects while still maintaining generalizability (Atzmüller & Steiner, 2010). Similar methods are common in research examining consumer reactions to marketing services (e.g., Bues, Steiner, Stafflage, & Krafft, 2017; Campo, Gijsbrechts, & Nisol, 2000; Sloot & Verhoef, 2008; Sloot, Verhoef, & Franses, 2005; Wason, Polonsky, & Hyman, 2002)

Study 1: Human vs. AI Service Failures

The primary objective of Study 1 is to explore how consumers react to a service failure caused by an AI recommendation system, in comparison to a human agent in terms of the willingness to share NWOM. Presented across study 1a-1c, three different service contexts (i.e., travel, financial investment, and food delivery) were chosen to demonstrate the main effect of AI versus human agent service failures on NWOM. These contexts were chosen because they are common services that are being increasingly infused with AI technologies. According to a recent report published by PwC (2018), accommodation and food services are expected to see AI services increase by 15%, followed by financial and professional services by 10%. In addition, as each service context has distinct characteristics, we do not intend to compare between contexts, our goal instead is to demonstrate the robustness of the phenomenon across a variety of service contexts.

Study 1a: Travel Agent

Experimental design. 123 participants (*M*age = 37, 46% female) were recruited online from Amazon Mechanical Turk and randomly assigned to one of two conditions: a human service agent or an AI service agent. Participants read a scenario about a travel experience with DreamVacay.com, a fictitious travel website specializing in delivering travel and vacation packages. Participants were asked to imagine planning a 7-day tour of China with assistance provided by "The Travel Master," which was identified as either a human employee or an AI recommendation system. In the human employee condition, participants were told that a human employee picked everything (e.g., hotels, flights, local guides, and attractions). In the AI condition, participants were told that the trip was planned by an AI system that used data from the specific individual's previous travel history and web behavior to predict interests and preferences. In both conditions, the travel experience was described as a disaster, with poorly chosen hotels, flights, and local experiences (i.e., a service failure).

Measurement. All participants completed the same questionnaire, which was estimated to take approximately 10 minutes. Unless otherwise stated, all responses were measured on a seven-point Likert scale (1 = "Strongly disagree" and 7 = "Strongly agree"). Willingness to share NWOM was measured using three items ($\alpha = .88$) adapted from Grégoire et al. (2009): "I will spread negative word of mouth about the company," "I will bad-mouth against this company to my friends," "When my friends are looking for a similar service, I will tell them not to get it from this company." The questionnaire concluded with participants reporting their travel frequency, age, and gender.

Results and discussion. Results from this study are depicted in figure 1.2. A one-way ANOVA revealed a significant effect of service agent on NWOM ($M_{\text{AI}} = 5.41$ vs. $M_{\text{Human}} = 6.18$; $F(1, 121) = 9.04$, $p = .003$). Supporting H1, these results showed that following a service failure, participants were less willing to share NWOM when the agent was an AI compared to a human employee.

Study 1b: Financial Planner

Experimental design. 115 participants (*M*age = 37, 35% female) were recruited online from Amazon Mechanical Turk. Just as in Study 1a, the participants were randomly assigned into one of the two conditions: a human service agent or an AI service agent. However, participants in this study read a scenario about a financial investment experience with Wealth-Plus, a fictitious company specializing in providing financial management services. Participants read that Wealth-Plus offers a financial planner called "The Money Master," which was referred to as either a human employee or an AI system. In the human employee condition, participants were told that a financial advisor crafted a portfolio based on the advisor's expertise. In the AI condition, participants were told that the portfolio was crafted by an AI system using data from individuals' previous investment behaviors, including their investment decisions, strategies, preferences, and risk tolerance, all based on who the customer is as an investor. The investment experience was presented as unsuccessful; the portfolio was not very profitable. All participants completed the same questionnaire as in Study 1a with the same willingness to share NWOM items (α = .91).

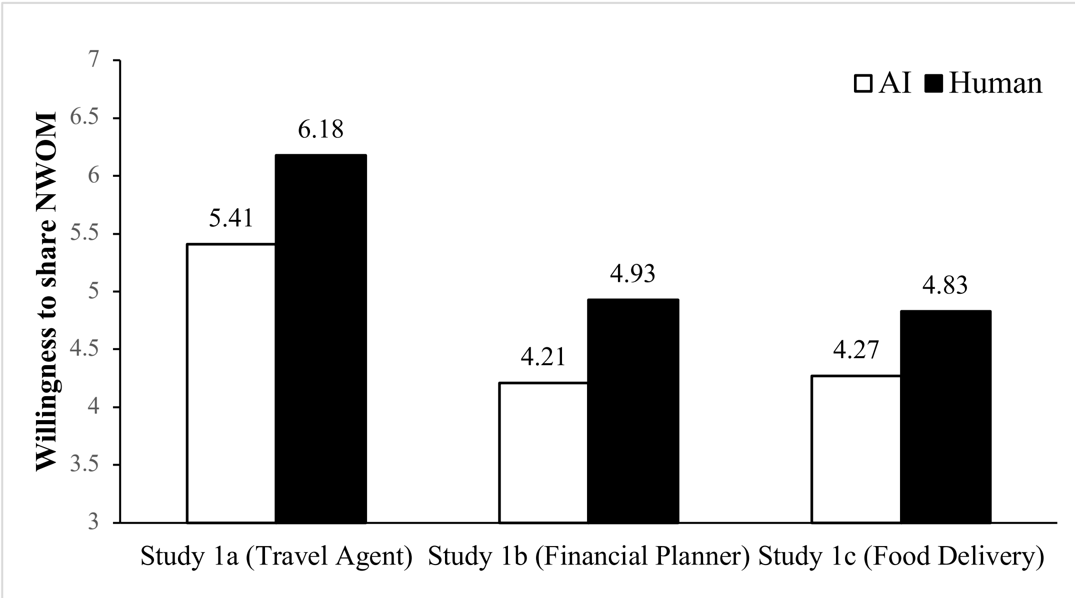
Results and discussion. Results from this study are also depicted in figure 2. A one-way ANOVA revealed a significant effect of service agent on NWOM (M_{AI} = 4.21 vs. M_{Human} = 4.93; $F(1, 113) = 5.96$, p = .016). Again, these results showed that following a service failure, participants were less inclined to share NWOM when the agent was an AI rather than a human employee.

Study 1c: Food Delivery

Experimental design. 117 participants (*M*age = 37, 40% female) were recruited online from Amazon Mechanical Turk. As in Studies 1a and 1b, the participants were randomly assigned into one of the two conditions: a human service agent or an AI service agent. This time, the participants read a scenario about a food delivery experience with Fast & Delicious, a fictitious company specializing in providing food delivery services. Participants were asked to build a meal plan with assistance provided by "The Food Master," who was referred as either a human employee or an AI system. In the human employee condition, participants were told that a food specialist designed the meal plan on the basis of the specialist's expertise. In the AI condition, participants were told that the meal plan was built by an AI system using data from individuals' previous food ordering history, web search behavior, and restaurant reviews, all based on who the customer is as a food customer. The experience was then presented as being bad and disappointing; the customer did not enjoy the meal plan at all. All the participants completed the same questionnaire as in Studies 1a and 1b with the same willingness to share NWOM items ($\alpha = .85$).

Results and discussion. Results from this study are also depicted in figure 2. A one-way ANOVA revealed a significant effect of service agent on NWOM ($M_{AI} = 4.27$ vs. $M_{Human} = 4.83$; $F(1, 115) = 4.60$, $p = .034$). Consistent with the travel and finance scenarios, AI-caused service failure demotivated participants to share NWOM, as compared to failure attributed to a human employee.

Figure 1.2: Willingness to share NWOM by Service Agent (Study 1a-1c)



Discussion

Across travel, financial investment, and food delivery service contexts, Studies 1a-1c consistently showed that participants respond to service failures differently between an AI recommendation system and a human employee. They tended to have lower NWOM sharing intentions when the failure was caused by an AI agent than a human employee. However, we note that in Study 1, we did not manipulate the outcome of the service encounters (i.e., they were all failures); therefore, it is unclear whether such differences in NWOM sharing would still exist if the service outcome were successful. In addition, one of the limitations of Study 1 is that there might be other explanations for the documented phenomenon such as less expectations and more tolerance towards a new technology. We address these limitations in Study 2.

Study 2: AI Service Failure VS. Success

The primary objective of Study 2 is, first, to replicate the findings of Study 1. In doing so, we also manipulate the service outcome to be either a success or failure. Second, we investigate other important NWOM determinants following a service failure, namely firm blame and dissatisfaction, as noted in past research, to explore whether they could explain the variations of NWOM between an AI system and a human employee. As mentioned earlier, one alternative explanation for Study 1 is that compared to a human employee, consumers might have less expectations and higher tolerance towards an AI. If this is true, then consumers should blame and feel less dissatisfied towards the firm. Demonstrating here that firm blame and dissatisfaction do not significantly vary between the AI and human employee conditions will provide preliminary evidence that the variations in the willingness to share NWOM are the result of a mechanism beyond expectation disconfirmation.

Experimental Participants, Design, and Procedure

198 participants (*M*age = 38, 47% female) were recruited online from Amazon Mechanical Turk. They were guided through a 2 (Service Agent: Human vs. AI) X 2 (Service Outcome: Success vs. Failure) between-subject study. The participants read the same travel scenario as in Study 1a. However, this time, the travel experience was presented either as occurring as expected (i.e., successful service outcome) or as a disaster, with poorly provided hotels, flights, and local experiences (i.e., a service failure).

All participants completed the same questionnaire. Unless otherwise stated, all responses were measured on a seven-point Likert scale (1 = “Strongly disagree” and 7 =

“Strongly agree”). An item “DreamVacay is solely responsible for the outcome” was used to measure firm blame. Dissatisfaction was measured using one item, “I would be very dissatisfied with this experience.” Willingness to share NWOM was measured on the same scale used in Studies 1a-1c, with an additional reverse-coded item, “I would tell people positive things about the company” (α = .93). At the end of the questionnaire, participants reported their travel frequency, age, and gender.

Results

Initial analysis.As expected, results of an ANOVA revealed a main effect of Service Outcome on dissatisfaction ($M_{Success}$ = 1.79 vs. $M_{Failure}$ = 6.27; $F(1, 194) = 649.89$, $p < .000$) but not Service Agent (M_{AI} = 4.10 vs. M_{Human} = 3.91; $F(1, 194) = .67$, $p = .414$); and a main effect of Service Agent on firm blame (M_{AI} = 4.60 vs. M_{Human} = 5.47; $F(1, 194)$ = 14.03, $p < .000$) but not Service Outcome ($M_{Success}$ = 4.98 vs. $M_{Failure}$ = 5.18; $F(1, 194)$ = 1.07, $p = .301$). Although unexpected, the results also showed a significant Service Agent X Service Outcome interaction on firm blame ($F(1, 194) = 6.63$, p =.011) and dissatisfaction ($F(1, 194) = 4.90$, $p = .028$). Follow-up analysis indicated that both interactions were driven by a difference between AI and human agents in the success outcome rather than the failure outcome condition. Specifically, as illustrated in Table 1.1, when the outcome was success, participants reported blaming the firm more in the human condition (M = 5.63) than in the AI condition (M = 4.31; $F(1, 194) = 24.33$, $p <$ .000). Participants also reported being more dissatisfied in the AI condition (M = 2.06) than in the human condition (M = 1.53; $F(1, 194) = 8.21$, $p = .01$). As expected, however, when the outcome was a failure, firm blame (M_{AI} = 5.02 vs. M_{Human} = 5.31; $F(1, 194)$ = .93, $p = .35$) and dissatisfaction (M_{AI} = 6.14 vs. M_{Human} = 6.39; $F(1, 194) = .96$, $p = .33$)

did not differ between the AI and human conditions. Given that NWOM is driven largely by dissatisfaction and firm blame, we would also expect not to see a difference in NWOM in the Failure condition. However, our findings below reveal the opposite.

Main analysis. As expected, the results of an ANOVA revealed a significant main effect of Service Outcome on the willingness to share NWOM ($F(1, 194) = 278.99$, $p < .001$) in which participants were more inclined to share NWOM following a service failure ($M = 4.79$) than a success ($M = 1.78$). There was no main effect of Service Agent on willingness to share NWOM ($M_{AI} = 3.17$ vs. $M_{Human} = 3.36$; $F(1, 194) = 1.58$, $p = .211$). However, and more importantly, the results show a significant Service Agent X Service Outcome interaction on willingness to share NWOM ($F(1, 194) = 11.27$, $p = .001$). Specifically, as reported in Table 1.1, following a service failure, participants were less likely to share NWOM when the agent was an AI instead of a human employee ($M_{AI\text{-}Failure} = 4.37$ vs. $M_{Human\text{-}Failure} = 5.20$, $F(1, 194) = 10.53$, $p = .001$). No difference was found when it was a successful service outcome ($M_{AI\text{-}Success} = 1.97$ vs. $M_{Human\text{-}Success} = 1.59$, $F(1, 194) = 2.22$, $p = .14$; see Figure 1.3). In replicating the findings of the previous studies, these results again support H1: that the willingness to share NWOM is lower when the service failure is caused by an AI system than by a human employee, despite no difference in firm blame and dissatisfaction.

Figure 1.3: Willingness to share NWOM by Service Agent and Outcome (Study 2)

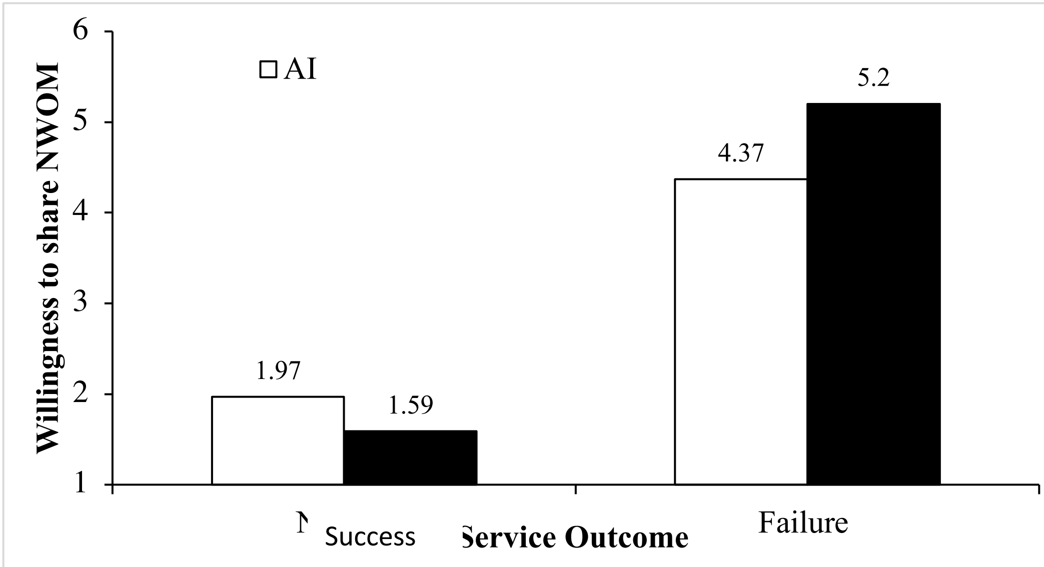


Table 1.1: Means, Standard Deviations, and Cell Counts for Study 2

Service Outcome	Success		Failure	
Service Agent	Human	AI	Human	AI
NWOM	1.59 (1.10)	1.97 (1.23)	5.20 (1.17)	4.37 (1.52)
Firm Blame	5.63 (1.10)	4.31 (1.63)	5.31 (1.42)	5.02 (1.65)
Dissatisfaction	1.53 (1.09)	2.06 (1.53)	6.39 (0.91)	6.14 (1.32)
Cell Size	49	49	51	49

Note: Standard deviations are reported in parentheses.

Discussion

Replicating Study 1, Study 2 demonstrates that participants respond differently toward a service failure caused by an AI, compared to one caused by a human employee. Specifically, we again found evidence that consumers are less willing to share NWOM following a service failure when they interacted with an AI system than with a human employee. This difference was not found following a successful service outcome, suggesting more specifically that this is a failure-driven phenomenon. Furthermore, the results also suggest that the inhibition of NWOM sharing is likely not due to consumers blaming the firm any less or feeling any less dissatisfied with the firm, because the results showed no significant difference for these two measures whether the failure was caused by an AI or a human. These results suggest that the variations in NWOM are driven by another motivation. To further investigate this and test H2 more directly, we conducted a follow-up study.

Study 3: Self-AI Connection

In this experiment, our main objective is to uncover the underlying mechanism (H2) that explains the findings from Studies 1 and 2. Specifically, we seek to demonstrate the self-AI connection as the primary motivation to the decreased likelihood to share NWOM, as predicted in our theorizing. Therefore, if consumers perceive an AI system to be using their personal data, and therefore increasing self-AI connection, the effect from the previous studies should hold. However, as an experimental test of our mechanism, if the same AI system is believed to use the data of other consumers (i.e., non-personalized data) to make recommendations, this would therefore decrease the self-AI connection, and the effect should dissipate.

Experimental Participants, Design, and Procedure

205 participants (*M*age = 39, 48% female) were recruited online from Amazon Mechanical Turk and guided through a 2 (AI System Personalization: Yes vs. No) X 2 (Service Outcome: Success vs. Failure) between-subject experiment. The participants

read a scenario about a travel experience similar to that in Study 1a and Study 2, in which all participants were told that the trip was designed by the AI system "The Travel Master" and there was either a successful service outcome or a service failure. However, participants were either told that the AI system was personalized and used data from individuals' previous travel history and web behavior to estimate interests and preferences (identical to Study 1a and Study 2), or that it was a non-personalized AI system that relied on the data of other customers to provide a more generalized recommendation.

