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Research article

Chatbots' effectiveness in service recovery

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ABSTRACT

Leveraging the computers are social actors theory, in this study, we explore traits of artificial intelligence-based chatbots that make them perceived as trustworthy, drive consumers to forgive the firm for service failure, and reduce their propensity to spread negative word-of-mouth against the firm. Across two scenario-based studies with UK consumers: one in a utilitarian product category (n = 586) and another in a hedonic product category (n = 508), and a qualitative study, our findings suggest that the perceived safety of chatbots enhances consumers' perceived ability and empathy, and anthropomorphism enhances the benevolence and integrity of chatbots, i.e., three traits of chatbots affect components of trustworthiness differently. Further, these traits have a positive influence on customer forgiveness and a negative influence on negative word-of-mouth.

1. Introduction

Firms are leveraging digital tools offered by artificial intelligence (AI) to enhance consumers' experience (Ramesh & Chawla, 2021). One such AI-based application is chatbots, which firms have widely used in rendering customer service (Dwivedi & Wang, 2022). *Chatbots* are "interactive, virtual agents that engage in verbal interactions with humans" (Przegalinska et al., 2019, p. 786). Also referred to as virtual agents or machine conversation systems (Collins et al., 2021), chatbots have significantly reduced interaction between customers and service providers. For customer service, chatbots provide 24/7 services for sales, support, and marketing.

Although chatbots can potentially reduce firms' annual costs by over USD 8 billion (Gilchrist, 2017), their dark side is more prominent, as recent research suggests that 87% of consumers find human interaction in a service context more favorable than chatbots (Press, 2019). Customers also experienced discomfort when communicating with chatbots (Luo et al., 2019). Studies have reported customers' anger, confusion, and dissatisfaction when AI-powered chatbots fail (Castillo et al., 2021). Chatbots, similar to humans, have to perform their job and depict relationship management with customers. Chatbots' functional-oriented behaviors assist consumers in their buying decisions. Chatbots' relational-oriented behaviors help in customer relationship management which renders long-term value (Fan et al., 2022). When chatbots cannot perform these roles, customers perceive them as mechanical machines that lack empathy and therefore deny accepting them (Fan et al., 2022).

Low acceptance of chatbots is likely to be even more challenging for firms when chatbots attempt to recover failed services experienced by consumers. Hoffman and Bateson, p.) (1997) defined service failure as "the service performance that falls below a customer's expectations." Service failure recovery (SRF) includes the initiatives taken by employees of an organization to "rectify, amend, and restore the loss experienced" by customers (Bell & Zemke, 1987; Gronroos, 1988). When these AI-powered interactions fail, they could potentially make consumers angry and dissatisfied.

Despite these emotions and the dark side of chatbots, it can be a significant gain for marketers if consumers forgive a brand for service failure and diminish their propensity to spread nWOM (negative word-of-mouth). Still, research is silent on guiding managers about traits of chatbots that can make them effective in managing SFR. Service marketing scholars have recently emphasized that SFR literature is at a crossroads and not keeping pace with innovation tools that firms adopt to manage services such as robots or chatbots (Grégoire et al., 2022).

Consumers tend to respond negatively to service failure issues through the attributes of taking revenge and spreading nWOM (Casidy & Shin, 2015), and such responses adversely influence a firm's brand image. It is thus vital to understand these post-failure reactions of consumers in the technology context, where chatbots conduct service recovery efforts (Sinha & Lu, 2016). Thus, if marketers could use chatbots to make consumers forgive firms for service failure and spread nWOM to a lesser extent, it could be of significant value to firms.

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However, a 2018 study by Invesp, a consulting firm specializing in conversion rate optimization, across seven sectors, like online retail and health, found that, on average, only 22% of consumers were willing to rely on chatbots for their needs (Shukairy, 2018). Where acceptance of chatbots by consumers is low, their usage in case of service failure portrays an even darker side of chatbots that could result in customer aggression (Huang & Dootson, 2022). Thus, it becomes vital for information systems and marketing managers to explore chatbot traits that could reduce a customer's negative response in case of service failure. In response to urges made by service scholars and changing service recovery landscape by firms, we bridge the gap in service failure-recovery literature by exploring the role of chatbots in effective service recovery.

Based on the research gaps mentioned above and their significance, the present study has two objectives: *First*, to explore traits of chatbots that make them more trustworthy. *Second,* to explore the mediating role of chatbot trustworthiness in consumer response to SRF efforts, i.e., consumer forgiveness and spreading nWOM. We thus explore the mediating role of trustworthiness.

Leveraging the computer are social actors (CASA) theory, we assert that those traits of chatbots that could make consumers perceive them as having more human-like attributes would enhance chatbots' trustworthiness. Consequently, consumers would be less likely to spread nWOM and more willing to forgive the company. In this context, two traits of chatbots can make consumers perceive them more as humans: their anthropomorphic appearance and empathy depicted in written communication, and one aspect that distinguishes them from humans: privacy concerns. In the context of service failure, consumers would want to speak to a customer representative who could resolve the problem empathetically. If chatbots could appear like humans and reflect empathy in their text messages, they, as per CASA, are more likely to be perceived as social actors (Pelau et al., 2021). Thus, anthropomorphic chatbots depicting an empathetic communication style should help raise consumers' positive responses toward the company after a service failure. However, although chatbots could be perceived as social actors by their communication and appearance, consumers are also aware that chatbots are machines and only behave human-like rather than human (Lutz & Tamó-Larrieux, 2020). Thus, their privacy concerns regarding personal information remain when interacting with chatbots.

Overall, these three attributes of chatbots, i.e., empathy, anthropomorphism, and privacy concerns, influence consumers' perceived trustworthiness toward chatbots. Perceived trustworthiness, where the consumer believes that a chatbot has securely taken service recovery steps after understanding customer problems, may calm the consumer's negative emotions (Vázquez-Casielles et al., 2007). Thus, a consumer might be more willing to forgive the firm for service failure and spread less nWOM.

Our study adds to the AI and marketing literature interface, where extant studies have shown how AI-based chatbots influence marketing practices in the healthcare industry or branding practices (Liu et al., 2021; Yan et al., 2022). We extend this stream of literature on chatbots to explain what traits of chatbots influence customer decisions to forgive a firm for service failure and diminish the propensity to spread nWOM. We discuss our contributions in detail in the discussion section.

This paper proceeds as follows: We first discuss extant literature and then explain our theory and hypothesis. This is followed by the methods and results sections. Lastly, we present the discussion, conclusion, and managerial implications sections.

2. Theory and hypothesis development

2.1. Role of chatbots in information systems & marketing

Chatbots use AI and machine learning (ML) to simulate human communication. AI allows chatbots to interpret and interact with human beings. ML helps chatbots improve through continuous learning through customer communication (Wang et al., 2022). AI-powered chatbots have altered the nature of service interfaces that humans earlier drove to one that is technology-dominant today (Castillo et al., 2021). Chatbots can bring forth conversations for commercial purposes, such as interacting with customers. They have specific traits that differentiate them from employees. For instance, chatbots continuously update themselves through machine learning algorithms and have infinite memory. They take only a fraction of a second to achieve these tasks, whereas humans, because of their backgrounds and learning abilities, are limited in executing such tasks quickly (Wirtz et al., 2018). Chatbots have been found to influence several marketing consequences, including customer engagement and customer loyalty (Mostafa & Kasamani, 2022); and purchase intention (Konya-Baumbach et al., 2023). Extant studies have also found that the interaction style of the chatbot, such as free text interaction or button interaction, influences customers' outcomes of interaction with a chatbot (Haugeland et al., 2022). Similarly, the communication quality of chatbots and the level of entertainment rendered by chatbots also influenced customer outcomes (Cheng & Jiang, 2022). Scholars have leveraged several theoretical frameworks to explain these marketing outcomes, such as the expectations confirmation theory (Eren, 2021), CASA (Ashfaq et al., 2020), and justice theory (Xing et al., 2022).

However, several users are hesitant to interact with chatbots as the personal touch is lacking when the agent is a chatbot than humans. Furthermore, as consumers have incurred economic or non-economic loss during service failure, they also want an agent who could express empathy with the loss experienced by the customer, which is generally possible with humans (Nguyen et al., 2022). Consequently, some firms hesitate to implement them (Press, 2019). Other issues, including privacy risks (Kopalle et al., 2022), are also a concern for chatbot interaction (Rapp et al., 2021). Although extant literature has explored customer satisfaction and dissatisfaction with chatbots (Ruan & Mezei, 2022; Suhaili et al., 2021), factors driving its trustworthiness, especially in service failures, are unknown, despite a plethora of literature explaining the significance of technology trustworthiness in chatbots acceptance (Al-Gahtani, 2011).

2.2. Dimensions of trustworthiness

Trust literature separates the concept of *trustworthiness* (i.e., the ability, benevolence, and integrity of a trustee) from *that of trust* (i.e., the intention to accept vulnerability to a trustee based on positive expectations of his or her actions) (Hong and Cho, 2011; Riyanto & Jonathan, 2018). Moreover, trustworthiness could lead to trust repair though vice versa does not happen (Xie & Peng, 2009). Information systems research also suggests that for the trustworthiness of technology, the technology must fulfill three criteria: perceived ability, benevolence, and integrity (Lankton et al., 2015). *Perceived ability* implies that with technology, a customer considers if it renders the assured performance (McKnight, 2005). For example, a payroll system having features necessary to give a correct payroll for employees would be perceived as being able to deliver the promised. Another critical trait of trustworthiness is *benevolence*, where individuals should perceive technology as offering enough help when needed. This aligns with individuals' hope that they care enough to offer help when needed (Johnson, 2007). For technology, users also hope that a technology's help function will assist them with the information necessary to complete a task (McKnight, 2005). The third component of trustworthiness is *integrity*, i.e., where individuals expect technology to remain consistent in its performance (Lankton et al., 2015). With humans, integrity implies that an individual can be relied upon to act predictably and consistently. Technology may not be persistent in its operations due to inherent defects or situational events causing failures (Mcknight et al., 2011). By responding predictably to inputs (such as responding to queries or printing on command), technology influences the user's perceptions of technology integrity.

