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When AI-based services fail: examining the effect of the self-AI connection on willingness to share negative word-of-mouth after service failures

当基于人工智能的服务失败时：检查自我概念-人工智能联结对服务失败后分享负面口碑的意愿的影响

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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 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.

摘要

人工智能（AI）在 服务遭遇中的最新普及引发了有关消费者如何响应这些新颖技术的问题。这项研究旨在研究AI服务失败对消费者分享负面口碑的倾向的影响。三个　实验表明，与人工员工相比，由AI推荐系统导致的服务失败后，消费者更不愿意分享负面的口碑，尽管失败本身，对企业的责怪或对服务的不满没有　差异。进一步的调查表明，这种影响是由消费者与AI的自我概念联结所驱动的，因为该AI使用他们过去的行为来预测他们的未来偏好。结论为对消 费者与AI交互的整体理解提供了启示。同时，还为企业有效和谨慎地在其服务产品中实施AI提供了管理上的启示。

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关键词
人工智能; 服务失败; 负面口碑; 自我增强; 归因

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

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(Belanche et al., 2020; Belk, 2020; Huang & Rust, 2018; Marinova et al., 2017; Van Doorn et al., 2017; Wirtz et al., 2018). 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 et al., 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 et al., 2017; Bechwati & Morrin, 2003; Hennig-Thurau et al., 2004; Wangenheim, 2005; Wangenheim & Bayón, 2004; Wetzer et al., 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 et al., 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 for the conceptual framework).

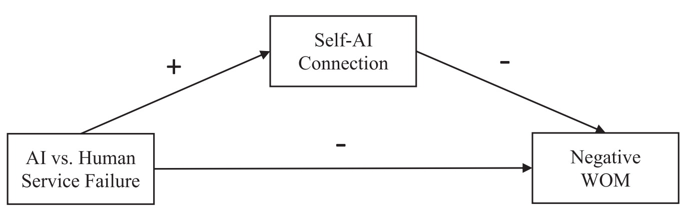

Figure 1. Conceptual Framework.

Conceptual development

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 et al. (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 et al. (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, 2015). 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 (Suri et al., 2019; Van Vaerenbergh et al., 2014). 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 et al., 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; Grégoire & Fisher, 2008; Holloway & Beatty, 2003; 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 (Hennig-Thurau et al., 2004; Wetzer et al., 2007). 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 et al., 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., 2017, 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 et al., 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 et al., 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 et al. (2019)'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 et al., 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 & Roedder John, 2005; Cheng et al., 2012; Ferraro et al., 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 et al., 2009; Ratan & Dawson, 2016; Suh et al., 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 et al., 1998) and avoids self-implication (Philp et al., 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 et al., 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. (2012)

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 et al., 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.

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 et al., 2017; Campo et al., 2000; Sloot et al., 2005; Sloot & Verhoef, 2008; Wason et al., 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 min. 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.

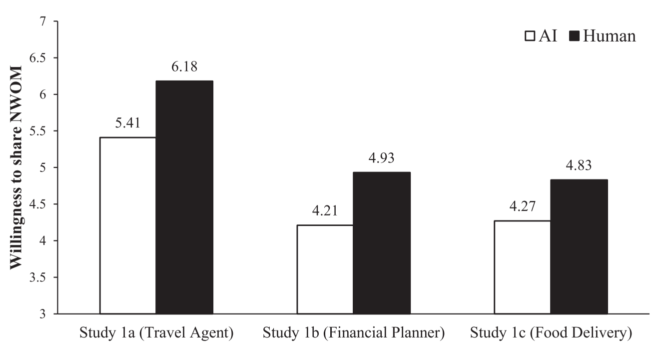

Figure 2. Willingness to share NWOM by Service Agent (Study 1a-1c).

Results and discussion

Results from this study are depicted in Figure 2. A one-way ANOVA revealed a significant effect of service agent on NWOM ($M_{AI} = 5.41$ vs. $M_{Human} = 6.18$; $F(1, 121) = 9.04$, $p = .003$). 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 ($\alpha = .91$).

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.

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 (Mage = 38, 47% female) were recruited online from Amazon Mechanical Turk. They were guided through a 2 (Service Agent: Human vs. AI) × 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' ($\alpha = .93$). 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 × 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, 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

Table 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.

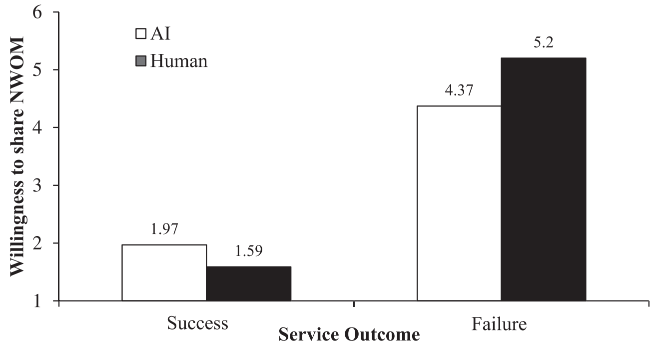

Figure 3. Willingness to share NWOM by Service Agent and Outcome (Study 2).

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 × Service Outcome interaction on willingness to share NWOM (F(1, 194) = 11.27, p = .001). Specifically, as reported in Table 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 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.

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 et al. (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 ($M_{Success} = 1.82$ vs. $M_{Failure} = 6.20$; $F(1, 201) = 579.44$, $p < .000$) but not on firm blame ($M_{Success} = 5.68$ vs. $M_{Failure} = 5.49$; $F(1, 201) = 1.28$, $p = .259$). The main effects of AI System Personalization on firm blame ($M_{Personalized} = 5.58$ vs. $M_{Non\text{-}Personalized} = 5.60$; $F(1, 201) = .01$, $p = .914$) and dissatisfaction ($M_{Personalized} = 3.84$ vs. $M_{Non\text{-}Personalized} = 4.82$; $F(1, 201) = .00$, $p = .997$) were both not significant. The results of the Service Outcome × 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 ($M_{Failure\text{-}Personalized} = 5.51$ vs. $M_{Failure\text{-}Non\text{-}Personalized} = 5.47$; $F(1, 201) = .03$, $p = .86$) or

Table 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.

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 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 × 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 ($M_{\text{Success}} = 2.87$ vs. $M_{\text{Failure}} = 2.09$; $F(1, 201) = 14.85$, $p < .000$). The result of the Service Outcome × 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. $M_{\text{Failure-Non-Personalized}} = 1.74$; $F(1, 201) = 1.02$, $p = .540$).

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

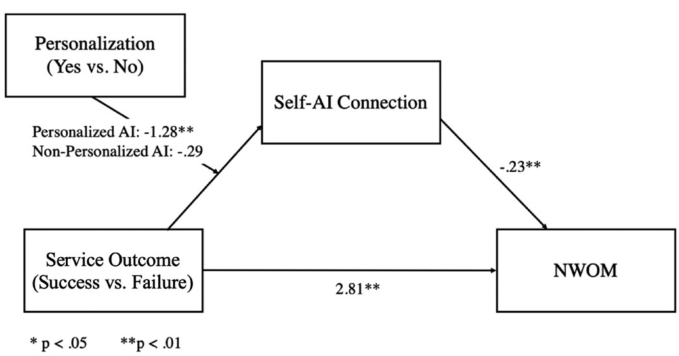

Figure 4. Mediating role of the Self-AI connection on the willingness to share NWOM (Study 3).

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 4).

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.

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, 2012; 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.

Limitations and directions for future research

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 (Groom et al., 2009; Krach et al., 2008). 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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No potential conflict of interest was reported by the author(s).

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