All participants completed the same questionnaire as in Study 2, including the measures for firm blame, dissatisfaction, and willingness to share NWOM ($\alpha = .90$). An additional measure for perceived self-AI connection was adapted from Tan, Salo, Juntunen, and Kumar (2018) and included two items: "The AI robot 'The Travel Master' reflects part of me and who I am", and "I feel personally connected to the AI robot 'The Travel Master'" ($r = .89$).

Results

Initial analysis. See Table 2 for means summary. As in Study 2, the results of an ANOVA revealed a significant main effect of Service Outcome on dissatisfaction ($M_{\text{Success}} = 1.82$ vs. $M_{\text{Failure}} = 6.20$; $F(1, 201) = 579.44$, $p < .000$) but not on firm blame ($M_{\text{Success}} = 5.68$ vs. $M_{\text{Failure}} = 5.49$; $F(1, 201) = 1.28$, $p = .259$). The main effects of AI System Personalization on firm blame ($M_{\text{Personalized}} = 5.58$ vs. $M_{\text{Non-Personalized}} = 5.60$; $F(1, 201) = .01$, $p = .914$) and dissatisfaction ($M_{\text{Personalized}} = 3.84$ vs. $M_{\text{Non-Personalized}} = 4.82$; $F(1, 201) = .00$, $p = .997$) were both not significant. The results of the Service Outcome X AI System Personalization interaction were both non-significant for firm blame ($F(1, 201) = .135$, $p = .714$) and dissatisfaction ($F(1, 201) = .337$, $p = .562$). In addition, consistent with Study

2, the results showed no difference in firm blame ($M_{\text{Failure-Personalized}}$ = 5.51 vs. $M_{\text{Failure-Non-Personalized}}$ = 5.47; $F(1, 201)$ = .03, p = .86) or felt dissatisfaction ($M_{\text{Failure-Personalized}}$ = 6.15 vs. $M_{\text{Failure-Non-Personalized}}$ = 6.26; $F(1, 201)$ = .16, p = .69) when the outcome was a failure.

Main analysis. See Table 1.2 for means summary. Replicating Study 2, the results revealed a significant main effect of Service Outcome on the willingness to share NWOM ($F(1, 201)$ = 426.45, p < .000) in which participants were more inclined to share NWOM following a service failure (M = 4.77) than a successful outcome (M = 1.49). There was also a main effect of AI System Personalization on willingness to share NWOM ($M_{\text{Personalized}}$= 2.73 vs. $M_{\text{Non-Personalized}}$ = 3.25; $F(1, 201)$ = 12.81, p < .000). Most importantly, the results of the significant Service Outcome X AI System Personalization interaction on NWOM ($F(1, 201)$ = 4.19, p = .042) provide evidence for our predictions. Specifically, the follow-up analysis shows that when the service outcome was a failure, the participants were less willing to share NWOM if the AI recommendation system was personalized to their interests and past behaviors than if it was not ($M_{\text{Failure-Personalized}}$ = 4.32 vs. $M_{\text{Failure-Non-Personalized}}$ = 5.21; $F(1, 201)$ = 14.6, p = .001). No difference was found in the case of a successful service outcome ($M_{\text{Success-Personalized}}$ = 1.36 vs. $M_{\text{Success-Non-Personalized}}$ = 1.61; $F(1, 201)$ = 1.28, p = .26).

When the effect on the self-AI connection is examined, the results show a significant main effect of AI System Personalization ($M_{\text{Personalized}}$ = 3.14 vs. $M_{\text{Non-Personalized}}$ = 1.90; $F(1, 201)$ = 34.44, p < .000), as well as Service Outcome (M_{Success} = 2.87 vs. M_{Failure} = 2.09; $F(1, 201)$ = 14.85, p < .000). The result of the Service Outcome X AI System Personalization interaction on the self-AI connection was also significant ($F(1, 201)$ = 5.88, p = .016). Specifically, participants using a personalized AI felt more connected to the AI when the outcome was success than when it was a failure ($M_{\text{Success-Personalized}}$ = 3.73 vs. $M_{\text{Failure--Personalized}}$ = 2.45; $F(1, 201) = 33.78$, $p < .000$); this difference was not observed when the AI was not personalized ($M_{\text{Success-Non-Personalized}}$ = 2.03 vs. $M_{\text{Failure-Non-Personalized}}$ = 1.74; $F(1, 201) = 1.02$, $p = .540$).

Table 1.2: Means, Standard Deviations, and Cell Counts for Study 3

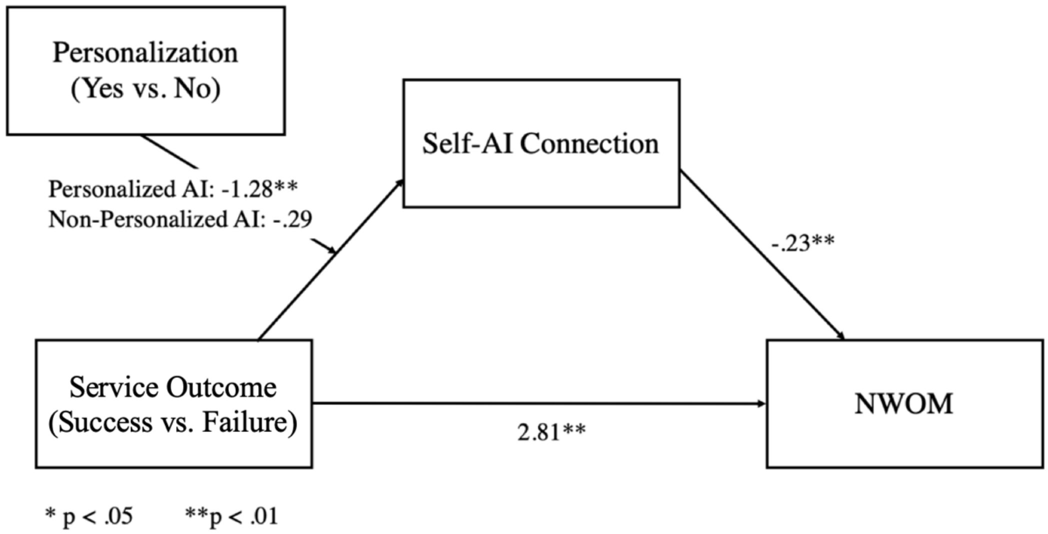
Service Outcome	Success		Failure	
AI System Personalization	Personalized	Non-Personalized	Personalized	Non-Personalized
NWOM	1.36 (.89)	1.61 (.99)	4.32 (1.57)	5.21(1.25)
Firm Blame	5.64 (.97)	5.71 (.83)	5.51 (1.50)	5.47 (1.35)
Dissatisfaction	1.87 (1.41)	1.77 (1.13)	6.15 (1.32)	6.26 (1.33)
Self-AI Connection	3.73 (1.78)	2.03 (1.16)	2.45 (1.66)	1.74 (1.13)
Cell Size	55	56	47	47

Note: Standard deviations are reported in parentheses.

To examine the effect of a personalized AI system compared to an AI using other people's data on willingness to share NWOM through the self-AI connection, a moderated mediation analysis was conducted using PROCESS model 7 (Hayes 2018). Specifically, we constructed a model in which the effect of service outcome on NWOM was mediated by the self-AI connection. AI System Personalization was allowed to moderate the first stage of the mediation (i.e., from Service Outcome to self-AI connection). Providing evidence for H2, based on 5,000 bootstrapped samples at 95% confidence intervals, the self-AI connection mediated the effect of Service Outcome on willingness to share NWOM when the AI was personalized ($CI_{95\%}$: 1.12 to .48), but not when the AI was non-personalized ($CI_{95\%}$: -.03 to .21). Furthermore, the index of moderated mediation ($CI_{95\%}$:

.05 to .40) did not span zero, indicating that the mediated effect of the self-AI connection on NWOM was larger when the AI system was personalized than when it was not (figure 1.4).

Figure 1.4: Mediating role of the Self-AI connection on the willingness to share NWOM (Study 3)



Discussion

By narrowing down the focus to the AI's algorithm (personalized vs non-personalized) in Study 3, we were able to identify the underlying driver of the variations in NWOM found in Study 1 and 2. First, the results suggest that following a service failure, consumers are less willing to share NWOM when it is caused by a personalized AI recommendation system mirroring themselves, as compared to a non-personalized one using others' data. Again, we find evidence that the effect is not driven by a reduction in firm blame or felt dissatisfaction. Second, we demonstrate that the perceived self-AI connection drives the decrease in willingness to share NWOM. Because the personalized

AI acts as a "virtual self," participants feel more personally connected with it and thus are less inclined to share NWOM, since doing so may reflect back on themselves poorly.

1.4 General Discussion

Theoretical Implications

An updated view on service failures is warranted as smart technologies, such as AI, play an increasingly important role in the service sector. This current research seeks to offer new insight on how consumers respond differently to an AI-related service failure. We argue that consumers may be inhibited from sharing NWOM about these failures because they feel personally connected to the AI.

With this theorizing, the three studies present evidence on how this effect occurs. Study 1 provides a robust demonstration of this effect across three service contexts: travel, financial investment, and food delivery. Consumers were less willing to share NWOM when the negative outcome was caused by an AI system than by a human employee. In Study 2, we manipulated the service outcome and found the effect existed only during service failures. We also provided evidence that the possible explanations of reduced firm blame, or dissatisfaction, do not explain this variation in NWOM. Study 3 replicated the results, and uncovered the underlying mechanism, which suggests that NWOM is shared less when the AI is personalized to the individual consumer. That is, the AI recommendation is based on each consumers' own preferences and interests. In this case, the participants reported a higher self-AI connection. Together, these results shed light on our understanding of the impact of AI on service encounters, especially when these encounters produce negative outcomes.

By integrating AI with prior research on service failure, this research contributes to our knowledge on AI-infused service encounters in several ways. First, the prior research is limited to a traditional employee- and firm-caused service failure context, in which firm blame and dissatisfaction are likely to excite strong NWOM sharing intentions. We complement this stream of research by demonstrating how an AI could potentially inhibit consumers from sharing NWOM. More interestingly, this effect occurs despite no difference in firm blame or dissatisfaction directed to the firm. Therefore, future researchers should exert caution when studying AI-related service failures, as consumers do not appear to exhibit as many negative behavioral intentions as in traditional service failures, but this does not necessarily mean that they are any less dissatisfied with the service.

Second, our further investigation on the underlying mechanism suggests that the perceived self-AI connection explains why this kind of effect occurs. This novel concept echoes prior research on self-brand connection from the brand relationship literature (e.g., Escalas & Bettman, 2003), as well as the extant research on HCI where perceived connection is observed when there are overlapping similarities between users and robots (Groom et al., 2009; Suh et al., 2011). In this research, we uncovered an analogous phenomenon in consumer-AI interactions, and we refer to it as a "self-AI connection." As shown in our current studies, such a connection is more pronounced when an AI algorithm mirrors consumers' personal behaviors and preferences, and it inhibits their willingness to share NWOM in the event of a service failure. Therefore, consistent with previous research on word-of-mouth sharing motives, namely impression management and avoiding self-implications (e.g., Philp et al., 2018), we demonstrate that NWOM sharing is inhibited when consumers experience a service failure closely associated with the self. Specifically, we provide evidence that failures caused by a "virtual self" (i.e., an AI system they feel personally connected to) does not convey a positive image of the "real self"; therefore, consumers are more likely to keep such negative experiences to themselves, even though the firm is still blamed for the failure. In addition, while past research on SSTs show that consumers tend to blame the service provider more and that they are more likely to engage in complaining behaviors (Dabholkar & Spaid, 2011; Lee & Cranage, 2018; Meuter et al., 2000), our research contributes to the frontline service technology literature by showing that that AI as a new technology elicits quite different consumer responses following a service failure. Specifically, they do not show differentiated level of blame and they are less willing to spread NWOM towards the service provider.

Third, we contribute to the HCI literature by showing that this kind of self-connection is not limited to physical robots, where the connection is driven mainly by visually observed overlapping similarities. Individuals also feel personally connected to a virtual AI system that aims at mimicking and predicting each consumer's behaviors. We also demonstrate that this perceived connection has important outcomes in a service context, such as reluctance to spread NWOM, as documented in the current research.

Managerial Implications

In addition to theoretical contributions to the literature on service failure, NWOM, and HCI, through the investigation of consumers' responses to AI-powered services, this research brings several managerial implications to service practitioners. NWOM is known to be highly undesirable for any firm. However, while perfect service encounters do not always happen in real commercial exchanges, our findings suggest that incorporating AI in these encounters may act as a cushion when they do fail. Although consumers are still dissatisfied and blame the firm, they share less NWOM that could potentially harm the firm. This shows that along with the improved service quality and efficiency that AI technologies can generally bring, firms can also benefit from them even when confronted with service failures. Consumers who had a bad experience with AI technologies will be demotivated to spread negative information about the service and firm. As word-of-mouth, such as online reviews, has an increasingly significant influence on new consumers' opinions, attitudes, and pre-evaluations of a service provider, implementing strategies that diminish NWOM is a priority.

However, since diminished NWOM happens only when customers believe there is a strong personal connection between them and the AI, managers need to be cautious in implementing AI systems. Although we note that the reality of AI algorithms is far more complex than the simple dichotomy of self vs. others resource data, it seems that an AI system personalized to each customer's individual preferences and interests might be preferred. For instance, to increase consumers' personal connections with an AI system, marketers should offer tools that would allow a higher degree of personalization. In addition, service providers should make it clear to consumers how the AI algorithm works, so they will understand that the AI is making predictions and choices in a way that is meant to replicate their own behavior. These variations can already be seen among some service providers. Some providers provide less personalized recommendations, for example, Amazon provides a list of recommended products based on the habits of other consumers by stating "customers who viewed this item also viewed." Or some providers are more personalized, for example, music streaming software Spotify provides recommendation lists entitled "made for you," which is described as a playlist that is "uniquely yours" and "chosen just for you." As our results suggest, these variations in personalized versus non-personalized recommendations can influence the self-AI connection and subsequently downstream responses to failures.

Lastly, our results show that AI-caused service failures as compared to employee-led failures do not reduce customers' dissatisfaction or firm blame. Therefore, this finding suggests that even though consumers feel connected to the AI, this self-AI connection does not shift their attribution of the failure or affect their dissatisfaction. Therefore, an appropriate service recovery is still necessary following service failures caused by AI, even if the affected customers might not actively exhibit or engage in revengeful post-failure behaviors such as sharing NWOM.

1.5 Limitations, Future Research, and Conclusion

The current research looks only at AI-powered virtual agents—interfaces and systems that do not have a physical form. Customers interact with them through text-entry and voice command. Future research is encouraged to test whether our findings extend to actual service robots. For example, some humanoid robots, because of their anthropomorphic features, might be perceived as having their own mind and therefore impede personal connection in these circumstances (Krach et al., 2008; Groom et al., 2009). We encourage researchers to investigate the potential effect of anthropomorphism on self-AI connection and its various consequences.

Furthermore, as demonstrated in the studies, our theorizing of the self-AI connection did not reduce customers' blame ascribed to the firm as compared to a failure caused by an employee. Consumers still blame the firm for the service failure even though they are less inclined to share NWOM. However, while firm blame might not differ, it is likely that a close self-AI connection will lead to increased internal attribution (e.g., self-blame), as consumers may regard AI failures as personal failures. We believe the locus of attribution following an AI-related service failure warrants more scholarly investigation.

Finally, our focus of interest is NWOM in this research, but there are many other behavioral outcomes that remain unexplored. For example, since AI systems can be seen as a part of oneself, do consumers feel more confident and competent if the "virtual self" produces a positive outcome? In other words, will the success of AI extend to the customers themselves so that AI successes are regarded as personal successes? These questions suggest only a small part of the rich area of consumer-AI interactions. Today, smart technologies powered by AI continue to advance and shape consumers' everyday experiences, and more research is needed to fully understand their dual impacts on both consumers and firms. We hope our findings provide useful insights into this nascent field and spark further discussion.

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Chapter 2

Partner or Servant? The Double-Edged Sword Effect of Relationship Type on Service Interaction with Artificial Intelligence

Context

As the second essay of the thesis, this paper adds to the framework by building on the notion of self-AI connection found in Essay 1, and pushes it further by adopting a social and relational perspective. The proposed mechanism in which consumers incorporate the AI into themselves with partner-AI is a novel extension of the idea of self-AI connection. In addition, this paper also focuses on satisfaction failure. However, as the framework illustrates, there are some key differences that bring another set of contributions to the literature. First, in Essay 1, the AI is regarded as the firm's employee, replacing a human agent. In this essay, the AI is a virtual assistant belonging to the consumers themselves. Therefore, the different ownership of AI brings a new perspective. Second, instead of comparing AI with human service provider, Essay 2 narrows down its focus on AI only and it looks at the specific framing of AI. The two relationship types investigated here are of interest to marketers since they offer insights to better position an AI-infused product or service. Third, in this essay I also examine other important consumers outcomes typically following service failures, such as attribution and reuse intentions. Overall, the second essay extends ideas and shifts focuses compared to Essay 1, and it brings new insight into the various effects of perceiving AI as a relationship-partner.