Past studies have found trustworthiness to influence several marketing and customer outcomes, such as customer engagement with the

brand and their loyalty towards the brand (Kosiba et al., 2018). Also, consumers varied in the age group for their perceived trustworthiness of technology. Younger consumers had a higher perceived ability, competence, and benevolence of technology than senior customers (Hallikainen et al., 2020). Consumers' trustworthiness of technology also differed from the trustworthiness they show toward humans. In online interactions, when people presented themselves through their avatars, the perceived trustworthiness of their avatars by others was different from how others rated individuals for their trustworthiness. Thus, the trustworthiness of avatars did not coincide with those of individuals who interacted with avatars (Machneva et al., 2022). Furthermore, in the service recovery scenario, researchers have found that trustworthiness depicted through interactional justice had a superior effect on consumer forgiveness than those who offered distributive justice (Babin et al., 2021).

However, we should also note that apart from the trustworthiness traits any agent depicts, an individual's underlying trusting propensity also impacts perceived trustworthiness. Trust propensity implies an individual's proclivity to believe in humanity and espouse a trusting outlook toward others (Furner et al., 2022). Those having a positive outlook toward humanity believe that humans are genuine and honest and can be relied on. Such individuals are less likely to be capricious of others and also easily forgive the mistakes of others (Pica et al., 2022). A trusting outlook implies that an individual believes that irrespective of the underlying nature of humans, the net outcome of dealing with people is always positive (Folkman & Moskowitz, 2000). If individuals, by their nature or personality, have less inclination to trust others, then their perceived trustworthiness of others is likely to be less.

2.3. Service failure recovery (SFR)

Scholars have categorized extant research on service failure recovery into three streams. The *first* stream of literature explores how SFR actions influence a firm's performance and recovered service quality (Baliga et al., 2021). For example, a firm's performance is increased from service recovery actions as the customer churn rate is reduced, which brings in more profits than the cost incurred in rectifying service failure (Knox and Van Oest, 2014).

The *second* stream of literature examines how consumer behavior varies with recovery strategies (Giebelhausen et al., 2014). Due to service recovery efforts, scholars have found that customer satisfaction increases and anger decreases, spreading less nWOM against the company (Casidy & Shin, 2015; DeWitt & Brady, 2003).

The *third* stream of literature examines what inspires consumers to get involved in customer co-creation for service recovery (Dao and Theotokis, 2021). Dong et al. (2016) suggested that customers' autonomy in driving SFR procedures enhanced their motivation to participate in service recovery procedures. In this paper, integrating information systems and marketing literature, we explore the second stream of literature. We identify factors that drive consumers to forgive firms for service failures and reduce nWOM when chatbots make service recovery efforts.

Customers' willingness to forgive a brand for service failure is critical. Extant literature also suggests that customers are sometimes willing to forgive a company for service failure due to perceived trustworthiness, even if the service recovery outcome is not up to the expectation (Wei et al., 2020). This willingness to forgive a service failure happens when customers are convinced that the service provider made efforts to resolve a service failure issue, i.e., they perceived that the agent (i.e., the brand) was benevolent and integral in their effort to resolve the problem. However, if a brand cannot resolve a service problem up to the expectation, trust is likely to be broken as the consumers may have hoped that the agent would be able to resolve the problem.

2.4. Attributes of chatbots determining perceived trustworthiness dimensions in service recovery

2.4.1. Privacy concerns

Privacy concerns refer to "the degree to which a consumer is worried about the potential invasion of the right to prevent the disclosure of personal information to others" (Baek & Morimoto, 2012, p. 63). Chatbots need to collect information before they can initiate service recovery actions. Such information is collected through direct requests from the customer. Such requests may scare consumers about data privacy (Huang & Chueh, 2021). Part of the concern could be the relative newness of technology combined with other data privacy scandals that happened in the recent past, such as with Facebook (Hinds et al., 2020).

2.4.1.1. Perceived ability of chatbots amidst privacy concerns. Consumers worry about losing control over the manner and process through which technology-driven agents such as chatbots could handle their personal information, i.e., consumers perceive that chatbots are less likely to be able to keep their information confidential (Wu et al., 2012). In the context of service failure, for instance, when refunds are required, consumers might doubt the ability of chatbots to safely process their financial information shared through credit or debit cards. Instead of resolving service failure, it may result in double service failure due to leakage of this information. Overall, consumers may perceive chatbots as less able to control their information and privacy. Therefore, we hypothesize:

H1a. **:** *Perceived privacy concerns about interacting with chatbots decrease consumers' perceived ability of chatbots.*

2.4.1.2. Perceived integrity of chatbots amidst privacy concerns. Frequently consumers believe that chatbots may indulge in fair utilization of personal information provided by consumers, and they may become suspicious of the integral intentions of chatbots (Rabbani, 2022). When consumers believe that for service recovery, they will need to risk sharing information with AI-based chatbots, where information could be misused, consumers' perceived integrity of chatbots for helping them with service recovery may decline. Again, when consumers realize that there is no way for them to ask or figure out mechanisms that chatbots would use to record the information, they may perceive that chatbots may not operate honestly and may misuse the data, thus lowering the perceived integrity of chatbots (Lauer & Deng, 2007). Hence, we hypothesize:

H1b. **:** *Perceived privacy concerns about interacting with chatbots decrease consumers' perceived integrity of chatbots.*

2.4.1.3. Perceived benevolence of chatbots amidst privacy concerns. As information asymmetry related to data privacy exists between AI-driven chatbots and consumers seeking resolution for service failure, it may encourage consumers to believe that chatbots are unconcerned about consumers' privacy and hence is less benevolent. Thus, the unavailability of accurate and holistic information about how customers' data, including both financial and non-financial, be protected may make consumers doubt chatbots' intention to care enough to resolve consumers' problems in a well-protected manner (Martin et al., 2017). Thus, when customers perceive that their data is vulnerable and unintended uses could harm them through data breaches or identity theft, they may believe that chatbots are not caring enough to protect the data and perceive them to be less benevolent.

Moreover, as service recovery takes place in an online environment with chatbots, customers do not get any opportunity to share their concerns about data privacy, unlike in a physical retail environment where consumer-human interaction may give an opportunity to consumer to get their suspicions clarified (Luo et al., 2017). The lack of clarity chatbots offer about data privacy may make consumers believe

chatbots need to be more benevolent to provide any assurance regarding data theft protection (M.K. Hasan et al., 2021; R. Hasan et al., 2021). Hence, we hypothesize:

H1c. **:** *Perceived privacy concerns about interacting with chatbots decrease consumers' perceived benevolence in chatbots.*

2.4.2. Anthropomorphism

According to the CASA theory, individuals subconsciously allocate human-like characteristics to technology and solicit gregarious directives and expectations when interacting with them (Reeves & Nass, 1996). The human-like distortions in the cognitive framework of consumers are even more potent when technology depicts human-like traits such as eyes, smiling faces, etc. These human-like traits result in the anthropomorphism of chatbots in the present study's context, where anthropomorphism refers to human-like traits depicted by chatbots (Sheehan et al., 2020).

2.4.2.1. Perceived ability of anthropomorphic chatbots. Users could have a stronger perception of personalized attention when an anthropomorphic chatbot asks questions about their specific concerns after a service failure (Adam et al., 2021). For instance, when an anthropomorphic chatbot asks questions like "How could I assist," consumers may believe that similar to humans, the chatbot is also competent in resolving the service failure issue. Thus, consumers might expect anthropomorphic chatbots to examine their queries like humans, render helpful information for resolving service failure issues, and further accomplish service recovery like human agents.

Scholars have shown that anthropomorphic agents could also be considered "creepy" and may raise customer dissatisfaction (Crolic et al., 2022; Rajaobelina et al., 2021). This behavior happens as the anthropomorphic response of AI-driven chatbots is considered by consumers as a technical representation design that is implanted through programming (Song et al., 2021). Thus, some users may perceive chatbots as non-emotional, cold, and mechanical when they show human-like traits.

However, in the context of service failure, consumers may want to share their concerns with an agent who is competent and able to resolve the issue. As predicted by CASA theory, anthropomorphic appearance in the context of service failure may make consumers perceive chatbots as agents that are not cold and programmed but able to resolve problems (Teodorescu et al., 2021). Thus, the anthropomorphic appearance of chatbots will make consumers perceive chatbots to be equally competent as humans in resolving service failures (Wang & Benbasat, 2007). Hence, we hypothesize:

H2a. *Anthropomorphic chatbots enhance consumers' perceived ability of chatbots.*

2.4.2.2. Perceived benevolence of anthropomorphic chatbots. When chatbots appear human-like, consumers based on CASA theory may also believe that chatbot has human qualities, i.e., good intention and motivation to resolve the customer issues associated with service failure (Epley et al., 2007). This goodwill belief about anthropomorphic chatbots makes consumers believe that chatbots are benevolent. As anthropomorphic chatbots resemble humans, consumers intend to form human-to-human relationships with chatbots (Lee & Choi, 2017). In this process, they begin to believe that even chatbots, by their resemblance to humans, also depict human traits. In the service failure context, the service agent is expected to show concern for consumers and help resolve the service failure issue. Accordingly, consumers would also perceive chatbots to be benevolent enough and work towards resolving service failure to help a customer recover from failure issues (Adam et al., 2021). We therefore hypothesize:

H2b. *Anthropomorphic chatbots enhance consumers' perceived benevolence of chatbots.*

2.4.2.3. Perceived integrity of anthropomorphic chatbot. The perceived integrity of anthropomorphic chatbots implies the extent to which consumers perceive chatbots to deal with service failure issues with utmost care and honesty (Schuetzler et al., 2021). In a service failure context, salesperson efforts to help resolve the issue make them appear integral (Khamitov et al., 2020). Accordingly, users may also apply the same integrity criterion that they apply to humans while evaluating a chatbot (Qiu & Benbasat, 2010). Human-like attributes of anthropomorphic chatbots, who try to help customers resolve issues, could also make them perceived as integral.