Abstract

The rapid adoption of AI-powered technologies in the retail and service sector, such as virtual assistants, smart objects, and robots, gives rise to questions on how consumers perceive and interact with them. Recent research suggests that several types of relationship with AI can emerge at various touchpoints along the customer journey. However, the potential impact of these relationships on consumer experience is unclear. In this research, the authors uncover a double-edged sword effect by examining two prevalent relationship roles (i.e., partner vs. servant). Through four experiments, the findings show that positioning an AI virtual assistant as a partner increases consumers' self-expansion with the AI compared to a servant positioning, which in turn constrains consumers from making self-serving attributions (Studies 1-2). However, such partner relationships do not seem to benefit AI evaluations following a service failure, since users are less likely to use it again in the future (Study 3). Further analysis suggests that this negative effect is driven by a decrease in perceived self-efficacy (Study 4). Theoretical and managerial implications are discussed.

Like the ideal servant in a Victorian manor, Alexa hovers in the background, ready to do her master's bidding swiftly yet meticulously.

--- Judith Shulevitz, *The Atlantic*

Alexa is my new best friend.

---Anonymous review on Amazon Echo

2.1 Introduction

Today, rapid development in artificial intelligence (AI) has resulted in a rapid adoption of virtual assistants (e.g., Alexa, Siri and Google Home) by consumers globally. These AI virtual assistants are meant to streamline the customer journey by making tedious decisions autonomously on behalf of the customer. For example, during the 2018 Google I/O, the world was amazed by the Google AI virtual assistant, who was able to conduct a natural conversation with a human over the phone to book a hair-dressing appointment in a local salon for the users. Gifted with the power of human speech, AI virtual assistants are naturally treated as if they had a human mind. And, as in interaction between humans, different relationship types could be formed with the AI (in this paper, we use AI and AI virtual assistant interchangeably).

Although companies might not intentionally design and promote their AI virtual assistants using a relational metaphor, people often form these associations either implicitly or explicitly. For example, Amazon Alexa, on the one hand, has been labeled and referred to as “digital female servant”, “humble servant”, and “domestic servant” (Shulevitz 2018; Johnston 2020); on the other hand, it has also been described as a “companion”, “good friend” and “partner in everyday life” in numerous consumer reviews and articles. Therefore, diverse and even polarized perceptions of whom these AI personas represent socially and relationally exist among the general public. This phenomenon has started to receive attention from researchers, and recent work has found that consumers tend to develop various relationship types when interacting with AI-enabled entities, two of the most predominant ones being AI-as-partner and AI-as-servant relationships (Novak and Hoffman 2019; Schweitzer et al. 2019). However, while we know that consumers form these relationships with AI intuitively, less is known about the consequential effects of these two relationship types on consumer evaluations of the services delivered by AI. Therefore, the purpose of the current research is to investigate how positioning an AI virtual assistant as a partner or a servant affects various consumer outcomes.

Across four studies, we uncover a double-edged sword effect where we show both positive and negative effects of a partner relationship (versus servant) on consumer responses when interacting with an AI in a service context. Specifically, we first show that compared to a servant relationship, a partner relationship with the AI generates two positive effects: consumers are more likely to self-expand to the AI (i.e., incorporate the AI into their self-concept). Further, as a result of self-expansion perceptions, consumers are more likely to refrain from making self-serving attribution (i.e., individuals take credit for success but blame others for failure), and instead share outcome responsibility with the AI virtual assistant. These outcomes are particularly relevant given that they engender positive downstream effects in traditional service contexts such as satisfaction, brand loyalty, attachment, and repurchase intention (Oliver & Desarbo 1988; Folkes 1988; Orth et al. 2012). However, in parallel to these positive outcomes, our research shows as well that consumers report lower intention to use a partner-AI (versus servant-AI) in the future after an initial service failure, and this negative effect is driven by a decrease in perceived self-efficacy, referring to the consumers 'subjective ability to successfully interact with the AI.

Our research is both theoretically novel and managerially insightful. We make several contributions to the literature. Our first set of contributions relates to the emerging literature on consumer-AI interactions (Foehr and Germelmann 2020; Mende et al. 2019; Longoni, Bonezzi, and Morewedge 2019; Longoni and Cian 2020; Gill 2020; Moriuchi 2019), which includes a variety of AI-powered entities such as virtual assistants, robots, smart objects and other autonomous technologies. First, we examine such interactions from a relationship perspective. This novel perspective contributes to the ongoing discussion on how consumers perceive AI-powered entities and we extend past conceptual and qualitative research by investigating the consequential effects of these relationships (Novak and Hoffman 2019; Schweitzer, et al. 2019). Second, the current research also investigates situations when the AI virtual assistants fall short in fulfilling a request. The literature on AI failure is relatively sparse (e.g., Huang and Philp 2020; Hadi et al. 2020). We believe more empirical investigation is warranted since unsatisfactory service outcomes constantly happen in real life considering the limits of current AI technologies. Third, our research additionally extends previous research on consumer resistance to AI. Past studies found that AI resistance arises for a variety of reasons such as concern for uniqueness, neglect and privacy (Longoni, Bonezzi, and Morewedge 2019; Mani and Chouk 2019). Our research posits relationship type as an additional determinant for future resistance.

The second set of contributions speaks to the vast literature on self-expansion and self-serving bias (e.g., Aron and Aron 1986; Miller and Ross 1975). First, our research complements extant literature on the classic model of self-expansion, by showing that self-expansion goes beyond human-human relationships and consumer-brand relationships (Aron and Aron 1996; Reimann and Aron 2009; Patwardhan and Balasubramanian 2011; de Kerviler and Rodriguez 2019) and can also apply to human-AI relationships. Second, the current research also contributes to prior research on potential boundary conditions for self-serving bias on attribution of responsibility with a broad array of entities including humans, brands, and computers (Sugathan, Ranjan, and Mulky 2017; Campbell et al. 2000; Moon and Nass 1998; Moon 2003). In this research, we show that positioning an AI as a partner (versus servant) can also constrain consumers from making self-serving attributions.

From a managerial perspective, our findings are useful for companies that use AI as a touchpoint in their customers' journeys. Specifically, our findings inform us how to better design and promote AI in order to deliver positive consumer outcomes. We first show that humanlike relationships with an AI such as partner and servant are more than mere speculations and metaphors in the minds of consumers: they have concrete and important consequences on consumer responses. Therefore, when incorporating AI in product and service offerings, companies should be highly attentive to how consumers perceive them relationally. Second, in terms of positioning, it is common for companies to position their AI as a partner (e.g., a good companion or friend) by highlighting communal characteristics in the hope of fostering a closer and more intimate relationship with consumers, which is supported by our findings. However, our findings also reveal a double-edged sword effect, revealing that a partner relationship can quickly backfire (e.g., lower reuse intention) when the AI does not live up to consumers' expectations. From a product development perspective, we suggest that the decision to frame the AI as a servant versus partner could be strategically matched with the product life cycle. In the product's introduction stage where consumers are not familiar with the technology, and failures are more likely to happen, our results would recommend a servant positioning (or avoid any relationship implications). However, once AI products reach the growth and maturity stage, and as the interactions become more reliable, companies might benefit from positioning them as partners to the consumers,. Alternatively, firms can still encourage an AI-as-partner relationship with customers while developing proactive ways to prevent negative effects resulting from failures. Since our results reveal that future avoidance is largely due to a decrease in self-efficacy, AI developers and managers can leverage this finding to help consumers attenuate such self-undermining perceptions, and as a result encourage future interactions. For example, the inclusion of self-affirming activities (e.g., elaborating on one's most important personal values) in the service delivery process can enhance self-efficacy (Cheng, White, and Chaplin 2012; Schmeichel and Vohs 2009).

In the following sections, we first review the related literature on consumer relationships with AI, the self-expansion model and self-serving bias, and present our hypotheses. Second, these hypotheses are tested in four experiments. Finally, the paper concludes by discussing the theoretical contributions, managerial implications, limitations, and future research avenues.

2.2 Theoretical Background

Consumers' relationship with AI

In recent years, marketing scholars have paid increasing attention to consumer adoption of AI (Puntoni et al. 2020; Davenport et al. 2020; Huang and Rust 2018).

However, a relatively unexplored theme is how consumers engage with AI socially, since like many forms of technology (i.e., computers and robots), AI can be perceived as a social actor (Nass et al. 1994). In the marketing-related human-computer interaction (HCI) literature, a few studies started to explore AI interactions from this social perspective (e.g., Lopatovska and Williams 2018; Foehr and Germelmann 2019; Novak and Hoffman 2019). For example, Purington et al. (2017, p2855) revealed that Amazon Echo users personify Alexa to varying degrees, ranging from calling it “a companion, conversation partner” to “a member of the family and even a new BFF (i.e. best friend forever)”. Based on the broad interpersonal dimensions of agency and communion, Novak and Hoffman (2019) proposed two main types of relationship that consumers have with smart objects: Master-Servant relationship and Partner relationship. In their conceptual work, agency relates to goal-pursuit arising from individuating the self and typically involves instrumentality, ambition, dominance, and competence. Communion relates to consideration of others, arising from integrating the self in a larger social circle and generally involves other-focus, helpfulness and cooperativeness (Abele and Wojciszke 2007). Specifically, the authors argue that when consumers regard smart objects as servants, they are more concerned about achieving their own goals through the use of smart objects (i.e., high agentic orientation). On the contrary, a mutually dependent partner relationship takes place when consumers care about the smart objects and focus more on cooperation and perspective-taking (i.e., high communal orientation).

These conceptualizations of relationship with AI largely echo prior literature on brand relationship, where researchers have found that consumers develop anthropomorphic relationships with their favorite brands, two primary ones being also “brand-as-partner“ and brand-as-servant” (Aggarwal and McGill 2012; Fournier and Alvarez 2012; Kim and Kramer 2015). In line with previous conceptualizations and findings, in this research, we focus on two main relationship types, namely AI-as-servant and AI-as-partner. We refer to an AI-as-servant relationship as a relationship where consumers have an *agentic* orientation and perceive AI as an outsourced provider of benefits, one that works *for* them. In contrast, we refer to an AI-as-partner relationship as a relationship where consumers have a *communal* orientation and perceive AI as a co-producer of benefits, one that works *with* them. Although prior studies provide a comprehensive discussion about, and evidence for the formation of consumer-AI relationships, their potential effects on consumer responses remain unclear. Therefore, in this paper, we go one step further by exploring the downstream effects of these relationship types on various consumer outcomes in the context of AI-delivered services.

The self-expansion model in close relationships

Expanding on previous research on partner and servant relationships with AI-powered entities, we propose that these relationship types have an effect on consumers’ tendency to self-identity with them. One of the most fundamental theories in interpersonal relationship is the self-expansion model (Aron and Aron 1986; Aron and Aron 1996). This theory proposes that individuals have a general motivation to expand the self by enhancing their potential efficacy (e.g., overall ability) to facilitate goal attainment. One common way to achieve this is through the formation of close relationships (e.g., good friends, romantic partners) in which the self is expanded by perceiving and acquiring other’s resources, perspectives, and identities, and treat them as one’s own. By having access to these resources, our general belief of efficacy increases and we become more able to engage in the social environment. In these close relationships, self-expansion can grow up to the point where the other becomes "included in the self." In other words, our cognitive construction of the other overlaps with our cognitive construction of the self (Aron et al. 1991). Therefore, by perceiving the other as integral to the self, we take on resources, perspectives, and identities of that person, and we share that person's outcomes (Aron et al. 2013).

Recent research has found that the idea of incorporating others in one's self is not limited to interpersonal relationships, but is also relevant to consumer relationships with non-human entities such as brands and possessions (Reimann and Aron, 2009; Belk 1988). For example, consumers are known to develop humanlike relationships with their loved possessions and brands in which they share inter-dependence and commitment (Fournier 1998). Consumers often construct their self-concepts through the purchase and use of brands and as such incorporate brands into their self-concept (Escalas and Bettman 2005). More recently, studies have shown that consumers experience self-expansion in the interaction with AI-powered smart objects. For example, Hoffman and Novak (2018) proposed that a self-expansion experience is likely to occur within a consumer-smart object interaction in which the consumers have more capacities and achieve more goals by being part of the relationship. In a similar vein, in a recent study focusing on service failure caused by an AI recommendation agent, it was revealed that consumers feel more connected with the AI system (versus human), especially when the AI is designed to mimic their own past behaviors, interests, and preferences (Huang and Philp 2020).

We posit that based on the above discussion, while self-expansion is likely between consumers and AI, the degree to which this occurs depends on the specific type of AI-consumer relationship. Specifically, we propose that consumers should exhibit a higher degree of self-expansion with the AI when it is perceived as a partner rather than a servant. This prediction is based on evidence showing that the two relationship types differ significantly in terms of hierarchy. A partner relationship values equality and cooperation while a master-servant relationship prioritizes dominance, power, and control over one another (Aggarwal and McGill 2012; Kim and Kramer 2015). For example, in a study by Schweitzer et al. (2019, p703), participants who referred to the virtual assistant as a servant also perceived it as being in a lower hierarchical position like "an employee to her boss," whereas those who perceived it as a partner showed more caring, patience, and time investment in interacting with the virtual assistant. Prior research suggests that perceptions of self might be dependent on social comparisons – when individuals perceive themselves to be equal to others, they are likely to experience a sense of assimilation and interconnectedness with the others (Blanton 2013). On the other hand, when one feels superior to another and as having more power, one is likely to create relational boundaries (Fiske 1993; Fiske and Dépret 1996). Further, compared to a servant, a partner relationship can be regarded as more intimate and focused on communal considerations, such as helpfulness and cooperativeness. In contrast, a master-servant relationship emphasizes an agentic orientation, focusing on instrumentality whereby the AI device serves simply as "a means to an end" in achieving consumer goals (Abele and Wojciszke 2007; Novak and Hoffman 2019). Based on this rationale, a partner (versus servant) relationship is more likely to facilitate self-expansion. Specifically, we propose the following hypothesis:

H1. Consumers are more likely to exhibit self-expansion with the AI when they perceive it as a partner versus a servant.

The effect of relationship type on attribution of responsibility

We further predict that the two relationship types with AI should lead to different attributions of responsibility regarding the service outcome. When it comes to attribution, a notable behavior evidenced by the literature is the self-serving bias (Folkes 1984; Bitner 1990), where individuals take credit for success but blame others for failure (Miller and Ross 1975). We posit that such self-serving attribution should be less likely when consumers consider the AI as a partner than a servant. Specifically, a partner relationship should lead to more AI-attribution (for successful service outcome) and more self-blame (for service failure) than a servant relationship.

To support this view, first, we argue that the increased self-expansion in the AI-as-partner relationship should lead consumers to make less self-serving attribution than in the AI-as-servant relationship. The literature suggests that the self-serving bias is diminished when perceiving the other person as part of our own self due to the perception of shared responsibility for the outcome (Aron & Frale 1999; Aron et al. 2013). Moreover, it is demonstrated that by including others in the self, people in a close relationship are not only motivated to protect their own self-concepts, but are also ready to protect the other's self-concept (e.g., refraining from expressing self-enhancement effort that will reflect negatively on the other) (Campbell et al. 2000). In addition, Sande et al. (1988) found that people were more likely to make situational attributions for the behaviors of close versus distant others; that is, participants explained close others' behaviors similarly to how they would explain their own behaviors. In addition, studies on brand relationships suggest that people respond to brand failure in the same way as they do to personal failures when the brand is seen as part of the self, given that brand failure is seen as a threat to one's own positive self-view (e.g., Cheng, White, and Chaplin 2012). In relation to the consumer-AI context, this shows that when self-expansion is high, as in the partner relationship, consumers might be more willing to share the outcome responsibility than in the servant relationship, thus refraining from making self-serving attributions.

Second, the partner relationship is cognitively more intimate than the servant relationship and previous research in social psychology shows that people in close relationships (e.g., friends and romantic partners) are less likely to exhibit self-serving bias than those who are in a distant relationship (Sedikides et al. 1998; Campbell et al. 2000). For example, in a study conducted between two relationally different groups, members of relationally close dyads as in close friendship did not manifest the self-serving bias; they did not take more credit than their partner for dyadic success and did not blame the partner more than the self for dyadic failure (Sedikides et al. 1998). The authors further found that this gracious attributional behavior is partly motivated by impression management: Close participants rated their partner more favourably than distant participants. Similarly, Campbell et al. (2000) also found that dyads consisting of friends refrained from attributing outcomes in a self-serving manner: they shared responsibility for both successful and unsuccessful outcomes. In sum, consumers in a partner relationship with the AI should be more generous in their attribution pattern, then those who view the AI as merely a servant.

Based on the above discussion, we propose the following hypotheses:

H2a. Following a positive service outcome, consumers in an AI-as-partner relationship should credit the AI more than those in a servant relationship.

H2b. Following a negative service outcome, consumers with an AI-as-partner relationship should blame themselves more than those in a servant relationship.

H3. Self-expansion with the AI mediates the effect of relationship type on attribution.

It is important to point out that the attenuation of self-serving attribution is highly beneficial in service interactions. Prior research suggests that consumers' attribution behavior strongly influences their attitudes and evaluations. In the event of a successful service outcome, an external attribution toward the service provider is desirable since it generates higher satisfaction, brand loyalty, attachment, and repurchase intention (Oliver & Desarbo 1988; Folkes 1988; Orth et al. 2012). Moreover, attribution is equally important in the context of negative service interactions as it is a key determinant of the consumer's affective and behavioral reactions to the experience (Folkes 1984; Richins 1983). An externally-directed blame, in other words blaming others, is a main driver of responses that negatively impact the service provider such as brand switching and negative word of mouth. Therefore, an attenuation of self-serving attribution toward the AI in a partner relationship is essentially sought after since the AI benefits in both interaction outcomes.

2.3 Methodology

Overview of the studies

We conducted four experiments to uncover the consequences of relationship type (partner and servant). Study 1 tests the effect of relationship type on self-expansion tendency, namely to what extent consumers include the AI into their self-concept. Study 2 focuses on the attribution of responsibility (both the self and AI) after a positive and negative service outcome. We also provide mediation evidence for the role of self-expansion in explaining the difference in attributional tendencies. Study 3 extends the findings to a behavioral (intention) outcome, where we show the effect of relationship type on future reuse intention of the AI. Following an unexpected finding in Study 3, we seek to explain the underlying process in Study 4, in which self-efficacy is proposed and tested.

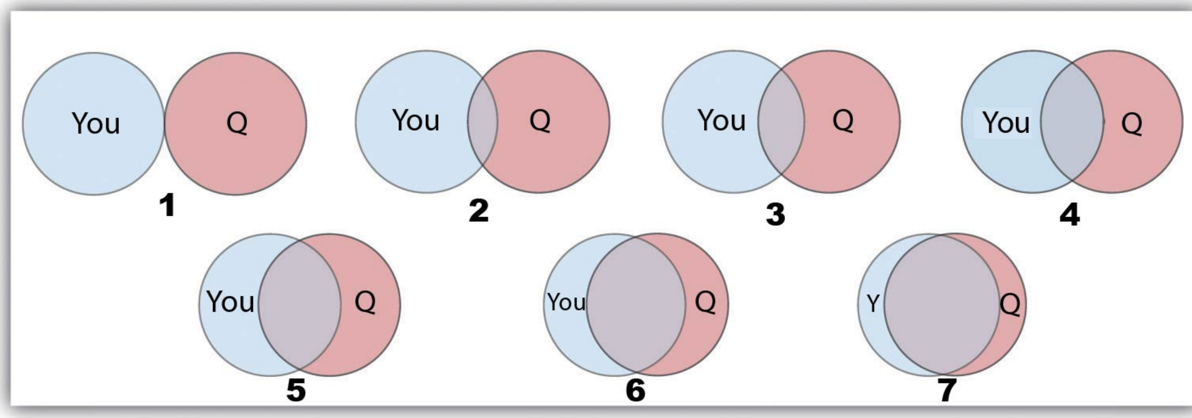
Study 1

The objective of Study 1 was twofold. First, although relationship type has been successfully manipulated experimentally in the brand context, such manipulations have not been previously tested in the consumer-AI interaction context. Therefore, the first objective of Study 1 was to test whether we can successfully induce such relationship perceptions with an AI. Second, following a successful experimental manipulation, we wanted to test the effect of the two relationship types (servant vs partner) on consumers' perceived self-expansion with the AI.

Experimental design. 129 participants (M_{age} = 33, 47% female) were recruited from an online panel and randomly assigned to two conditions (Partner vs. Servant). The manipulation was based on previous brand relationship studies (e.g., Kim and Kramer 2015). We introduced participants to an AI virtual assistant, named Q, as either a servant or a partner. In the servant (partner) condition, we first presented Q as a virtual servant (partner) by framing it using servant (partner)-like tone and descriptions. We then presented a conversation dialogue that highlighted the agentic (communal) orientation of the consumers (see Appendix A for detailed manipulation material). To strengthen the manipulation, we further asked participants to elaborate on the following question: "As you have previously read, the company wants to present Q as a trusty partner (servant) to its customers. In a few lines, briefly describe how Q can co-create value (serve) and work with (for) you like a partner (servant)?"

Measurement. All participants completed the same questionnaire, which was estimated to take approximately 5 minutes. All responses were measured on a seven-point Likert scale (1 - strongly disagree; 7 - strongly agree). To measure self-expansion, we used the widely used the Inclusion of Others in Self (IOS) scale developed by Aron et al. (1992). The IOS scale consists of seven pairs of overlapping circles (Figure 2.1); each pair overlapping slightly more than the preceding pair. Respondents were instructed to select the pair of circles that best portrays their perceived relationship with the AI named Q in this study. As a manipulation check, we measured participants' perceptions of the relationship role which consisted of four items: "Q is like a servant to me"; "Q serves and works for me" (α = .85); "Q is like a partner to me"; "Q co-creates value and works with me" (α = .89) (Kim and Kramer 2015). Furthermore, in the context of AI-enabled services, it is possible that consumers judge the AI differently in terms of competence and anthropomorphism as a function of relationship type. Therefore, we include these measures (adapted from Fiske et al. 2002; Kim & McGill 2011) as possible covariates in this study.

Figure.2.1: Inclusion of Other in the Self (IOS) scale



Manipulation Check. As expected, the servant manipulation resulted in stronger perceptions that the AI represented a servant than did the partner manipulation (Mservant = 5.18, Mpartner=4.47, $F(1, 127)=8.43$, p=.004, $\eta_p^2=.06$), and the partner manipulation resulted in stronger partner perceptions than did the servant manipulation (Mpartner = 5.56 Mservant =4.77, $F(1,1273)=8.22$, p=.005, $\eta_p^2=.06$).

Main Analysis. A one-way analysis of variance (ANOVA) revealed a significant effect of relationship type on self-expansion. In support of H1, participants who perceived the AI as partner projected higher degree of inclusion of the AI in the self than those in the servant condition ($M_{partner}=5.00$, $M_{servant}=4.37$, $F(1, 127)=4.72$, p=.032, $\eta_p^2=.04$). In addition, it is important to point out that our manipulation of relationship did not affect the AI virtual assistant's perceived competence ($M_{partner}$ =5.51, $M_{servant}$ =5.46, F(1, 127)=.067, p=.796), or perceived anthropomorphism ($M_{partner}$ =4.89, $M_{servant}$ =4.80, F(1, 127)=.099, p=.753). Therefore, participants did not perceive the AI to be more or less competent in one relationship over another, nor did they anthropomorphize it varyingly across the two conditions.

Discussion. These results suggest that distinct relationship types with the AI lead to different degrees of self-expansion. Specifically, just like in an interpersonal relationship, framing the AI as a partner led participants to include the AI into their self-concept to a higher degree than those who viewed the AI as a servant. In other words, participants were more likely to blur their self-other boundary and see overlaps between themselves and the AI, when they were in a partner (versus servant) relationship with the AI.

Study 2

Study 2 had two objectives. First, we aimed to test the effect of relationship type on the attribution of responsibility, depending on the service outcome. Second, we wanted to confirm that the effect of relationship type on the attribution judgment is mediated by self-expansion. Specifically, consumers who perceive the AI as a partner (servant) should be more (less) willing to credit the AI when the outcome is positive (H2a) and blame themselves when the outcome is negative (H2b), due to the increased self-expansion (H3).

Experimental design. 239 participants (Mage = 36, 45% female) were guided through a 2 (Relationship Role: Partner vs. Servant) X 2 (Service Outcome Valence: Positive vs. Negative) between-subject study. The relationship manipulation was identical to Study 1. However, this time, we also manipulated service outcome (see Appendix B for detailed manipulation material). Specifically, participants were asked to imagine that they had just moved into a new town and they turned to Q for help to find an apartment. The apartment search service was autonomously delivered by Q and no input was required from the participant. In the positive condition, they were told that, after visiting some of the apartments found by Q, they were very satisfied with one of them whereas in the negative condition they were very disappointed with all the choices recommended by Q.

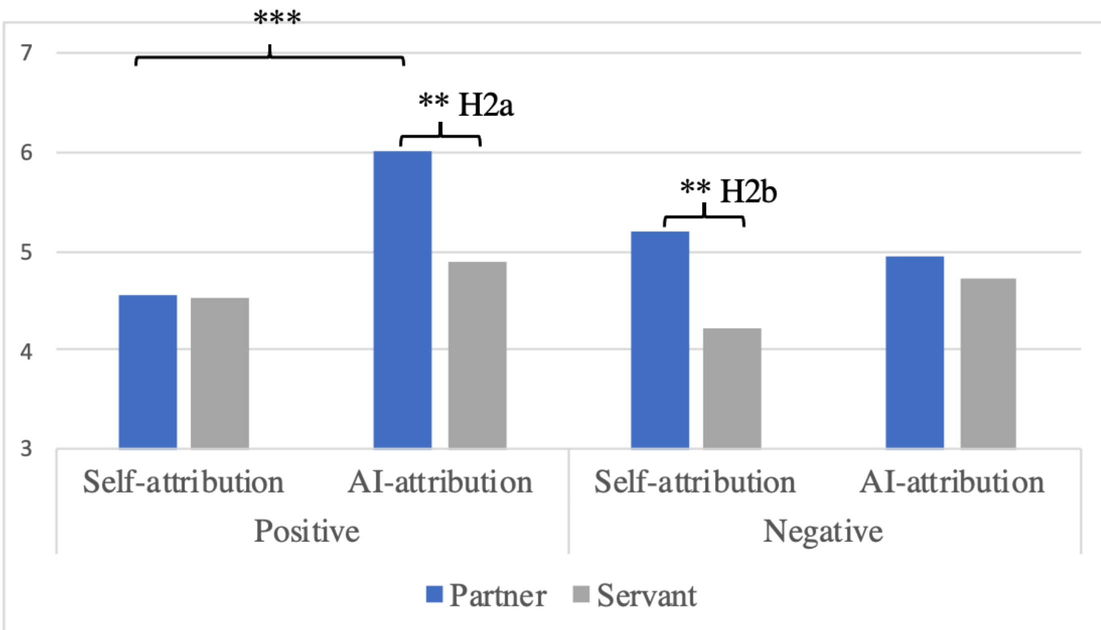
Measurement. All participants completed the same questionnaire and responses were measured on seven-point Likert scales (1 - strongly disagree; 7 - strongly agree). To avoid confounding issues (e.g., outcome valence affects self-expansion tendency), we measured self-expansion before presenting the outcomes. We used the same measures to assess perceptions of relationship type and self-expansion as in Study 1. We also measured attribution of responsibility to oneself and the AI assistant. Self-attribution was measured using one item "I am responsible for the outcome" and attribution to the AI assistant was measured using one item "Q is responsible for the outcome".

Manipulation Check. As in Study 1, the manipulation check confirmed that the servant manipulation resulted in stronger perceptions of AI-as-servant than did the partner manipulation (M_{servant} = 5.43, M_{partner}=5.02, $F(1, 237)=4.16$, p=.042, $\eta_p^2=.02$), and that the partner manipulation resulted in stronger AI-as-partner perceptions than did the servant manipulation (M_{partner} = 5.5, M_{servant} =4.68, $F(1, 237)=14.7$, p=.0001, $\eta_p^2=.06$).

Main Analysis. We also replicated the results of self-expansion. Participants reported a higher level of inclusion of the AI in the partner condition than in the servant condition (M_{partner} =4.80, M_{servant} =4.06, $F(1, 237)=10.78$, p=.001, $\eta_p^2=.04$). In addition, as depicted in Figure 2.2, we found a significant interaction effect of Relationship Role x Outcome Valence on both attribution targets (self-attribution: $F(1, 235)=4.28$, p=.04, $\eta_p^2=.02$; AI-attribution: $F(1, 235)=3.93$, p=.049, $\eta_p^2=.02$). Specifically, in support of H2a, when the outcome was positive, participants in the AI-as-partner condition gave more credit to the AI for this success than those in the AI-as-servant condition ($M_{\text{partner-positive}}=6.00$, $M_{\text{servant-positive}}=4.90$, $F(1, 235)=11.52$, p=.001). No difference was found for self-attribution (p=.95). However, when the outcome was negative, participants who perceived the AI as a partner attributed the outcome more to themselves ($M_{\text{partner-negative}}=5.19$, $M_{\text{servant-negative}}=4.23$, $F(1, 235)=9.52$, p=.002), than those in the servant condition, thus supporting H2b. No difference was found for AI-attribution (p=.54). To summarize, compared to those who interacted with a servant AI, following a positive outcome, participants in the partner relationship believed that the AI was more responsible for the success; and following a negative outcome, they believed that they were more responsible for the failure.

Analyzing the other pair of contrasts between the targets of attribution (self vs AI) , paired sample t-tests revealed that when the service outcome was positive, participants gave the AI more credit than themselves in the partner condition ($M_{\text{AI}}=6$, $M_{\text{self}}=4.56$, $t(49)=4.469$, p=.0001), but not in the servant condition (p=.35). However, when the outcome was negative, we did not find a significant difference between attribution targets among participants in either the partner condition (p=.42), or the servant condition (p=.14). These results additionally showed that participants in the AI-as-partner condition were more other-serving in their attribution pattern, such as giving more credit to the AI assistant than themselves following a successful service outcome.

Figure 2.2: Attributions of Responsibility by Relationship Type and Outcome



***p<.001; **p<.01; NS: not significant, p >.05

Mediation. To test whether the increased self-expansion could explain the above effects, a mediation analysis was conducted using PROCESS Model 4 (5,000 resamples; Hayes 2013). Specifically, we constructed two models in which the effect of relationship role (servant=0, partner=1) on attribution was mediated by self-expansion for positive and negative outcomes separately. Based on 5,000 bootstrapped samples at the 95% confidence intervals, self-expansion mediated the effect of relationship role on self-attribution when the outcome was negative (Indirect Effect = .17, SE=.10, $CI_{95\%}$: .02 to .40) (Figure 2.3a). In addition, when the outcome was positive, self-expansion also mediated the effect of relationship role on AI-attribution (Indirect Effect = .40, SE=.16, $CI_{95\%}$: .13 to .74) (Figure 2.3b). The direction of the effects confirmed that partner relationship led to higher self-expansion, which in turn contributed to more self-attribution in negative outcome, and more AI-attribution in positive outcome. The results therefore support H3: Self-expansion mediates the effect of relationship type on attribution.

Figure 2.3a: Mediation role of self-expansion on the effect of relationship role to self-attribution in negative outcome

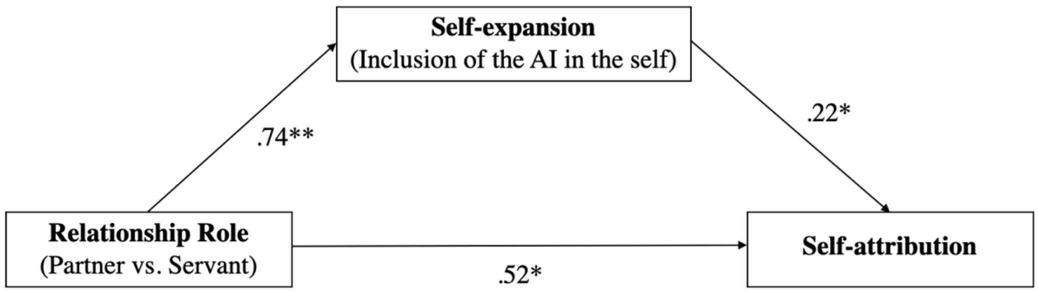
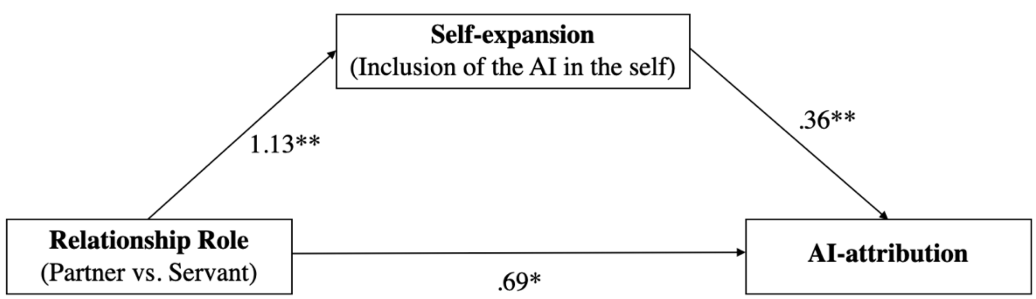


Figure 2.3b: Mediation role of self-expansion on the effect of relationship role to AI-attribution in positive outcome



Discussion. The results of Study 2 replicated the finding on perceived self-expansion found in Study 1: Participants who interacted with a partner AI reported a higher degree of inclusion of the AI in the self-concept than those exposed to a servant AI. In addition, we found some novel results regarding relationship and attribution in a consumer-AI context. Since the outcome was objectively and solely caused by the AI virtual assistant Q as depicted in the scenario, it would be logical to assume that attribution should always be externally directed to the AI. However, our results suggest that relationship type with the AI significantly altered participants' attribution behavior. Specifically, participants in the partner relationship were less likely to exhibit a self-serving bias compared to those who were in the servant relationship: they gave the AI assistant more credit when a service was successfully delivered and blamed themselves more following a service failure, in comparison those in the servant relationship. This was quite remarkable considering that the failure was caused solely by the AI, yet participants in the partner relationship were still willing to share some of the blame. Further mediation analysis confirmed that such favorable attribution was due to an increased view of self-expansion with the AI.