Moreover, as the CASA theory explains, customers may have a positive response due to an enhanced level of social identity (Bickmore & Schulman, 2007). This social identity could reduce the psychological distance between customers and AI, making chatbots appear more benevolent and integral. Hence, we hypothesize:

H2c. **:** Anthropomorphic *chatbots enhance consumers' perceived integrity in chatbots.*

2.4.3. Perceived empathy

Empathy is the act of depicting another person's emotional experience (Plank et al., 1996). Leveraging CASA theory, we examine the remedial effect of empathy of chatbots that enhances their trustworthiness after a service failure episode. CASA suggests that individuals tend to regard computers and related technologies, such as chatbots, to have a human role, even if they are aware that the technologies, such as chatbots, have no senses (Nass & Moon, 2000). Chatbots can give interactive and language cues to customers that could evoke social responses among consumers (Nass & Steuer, 1993). As humans are empathetic, when service failure takes place, empathy has to be depicted via communication. For instance, consumers may find service recovery efforts imputed if a customer representative sounds rude or ignores customer requests (Migacz et al., 2018). Thus, it may not be easy to assume all underlying traits of anthropomorphism as resembling humans. For this reason, scholars have treated empathy and anthropomorphism as independent of each other (Pelau et al., 2021).

2.4.3.1. Perceived ability of empathetic chatbots. Ability implies whether the customers are likely to perceive chatbots as competent, i.e., consumers believe they have knowledge notable to the expected behavior (Park et al., 2021). Doctors are perceived as competent when they display knowledge about a patient's disease. Psychologists are perceived as competent when they display psychological knowledge about human behavior. In the context of service failure, an expected response from the agent resolving the problem is to show empathy. Thus, when chatbots reflect empathy, they are perceived as competent and able to resolve customer problems. The empathic response of chatbots could make consumers believe that chatbots have the ability to understand their concerns. Hence, we hypothesize:

H3a. *Perceived empathy of chatbots towards consumers enhances consumers' perceived ability of chatbots.*

2.4.3.2. Perceived benevolence of empathetic chatbots. In a service failure context, if chatbots could respond warmly and compassionately, it could elicit within consumers gloomy feelings caused by the service failure, thus making consumers perceive the chatbots to be benevolent, i.e., caring about customer issues (Rapp et al., 2021). Studies suggest that in human-to-human interaction, language and rhetoric have the power to signal the intent and character of parties in the conversation. For instance, when leaders give compassionate speeches, they are considered more benevolent (Karakas & Sarigollu, 2013). In an employee-customer conversation context, when employees issue a superfluous apology, they signal that they have acknowledged the customers' perspective on service failure and expressed regret for the same, making the employees perceived as more benevolent (Brooks et al.,

2014). Chatbots could also provide empathetic cues as they converse with consumers for service recovery, making consumers perceive them as empathetic.

H3b. *Perceived empathy of chatbots towards consumers enhances consumers' perceived benevolence of chatbots.*

2.4.3.3. Perceived integrity of empathetic chatbot. Integrity implies that chatbots will continue to show empathetic responses as the communication proceeds between the customer and the chatbot to resolve the service failure issue (Ramesh & Chawla, 2022). Consumers apply societal principles and interpersonal interaction practices in this communication process with chatbots (Park et al., 2021). As chatbots remain consistently compassionate while resolving customer queries through bicommunication, the consistent caring and genuine attitude of chatbots in this bicommunication will likely make them be perceived as integral (Schiemann et al., 2019), thus enhancing trustworthiness. Hence, we hypothesize:

H3c. *Perceived empathy of chatbots towards consumers enhances consumers' perceived integrity in chatbots.*

2.5. Trustworthiness of chatbots and consumer's propensity to forgive service failure and nWOM

When service failure happens, consumers stop doing business with the service provider (Grégoire et al., 2009) or seek retaliation by spreading nWOM (Wangenheim, 2005). Fetscherin and Sampedro (2019) defined *forgiveness* as letting negative emotions waive off, resulting from the wrongdoing of oneself, others, or situations. Once consumers encounter service failure, they experience emotional state changes (Gaudine & Thorne, 2001). Several factors influence the way consumers deal with their disappointment. For example, the prior relational bond between the customer and the service provider could influence the consumer's propensity to regulate their emotional state positively and forgive the brand (Joireman et al., 2016).

In the context of service failure, scholars have reported that consumer personalities such as religiosity and spirituality influence their propensity to forgive the firm for service failure (Tsarenko & Tojib, 2012). Among firm-level efforts, extant literature has found that asking for apologies, giving voice to consumers, and offering compensation enhances consumers' propensity to forgive the firm (Harrison-Walker, 2019). Scholars have also found the role of perceived justice in consumers' willingness to forgive the firm after service failure (Babin et al., 2021); for some consumers, forgiveness happens when a firm offers both apologies and compensation (Casidy & Shin, 2015).

Studies also suggest that when consumers exhibit a positive attitude toward brands, i.e., perceive the brand as trustworthy, they pardon service failures (Cheng et al., 2012); and are not much influenced by nWOM (Ho-Dac et al., 2013). Extending this literature to chatbots, when chatbots are perceived as more able, competent, compassionate, and caring, i.e., trustworthy, consumers having a positive attitude towards chatbots may intend to forgive the service provider for service failure.

Word-of-mouth is another critical outcome of service failure and recovery efforts (Choi & Choi, 2014). Harrison-Walker (2001, p. 63) defined *word-of-mouth* as "informal, person-to-person communication between a perceived non-commercial communicator and a receiver regarding a brand, a product, an organization, or a service." Word-of-mouth can be positive or negative depending on how fairly a brand treats its customers (Wang et al., 2021).

Dissatisfied customers are more likely to use nWOM as they want to express their displeasure. Consumers may spread negative word of mouth for three reasons: when they want the firm to pay attention to dissatisfaction causes or when they want their friends and relatives to not suffer similar negative experiences with the focal service provider, or when consumers want to express their feelings so that company could rectify the same (Verhagen et al., 2013).

However, when firms take actions to recover from a service failure, such as chatbots resolving consumer issues, consumers are likely to focus on efforts made by an able, benevolent, and integral chatbot to resolve the issue. When consumers perceive chatbots to be trustworthy by their benevolence and integrity towards resolving the problem, consumers' intent to penalize the company may decline, resulting in less spread of nWOM. Hence, we hypothesize:

H4a. *Perceived ability of chatbots encourages consumers to forgive firms for service failures.*

H4b. *Perceived benevolence of chatbots encourages consumers to forgive firms for service failures.*

H4c. *Perceived integrity of chatbots encourages consumers to forgive firms for service failures.*

H5a. **:** Perceived ability of chatbots encourages consumers to reduce nWOM against firms in case of service failures.

H5b. : Perceived benevolence of chatbots encourages consumers to reduce nWOM against firms in case of service failures.

H5c. : Perceived integrity of chatbots encourages consumers to reduce nWOM against firms in case of service failures.

In the above five sets of hypotheses, we discussed how chatbots' traits influence their perceived trustworthiness and how this trustworthiness influences consumers' willingness to forgive service providers and spread less nWOM. Corollary, the trustworthiness dimensions mediate chatbot traits and consumer response to service failure relationships. Hence, we hypothesize:

H6. **:** Perceived *ability, benevolence, and integrity mediate chatbot traits (*i.e*., privacy concerns, anthropomorphism, and perceived empathy) and customer outcome (i.e., forgiveness and nWOM) relationship.*

Fig. 1 presents the conceptual model.

3. Data and method

3.1. Design

Across two studies, we used scenario-based approach which researchers have extensively used in studies related to service failure and recovery (Park & Ha, 2016; Singh & Crisafulli, 2015; Smith et al., 1999). This suitability of scenario-based studies is because a) compared to the recall-based approach or retrospective self-reports (Roggeveen et al., 2012), they are more robust, as a recall-based approach is sensitive to respondent's memory lapses, "rationalization tendencies and consistency factor" (Roggeveen et al., 2012; p. 774), b) the scenario-based approach is also better than the enactment of real-life setting service failure, given it is more prone to ethical and managerial issues (Park & Ha, 2016), and c) the scenario-based approach is also favorable than observation or enactment-based field studies because it reduces the challenges with expenses and times involved (Smith et al., 1999).

In the two studies, we created hypothetical service failure and recovery scenarios with an online retailer. Exploratory research with 47 [Females= 25] postgraduate students in a university in the North East of the UK revealed that they experienced most instances of service failure in online retailing (34%), followed by banking (26%) and airline bookings (24%). The exploratory study further revealed that firms used chatbots during the service recovery process, with participants experiencing the most exposure to chatbots in online retailing (30%), followed by banking and airline bookings (28%). We also asked participants about their experience with service recovery efforts when interacting with chatbots. Surprisingly, on average, 28% reported having a positive experience with service recovery efforts across online retailing, banking, and airline bookings. Based on these exploratory research findings, we

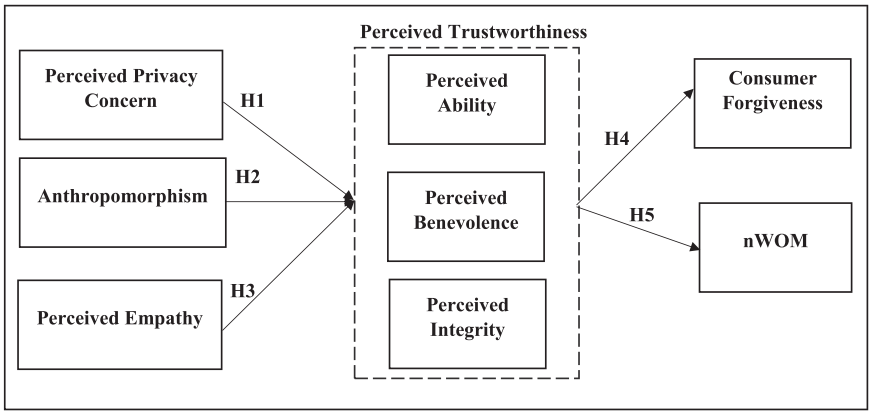

Fig. 1. Conceptual Model.

identified online retailing as the service setting of our hypothetical scenario.