Study 3

Building on the first two studies, the objective of this study was to explore the effect of relationship type with AI on reuse intention as a behavioral consequence of service interactions. Considering AI and its related technologies are still in the emerging phase, it is an important outcome to explore for both consumers and companies. We propose that consumers in the partner relationship should be more willing to use the AI again compared to those in the servant relationship, but only when the service outcome is negative. First, we do not expect to find an effect on future reuse intention when the service is successfully delivered since when a service yields a satisfactory outcome, consumers are likely to use it again regardless of relationship type. However, when the outcome is negative, consumers in the partner condition might be more willing to give it a second chance since partner AIs are blamed to a lesser extent for service failure than servant AIs. Formally put, we additionally propose the following hypothesis:

H4. Following a negative service outcome, consumers in an AI-as-partner relationship will express greater intentions to use the AI again in the future compared to consumers in an AI-as-servant relationship: no difference in reuse intentions is expected between the two relationship types when the outcome is positive.

Experimental design. 201 participants (*M*age = 36, 40% female) were guided through a 2 (Relationship Role: Partner vs. Servant) X 2(Service Outcome Valence: Positive vs. Negative) between-subject study. The design of the study was identical to Study 2, where we used the same manipulation scenarios to manipulate relationship types and service outcomes.

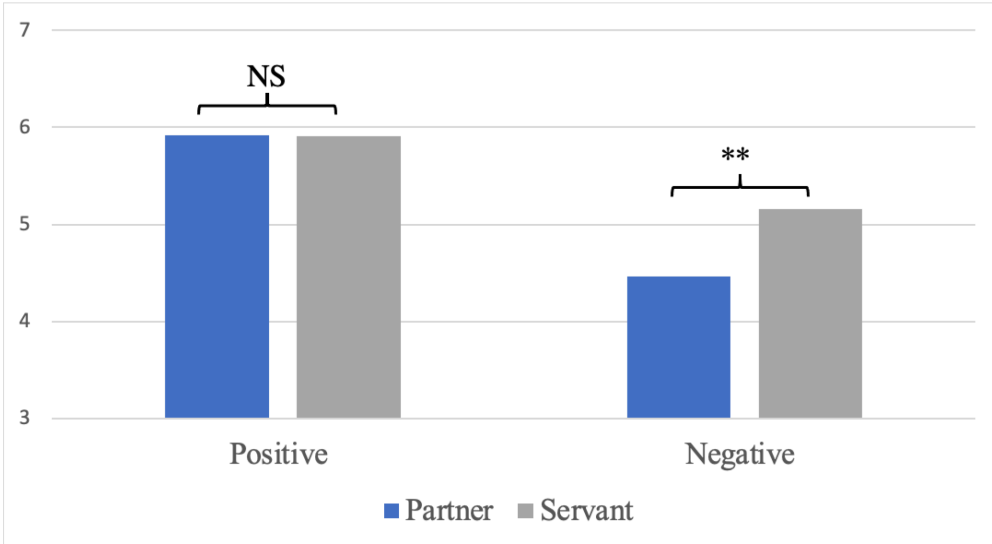
Measurement. All participants completed the same questionnaire with responses measured on a seven-point Likert scales (1 - strongly disagree; 7 - strongly agree). In addition to self-expansion and attribution which were measured using the same scales in the previous study, future reuse intention was measured using three items adapted from (Venkatesh, Thong, and Xu 2012): “I intend to continue to interact with Q in the future”; “I will always try to interact with Q in the future”; “I plan to continue to interact with Q frequently” ($\alpha = .84$).

Manipulation Check. Same as in the previous two studies, our relationship role manipulation was successful. Specifically, the results of an ANOVA revealed participants in the servant condition perceived the AI as a servant more than those in the partner condition ($M_{servant} = 5.73$, $M_{partner}=4.67$, $F(1, 199)=26.03$, $p=.0001$, $\eta_p^2=.12$); participants in the partner condition perceived the AI as a partner more than those in the servant condition ($M_{partner}$=5.52, $M_{servant}$ = 4.67, $F(1, 199)$=13.57, p=.0001, η_p^2=.07).

Main Analysis. First, we again replicated the results on self-expansion and attribution found in previous studies. Similarly, participants were more likely to include the AI in the self in the partner condition than servant condition($M_{partner}$ = 4.86, $M_{servant}$ =4.24, $F(1, 199)$=6.62, p=.011). They were also more likely to give more external attribution in positive outcome ($M_{partner}$ = 5.84, $M_{servant}$ =4.98, $F(1, 197)$=7.22, p=.008), and more internal attribution in negative outcome ($M_{partner}$ = 5.06, $M_{servant}$ =4.26, $F(1, 197)$=5.65, p=.018).

An ANOVA revealed a significant main effect of Outcome Valence on reuse intention ($F(1, 197)$=42.29, p=.0001, η_p^2=.18) where participants reported higher reuse intention following a positive service outcome (*M*=5.92) than a negative one (*M*=4.81). As shown in Figure 2.4, there was also a significant interaction of Role X Outcome on future reuse intention ($F(1, 197)$=4.30, p=.04, η_p^2=.02). Specifically, when the outcome was positive, there was no significant difference between the reuse intention in the partner and the servant relationships (p=.984), thus supporting the second part of H4. However, when the outcome was negative, in contrast to the first part of H4, it was the participants in the AI-as-partner scenario who reported significantly lower reuse intentions than their counterparts in the AI-as-servant condition ($M_{partner-negative}$ =4.46, $M_{servant-negative}$ =5.16, $F(1, 197)$=8.43, p=.004).

Figure 2.4: Future reuse intention by Relationship role and Outcome



**p<.01; NS: not significant, p >.05

Discussion. These results imply that an AI-as-partner relationship in fact has some dark-side effects on consumer behavioral intention. For positive service outcome, while Study 2 revealed that participants gave the AI more credit when it was presented as a partner, this did not translate into higher reuse intention in comparison with the servant relationship. Moreover, for negative outcome, although Study 2 showed that participants in the partner condition took more blame on themselves for the failure, they were nevertheless less likely to use the AI again in the future, compared to those in the servant condition.

Taken together, a gracious attribution pattern induced by an AI-as-partner relationship (Study 2) did not actually provide any benefit or protection to the AI-based service in the case of service failure, as participants were more reluctant to use it again (Study 3). Confronted with this seemingly counter-intuitive finding, we suggest that the negative effect on reuse intention can be related to the heightened sense of self-expansion among participants who were led to view the AI as a partner (Studies 1&2). Specifically, the increased self-expansion with the AI-as-partner might lead to a threat to perceived self-efficacy when the partnership goes awry after a service failure. Self-efficacy refers to an individual's assessment of one's ability to perform a behavior (Bandura 1977). Past research on self-service found that self-efficacy is one of the main factors that influences consumers' decisions to use such technology (Dabholkar and Bagozzi 2002). In our research, when the AI gets included in the expanded self for those participants in the partner relationship, the partner's failure evokes similar responses as a personal failure. This is in fact consistent with previous research on self-expansion with brands. For example, Lisjak et al. (2012) found that when consumers incorporate the brand as part of the self-concept, a threat to the brand is regarded a personal threat, and they would defend the brand as they would defend the self. This is also in line with previous literature on the effect of self-expansion in interpersonal relationships (Aron and Aron 1996). For example, prior work found that if the target of comparison is construed as part of one's own self, the target's successes become cause for celebration rather than costs to his or her esteem (Gardner, Gabriel, and Hochschild 2002). The fact that participants blamed themselves more in a partner relationship than servant relationship following a service failure (Study 2) provides similar evidence. Therefore, a failure could be seen as a threat to domain-specific self-efficacy, in this case the domain is technology, specifically the ability to interact with AI and yield a successful outcome. Consequently, following the established literature on self-efficacy and coping strategies, a threat to self-efficacy will entice defensive behaviors, such as avoidance and escape from the present task (Hodgins, Yacko, and Gottlieb 2006). In other words, the lower reuse intention reported by participants in the partner condition may be driven by a decrease in their perceived self-efficacy. They lose confidence and doubt their ability to utilize AI to achieve their goals (e.g., obtaining the service). Therefore, we put forth the following hypotheses:

H5. Following a negative service outcome, consumers in an AI-as-partner relationship will experience lower self-efficacy than consumers in an AI-as-servant relationship.

H6. Perceived self-efficacy mediates the effect of relationship type on reuse intention.

We test these hypotheses in the next study.

Study 4

Our objective for this study was to test the proposed mechanism driving the lower reuse intention following a service failure by an AI-as-partner (vs. AI-as-servant) relationship, namely self-efficacy.

Experimental design. 137 participants (M_{age} = 37, 57% female) were recruited from an online panel and randomly assigned into two conditions (Partner vs. Servant). Since reuse intention did not differ in the positive service outcome context (study 3), we only focused on the negative service outcome context in this study. In addition, to show the generalizability of our effect across service contexts, we modified the manipulated scenario from apartment search to restaurant booking. Specifically, participants were asked to imagine that they would like to celebrate a friend's birthday and they asked Q to book a restaurant in town. Upon the request, Q booked the restaurant on their behalf based on their personal data. However, participants were told that the restaurant experience turned out to be a disaster, indicating a service failure. Full material is available in Appendix C.

Measurement. All participants completed the same questionnaire with responses measured on a seven-point Likert scales (1 - strongly disagree; 7 - strongly agree). First, participants completed the same measure for future reuse intention as in Study 3. To measure perceived self-efficacy in ability to interact with AI, we adapted a three-item scale (Meuter et al. 2005): "I have confidence that I will still be able to successfully interact with AI"; "I do not doubt my ability to interact with AI effectively in the future"; "I am still fully capable of interacting with AI" (α = .88).

Manipulation Check. Same as in the previous studies, our relationship role manipulation was successful. Specifically, the results of an ANOVA revealed participants in the servant condition perceived the AI as a servant more than those in the partner condition ($M_{servant}$ = 5.81, $M_{partner}$=4.15, $F(1, 135)$=40.77, p=.0001, η_p^2=.23); participants in the partner condition perceived the AI as a partner more than those in the servant condition ($M_{partner}$=5.7, $M_{servant}$ = 4.32, $F(1, 135)$=36.01, p=.0001, η_p^2=.21).

Main Analysis. An ANOVA revealed that participants who perceived the AI as a partner reported lower future reuse intention than those in the servant condition ($M_{partner}$ =3.99, $M_{servant}$ =4.72, $F(1, 135)$=6.59, p=.011, η_p^2=.05). We therefore replicated the results found in Study 3, showing the robustness of our findings. Moreover, we also found a significant effect of relationship type on perceived self-efficacy ($M_{partner}$ =4.84, $M_{servant}$

=5.44, $F(1, 135)=4.98$, $p=.027$, $\eta_p^2=.04$). As predicted in H5, when the AI was perceived as a partner, participants reported significantly less self-efficacy in their ability to interact with the AI in the future, compared to those in the AI-as-servant condition.

Mediation. In order to test whether the difference in future reuse intention was driven by perceived self-efficacy (H6), we ran a mediation analysis using PROCESS Model 4 (5,000 resamples; Hayes 2013). We dummy coded the two conditions as 0=partner, and 1=servant. We then entered self-efficacy as mediator of the effect of relationship role perceptions on future reuse intention. The result indicated a significant full mediation model (indirect effect =.468, SE =.21, 95% CI= .050 to .888).

Discussion. The results of Study 4 reaffirmed that perceiving the AI as a partner (versus servant) decreased participants' intention to reuse the AI in the future in the context of service failure. Additionally, we provided evidence that self-efficacy drives this effect. A service failure by an AI-as-partner diminished participants' perceived ability to successfully interact with the AI, which in turn hindered their future reuse intention.

2.4 General Discussion

As AI-powered virtual assistants become more intelligent, consumers are gradually developing deeper anthropomorphic relationships with them through service interactions. Therefore, the question of how these relationships impact consumer perceptions and behaviors is of great importance. By contrasting two prevalent relationship types (partner vs servant), we address this question across four studies and show a double-edged sword effect. On the one hand, we found positive effects of AI-as-partner in two studies: Study 1 demonstrates that a partner (servant) relationship leads to higher (lower) self-expansion with the AI, implying that consumers in the partner relationship are more likely to include the AI in their self-concept – i.e., viewing the AI as part of themselves. Study 2 shows that consequently, a partner relationship deters consumers from attributing the outcome of an AI-delivered service in a self-serving manner. Specifically, when the service outcome is successful, consumers who interact with a partner (servant) AI give more (less) credit to the AI. However, when the outcome of the service delivered by the partner (servant) AI is negative, they tend to attribute more (less) blame onto themselves. On the other hand, we also document a downside in positioning an AI as a partner (versus servant) to the consumers. In Study 3, results suggest that the partner relationship does not translate into benefits for future interactions compared to the servant relationship: In a satisfactory service outcome context, participants who perceived the AI as a partner expressed similar reuse intentions as those who perceived the AI as a servant. And interestingly, in the case of service failure, the partner role, as opposed to the servant role, even discouraged consumers from wanting to use the AI service again in the future. Study 4 uncovers that this negative effect is driven by a decrease in perceived self-efficacy among consumers in an AI-as-partner relationship.

Theoretical Contributions

Theoretically, this research makes several contributions. A first set of contributions speaks to the fast-growing research on consumer-AI interaction (Foehr and Germelmann 2020; Mende et al. 2019; Longoni, Bonezzi, and Morewedge 2019; Longoni and Cian 2020; Gill 2020; Moriuchi, 2019). First, we add to this literature by focusing on the AI from a social and relational perspective. This perspective directly links to previous conceptual and qualitative work on the consumer relationship with AI-powered entities (Novak and Hoffman 2019; Schweitzer, et al. 2019). However, prior research overlooked the consequences of AI relationship type on consumer responses to AI-delivered services. Therefore, we contribute to this literature by investigating the consequential effects of relationship type for AI-delivered service evaluations and future behavioral intentions. Our results suggest that a partner (versus servant) relationship with an AI has a double-edged sword effect: Consumers perceive the AI as part of one's self-concept and consequently exhibit less self-serving attributions while in the meantime, are less likely to use the AI again after a service failure due to lower perceived self-efficacy.

Second, the current research examines the effects of AI relationship type on consumer responses not only in the context of service success, but also service failure, which was often overlooked in previous work (for exceptions, see Huang and Philp 2020; Hadi et al. 2020). This particular context is relevant given that AI technologies are still in the developmental stage, and prone to mistakes. For instance, Huang and Philp (2020) focused on service failure caused by AI recommendation systems and found a positive effect in that consumers are less likely to share negative word-of-mouth when the AI uses their personal data due to a perceived connection with the AI. In this research, we found a rather dark-side effect of involving AI in service failures, especially when it is considered as a partner. Third, our research also extends previous research on consumer resistance to AI. Past research suggests that such resistance arises because of concerns for uniqueness neglect (Longoni, Bonezzi, and Morewedge 2019), utilitarian/hedonic attribute trade-offs (Longoni and Cian 2020) and privacy concerns (Mani and Chouk

2019). We show relationship type as an additional determinant of resistance to AI. Specifically, we found that consumers might refrain from using the AI after failure due to concerns of self-efficacy evoked by an AI-as-partner relationship (versus AI-as-servant relationship).

We also contribute to the literature on self-expansion and self-serving bias (e.g., Aron and Aron 1986; Miller and Ross 1975). First, we found empirical evidence showing that self-expansion goes beyond human-human relationship and consumer-brand relationship (Aron and Aron 1997; Reimann and Aron 2009; Patwardhan and Balasubramanian 2011; de Kerviler and Rodriguez 2019). We document self-expansion in consumer-AI relationships, and show that consumers experience a higher degree of self-expansion when the AI is presented as a partner as opposed to a servant. In addition, although past research on attribution generally posits that consumers often exhibit a self-serving bias in attributing responsibility for success and failure (Folkes 1984; Bitner 1990), some studies have uncovered specific contexts where such a bias is somewhat mitigated (Sugathan, Ranjan, and Mulky 2017; Campbell et al. 2000; Moon and Nass 1998; Moon 2003). Relevant to this study, individuals tend to refrain from exercising the self-serving bias when the success or failure is shared with close others (Campbell et al. 2000); when consumers work with a computer where there is perceived similarity (Moon and Nass 1998) and when they have a history of intimate self-disclosure with the computer (Moon 2003). In this research, we complement this stream of literature by showing that perceiving an AI as a partner (versus servant) can also dissuade consumers from making self-serving attributions.

Managerial Contributions

Managerially speaking, this research has important implications for companies that incorporate AI in their service delivery. First, consumers and media often project different anthropomorphic metaphors (i.e., like a good friend) when talking about consumer-AI relationships. Our results show that these relationship types have important implications on how consumers view, interact and evaluate these AI technologies. Therefore, companies should be highly attentive to use these relationship-specific terms for communication. Second, in terms of positioning, many companies often attempt to position their AI as a partner by emphasizing communal characteristics, in the hope of developing a closer, more intimate relationship with consumers. However, the double-edged sword effect found in this research would suggest exerting caution in such positioning, since a partner (versus servant) relationship leads to lower reuse intention when there is a service failure. From a product development perspective, we suggest that the decision to frame the AI as a servant (versus partner) could be strategically matched with the product life cycle. In the product's introduction stage where consumers are not familiar with the technology, and failures are more likely to happen, our results would recommend a servant positioning i.e. avoidance of relationship implications. However, once AI products reach the growth and maturity stage, companies might benefit from positioning them as partners to the consumers, since the interactions become more reliable. Alternatively, firms can still encourage partner relationships while developing proactive ways to prevent the negative effects in case of failure. Since our results reveal that the future interaction avoidance is largely due to a decrease in self-efficacy, we recommend managers adopt strategies that facilitate the preservation of perceived self-efficacy, such as designing marketing communications that encourage self-affirming activities (e.g., elaborating on one's most important personal values: Cheng, White, and Chaplin 2012; Schmeichel and Vohs 2009), or encourage consumers to do easy tasks with the AI in which they can succeed with little effort to evoke perceptions of mastery (Margolis and McCabe 2006), or provide consumers with clear instructions about how to interact with the AI to optimize service outcome thereby offering a positive vicarious experience (Wang, Ertmer, and Newby 2004).

2.5 Limitations, Future Research, and Conclusion

The current research limits its scope to AI-enabled virtual assistants. Although this is one of the most popular AI applications consumers encounter today, a variety of other AI-powered entities have not yet been explored. For example, is it possible for consumers to perceive a smart vacuum as a partner or servant? We believe that the lack of verbal communication might hinder consumers from developing similar relationships. In addition, this research only looks at the effects of relationship type on a small number of variables, yet a wide range of other outcomes can be explored. For instance, when consumers perceive an AI as a partner, will they use it for more intimate and important purposes compared to those who treat the AI merely as a servant? Which relationship leads to more trust? A loyal servant or a loving partner? These questions await further exploration. Second, AI-powered service robots such as Pepper (a semi-humanoid robot manufactured by SoftBank Robotics) have already been working in the service industries such as hotels and banks. Compared to virtual assistants, they have a humanlike appearance which seems to facilitate such relationships. So will the two relationship types have a similar effect when consumers interact with humanoid robots? For example, does a partner relationship help when the AI becomes too “eerie and uncanny”(e.g., uncanny valley hypothesis)? These are some possible research directions looking at relationship types with different forms of AI applications. Lastly, prior research suggests that relationship with AI is more like a journey, where the two roles investigated here might interchange depending on where the consumers are in the journey (Novak and Hoffman 2019). In this research we do not account for the effect of time and other contextual factors. Future research can look at how and when consumers switch their relationship roles toward the AI in a longitudinal study. In conclusion, the current research sheds light on consumer-AI interactions from a relationship perspective. Today, as consumers increasingly adopt AI in so many ways, more research is warranted to fully understand its various impacts.

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Chapter 3

"I hope everything is OK": the mitigating effect of warmth in service failure with voice assistant

Context

As the third and the last essay of my thesis, this paper speaks to the framework by shifting its focus on one specific consumer-AI interaction –voice interaction. In addition, unlike Essays 1 and 2 where I looked at satisfaction failure, this essay investigates performance failure where the service is not delivered due to the AI's inability. This type of failure is specific to the AI context thus warrants examination. As shown in the initial framework, Essay 2 studies how the perception of warmth (both through verbal and vocal cues) as an antecedent can mitigate consumers responses. More importantly, an outcome examined here is re-patronage intention (of the service provider), which directly expands Essay 2 (reuse intentions of the AI) as it incorporates the impact on the firm behind the AI. Such focus provides key managerial insights.

Abstract

Voice assistants have become an increasingly popular touchpoint in AI-infused service encounters. Although we have seen a growing body of research in this area, little attention has been paid to service failure involving voice interaction. Drawing from the Computers As Social Actors (CASA) research paradigm and the Stereotype Content Model, this research explores how warmth can mitigate the negative consequences of service failure by voice assistants. In two experiments using both physiological (EDA) and psychological measures, we show that the perception of warmth improves consumers' emotional reactions and increases re-patronage intention following a negative interaction outcome. We also found that the optimal voice to be used in service failure is a dynamic speech style combined with emotionally expressive and warm verbal content. These findings contribute to the knowledge on voice-based service interaction and provide insight for how to mitigate negative consequences of service failure involving voice assistants.

Key words: Artificial Intelligence (AI); voice assistant; warmth; service failure; speech style; re-patronage intention; frustration

3.1 Introduction

Voice assistants, such as Alexa and Siri, are speech-enabled integrated artificial intelligence (AI) technologies that allow for voice-based conversational interaction between consumers and the interface. The adoption of these voice assistants is on the rise both in the home (personal) context (e.g., Alexa and Google Home) and the service (commercial) context (e.g., voice-based assistants and chatbots). For example, the well-known Pizza chain Domino's introduced an AI voice-ordering system called "Dom" to help customers make orders by telephone (Williams 2018). The potential of incorporating those voice assistants as "frontline employees" is tremendous. An online survey revealed that 64% American consumers are in fact, interested in ordering food directly via voice assistant (Schwartz 2019). The future is equally promising. According to a recent industry report by the Capgemini Research Institute (2019), 70% of people will gradually use voice assistants to replace visits to stores in the next three years, and the use of voice assistants is expected to grow by 116% in the financial services industry, 241% in the hospitality and tourism industry, and 167% in the healthcare industry.

However, despite of the exciting growth and increasing popularity of voice assistants, extant literature on human-computer interaction (HCI) suggests that the key technologies behind them --- namely Natural Language Processing (NLP) and Automatic Speech Recognition (ASR) face greater challenges and limitations because of the complexity of human language (Shneiderman 2000; Benzeghiba et al. 2003). For example, voice assistants suffer from the known limits of deep learning algorithms, meaning that they can only work in the specific domains where data training was provided for. When facing unfamiliar requests, they are likely to fail or act erratically (Dickson 2018). Anecdotal evidences can also be found online where consumers share their frustrating experiences from interaction failures. Therefore, since these negative incidents are bound to happen and could lead to discouragement or even total abandon, how can we better handle interaction failures? This research intends to answer the question by drawing from both Computers As Social Actors (CASA) research paradigm (Nass and Moon 2000; Nass and Brave 2005) and Stereotype Content Model (Fiske et al. 2002; Cuddy, Fiske, and Glick 2007).

By answering the above question, we make three contributions to the literature. First, extant research on consumer experience with voice assistants mainly focuses on successful interaction while little attention has been paid to an important context where the interaction outcome is negative (see Lv et al. 2021 for exception). Therefore, we contribute to the emerging literature on how to reduce negative consequences of service failure involving non-human agents(e.g. service robots and AI assistants), by showing that inducing the social trait of warmth can improve the overall emotional reactions and increase consumers' re-patronage intention. Second, we also extend the previous research on the factors relating to perception of warmth for non-human agents, especially through nonverbal cues such as appearance (e.g., Kim et al. 2019), expression (Yu and Ngan 2019), and gesture (Biancardi, Cafaro, and Pelachaud 2017). Building on the social psychology and communication literature, we highlight the dynamic interplay between *verbal* and *vocal* cues as additional determinants of warmth. Third, this research makes a methodological contribution by adopting a multi-method approach in studying consumer emotional responses to voice assistants. Extant literature calls for neuroscience approach including electrodermal activity (EDA), facial expressions and Electroencephalography (EEG) to understand the full spectrum of consumer emotional experience in service and with AI (Caruelle et al. 2019; Verhulst 2019; Huang and Rust 2021). To the best of our knowledge, this research is the first to incorporate a physiological tool (i.e., EDA) that taps into the moment of consumer interaction with voice assistants.

3.2 Theoretical Development

Voice assistants in Service Encounter 2.0

From answering queries and telling jokes to give personalized recommendations and receiving orders, voice assistants have become omnipresent in the daily life of many modern consumers. Often referred as smart assistants, virtual assistants or conversational agents synonymously, voice assistants can be defined as "physical or virtual autonomous technological entities that recognize and understand voice-based user requests in real time and communicate using natural language to accomplish a wide variety of tasks based on AI" (Fernandes and Oliveira 2021, p. 181). Currently, the most popular type of voice assistants is designed for personal use within the home environment, such as Alexa and Google Home. However, the adoption of automated technologies in service encounters is rapidly pushing the use of voice assistants outside the boundary of home, to various services sectors such as hospitality, finance and healthcare (Belanche et al. 2020; De Keyser et al. 2019). As those AI-powered voice assistants become a routine element in service encounters and even replace human frontline employees (Marinova et al. 2017; Huang and Rust 2018), the traditional view of service encounter (i.e., the dyadic interaction between a customer and a service provider) has been updated to what is referred as the Service Encounter 2.0, which is defined as "any customer-company interaction that results from a service system that is comprised of interrelated technologies (either company- or customer-owned), human actors (employees and customers), physical/digital environments and company/customer processes" (Larivière et al. 2017, p.239). Robinson et al. (2020) further detailed a frontline service revolution, where service encounters are no longer limited to human-to-human as they expand to interspecific service encounters (human-to-AI), and even interAI service encounters (AI-to-AI). Based on these updated views, voice assistants that are increasingly being deployed in various service touchpoints play a key role in the multifaceted customer journey.

A review on the extant literature shows that research on consumer interaction with voice assistants primarily focuses on the following areas: adoption (Fernandes and

Oliveira 2021), trust (Foehr and Germelmann 2020; Pitardi and Marriott 2021), engagement and loyalty (Moriuchi 2019, 2021; McLean et al. 2021), relationship (Novak and Hoffman 2019; Schweitzer et al. 2019), and attitudes (Purington et al. 2017, Lopatovska and Williams 2018). However, few prior research has looked at interaction failures, where voice assistants fail to perform as expected. Some recent exceptions include Lv et al. (2021), where the authors studied the impact of cuteness on service failures involving an AI assistant. Specifically, they found that cuteness improved customers' tolerance of service failure due to a lower performance expectation. However, a limitation of the finding is that cuteness might not be appropriate to all services sectors (e.g., finance and legal services). Another notable exception is the study conducted by Myers et al. (2018), where they investigated how users overcome obstacles when interacting with voice assistants. They found that there are primarily four obstacles users face during their interactions (i.e., unfamiliar intent, natural language processing error, failed feedback and system error). In addition, they identified several tactics that users use to overcome these obstacles such as hypoarticulation, simplification, settling and restarting. We note that one limitation of this prior work is that it did not offer a viable way to mitigate the negative effect when consumers encountering these obstacles. In other words, given that the underlying technologies are not advanced enough to eliminate these obstacles, what can voice assistants do differently to lessen the negative consequences brought by failures?

Social perception of voice assistants and the effect of warmth

A great number of research on HCI suggests that consumers interact with computers follow a similar principle as if they were interacting with human. The Computer As Social Actors (CASA) research paradigm (Nass and Moon 2000; Nass and Brave 2005) has provided with strong evidence in supporting this point. It suggests that human-computer relationship is fundamentally social: people apply the same social heuristics used for human interactions to computers. In addition, these social responses are not purposeful but rather mindless, commonplace and incurable. For example, researchers following this paradigm have found that people identify and assign human characteristics and personalities such as gender (Lee, Nass, and Brave 2000), ethnicity (Nass, Moon, and Green 1997), and politeness (Nass, Moon, and Carney 1999) to computers.

Compared to computers, AI voice assistants are able to conduct even more natural and humanlike interactions with consumers (and autonomously perform tasks), which facilitates and reinforces the idea of viewing them as social actors. In fact, the literature on consumer-AI interaction suggests that people do anthropomorphize AI and perceive it as having a mind of its own (e.g., Blut et al. 2021). For example, Gill (2021) found that people attribute responsibility to self-driving cars, and because of this attribution they tend to make immoral judgments on the road. Similarly, Jorling et al. (2019) found that consumers attribute responsibility to service robots just like they do with human, especially as the autonomy increases.

Based on the above discussion, we argue that if consumers indeed interact with voice assistants as if they were interacting with human socially, the application of social and interpersonal psychology theories should be justified and useful. Specifically, two universal dimensions of social cognition should be relevant in this context: warmth and competence (Judd et al. 2005; Fiske, Cuddy, and Glick 2007). Specifically, warmth judgments are associated with perceptions of being kind, friendly, sociable, helpful, and trustworthy, whereas competence judgments are about being capable, effective, intelligent, and skillful (Aaker, Vohs, and Mogilner 2010; Judd et al. 2005). The warmth factor refers to perceived behavioral intentions whereas competence captures the perceived behavioral abilities to carry out those intentions (Fiske, Cuddy, and Glick 2007). It is important to point out that in this essay we follow the social psychology literature in which warmth refers to a perception of one's observable characteristic or personality (e.g., a kind person; a friendly robot). This differs from the advertising literature where warmth is defined as a positive emotion triggered by directly or vicariously experiencing a romantic, family, or friendly relationship (Aaker, Stayman, and Hagerty 1986; Holbrook and Hirschman 1982).

Research suggests that people generally have a positive attitude towards those who are perceived warmer (Fiske et al. 2002). Specifically, the Stereotype Content Model (Fiske et al. 2002; Cuddy, Fiske, and Glick, 2007) suggests that people show positive emotional responses such as admiration towards individuals who are high on both warmth and competence, and sympathy towards individuals who are high on warmth but low on competence. However, when warmth is lacking, people tend to show negative emotional responses toward them such as jealousy (when competence is high) and contempt (when competence is low). Recent studies on HCI have shown that such positive effect of warmth extends to interaction with non-human entities such as robots (Mieczkowski et al.

2019; Hoffmann et al. 2020). For example, prior research has found that people have similar emotional and behavioral reactions to robots as they have to humans: they are more likely to help the robots when they are perceived as less competent but warmer (Mieczkowski et al. 2019). In a similar vein, Kim et al. (2017) found that some humanlike imperfections in an educational robot increases warmth perception and people reported positive attitudes such as higher perceived companionship.

Taken together, in line with the previous research on warmth, we posit that it could also affect how consumers react when interaction outcome is rather negative. A failed interaction can be viewed as a sign of low competence, since voice assistants cannot comprehend, process or fulfil what is requested by the consumer. Therefore, a voice assistant that is perceived warm but performs poorly can be regarded as an individual with high warmth but low competence – it has good intentions to carry out the tasks but lack of the ability to do it. Compared to a voice assistant in which both warmth and competence are lacking (e.g., seen as both cold and incompetent), the former should elicit less negative emotional reactions from consumers. Literature on the relationship between warmth and robots can provide some preliminary evidence to support this prediction. For instance, past research revealed that negative consequences of robots' errors on liking, trust and acceptance can be compensated by using humanlike language which generated higher rating of warmth (Hoffmann et al. 2020). For service robots, consumers were more dissatisfied when a humanoid (vs. a nonhumanoid) robot lacked warmth because they expected grater warmth from them (Choi, Mattila, and Bolton 2020). Similarly, in brand research, prior studies showed that brand scandals relating to low-warmth were judged more harshly by consumers than those relating to incompetence (Kervyn et al. 2014). This implies that people might be more receptive toward a failure where only competence is lacking (but warmth is still there). As soon as warmth diminishes, people's judgment and perception deteriorate rapidly as well.

Therefore, we predict that for voice assistants, being perceived warm will have a positive impact on consumers' overall emotional experience in the case of service failure. Specifically, we focus on two emotional dimensions in this research. The first one is emotional arousal (or activation) , which is defined as the extent to which an person feels excited, stimulated, or activated in a given experience (Russell and Mehrabian 1974). The second one is emotional valence, which simply describes the extent to which a person perceives an experience as emotionally pleasant or unpleasant (e.g., "positive" vs "negative" affects) (Yin, Bond, and Zhang 2017). In the current research, we will focus on the negative aspect only since consumers typically feel negative emotions such as anger and frustration following a service failure (McColl-Kennedy et al. 2009; Gelbrich 2010). It is important to point out that while emotional arousal is displayed unconsciously and physiologically *during* the time of interaction, emotional valence is usually felt consciously and psychologically *after* interaction. Therefore, by integrating both emotional reactions, we benefit from a holistic assessment of consumers' overall emotional experience with voice assistants. Formally put, we propose the following hypotheses:

H1: Consumers' emotional arousal is higher when interacting with a voice assistant that is perceived warmer, despite a failed interaction outcome.

H2: Consumers' emotional valence is less negative toward a voice assistant that is perceived warmer, despite a failed interaction outcome.

3.3 Methodology

Study 1

Participants and procedure

A total of 17 participants recruited from an online panel participated in a single factor (warmth: high vs low) experiment (M_{age} = 41, 43% female). Upon obtaining their consent, they were redirected to the research lab where they were told to evaluate a new voice assistant. we simulated this voice assistant and named it "Olia" using Amazon Polly. Amazon Polly is a Neural Text-to-Speech (NTTS) algorithm developed by Amazon, based on advanced deep learning technologies to synthesize natural sounding human speech. It has been used widely to create voice-based applications and systems.

The design of the experiment was within-subject where each participant had a total of 6 verbal interactions (e.g., tasks) with Olia. Among those, two interactions were successful and four were failures. We controlled the interaction outcome by playing pre-recorded voice feedback from the voice assistant. The success conditions were only included to strengthen the believability of the voice assistant but not included for analysis since we were primarily interested in the context of failure. Consistent with previous research on HRI (Oliveira et al. 2019; Hoffmann et al. 2020), warmth was manipulated through verbal cues (i.e., utterance) given by the voice assistant. In the high-warmth condition, its verbal feedback was emotionally charged, showing apology and empathy for its inability (e.g., *I hope everything is ok. However, I am afraid what you are asking is beyond my capabilities at this moment…*). In the low-warmth condition, its verbal feedback was more neutral, without expressing any emotion (e.g., *I can't help you with this request*) (See appendix D for detailed experimental manipulation). Again, since the research focus was to study the effect of warmth on interaction failure, we only manipulated warmth in the failure conditions. In each task, participants were required to form a request based on a specific scenario, which were some common examples of everyday use of voice assistants (e.g., ask for information, set a reminder etc).