In another exploratory study with 28[Females= 15] postgraduate students from another UK university, 57% of participants considered delays in receiving an order as a major service failure instance in online retailing. Therefore, in both the studies, we developed scenarios in the online retailing failure context, specifically delays in receiving an ordered item. Using the services of a professional graphics designer, we developed a chatbot, "Russell," trying to recover a service failure instance. We developed four scenarios of service failure and recovery.

In the first two scenarios, the product category was toilet tissue rolls, a utilitarian product. In the remaining two scenarios, the product category was earphones, a hedonic product. To identify the product categories, we undertook exploratory research with 37 [Females= 18] postgraduate students from a UK university. We provided the students with a list of ten product categories, and using the Voss et al. (2003) ten-item hedonic and utilitarian scale, we identified toilet tissue rolls and earphones as the utilitarian and hedonic products for Study 1 and 2, respectively. The Voss et al. (2003) scale is a ten-item semantic differential scale. Utilitarian items included: "effective/ineffective, helpful/unhelpful, functional/not functional, necessary/unnecessary, and practical/impractical." The hedonic items of the scale were: "not fun/-fun, dull/exciting, not delightful/delightful, not thrilling/thrilling, and enjoyable/unenjoyable." We considered utilitarian and hedonic product categories as consumer behavior could change across utilitarian versus hedonic product categories (Roy & Ng, 2012).

We also conducted another exploratory study with 46 [Females = 23] postgraduate students from a UK university to identify the scenarios we could use in the two studies. Based on students' responses, we used the following scenario across the two studies: A customer was experiencing a service failure as their ordered item [toilet tissue rolls in Study 1 and an earphone in Study 2] was not delivered by the promised date by Tuple.com, a hypothetical e-retailer. Russell, the chatbot of Tuple.com, first tried to understand the failure issue that the customer was experiencing. Next, they apologized for the inconvenience, tracked the package, and offered an alternate date and time for the delivery of the ordered item or a full refund. The customer agreed to an alternate delivery date and time. We also asked participants of this exploratory research about a) the believability of the scenario using the following question: "I think the scenario is believable," b) the believability of the chatbot: "I believe in the scenario the customer was interacting with a chatbot" and c) that the context of the scenario was "service failure and recovery." The first two items were measured using seven-point Likert scales ranging from "1" not at all believable to "7" "completely believable." The third item was measured using a seven-point Likert scale ranging from "1" strongly disagree to "7" strongly agree. Appendices 1.1 and 1.2 present the scenarios of studies 1 and 2.

3.2. Pretest

Before we conducted the two studies, we employed a pretest. The objective of the pretest was to a) evaluate if the developed scenarios performed as expected, b) check the validity of measurement scales, c) enhance the survey questions' quality and d) test and adjust the survey. Eighty-one postgraduate students (Females = 40) participated in this pilot test. After making the necessary improvements, we proceeded with the scenario-based studies.

3.3. Participants

In Study 1, we collected data from UK consumers using a purposive sampling strategy (Dörnyei & Lunardo, 2021; Talwar et al., 2021). We used purposive sampling because past literature has used this sampling strategy to examine consumer-related specific issues. For example, Tsai and Su (2009) in the service failure and recovery context and Ameen et al. (2022) in the context of chatbots, augmented reality, and social media. We also used purposive sampling because the criteria for being a part of this study was consumers having experienced service failure and recovery in an e-retailing context and interaction with chatbots in this process. The data for the study was obtained between January 2022 to February 2022. We used Prolific for administering the survey questionnaire. Extant research has extensively used Prolific, an online platform for respondent recruitment. First, we invited respondents to participate in the study. Once they accepted the invitation, we asked filtering questions about their experience with service failure and recovery in an e-retailing context and interaction with chatbots in that process.

Next, study participants responded to the scale items, followed by demographic questions on age, gender, education, and annual income. We obtained 628 questionnaires, which also met the filtering criteria. Of these 628 responses, we obtained 586 [Females= 304] completely filled-in questionnaires. The final sample consisted of UK consumers only. The median age and income of the respondents were 31.02 years and £ 32,000, respectively.

Following a similar strategy as Study 1, in Study 2, we obtained 508 [Females= 260] filled-in questionnaires from UK-based participants [Median Age= 33.78 years; Median Income= £32,820]. In both studies, our final sample was skewed toward younger adults compared to the UK population. Table 1 presents the sample demographics of studies 1 and 2.

3.4. Measures

3.4.1. Consumer forgiveness

Following extant literature (Harrison-Walker, 2019; McCullough et al., 2003; Rye et al., 2001), we measured consumer forgiveness using

Table 1
Demography of the sample.

		Study 1 (N = 586)		Study 2 (N = 508)	
Age		*Male (282)*	*Female (304)*	*Male (248)*	*Female (260)*
	18–25 years	26%	29%	25%	27%
	25–35 years	37%	35%	35%	36%
	36–45 years	20%	19%	23%	22%
	46 years and above	17%	17%	17%	15%
Annual Income	*<£25,000*	24%	27%	21%	23%
	£25,000-£35,000	49%	44%	52%	53%
	>£35,000	27%	29%	27%	23%
Education	*Less than high school diploma*	7%	7%	6%	8%
	High school diploma	17%	18%	15%	17%
	Some college associate degree	24%	23%	22%	26%
	Undergraduate degree	33%	31%	35%	32%
	Postgraduate degree	15%	15%	17%	13%
	Greater than Postgraduate degree	5%	6%	6%	5%

a 12-item scale. The consumer forgiveness scale consists of two sub-scales: the absence of negative responses (six items) and the presence of positive responses (six items). A sample of items measuring the absence of negative responses scale is: "I won't stop thinking about how I was wronged by the e-retailer," "This e-retailer's wrongful actions will keep me from enjoying life," and "I will spend time thinking about ways to get back at the e-retailer who wronged me." A sample of items measuring the presence of positive responses scale is: "I wish for good things to happen to the e-retailer who wronged me," I have compassion for the e-retailer who wronged me," and "I forgive the e-retailer for what they did to me." In the present study, we found both the sub-scales to be positively (0.426) and significantly related ($p < 0.001$), which is consistent with extant literature on forgiveness (Harrison-Walker, 2019; Rye et al., 2001). Forgiveness literature also explicitly mentions that both the sub-components of forgiveness are "intertwined and therefore inseparable" (Harrison-Walker, 2019; p. 382), and researchers should conduct further analysis using the scale in its completeness and not as two sub-constructs (Asgari & Roshani, 2013; Harrison-Walker, 2019; Rye et al., 2021). Thus, we considered all the 12 items together and not as separate scales. We used seven-point Likert scales ranging from "1" (strongly disagree) to "7" (strongly agree) to measure the scale items. The Cronbach's alpha of the total scale was 0.89 for study 1 and 0.86 for study 2.

3.4.2. nWOM

We measured nWOM using a six-item scale adopted from Harrison-Walker (2019). Sample scale items included: "I will complain to friends or family about this e-retailer," "I will say negative things to others in the community about this e-retailer," and "I will try to convince friends or relatives not to use this e-retailer." We used seven-point Likert scales ranging from "1" (strongly disagree) to "7" (strongly agree) to measure the scale items. The Cronbach's alpha of the total scale for studies 1 and 2 were 0.87 and 0.89, respectively.

3.4.3. Perceived privacy concerns

We measured consumers' perceived privacy concerns about chatbots, adapting a three-item scale from Zhang et al. (2019). The scale items included: "I am concerned that the chatbot will collect too much personal information from me," "I am concerned that the chatbot will use my personal information for other purposes without my authorization," and "I am concerned that the chatbot will share my personal information with other entities without my authorization." We used seven-point Likert scales ranging from "1" (strongly disagree) to "7" (strongly agree) to measure the scale items. The Cronbach's alpha of the scale was 0.83 and 0.80 for studies 1 and 2, respectively.

3.4.4. Anthropomorphism

We measured the perceived anthropomorphism of chatbot by asking participants to rate four adjectives: likable, sociable, friendly, and personal, on a seven-point scale ranging from "1" (describes very poorly) to "7" (describes very well) (Araujo, 2018; Kim and Sundar, 2012). The Cronbach's alpha of the scale was 0.86 and 0.87 for studies 1 and 2, respectively.

3.4.5. Perceived empathy

We measured perceived empathy using a five-item scale adopted from Croes and Antheunis (2021) and Stiff et al. (1988). Sample of scale items was: "The chatbot said the right thing to make me feel better," "The chatbot responded appropriately to my feelings and emotions," and "The chatbot came across as empathic." Consumers rated each of the items on a seven-point Likert scale ranging from "1" (strongly disagree) to "7" (strongly agree) to measure the scale items. The Cronbach's alpha of the total scale was 0.82 and 0.79 for studies 1 and 2, respectively.

3.4.6. Perceived ability, perceived benevolence, and perceived integrity

We measured each of the constructs of perceived ability, perceived benevolence, and perceived integrity using four-item scales adapted from Akter et al. (2011). Sample scale items are: "The chatbot performs its role very well," "The chatbot has good intentions towards me," and "I would characterize the chatbot as honest." All the 12 items were measured using a seven-point Likert scale ranging from "1" (strongly disagree) to "7" (strongly agree). The Cronbach's alpha values of perceived ability, perceived benevolence, and perceived integrity scales were 0.91, 0.86, and 0.92 for study 1 and 0.85, 0.84, and 0.87 for study 2.

3.5. Control variables

Following extant research studies (Zafar et al., 2021), particularly in the technological context (Cheng & Mitomo, 2017), we controlled demographic variables such as age (we took natural logarithm to reduce variability), gender (Female dummy coded as "1" and male "0"), and education (dummy variable) to ensure variance in these demographic variables does not influence the results of the empirical analysis.