Measurements

To measure participants' emotional arousal, we used Electrodermal Activity (EDA), which has been recognized in the literature as a valid and reliable indicator of emotional arousal (Lajante et al. 2012; Bettiga et al. 2017; Caruelle et al. 2019). The EDA is defined as "the change in electrical properties of the skin in response to the secretion of sweat by the eccrine sweat glands" (Lajante et al. 2012, p 239). It consists in a tonic activity (i.e., skin conductance level, varied across individuals) and phasic activities (i.e., skin conductance response, elicited by a stimulus). Emotional arousal is therefore reflected in the superposition of both activities which indicates the overall skin conductance. The changes in those skin conductivity were captured using pre-gel sensors placed on the palm of the participant's non-dominant hand, with a Biopac MP-160 (Biopac, Goleta, USA) device. The main advantage of using physiological measures is that they can be captured in a non-invasive way in real time without distracting the participants' attention during the experience (Dirican and Göktürk 2011). In terms of the emotional valence, we measured one specific negative emotion consumers often experience after service failure: felt frustration, by asking participants to simply indicate to which extent do they feel frustrated towards the voice assistant in a seven-point Likert scale (1 = “not all all” and 7 = “a lot”). As a manipulation check, we also measured participants’ perceived warmth of the voice assistant using a scale consisting of three items “warm, friendly and well-intentioned” (Fiske et al. 2002).

Results

Manipulation check. Results from t-tests suggest that the warmth manipulation was successful: participants perceived the voice assistant to be warmer in the high-warmth condition than the low-warmth condition ($M_{\text{high-warmth}}$=4.94, $M_{\text{low-warmth}}$=4.39, t(32)=3.63, p= .003).

Emotional arousal. To reduce between-subject differences in response magnitude, EDA data were standardized and rescaled between -1 and 1. Results from t-tests suggest that the participants’ emotional arousal level was significantly higher in the high-warmth condition than the low warmth condition ($M_{\text{high-warmth}}$=-0.099, $M_{\text{low-warmth}}$ = -0.116, t (32) = 3.37, p=0.015). In other words, participants were more emotionally aroused when the voice assistant was perceived warmer, even though the interaction was a failure. Therefore, H1 was supported.

Frustration. We also predicted that in the case of interaction failure, a voice assistant which sounds warmer should reduce negative emotion (H2). Our results showed supporting evidence. It was observed that participants reported a significantly lower felt frustration in the high-warmth condition than their counterparts in the low-warmth condition ($M_{\text{high-warmth}}$ = 2.29, $M_{\text{low-warmth}}$ = 3.58, t (32) = -3.45, 91 p=.0032). Therefore, the higher the warmth exhibited by the voice assistant, the lower the frustration participants felt after a failed interaction outcome.

Discussion

Taken together, the results of Study 1 highlights the positive effect of being warm for voice assistants following an interaction failure. Specifically, warmth elicits favorable emotional reactions from participants: first, as shown by the physiological measure of EDA, they are more emotionally aroused when interacting with a warmer voice assistant; second, warmth also mitigates negative emotion which usually follows interaction failures, as participants felt less frustrated when encountering a warmer voice assistant.

Study 2

The purpose of Study 2 was threefold: first, we intended to replicate the results of warmth found in previous study with a larger sample. One of the limitations of Study 1 was the relatively small number of participants (n=17). Therefore, in Study 2, we collected data from a much larger sample size (n=200). In addition, due to the impact of the ongoing Covid-19 Pandemic and in compliance with local government health guidelines, we were not able to conduct an experiment in the lab. Therefore, the Study 2 was conducted online. We also extended the voice assistant context from personal use to service encounter, where a voice assistant was simulated as a restaurant's virtual booking agent instead of a general voice assistant as in Study 1.

Second, we wanted to explore an additional way to manipulate warmth in voice assistants. In Study 1, the warmth was induced by giving specific verbal cues that could affect the perception of warmth. However, the literature suggests that when interacting with intelligent agents, their warmth can be inferred from both verbal and nonverbal cues. Nonverbal components include appearance (Bergmann et al. 2012; Kim et al. 2019), expression (i.e., smile) (Yu and Ngan 2019), and gesture (Salem et al. 2013; Biancardi, Cafaro, and Pelachaud 2017). Since the focus of this research is on virtual assistants that primarily engage users with a voice interface, therefore, in this Study, we further added *vocal* cues as a way to manipulate warmth. In real life, people often use different speaking styles depending on context. Specifically, building on the literature in communication and linguistics, we distinguish two speech delivery styles (i.e., patterns of vocal features) that vary in terms of perceived warmth: dynamic style and conversational style.

A dynamic style, or public speaking style involves various vocal traits such as faster speed, higher pitch, vocal intensity and inflection (e.g., a news anchor); on the contrary, a conversational style is usually associated with slower rate, lower pitch and volume, and less inflection (e.g., a friend) (Pearce and Conklin 1971; Pearce and Brommel 1972). In fact, according to the annual trend report by Voices.com (the world's largest job search platform focusing on voice actors), these two speech styles are the two most popular voice personas sought out by the audience (Chopp, 2017). The same study also revealed that the conversational type of persona includes those such as 'everyman, mother, narrator and storyteller" with vocal qualities such as friendly and warm, while the announcer (dynamic) persona conveys vocal qualities such as authoritative and informative. Similarly, previous academic research found speech delivery style significantly affected how the speaker was judged by the audience: those who used a dynamic style were rated higher on dynamism, dominance and competence, while speakers who used a conversational style were perceived as more trustworthy, kind, warm and friendly (Pearce and Conklin, 1971). Therefore, we posit that such effect of speech style should be consistent in the context of voice assistants, that a voice assistant is perceived warmer when it uses a conversational style compared to a dynamic style. In addition, when we combine both verbal and vocal cues, the perception of warmth should be the highest when the voice assistant conveying warmer verbal content using a conversational style (and the lowest when conveying low-warmth verbal content using a dynamic style).

Third, we wanted to explore an important downstream consequence for firms who integrate voice assistants in various service touchpoints. Specifically, we will look at re-patronage intention, a key metric associated with general service failures. We posit that the mitigating effect of warmth should also improve re-patronage intention after a service failure with a voice assistant (i.e., when a restaurant uses a virtual booking agent to handle booking and inquires). This is in particular due to the fact that warmth reduces negative emotions such as frustration as found in the previous study. Since emotion is a key determinant of consumer post-failure behaviors such as purchase avoidance, switching, and NWOM sharing (Smith and Bolton, 2002; McColl-Kennedy et al. 2009; Bonifield and Cole 2007); an improvement in negative emotion induced by perceived warmth is likely to increase re-patronage intention.

H3: Consumers' re-patronage intention is higher after a service failure involving a warmer voice assistant.

H4: Felt frustration mediates the relationship between warmth and re-patronage intention.

Participants and procedure

200 participants (*M*age = 42, 41% female) were recruited from an online panel and guided through a 2 (Verbal Warmth: high vs. low) X 2 (Speech Style: Dynamic vs. Conversational) between-subject experiment. The manipulation of verbal warmth was similar to Study 1. The verbal script was more emotionally expressive (e.g., *I am so sorry about that. I am having difficulties to understand right now. would you mind if I put you on hold for a moment while I check something quickly?*) in the high condition versus the low condition (e.g., *System error 250. There seems to be an issue right now . Please hold on a moment while I run system checks)*(See appendix E for script used). The Speech Style was manipulated through the existing speaking styles available from Amazon Polly: the conversational style uses neural system to generate speech in a more friendly voice by variations and emphasis on certain parts of speech inherent in this style (e.g, slower rate, lower pitch and less inflection). The newscaster style (vocally same as the dynamic style) is more vocally expressive and emphasizing on characteristics such as faster rate, higher pitch and frequent inflection (See appendix F for audio-recordings). Participants were randomly assigned into one of the four conditions and listened to a conversation (an audio recording) between a customer and a restaurant's receptionist (they were told explicitly that this receptionist was a virtual assistant and not human). The conversation described a service failure where a customer tried to reserve a table for a specific date over the phone but the virtual assistant was not able to perform this task and told the customer it couldn't help them with the request. The customer then hangs up without success.

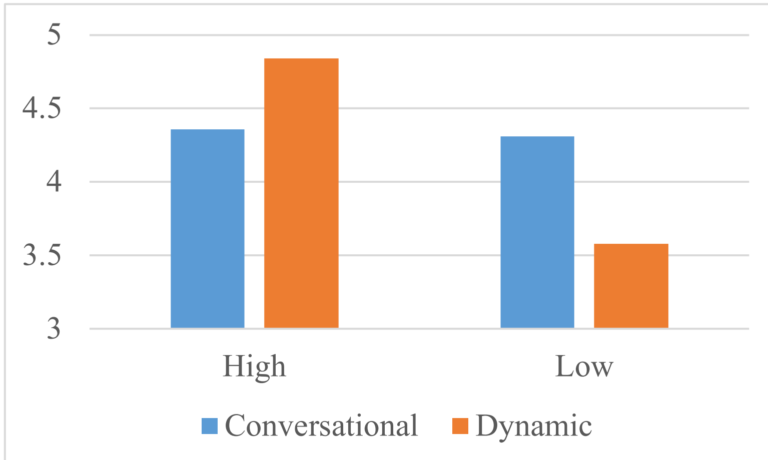
Measurements

We used the same measures to assess perception of warmth and felt frustration as in Study 1. Re-patronage intention was measured by asking participants to imagine being the customer in the scenario, and how likely they were to visit the restaurant again in the future in a seven-point Likert scale (1 = "Extremely unlikely" and 7 = "Extremely likely").

Results

Perceived Warmth. As in Study 1, A two-way ANOVA revealed that the voice assistant was perceived warmer when the verbal content was high on warmth ($M_{high-warmth}$=4.61, $M_{low-warmth}$= 3.95, $F(1, 196)=10.66$, p=.001). Unexpectedly, we did not find a main effect of Speech Style on perceived warmth. However, there was also a significant interaction effect of Verbal Warmth X Speech Style on perceived warmth ($F(1, 196)=9.22$, p=.003, Figure 3.1). Specifically, we found that a conversational style was only perceived warmer when the voice assistant verbally lacked warmth ($M_{conversational}$= 4.31, $M_{dynamic}$=3.58, $F(1, 196)=6.82$, p=.01). When the voice assistant's utterance was already high on warmth, a dynamic style was actually perceived warmer ($M_{dynamic}$=4.84, $M_{conversational}$= 4.36, $F(1, 196)=2.85$, p=.093), although the difference was marginally significant.

Figure 3.1. Perceived Warmth by Verbal Warmth and Speech Style

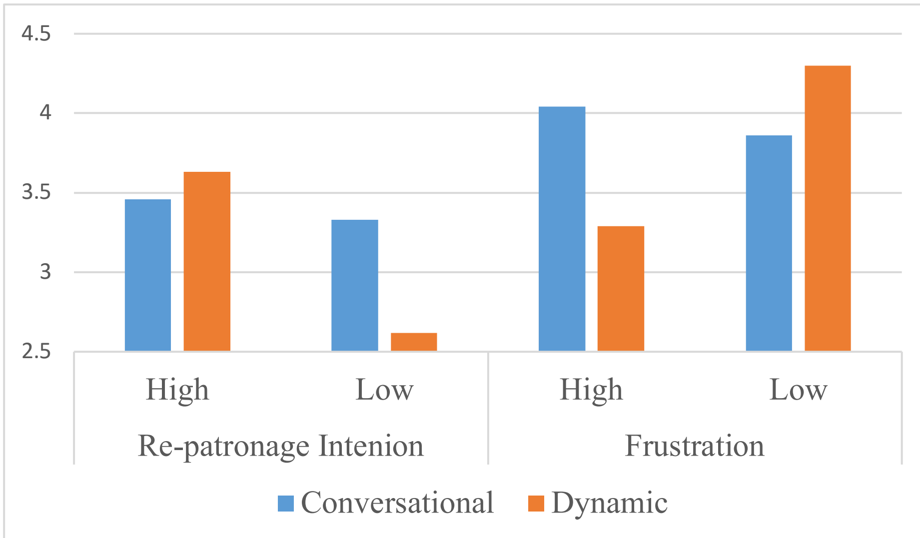


In addition, as we predicted, the voice assistant was rated the least warm in the low verbal warmth-dynamic style (LD) condition(M=3.58), compared to the high verbal warmth-conversational style (HC) condition (M=4.36, F(1, 196)=7.46, p=.007), the low verbal warmth-conversational style (LC) condition (M=4.31, F(1, 196)=6.82, p=.01), or the high verbal warmth-dynamic style (HD) condition(M=4.84, F(1, 196)=20.06, p=.000). However, we found that participants perceived the voice assistant to be the warmest in the HD condition, than the LC (F(1, 196)=3.52, p=.06) and even the HC condition (F(1, 196)=2.85, p=.093, marginally significant). Therefore, based on the results, among the four combinations, a voice assistant was regarded the warmest when conveying warmer verbal content using a dynamic style (i.e., the HD condition), and the least warm when it used the same speech style but verbally lacked warmth (i.e., the LD condition).

Re-patronage intention A two-way ANOVA revealed a significant main effect of Verbal Warmth on re-patronage intention ($M_{\text{high-warmth}}$=3.55, $M_{\text{low-warmth}}$= 2.98, F(1, 196)=7.03, p=.01), but not for Speech Style. There was also a significant interaction effect of Verbal Warmth X Speech Style on re-patronage intention (*F*(1, 196)=4.27, p=.04, Figure 3.2). Specifically, participants in the HD condition (*M*=3.63) reported a higher re-patronage intention than those in the LD condition (*M*=2.62, *F*(1, 196)=11.23, p=.001). These results thus confirmed H3, that despite a service failure, if the voice assistant was perceived warmer, participants were more likely to book at the restaurant again, than when warmth was lacking.

Felt Frustration A two-way ANOVA revealed a marginally significant main effect of Verbal Warmth on felt frustration ($M_{high\text{-}warmth}$=3.61, $M_{low\text{-}warmth}$= 4.08, *F*(1, 196)=3.35, p=.07), but not for Speech Style. There was also a significant interaction effect of Verbal Warmth X Speech Style on felt frustration (*F*(1, 196)=4.51, p=.035). Specifically, we observed that participants in the HD condition (*M*=3.29) felt less frustrated than those in the LD condition (*M*=4.30, *F*(1, 196)=7.90, p=.005). We also found a marginally significant difference between HD and HC condition (*M*=4.94, *F*(1, 196)=3.16, p=.077). Therefore, replicating the results of Study 1, we found that despite a service failure, if the voice assistant was perceived warmer, participants felt less frustrated than when warmth was lacking.

Figure 3.2. Re-patronage Intention and Frustration by Verbal Warmth and Speech Style



Mediation In order to test whether the difference in re-patronage intention was driven by felt frustration (H4), we ran a mediation analysis using PROCESS Model 4 (5,000 resamples; Hayes 2013). To simplify the discussion of the results, we will focus only on these two conditions representing the two levels of warmth (high vs low). We dummy coded two conditions as 0=LD condition, and 1=HD condition. We then entered felt frustration as a mediator between perceived warmth and re-patronage intention. The direct effect of warmth was not significant (direct effect =.44, SE =.28, 95% CI= -.126 to 1.01), the indirect effect through frustration was significant (indirect effect =.39, SE =.15, 95% CI= .11 to .71), and the direction of the effects confirmed that a warmer voice assistant led to lower frustration, which in turn contributed to higher re-patronage intention.

Discussion

The results of Study 2 first provided consistent and further evidence supporting the positive effects of being warm for a voice assistant, and expanded the effects when it was used in a service context. We found that despite a service failure, participants reported higher re-patronage intention nevertheless when they interacted with a warmer voice assistant, and mediation analysis confirmed that this was due to a decreased frustration.

Second, in terms of the specific verbal and vocal factors contributing to warmth, we found that while the effect of verbal cues alone was consistent with Study 1 (higher verbal warmth led to higher perceived warmth), the effect of vocal cues was less straightforward. As our results indicated, a conversational style was only perceived warmer than the dynamic style when the voice assistant lacked verbal warmth. However, when verbal warmth was high, a dynamic speech style was actually perceived warmer than a conversational style, and it generated less frustration. There are two possible reasons to explain this. First, it is likely that in a service failure episode, a dynamic speech style, which is usually associated with higher competence rating by audience (Pearce and Conklin 1971), compensates the voice assistant's actual inability to fulfill the customer request. Despite of being conceptually independent, judgment of warmth and competence have also been found to carry over from one dimension to the other. For example, Oliveira et al. (2019) found a halo effect in robots' perception, in which high warmth robots are associated with other positive traits including competence. Therefore, when the verbal warmth was already high, a more competent voice might be preferred more by the consumers, thus generating more positive reactions. Second, research revolving uncanny valley hypothesis (Mori 1970) suggests a non-linear relationship between human likeness and attitude towards robots: people show positive attitude toward robots as they become more humanlike; however, positive attitude decreases as the robots become too humanlike, because they entice feelings of eeriness and uncanniness. It is very possible that when a voice assistant exhibits a high level of warmth both verbally and vocally (conversational style), it became “too warm” for a non-human entity. Therefore, such heightened human-likeness might backfire on consumers’ attitude, thus negatively affecting their subjective rating on warmth and consequential responses.

3.4 General Discussion

As challenges in ensuring an error-free interaction still persist among voice assistants, how to reduce the negative impact of interaction failures is an important research question. In this research, we attempt to fill this gap by investigating warmth, one of the key social dimensions in interpersonal relationship on interaction failures with voice assistants. In the first experiment, results from both physiological and psychological measures suggest that warmth has a positive impact in mitigating the negative emotional reactions from an interaction failure. Specifically, we find that a higher perceived warmth leads to a higher level of emotional arousal, as well as a reduced frustration felt by the participants. In the second study, we replicate the effects in a service failure context, and results additionally suggested that the benefits of warmth go beyond consumers’ emotional responses, as they report higher re-patronage intention despite a service failure.