We also controlled consumers' trait anger (Gambetti & Giusberti, 2009) and dispositional compassion (Shiota et al., 2006) as they have been found to influence the propensity to forgive (Fehr et al., 2010). Consumers who tend to be short-tempered or angered easily are less likely to forgive firms for their mistakes. We measured trait anger using a 10-item scale (Gambetti & Giusberti, 2009). Sample items included: "I get angry when I have to wait because of other's mistakes" and "I feel infuriated when I do a good job and get a poor evaluation." We measured dispositional compassion using Shiota et al.'s (2006) five items scale. Sample items included: "It's important to take care of people who are vulnerable" and "I often notice people,e who need help." We used a seven-point Likert scale to measure each item of dispositional anger and dispositional compassion scales ("1" = strongly disagree and "7" = strongly disagree"). Dispositional compassion could make consumers

concerned about the pain and problem of others. Consequently, given consumers' dispositional compassion for the company, they are less concerned about their problems and are more willing to forgive or less willing to spread nWOM. The reliability of the dispositional anger and dispositional scales were 0.77 and 0.81, respectively, in study 1 and 0.79 and 0.80 in study 2.

4. Study 1: Results

4.1. Test of scenario believability and chatbot and identification of context

Similar to one of the exploratory research projects, we asked participants about a) the believability of the scenario, b) the believability of the chatbot, and c) the context of the scenario. Respondents reported that a) the scenario was believable [M= 5.89, t(584) < 0.001], b) the chatbot was believable [M= 6.01, t(584) < 0.001], and c) the context of the scenario was service failure and recovery [M= 5.23, t(584) < 0.001]. Additionally, we also employed Voss et al.'s (2003), ten-item hedonic and utilitarian scale. Study 1 participants, overwhelmingly, considered toilet tissue rolls as utilitarian product.

4.2. Descriptive Statistics

In Table 2, we present the descriptive statistics of the variables in the study. There are positive and statistically significant correlations between the antecedents (i.e., perceived privacy concern, anthropomorphic chatbots, and perceived empathy) and the mediators [i.e., perceived ability ($r_{\text{privacy concerns, perceived ability}}=-0.21$, $p < 0.001$; $r_{\text{anthropomorphic chatbots, perceived ability}}=0.25$, $p < 0.001$; $r_{\text{perceived empathy, perceived ability}}=0.34$, $p < 0.001$), perceived benevolence ($r_{\text{privacy concerns, perceived benevolence}}=-0.06$, $p < 0.10$; $r_{\text{anthropomorphic chatbots, perceived benevolence}}=0.28$, $p < 0.001$; $r_{\text{perceived empathy, perceived beenvolence}}=0.24$, $p < 0.001$), and perceived integrity ($r_{\text{privacy concern, perceived intergrity}}=-0.05$, $p < 0.10$; $r_{\text{anthropomorphic chatbots, perceived integrity}}=0.33$, $p < 0.001$; $r_{\text{perceived empathy, perceived integrity}}=0.28$, $p < 0.001$).

Further, perceived ability, perceived benevolence, and perceived integrity are statistically significantly correlated in the expected direction to consumer forgiveness ($r_{\text{perceived ability, consumer forgiveness}}=0.26$, $p < 0.001$; $r_{\text{perceived benevolence, consumer forgiveness}}=0.25$, $p < 0.001$; $r_{\text{perceived integrity, consumer forgiveness}}=0.31$, $p < 0.001$) and nWOM ($r_{\text{perceived ability, nWOM}}=-0.20$, $p < 0.001$; $r_{\text{perceived benevolence, nWOM}}=-0.22$, $p < 0.001$; $r_{\text{perceived integrity, nWOM}}=-0.26$, $p < 0.001$), respectively. These initial results provide elementary evidence regarding our stated hypotheses.

4.3. Common method bias

According to Podsakoff et al. (2003), common method bias is a critical issue in questionnaire-based single-survey studies. Following the procedures recommended by Podsakoff et al. (2003) and Lindell and Whitney (2001), we followed several steps to control common method bias in the present study. As a first step, respondent anonymity was maintained, and they also received assurance for the same.

Next, we made efforts to randomize the order of the questions. Third, we employed a single-factor CFA, which revealed an extremely poor fit (Chi-square/df =13.26; RMSEA = 0.308; CFI = 0.577; TLI = 0.512), indicating the least influence of common method bias. We also carefully placed in the questionnaire several filler questions and two marker variables to achieve psychological separation. Following extant literature and the guidelines provided by Malhotra et al. (2006) that a marker variable should be theoretically unrelated to the focal constructs of the study, we included the seven-item generalized anxiety disorder (Fitzsimmons-Craft et al., 2022) and income (Blut et al., 2021) as marker variables. The marker variables had insignificant correlations (>p = 0.10) with the study's focal constructs (Lindell & Whitney, 2001). These steps indicated that common method bias was not an issue in the present study.

4.4. Social desirability bias

In the present study, we also checked for the influence of social desirability bias (De Vellis, 1991; Richins & Dawson, 1992), employing the short version (i.e., ten items) of Crowne and Marlowe's (1960) social desirability scale. Sample of items included was: "I'm always willing to admit to when I make a mistake" and "I always pay attention to the way I dress." We measured each scale item using a "True" or "False" dichotomous scale. The calculated social desirability had weak and insignificant correlations with the study constructs. Therefore, our overall conclusion was responses to perceived privacy concerns, anthropomorphism, perceived empathy, perceived benevolence, perceived ability, perceived integrity, consumer forgiveness, and nWOM were not influenced by social desirability.

4.5. Measurement model

Using MPLUS 8.0, we conducted a confirmatory factor analysis for a test of the confirmatory model. The measurement model reported a good fit (Chi-square/df =2.01; RMSEA = 0.04; CFI = 0.96; TLI = 0.97).

Next, using Fornell and Larcker's (1981) mechanism, we assessed the constructs' convergent and discriminant validities. The steps involved: a) calculating for each construct the average variance extracted (AVE) and the composite reliability (CR) and b) comparison of the constructs'

Table 2
Study 1- Correlation matrix and descriptive statistics.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Consumer forgiveness	1												
2	nWOM	-0.43	1											
3	Perceived privacy concerns	-0.16	0.21	1										
4	Anthropomorphism	0.21	-0.15	-0.18	1									
5	Perceived empathy	0.18	-0.11	-0.07	0.20	1								
6	Perceived ability	0.26	-0.20	-0.21	0.25	0.34	1							
7	Perceived benevolence	0.25	-0.22	-0.06	0.28	0.24	0.41	1						
8	Perceived integrity	0.31	-0.26	-0.05	0.33	0.28	0.48	0.51	1					
9	Ln Age	0.13	-0.18	0.10	0.09	0.21	0.07	0.05	0.11	1				
10	Gender	0.14	-0.13	0.18	0.04	0.10	0.03	0.09	0.05	0.03	1			
11	Education	0.11	-0.21	0.10	0.07	0.09	0.08	0.03	0.02	0.05	0.05	1		
12	Dispositional anger	-0.25	0.17	0.06	0.05	0.10	- 0.11	- 0.08	-0.06	-0.09	-0.03	-0.14	1	
13	Dispositional compassion	0.31	-0.22	0.08	0.06	0.14	0.13	0.13	0.09	0.12	0.07	0.15	-0.25	1
	Mean	5.73	5.92	5.84	5.31	5.16	5.21	5.65	4.92	3.37	0.53	0.65	4.53	4.81
	S.D.	1.31	1.12	1.43	0.89	1.1	0.91	1.13	1.06	2.9	0.49	0.41	1.05	1.16

* **r > 0.136, p < 0.001; * *r = 0.11–0.13, p < 0.01, *r = 0.083–0.010, p < 0.05; #, r = 0.07–0.082, p < 0.10

square root of AVEs with the construct correlations. All the constructs had acceptable convergent and discriminant validities. In Table 3, we present the constructs' reliability and validity measures.

4.6. Test of Hypotheses

We tested hypotheses 1–6 using a structural equation model. We employed MPLUS 8.0 to test the structural model. Table 4 presents the results of the hypothesis tests.

Through hypothesis 1, we predicted that perceived privacy concern was negatively associated with perceived ability, benevolence, and integrity. Our analysis indicated that perceived privacy concerns had a negative and statistically significant effect on perceived ability ($\beta = -0.104$ $p < 0.001$). However, the effect of perceived privacy concern on perceived benevolence ($\beta = -0.108$ $p < 0.1$) and perceived integrity ($\beta = -0.112$ $p < 0.1$) though negative, was insignificant. Hence, we receive only partial evidence in support of the first hypothesis.

A test of hypothesis two revealed that chatbot anthropomorphism had a positive impact on perceived ability ($\beta = 0.146$, $p < .001$), perceived benevolence ($\beta = 0.157$, $p < 0.01$), and perceived integrity ($\beta = 0.163$ $p < .001$) of chatbot. We thus receive evidence in support of the second hypothesis.

According to the third hypothesis, the perceived empathy of the chatbot was positively and significantly associated with the chatbot's perceived ability ($\beta = 0.201$, $p < .001$), perceived benevolence ($\beta = 0.198$, $p < .001$), and perceived integrity ($\beta = 0.164$, $p < 0.01$). Hence, we receive evidence in support of hypothesis 3.

Next, as predicted through hypotheses 4 and 5, perceived ability, perceived benevolence, and perceived integrity had a positive influence on customer forgiveness ($\beta_{Ability} = 0.085$, $p < .001$; $\beta_{Benevolence} = 0.133$, $p < .001$; $\beta_{Integrity} = 0.186$ $p < .001$) and negative influence on nWOM ($\beta_{Ability} = -0.092$, $p < .001$; $\beta_{Benevolence} = -0.118$, $p < .001$; $\beta_{Integrity} = -0.223$, $p < .001$). The perceived ability of chatbots increased consumers' willingness to forgive the brand for service failure. This implies that chatbots' ability to demonstrate their efforts towards recovering from service failures calmed the consumers' and they acknowledged the efforts of chatbots by being willing to forgive the firm for service failure. Thus, we receive evidence in support of H4a.

Perceived benevolence of the chatbot also increased consumers' willingness to forgive the firm for service failure. Thus, consumers were willing to give up their retaliation, intent, and other kinds of destructive behaviors and to respond positively to the benevolent behavior of chatbots. We thus receive evidence in support of H4b.

Integrity-based service failure implies that there exist potential fundamental flaws in moral character. Thus, when chatbots are perceived to be integral, it adds to their social evaluation, and consumers may believe that the failure was not intentional to harm the consumer. Thus, the recovery efforts made by a perceived integral chatbot would reduce retaliation intent among consumers, and they would be more willing to forgive the firm for service failure. Thus, we receive evidence in support of H4c.

For our fifth hypothesis, we suggested that chatbots' perceived ability, benevolence, and integrity would reduce consumers' propensity to spread nWOM. Our findings suggest that the perceived ability of chatbots reduced consumers' propensity to spread negative word of mouth. The perceived ability of chatbots implies their perceived level of technical know-how and skills for conducting effective service recovery efforts. As chatbots depict service recovery efforts, it signals their intelligence and efficiency. Given that chatbots have demonstrated their expertise, it made consumers believe in chatbots' ability to resolve the issue, and accordingly, they lowered their propensity to spread negative word of mouth against chatbots. Thus, we receive evidence in support of H5a.

Through the second subsection of the fifth hypothesis, we asserted that the perceived benevolence of chatbots decreases consumers' willingness to spread negative word of mouth. Benevolence implies that the agent is a well-wisher of the focal party and that efforts are intended to benefit the focal party. Thus, when consumers perceive chatbots to be benevolent, consumers realize that chatbots are doing their best to recover from service failures and help the customer to the best possible extent. Thus, realizing the benevolent intent of chatbots, consumers decide not to retaliate by spreading negative word of mouth against the company. Thus, we receive evidence in support of H5b.

Through H5c, we hypothesized that the perceived integrity of chatbots reduces consumers' willingness to spread nWOM. Perceived integrity implies adherence to a set of sound principles. The perceived integrity of chatbotS during service recovery implies that consumers believed in chatbots and used set standards of moral principles to resolve customer issues. Due to this perceived morality of chatbots, consumers drop their intention of spreading negative word of mouth against the company. Thus, we receive evidence in support of H5c. Overall, we receive evidence in support of H4 and H5.

We predicted through the sixth hypothesis that perceived ability, perceived benevolence, and perceived integrity act as mediators between the antecedents (perceived privacy concerns, anthropomorphism, and perceived empathy) and customer outcome (i.e., consumer forgiveness and nWOM). To test the mediation models, we employed Hayes' (2018) procedure and further employed a bootstrapping re-sample value of 5000. In Table 5, we present the results of the mediation analyses.

In Column 1 of Table 5, we observe that the estimated path coefficient for the indirect effect of perceived privacy concerns on consumer forgiveness through perceived ability was statistically significant ($\theta = -0.0084$; LCI=−0.0127; UCI=−0.0041). Also, from Column 2 of Table 5, we observe that the estimated path coefficient for the indirect effect of perceived privacy concerns on nWOM through perceived ability was statistically significant ($\theta = 0.0095$; LCI=0.0036; UCI=0.0154).

In Column 3 of Table 5, we observe that the estimated path coefficients for the indirect effects of anthropomorphism through perceived ability ($\theta = 0.0124$; LCI=0.0055; UCI=0.0193), perceived benevolence ($\theta = 0.0209$; LCI=0.0138; UCI=0.0281), and perceived integrity ($\theta = 0.0303$; LCI=0.0159; UCI=0.0447) on consumer forgiveness were statistically significant. Also, in Column 4 of Table 5, we observe that the estimated path coefficients for the indirect effects of anthropomorphism through perceived ability ($\theta = -0.0134$; LCI=−0.0200; UCI=−0.0068), perceived benevolence ($\theta = -0.0185$; LCI=−0.0276; UCI=−0.0094)), and perceived integrity ($\theta = -0.0363$; LCI=−0.0514; UCI=−0.0212)) on nWOM were statistically significant.

Finally, in Column 5 of Table 5, we observe that the estimated path coefficients for the indirect effects of perceived empathy through perceived ability ($\theta = 0.0171$; LCI=0.0092; UCI=0.0250), perceived benevolence ($\theta = 0.0263$; LCI=0.0162; UCI=0.0364), and perceived integrity ($\theta = 0.0305$; LCI=0.0154; UCI=0.0457) on consumer forgiveness were statistically significant. Similarly, in Column 6 of Table 5, we observe that the estimated path coefficients for the indirect effects of perceived empathy through perceived ability ($\theta = -0.0184$; LCI=−0.0272; UCI=−0.0096), perceived benevolence ($\theta = -0.0233$; LCI=−0.0355; UCI=−0.0113), and perceived integrity ($\theta = -0.0365$; LCI=−0.0529; UCI=−0.0201) on nWOM were statistically significant. Thus, we receive evidence in support of hypothesis six.

4.7. Discussion

Overall, we find that three dimensions of perceived trustworthiness, i.e., perceived ability, perceived benevolence, and perceived integrity, act as mediators of perceived privacy concerns, chatbot anthropomorphism, and perceived empathy traits and consumer response to service recovery efforts relationship. However, only perceived ability acted as a mediator for perceived privacy concerns about chatbots. As such, the perceived privacy concerns reduced the perceived ability of chatbots, which decreased consumer propensity to forgive service failure and

Table 3
Study 1- Convergent and Discriminant Validity.

				Convergent Validity		Discriminant Validity							
Constructs	Items	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE	Consumer forgiveness	nWOM	Perceived privacy concerns	Anthropomorphism	Perceived empathy	Perceived ability	Perceived benevolence	Perceived integrity
Consumer forgiveness	I won't stop thinking about how I was wronged by the e-retailer. (R)	0.88	0.89	0.95	0.61	0.78 *							
	I will spend time thinking about ways to get back at the e-retailer who wronged me. (R)	0.78											
	I will avoid certain websites because they will remind me of the e-retailer who wronged me. (R)	0.66											
	This e-retailer's wrongful actions will keep me from enjoying life. (R)	0.79											
	I think that many of the emotional wounds related to the e-retailer's wrongful actions will heal.	0.89											
	I think my life will be ruined because of the e-retailer's wrongful actions. (R)	0.91											
	I wish for good things to happen to the e-retailer who wronged me.	0.88											
	If I encounter the e-retailer who wronged me, I will feel at peace.	0.82											
	I have compassion for the e-retailer who wronged me.	0.70											
	I hope the e-retailer who wronged me is treated fairly by others in the future.	0.71											
	I forgive the e-retailer for what they did to me.	0.66											
	Even though the e-retailer's actions hurt me, I have goodwill for the e-retailer.	0.66											
nWOM	I will complain to friends or family about this e-retailer.	0.67	0.87	0.89	0.58	-0.43	0.76 *						
	I will say negative things to others in the community about this e-retailer.	0.84											
	I will speak highly of this e-retailer. (R)	0.81											
	When asked by someone I know, I will speak negatively about this e-retailer.	0.82											

(*continued on next page*)

Table 3 (*continued*)

Constructs	Items	Factor Loading	Cronbach's Alpha	Convergent Validity: Composite Reliability	Convergent Validity: AVE	Discriminant Validity: Consumer forgiveness	Discriminant Validity: nWOM	Discriminant Validity: Perceived privacy concerns	Discriminant Validity: Anthropomorphism	Discriminant Validity: Perceived empathy	Discriminant Validity: Perceived ability	Discriminant Validity: Perceived benevolence	Discriminant Validity: Perceived integrity
	I will tell friends and relatives about my bad experience.	0.70											
	I will try to convince friends or relatives not to use this e-retailer.	0.71											
Perceived privacy concerns	I am concerned that the chatbot will collect too much personal information from me.	0.77	0.83	0.85	0.66	-0.16	0.21	0.81 *					
	I am concerned that the chatbot will use my personal information for other purposes without my authorization.	0.85											
	I am concerned that the chatbot will share my personal information with other entities without my authorization.	0.82											
Anthropomorphism	The chatbot is:		0.86	0.89	0.67	0.21	-0.15	-0.18	0.82 *				
	likable	0.79											
	sociable	0.83											
	friendly	0.77											
	personal	0.88											
Perceived empathy	The chatbot said the right thing to make me feel better.	0.90	0.82	0.86	0.56	0.18	-0.11	-0.07	0.20	0.75 *			
	The chatbot responded appropriately to my feelings and emotions.	0.84											
	The chatbot came across as empathic.	0.87											
	The chatbot said the right thing at the right time.	0.72											
	The chatbot was good at understanding my problem.	0.70											
Perceived ability	The chatbot is competent in providing solution to the problem.	0.88	0.91	0.94	0.81	0.26	-0.20	-0.21	0.25	0.34	0.90 *		
	The chatbot performs its role very well.	0.93											
	The chatbot understands the needs of customers it serves.	0.87											
	The chatbot is knowledgeable in providing solution to the problem.	0.92											
Perceived benevolence	The chatbot is ready and willing to assist me.	0.77	0.86	0.90	0.70	0.25	-0.22	-0.06	0.28	0.24	0.41	0.84 *	
	The chatbot's intentions are benevolent.	0.92											
	The chatbot has good intentions towards me.	0.84											

(*continued on next page*)

Table 3 (*continued*)

Constructs	Items	Convergent Validity				Discriminant Validity							
		Factor Loading	Cronbach's Alpha	Composite Reliability	AVE	Consumer forgiveness	nWOM	Perceived privacy concerns	Anthropomorphism	Perceived empathy	Perceived ability	Perceived benevolence	Perceived integrity
	The chatbot is well meaning.	0.81											
Perceived integrity	Promises made by the chatbot are reliable.	0.94	0.92	0.93	0.78	0.31	-0.26	-0.05	0.33	0.28	0.48	0.51	0.88 *
	I would characterize the chatbot as honest.	0.85											
	The chatbot keeps its commitment.	0.90											
	Resolution of problem given by the chatbot are its best judgment.	0.84											

Note: *Italic values are square root of AVE

enhanced nWOM intention. Thus, we received only partial support for the first hypothesis. Finally, we tested the chatbot's perceived efficiency and effectiveness as alternate mediators. However, we did not find them apt mediators (Jones et al., 2022). This may happen because technology-driven chatbots could be assumed to be effective in general. However, post a service failure, can chatbots help customers with service recovery is more of a trust issue. Thus, chatbots need to demonstrate their trustworthiness rather than efficiency or effectiveness.