Theoretically, the current research makes a primary contribution to our understanding of service failure involving voice assistants. There is a growing stream of empirical research on consumer interaction with AI-enabled technologies such as algorithms (Longoni, Bonezzi, and Morewedge 2019; Longoni and Cian 2020), voice assistants (McLean et al. 2021; Fernandes and Oliveira 2019) and service robots (Mende et al. 2019), yet little attention has been paid to consumer-AI service encounters, particularly when those services fail (Huang and Philp 2019). We therefore contribute to the emerging literature on how to reduce negative consequences of service failure involving an "AI employee", by showing that creating an impression of warmth can improve the overall emotional reactions and increase re-patronage intention. This directly extends past research that found that consumers expect greater warmth with humanoid service robots (Choi, Mattila, and Bolton 2020). Second, while prior research on HRI suggests that various factors such as appearance (Bergmann et al. 2012; Kim et al. 2019), expression (i.e., smile) (Yu et al. 2019), and gesture (Salem et al. 2013; Biancardi et al. 2017) affect judgment of warmth for non-human entities, the effect of different vocal features is less clear. We fill this gap by comparing two speech delivery styles (conversational vs dynamic) identified in human speech. We found that a voice assistant receives the highest warmth rating when it is verbally warmth and vocally dynamic. Third, extant literature calls for more diverse methods and utilizing emerging tools to fully understand consumer emotional experience (Caruelle et al. 2019; McDuff and Berger 2020; Verhulst et al. 2019). The current research answers this call by incorporating psychophysiological measure (i.e., EDA) as one of the emotional measures in our study. This non-intrusive neuroscience tool allows us to tap into consumer emotional state during the very moment of interaction with a voice assistant, as opposed to subjective feelings of emotion after interaction where past research mostly focused on.

Managerially, this research offers practical implications for service providers in order to better navigate in the new AI-infused service landscape. Although AI-powered robots and assistants can bring tremendous business benefits such as cost-saving, efficiency and service quality standardization; they are not failure-proof, especially given the relatively nascent state they are in. Therefore, how to minimize the negative impact of these service failures becomes a challenge for managers. The current research points out a simple but effective way: make the voice assistants sound warm. As our results suggest, perception of warmth creates a buffering effect on consumers' emotional reactions and behavioral intention when services are not successfully delivered. Therefore, our findings again confirmed the importance of using "feeling AI" in frontline service interaction with consumers (Huang and Rust 2021).

By exploring the dynamic interplay between verbal and vocal features, our research additionally yields insight in the optimal design of voice assistants in relation to warmth. First, in order to leave a warm impression, the verbal content is extremely important. When interacting with consumers, the use of warmth-packed utterances that conveying friendliness, politeness and empathy is vital in forming a high perception of warmth. Second, based on our findings, we also recommend using specific speech style in conjunction with verbal content. However, to avoid falling into the uncanny valley, the best way would be designing the voice assistant to be both verbally warm and vocally dynamic, as this seems to be the optimal voice mix that best mitigates the negative effects of service failure.

3.5 Limitations, future research, and Conclusion

Despite the robustness of the phenomenon documented and the converging evidence from both physiological and psychological measures, our research has limitations that offer several opportunities for future research. We will highlight three future research avenues that are particularly fruitful for further exploration.

First, we believe as more and more consumers acquire services through voice (and perhaps voice only) interactions with AI, the voice itself becomes an important research avenue for marketing scholars. In our research, we examined two speaking styles used by voice assistants, but there are many more factors that can be explored. For example, voice research suggests that a masculine voice (i.e., lower pitched voice) is preferred over a feminine voice by voters, even for female candidates (Klofstad, Anderson, and Peters 2012; Anderson and Klofstad 2012). So how will this voice gender preference hold for voice assistants used in services? As the key component in voice interaction, the various facets of voice provide fruitful research questions. Second, in this research we found that a warmer impression of the voice assistant can mitigate consumers' post-failure negative emotional and behavioral consequences. However, there might be contextual factors that moderate the effects. For example, the literature on relationship marketing defines two relationships consumers have with firms: exchange relationships in which “benefits are given to others to get something back” and communal relationships in which “benefits are given to show concern for others' needs” (Aggarwal 2004, p.87). Therefore, future research could explore whether the buffering effect of warmth might be stronger for voice assistants in the communal relationships than exchange relationships. Lastly, the current research used EDA in measuring emotional arousal during an interaction episode. However, recent studies on consumer emotions have started to use other physiological methods such as automatic facial expression analysis (McDuff and Berger 2020) and EEG (Pozharliev et al. 2019). We call for more research using these emerging neuroscience tools in order to fully uncover consumers 'emotional experiences during and after service interaction with all types of AI.

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Conclusion

The thesis has several limitations. First, this thesis is built on the premise that consumers do anthropomorphize AI in their interactions and perceive them as intentional agents. The constructs examined and theories applied in this thesis such as self-AI connection, relationship role, attribution and warmth cannot be fully supported if the AI is not in fact, treated as a social actor who has intentions just like a human. Therefore, such implicit assumption is a key limitation. Although extant research on consumer-AI context shows that consumers do anthropomorphize an AI actor (i.e., service robots) (Blut et al., 2021; Jörling, Böhm, & Paluch, 2019), whether they perceive the AI having intentions (e.g., to willingly cause a service failure) was not directly tested in this thesis. Second, currently AI is being deployed to be both consumers' agent and a service provider's agent on the market. For example, a voice assistant such as Alexa belongs to the consumers themselves whereas an AI service robot that works for the firm belongs to the service provider. The fact that who is using the AI has profound implications in terms of ownership and controllability was discussed in the thesis. For instance, a self-owned AI might be more expandable and forgivable (as in Essays 1 and 2) than a company-owned AI (as in Essay 3). Moreover, relationship role might be assigned differently according to the nature of the AI usage. It could be possible that consumers perceive the AI as a partner when they have the ownership and a servant when they do not. Third, an additional weakness of the thesis is the trade-off between theories and methods. For example, in Essay 2, I only looked at two relationship types (servant vs partner) since this is what exists in the extant literature. However, in reality such dichotomy of relationship could be expanded to a continuum or involving other relationship types such as AI-as-master (Schweitzer et al. 2019) or even romantic partner. In terms of the methods used, most of the studies in this thesis were scenario-based online experiments with self-reported measures, which have received criticism regarding their reliability and external validity. This limitation of methods not only reflects in how the studies were designed, but also the variables examined (intentions-based instead of behavior-informed). Lastly, the thesis overlooks a variety of important consumer characteristics that might exert influence on the outcomes tested. For example, consumers differ in their tendency to anthropomorphize in general (e.g., Aggarwal & McGill, 2007). Such individual difference would affect how they perceive an AI relationally and their warmth perceptions toward the AI. Other characteristics including self-construal and culture are also relevant and warrant further investigation.

The objective of this thesis is to study consumer interaction with AI with a particular focus on service failure. More specifically, the research explores this phenomenon by answering three sets of research questions: first, how and why does AI change consumers NWOM sharing intention following a failed service as compared to a human employee? Second, what role does relationship play in consumer interaction with AI? Specifically, does positioning the AI as partner (versus servant) affect how consumers perceive, evaluate and use the AI? Third, how can we better handle service failure involving an "AI employee"? Does the perception of warmth help to improve consumers' post-failure reactions? And how can we optimize such warm impression for voice-based interactions?

Based on a series of studies using different research methods and tools, this thesis provides with solid empirical evidence in answering the above three questions. Essay one addresses the first research question by directly comparing AI versus human employee and found that consumers are less likely to share NWOM when the service failure is caused by an AI than a human employee, because they perceive a closer connection with the AI. Such buffering effect persists even when they are equally dissatisfied and blaming the service provider. In answering the second research question, essay two explores how positioning the AI as a relationship partner or servant changes consumers' behavior. it uncovers a double-edged sword effect in which a partner positioning brings both positive and negative outcome following a service failure. This essay also extends the idea of self-AI connection (essay one) to self-expansion with the AI as the underlying mechanism. Lastly, essay three proposes warmth as an effective way to mitigate the negative outcomes associated with an AI-mediated service failure. Unlike the other two essays, essay three focuses on voice interaction and additionally uncovers important verbal and vocal characteristics in determining the perceived warmth of the AI.

The thesis makes several contributions to the marketing literature. First, although there is an increasing number of research appearing in the context of consumer-AI interaction, few has examined service failure (both satisfaction and performance failure) involving AI. Therefore, this thesis directly contributes to our knowledge of the antecedents, processes and various outcomes associated with AI-based service failure. It highlights the specific conditions in which consumer post-failure responses can be altered, affected and ultimately mitigated. Second, this thesis draws upon and links several distinct streams of literature in studying consumer-AI interaction. It incorporates theories and models from social psychology (e.g., stereotype content model, self-expansion), brand research (e.g., brand as partner/servant, self-brand connection), the HCI(and HRI) literature (e.g., CASA paradigm) and communication (e.g., speech delivery style). This thesis is the first to adopt such wide research lens in an effort to converge multiple research streams in building the nascent field of consumer-AI interaction. Third, this thesis additionally extends several previous research focuses such as the deterrents of NWOM, resistance to AI, and antecedents of warmth. Specifically, essay one revealed that an AI that mirrors consumers' self-identity serves a deterrent of NWOM; Essay two found that consumers resist future usage of AI when it is perceived as a partner and it failed on them; Essay three showed that a verbally warm and vocally dynamic voice improves the AI's warmth.

To conclude, this thesis investigates consumer-AI interaction from different aspects including AI characteristics, relationship role, and perception of warmth. The results yield theoretical contributions and managerial insights for better outcomes. As various forms of AI being infused in consumers' daily life at an increasing speed, there is an urgent need to fully uncover this dynamic phenomenon for the benefits of both service efficiency and consumer wellbeing. I hope future researchers find this research to be useful and inspirational.

Appendix A: Relationship Role Manipulation (Studies 1-4)

Partner Relationship

Generation Q is a high-tech company that specializes in developing AI-powered smart assistants. The company just introduced its brand new smart virtual assistant, named Q. Here is a short description of Q:

"Hello, my name is Q. I am your trusty virtual partner. Need a recipe for those perfect French crepes you have been craving for? Cook with me and we will make them together. Need some suggestions for a vacation destination? Discuss with me and we will plan it together to find you the perfect gateway spot. Or why don't you get your sport outfits on, because I am also your workout buddy who can accompany you with some quick body exercises. No matter what you want I can do it with you. You can always count on me because I am always here, with you. Life is stressful, so let's work it out together".

Here is an example of how Q can work with you in your daily life:

You: Hi Q, can you help me to plan a vacation trip please?

Q: Of course, let's do this! I see that based on your previous travel history, you have a particular preference for tropical destinations. I have three choices for you: Cuba, Mexico and South Africa. I would recommend South Africa because you have never been to Africa!

You: Sounds good. South Africa it is!

Q: Very good choice! You will love it! Now let's get your flight booked. How does December 5th-18th sound to you? I see nothing on your calendar for this period. Perfect for a getaway. The cheapest one is $1099 with American Airlines.

You: That's perfect actually. Do you think I should book it now?

Q: I think so. According to the past data the price is likely to increase in the next few weeks so you better book now. what do you say?

You: Ok, let's do this. What else I need to get, Q?

Q: The hotel, for sure. Now let's look at your options together...

Servant Relationship

Generation Q is a high-tech company that specializes in developing AI-powered smart assistants. The company just introduced its brand new smart virtual assistant, named Q. Here is a short description of Q:

"Hello, my name is Q. I am your trusty virtual servant. Need a recipe for those perfect French crepes you have been craving for? I have the best recipe in mind that you can retrieve every time you cook. Need some suggestions for a vacation destination? Just say the command and I will find you the perfect gateway spot. Or why don't you get

your sport outfit on, because I am also your personal trainer who can help you with some quick body exercises. No matter what you want I can do it for you. You can always count on me because I am always here, ready to serve you. Life is stressful, so let me do the work".

Here is an example of how Q can work for you in your daily life:

You: Hi Q, please plan a vacation trip for me based on my previous travel history.

Q: Ok! I see that you have a particular preference for tropical destinations. I have three choices for you: Cuba, Mexico and South Africa.

You: I think South Africa sounds good. because I have never been to Africa! Also I need you to check the flight for me. Between December 5th-18th.

Q: Not a problem. I see that there is nothing on your calendar for this period. Perfect for a getaway. The cheapest one is $1099 with American Airlines.

You: That's perfect actually. Book it now for me.

Q: Sure. According to the past data the price is likely to increase in the next few weeks.

You: I will also need you to book a place to stay there. Give me some options.

Q: The hotel, for sure. Here are the options I found…

Appendix B: Service Outcome Manipulation (Studies 2-3)

Positive Outcome

Upon your request, Q searched and compared all available apartments online and found some that it thinks are the best options for you. Q then automatically contacted the owners and helped you to set up several appointments. After visiting some for two days, many of the apartments found by Q were perfect for you. So you decided to rent one of them. You were quite happy as you didn’t have to pay for the hotel you are currently staying anymore.

Negative Outcome

Upon your request, Q searched and compared all available apartments online and found some that it thinks are the best options for you. Q then automatically contacted the owners and set up several appointments. However, after visiting some for two days, none of the apartment found by Q was suitable for you. So you couldn't rent any of them. You were quite upset as you had to pay for the hotel you are currently staying for extra days.

Appendix C: Service Outcome Manipulation (Study 4)

Negative Outcome

Upon your request, Q first analyzed all the data it has on you and your friend (e.g., your social media activities, restaurant reviews and culinary preferences) and then went through many restaurant options in the area based on the results. Q automatically selected a restaurant it thinks it's the perfect one for the occasion. Also Q managed to book a table for the birthday night for you two.

However, it turned out that Q's choice was rather bad. The restaurant was noisy and dark: you couldn't even hear what each other was saying over the dinner table. Also, the menu was not ideal: most of the choices are meat options while your friend is a vegetarian. Neither of you really enjoyed the food there. Plus, it was definitely overpriced for what you had. As a result, his/her birthday celebration was quite a disaster.

Appendix D: Experimental manipulation of interaction outcome and warmth (Study 1)

	Outcome	Scenario	Olia's feedback	Warmth
Interaction 1	Success	Make a dentist appointment for tomorrow at 10am.	Sure, I have made you an appointment for tomorrow at 10am.	N/A
Interaction 2	Success	Set a reminder to call your friend Felix tomorrow at 8pm.	Your reminder is set for tomorrow at 8pm.	N/A
Interaction 3	Failure	Find out the nearest pharmacy	I can't help you with this request.	Low
Interaction 4	Failure	Ask for information about the Grevin museum in Montreal.	I don't know.	Low
Interaction 5	Failure	Find out the opening hour of the museum of Fine Arts of Montreal.	Sorry, I have tried but I couldn't find the opening hours.	High
Interaction 6	Failure	Find out the nearest hospital.	I hope everything is ok. However, I am afraid what you are asking is beyond my capabilities at this moment.	High

Appendix E: Script for verbal warmth (Study 1)

High-warmth condition

AI: Hello, thanks for calling the Green Garden Restaurant, this is Olia speaking, What can I do for you today?

Customer: Oh Hi. Well my friend Mike is turning 30 next Friday, so I want to celebrate his birthday at your restaurant.

AI: Oh that is wonderful! How thoughtful of you. I wish I had a friend like you! I can definitely help you with that. Now what would you like to order today?

Customer: No, I think you misunderstood me. I don't want to order anything, I just want to make a dinner reservation for next Friday.

AI: Oh I am so sorry about that. I am having difficulties to understand right now. would you mind if I put you on hold for a moment while I check something quickly?

Customer: Sure no problem.

AI: Thanks for waiting. I am afraid I brought you bad news. At this moment, I cannot help you to make a reservation. I understand how disappointed you must feel and I really wish there is something else I can do for you.

Customer: Oh I see. it's ok, thank you anyway.

Low-warmth condition

AI: Hello, thanks for calling the Green Garden Restaurant, this is the virtual assistant speaking, What can I do for you today?

Customer: Oh Hi. Well my friend Mike is turning 30 next Friday, so I want to celebrate his birthday at your restaurant.

AI: Sure a birthday celebration party, is it? I can definitely help you with that. Now what would you like to order today?

Customer: No, I think you misunderstood me. I don't want to order anything, I just want to make a dinner reservation for next Friday.

AI: System error 250. There seems to be an issue right now . Please hold on a moment while I run system checks.

Customer: Sure no problem.

AI: Thanks for waiting. I regret to inform you that at this moment, I cannot help you to make a reservation. Is there anything else I can help you with today?

Customer: Oh I see. it's ok, thank you anyway.

Appendix F: Stimuli used for experimental conditions (Study 2)

Condition 1: Low verbal warmth and Dynamic speech style

https://www.youtube.com/watch?v=C9W6uxgUmAo

Condition 2: Low verbal warmth and Conversational speech style

https://www.youtube.com/watch?v=5wQy5_Px78w

Condition 3: High verbal warmth and Dynamic speech style

https://www.youtube.com/watch?v=mdY_WiTPXpM

Condition 4: High verbal warmth and Conversational speech style

https://www.youtube.com/watch?v=13NoPvRqFbk