5. Study 2: Results

In Study 2, where we had a hedonic product in the scenario, i.e., an earphone, we followed a similar approach as Study 1 to analyze the data. Respondents of Study 2 found the scenario and the chatbot believable [$M_{Scenario}$= 5.76, t(506) < 0.001] [$M_{Chatbot}$= 5,92, t(506) < 0.001]. The study respondents also found the context of the scenario as one representing service failure and recovery [M= 5.70, t(506) < 0.001]. Using the Voss et al. (2003) hedonic and utilitarian scale, we found that participants considered earphones as more hedonic than utilitarian.

Next, from Table 6, we can observe that the correlations of the antecedents and the mediators are positive and statistically significant, and the correlations of the mediators and the two outcome variables: consumer forgiveness and nWOM, are in the expected directions. These encouraging findings provide preliminary evidence in support of the study hypotheses.

Similar to the steps employed in Study 1 to check for common method bias, in Study 2, following Podsakoff et al. (2003) and Lindell and Whitney's (2001) recommendations, we found that common method bias was not a concern. Further, employing the ten-item social desirability scale (Crowne & Marlowe, 1960), we checked whether social desirability bias (De Vellis, 1991; Richins & Dawson, 1992) influenced the present study. We observed that the calculated social desirability had weak and insignificant correlations with the study constructs.

Next, we tested the measurement model using MPLUS 8.0. The Study 2 measurement model reported a good fit (Chi-square/df= 2.83; RMSEA= 0.042; CFI= 0.955; TLI= 0.963). We also assessed the constructs' convergent and discriminant validities (Fornell & Larcker, 1981) that we report in Table 7.

5.1. Test of Hypotheses

We employed a structural equation model to test the study hypotheses. In Table 4, we present the results of the hypothesis tests.

A test of hypothesis 1, revealed that the association of perceived privacy concern with perceived ability was negative and significant ($\beta = -0.102$, $p < 0.001$). However, perceived privacy concern's association with perceived benevolence ($\beta = -0.105$, $p > 0.10$) and perceived integrity ($\beta = -0.110$, $p > 0.10$) were in the expected direction, nevertheless, insignificant. A test of hypotheses 2 and 3 revealed that the association of chatbot anthropomorphism and perceived empathy of the chatbot with perceived ability ($\beta_{\text{chatbot anthropomorphism}} = 0.142$, $p < .001$; $\beta_{\text{perceived empathy}} = 0.195$, $p < .001$), perceived benevolence ($\beta_{\text{chatbot anthropomorphism}} = 0.153$, $p < 0.01$; $\beta_{\text{perceived empathy}} = 0.192$, $p < .001$) and perceived integrity ($\beta_{\text{chatbot anthropomorphism}} = 0.160$, $p < .001$; $\beta_{\text{perceived empathy}} = 0.160$, $p < 0.01$) were significant and in the expected direction. Thus, we receive only partial evidence in support of the first hypothesis and while the second and third hypotheses were completely supported.

Next, we found that the mediators: perceived ability, perceived benevolence, and perceived integrity had a positive influence on customer forgiveness ($\beta_{Ability} = 0.088$, $p < .001$; $\beta_{Benevolence} = 0.136$, $p < .001$; $\beta_{Integrity} = 0.183$, $p < .001$) and negative influence on nWOM ($\beta_{Ability} = -0.090$, $p < .001$; $\beta_{Benevolence} = -0.115$, $p < .001$; $\beta_{Integrity} = -0.220$, $p < .001$). Overall, we receive evidence in support of hypotheses 4 and 5.

Table 4
Results of the Structural Equation Model.

		Study 1 (N = 586)			Study 2 (N = 508)		
	Hypothesized relationship			Conclusion	Estimate	t-value	Conclusion
H1	Perceived privacy concerns ——————— > Perceived ability	-0.104 * **	-4.72	Partially supported	-0.102 * **	-4.25	Partially supported
	Perceived privacy concerns ——————— > Perceived benevolence	-0.108	-1.40		-0.105	-1.24	
	Perceived privacy concerns ——————— > Perceived integrity	-0.112	-1.37		-0.110	-1.39	
H2	Anthropomorphism ——————— > Perceived ability	0.146 * **	3.95	Supported	0.142 * **	3.74	Supported
	Anthropomorphism ——————— > Perceived benevolence	0.157 * **	4.03		0.153 * **	3.83	
	Anthropomorphism ——————— > Perceived integrity	0.163 * **	3.98		0.160 * **	3.90	
H3	Perceived empathy ——————— > Perceived ability	0.201 * **	4.28	Supported	0.195 * **	4.06	Supported
	Perceived empathy ——————— > Perceived benevolence	0.198 * **	4.13		0.192 * **	3.92	
	Perceived empathy ——————— > Perceived integrity	0.164 * **	3.90		0.160 * **	3.81	
H4	Perceived ability ——————— > Consumer forgiveness	0.085 * **	3.86	Supported	0.088 * **	3.67	Supported
	Perceived benevolence ——————— > Consumer forgiveness	0.133 * **	4.29		0.136 * **	4.12	
	Perceived integrity ——————— > Consumer forgiveness	0.186 * **	4.23		0.183 * **	3.98	
H5	Perceived ability ——————— > nWOM	-0.092 * **	-4.18		-0.09 * **	-3.91	
				Supported			Supported
	Perceived benevolence ——————— > nWOM	-0.118 * **	-3.93		-0.115 * **	-3.97	
	Perceived integrity ——————— > nWOM	-0.223 * **	-3.82		-0.220 * **	-3.73	
		R^2 (i.e., squared multiple correlation) ranged between 0.06 and 0.62. Fit index: Chi-square/d.f. = 2.47, RMSEA = 0.04; CFI = 0.95; TLI = 0.96. Note: a. t-value is significant at $p < 0.05$ when the t-value exceeds 1.96;			R^2 ranged between 0.09 and 0.58. Fit index: Chi-square/df= 2.83; RMSEA= 0.042; CFI= 0.955; TLI= 0.963. Note: a. t-value is significant at $p < 0.05$ when the t-value exceeds 1.96;		

Table 5
Study 1- Indirect Effects Mediation Models.

Indirect effect	1	Indirect effect	2	Indirect effects	3
Perceived privacy concerns——————> Perceived ability ——————> Consumer forgiveness	(θ = −0.0084; LCI=−0.0127; UCI=−0.0041)	Perceived privacy concerns——————> Perceived ability ——————> nWOM	(θ = 0.0095; LCI=0.0036; UCI=0.0154)	Anthropomorphism——————> Perceived ability ——————> Consumer forgiveness	(θ = 0.0124; LCI=0.0055; UCI=0.0193)
				Anthropomorphism——————> Perceived benevolence ——————> Consumer forgiveness	(θ = 0.0209; LCI=0.0138; UCI=0.0281)
				Anthropomorphism——————> Perceived integrity ——————> Consumer forgiveness	(θ = 0.0303; LCI=0.0159; UCI=0.0447)

Indirect effect	4	Indirect effects	5	Indirect effects	6
Anthropomorphism——————> Perceived ability ——————> nWOM	θ = −0.0134; LCI= −0.0200; UCI= −0.0068)	Perceived empathy——————> Perceived ability ——————> Consumer forgiveness	(θ = 0.0171; LCI=0.0092; UCI=0.0250)	Perceived empathy——————> Perceived ability ——————> nWOM	(θ = −0.0184; LCI=−0.0272; UCI=−0.0096)
Anthropomorphism ——————> Perceived benevolence ——————> nWOM	(θ = −0.0185; LCI=−0.0276; UCI=−0.0094)	Perceived empathy——————> Perceived benevolence ——————> Consumer forgiveness	(θ = 0.0263; LCI=0.0162; UCI=0.0364)	Perceived empathy——————> Perceived benevolence ——————> nWOM	(θ = −0.0233; LCI=−0.0355; UCI=−0.0113)
Anthropomorphism——————> Perceived integrity ——————> nWOM	(θ = −0.0363; LCI=−0.0514; UCI=−0.0212)	Perceived empathy——————> Perceived integrity ——————> Consumer forgiveness	(θ = 0.0305; LCI=0.0154; UCI=0.0457)	Perceived empathy——————> Perceived integrity ——————> nWOM	(θ = −0.0365; LCI=−0.0529; UCI=−0.0201)

Finally, to test hypothesis six, we employed a strategy similar to Study 1, i.e., Hayes's (2018) mediation procedure with a bootstrapping resample value 5000. We present the results of the mediation analyses in Table 8.

The estimated path coefficient for the indirect effect of perceived privacy concerns on consumer forgiveness through perceived ability (Column 1 of Table 8) was statistically significant (θ = −0.0089; LCI=−0.0122; UCI=−0.0056). Also, the estimated path coefficient for the indirect effect of perceived privacy concerns on nWOM through perceived ability (Column 2 of Table 8) was statistically significant (θ = 0.0092; LCI=0.0044; UCI=0.0140).

From Column 3 of Table 8, we observe that the estimated path coefficients for the indirect effects of chatbot anthropomorphism through perceived ability (θ = 0.0125; LCI=0.0062; UCI=0.0188), perceived benevolence (θ = 0.0208; LCI=0.0124; UCI=0.0292), and perceived integrity (θ = 0.0298; LCI=0.0204; UCI=0.0392) on consumer forgiveness were statistically significant. Also, in Column 4 of Table 8, we observe that the estimated path coefficients for the indirect effects of anthropomorphism through perceived ability (θ = −0.0127; LCI=−0.0178; UCI=−0.0076), perceived benevolence (θ = −0.0175; LCI=−0.0246; UCI=−0.0104), and perceived integrity (θ = −0.0352; LCI=−0.0481; UCI=−0.0223) on nWOM were statistically significant.

Finally, in Column 5 of Table 8, we observe that the estimated path coefficients for the indirect effects of perceived empathy through perceived ability (θ = 0.0193; LCI=0.0107; UCI=0.0279), perceived benevolence (θ = 0.0261; LCI=0.0169; UCI=0.0353), and perceived integrity (θ = 0.0292; LCI=0.0190; UCI=0.0394) on consumer forgiveness were statistically significant. Similarly, in Column 6 of Table 8, we observe that the estimated path coefficients for the indirect effects of perceived empathy through perceived ability (θ = −0.0175;

Table 6
Study 2- Correlation matrix and descriptive statistics.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Consumer forgiveness	1												
2	nWOM	-0.41	1											
3	Perceived privacy concerns	-0.15	0.24	1										
4	Anthropomorphism	0.25	-0.17	-0.21	1									
5	Perceived empathy	0.20	-0.14	-0.10	0.16	1								
6	Perceived ability	0.24	-0.23	-0.23	0.22	0.32	1							
7	Perceived benevolence	0.21	-0.25	-0.09	0.25	0.26	0.39	1						
8	Perceived integrity	0.27	-0.22	-0.08	0.34	0.27	0.44	0.49	1					
9	Ln Age	0.17	-0.20	0.13	0.1	0.24	0.09	0.06	0.12	1				
10	Gender	0.18	-0.16	0.15	0.06	0.08	0.02	0.08	0.07	0.02	1			
11	Education	0.09	-0.18	0.13	0.09	0.11	0.07	0.04	0.03	0.06	0.07	1		
12	Dispositional anger	-0.22	0.21	0.09	0.06	0.13	- 0.12	- 0.07	-0.05	-0.07	-0.04	-0.13	1	
13	Dispositional compassion	0.26	-0.25	0.11	0.08	0.16	0.11	0.12	0.08	0.11	0.05	0.14	-0.23	1
	Mean	5.71	5.94	5.78	5.34	5.06	5.19	5.61	4.91	3.35	0.51	0.62	4.51	4.62
	S.D.	1.29	1.02	1.41	0.84	1.12	0.92	1.12	1.07	2.70	0.47	0.39	1.03	1.13

* **r > 0.15, p < 0.001; * *r = 0.12–0.14, p < 0.01, *r = 0.088–0.11, p < 0.05; #, r = 0.075–0.087, p < 0.10

Table 7
Study 2- Convergent and Discriminant Validity.

		Convergent Validity		Discriminant Validity							
Constructs	Cronbach's Alpha	Composite Reliability	AVE	*Consumer forgiveness*	*nWOM*	*Perceived privacy concerns*	*Anthropomorphism*	*Perceived empathy*	*Perceived ability*	*Perceived benevolence*	*Perceived integrity*
Consumer forgiveness	0.86	0.92	0.53	0.73							
nWOM	0.89	0.91	0.64	-0.41	0.80						
Perceived privacy concerns	0.8	0.83	0.62	-0.15	0.24	0.79					
Anthropomorphism	0.87	0.93	0.78	0.25	-0.17	-0.21	0.88				
Perceived empathy	0.79	0.86	0.56	0.20	-0.14	-0.10	0.16	0.75			
Perceived ability	0.85	0.9	0.7	0.24	-0.23	-0.23	0.22	0.32	0.84		
Perceived benevolence	0.84	0.86	0.61	0.21	-0.25	-0.09	0.25	0.26	0.39	0.78	
Perceived integrity	0.87	0.91	0.72	0.27	-0.22	-0.08	0.34	0.27	0.44	0.49	0.85

Note: *Italic values are square root of AVE

Table 8
Study 2- Indirect Effects Mediation Models.

Indirect effect	1	Indirect effect	2	Indirect effects	3
Perceived privacy concerns————— > Perceived ability ————— > Consumer forgiveness	(θ = −0.0089; LCI=−0.0122; UCI=−0.0056)	Perceived privacy concerns————— > Perceived ability ————— > nWOM	(θ = 0.0092; LCI=0.0044; UCI=0.0140)	Anthropomorphism————— > Perceived ability ————— > Consumer forgiveness	(θ = 0.0125; LCI=0.0062; UCI=0.0188)
				Anthropomorphism————— > Perceived benevolence ————— > Consumer forgiveness	(θ = 0.0208; LCI=0.0124; UCI=0.0292)
				Anthropomorphism————— > Perceived integrity ————— > Consumer forgiveness	(θ = 0.0298; LCI=0.0204; UCI=0.0392)

Indirect effect	**4**	Indirect effects	**5**	Indirect effects	**6**
Anthropomorphism————— > Perceived ability ————— > nWOM	(θ = −0.0127; LCI=−0.0178; UCI=−0.0076)	Perceived empathy————— > Perceived ability ————— > Consumer forgiveness	(θ = 0.0193; LCI=0.0107; UCI=0.0279)	Perceived empathy————— > Perceived ability ————— > nWOM	(θ = −0.0175; LCI=−0.0269; UCI=−0.0081)
Anthropomorphism ————— > Perceived benevolence ————— > nWOM	(θ = −0.0175; LCI=−0.0246; UCI=−0.0104)	Perceived empathy————— > Perceived benevolence ————— > Consumer forgiveness	(θ = 0.0261; LCI=0.0169; UCI=0.0353)	Perceived empathy————— > Perceived benevolence ————— > nWOM	(θ = −0.0220; LCI=−0.0329; UCI=−0.0111)
Anthropomorphism————— > Perceived integrity ————— > nWOM	(θ = −0.0352; LCI=−0.0481; UCI=−0.0223)	Perceived empathy————— > Perceived integrity ————— > Consumer forgiveness	(θ = 0.0292; LCI=0.0190; UCI=0.0394)	Perceived empathy————— > Perceived integrity ————— > nWOM	(θ = −0.0352; LCI=−0.0494; UCI=−0.0210)

LCI=−0.0269; UCI=−0.0081), perceived benevolence (θ = −0.0220; LCI=−0.0329; UCI=−0.0111), and perceived integrity (θ = −0.0352; LCI=−0.0494; UCI=−0.0210) on nWOM were statistically significant.

5.2. Discussion

Similar to Study 1, we received evidence in support of all but one hypothesis, i.e., hypothesis 1. For the first hypothesis, we received only partial evidence supporting our hypothesis as perceived privacy concern influenced only perceived ability and not benevolence and integrity of the chatbot to influence consumer forgiveness and spread negative word of mouth.

5.3. Robustness

As a matter of robustness, we conducted another study (n = 201; Females=103; Median Income= £34,300; Median Age= 32.00 years) in the context of airline booking. We followed the same procedures as the main study. Further, we re-ran the same models and tested hypotheses 1–6. Although the path coefficients changed, the overall statistical significance of the results remained unchanged. In Appendix 2.1 and 2.2, we present the robustness test results.

We also conducted another study (n = 212; Females=208; Median Income= £31,700; Median Age= 29.30 years) in the e-retailing industry where service recovery efforts failed, i.e., the chatbot could not resolve the issue. Though path coefficients changed, results were statistically significant, i.e., traits of chatbot still influenced trustworthiness dimensions in a statistically significant manner, which then enhanced consumer propensity to forgive and reduced intention to spread nWOM. In Appendix 3.1 and 3.2, we present the robustness test results.

6. Qualitative study

For emerging topics like chatbots, where only scant literature explores their effectiveness in service failure-recovery interface, a mixed-methods approach has the benefits of qualitative and quantitative research designs (Venkatesh et al., 2016). Although we drew constructs and relationships between them based on extant literature, it was vital to verify if our constructs and empirically tested relationships corroborated with consumers' perceptions of chatbots in the context of service failure and recovery (Cheng et al., 2020). Consequently, we conducted a qualitative study as well.

6.1. Data and method

We used a convenience sampling procedure to recruit interviewees through the social media platform. The users were filtered based on the following two criteria: a) they had a problem with services offered by an e-retailer in the past three months, and b) when they tried to contact the company, the issue was addressed by a chatbot. Based on these criteria, 29 social media users were found suitable for the study and invited for an interview. Nine social media users did not respond to our invitation. We interviewed 18 UK-based participants (Females=10; Median Age= 27 years; Average interview length=23 mins). Sample questions included: a) if they have ever incurred a chance to interact with chatbots after service was not delivered up to their expectations, b) what attributes they liked about the chatbot, and c) were they happy with the way chatbot attempted to resolve the issue.

We took several measures to avert the risk of any information bias (Chenail, 2011). *First*, we trained interviewers (two postgraduate researchers from a UK university) to remain acquiescent to interviewees' answers, and when they received any novel opinion, the interviewers asked new questions accordingly. *Second*, we also promised interviewees that their responses would remain anonymous and that information would be kept confidential (Chenail, 2011). The interviewers recorded the interviews, and we employed the services of a professional transcriber to transcribe the qualitative data for further analysis. Below we discuss some excerpts of interviews that corroborated our findings on traits of chatbots resulting in consumer forgiveness and less nWOM via the three dimensions of trustworthiness.

6.2. Results

Perceived empathy (benevolence): "I warned my friend not to order anything from …store. When I did not receive my delivery though the order status showed- "Item Delivered," I contacted the company. It was a text-based conversation with a chatbot. When I complained about the problem, I was shocked to notice there were no apologies. The chatbot's response was to check after two days. What went wrong? Why it went wrong? Is it just a technical glitch? Nothing was explained to me" (Gender=Female; Age=32 years).

Perceived empathy (ability): "I don't think the chatbot understood my concern. The product I received was damaged. The chatbot said: "It is a non-returnable item; check policy." I wanted a replacement, and the chatbot did not understand my concern. I have never observed such a cold response from a chat agent. This behavior is difficult to forget and unforgivable" (Gender=Male; Age=25 years).

Perceived empathy (integrity): "I liked the chatbot's honesty, where it acknowledged the problem and mentioned delivery driver shortage as the reason for the undue delay in my delivery, rather than repeatedly changing my delivery dates. Mistakes happen! That is ok! I encourage my friends also to order from this e-retailer" (Gender=Male; Age=29 years).

Anthropomorphism (ability): "It was clearly a chatbot with whom I was conversing. Nevertheless, I liked the fact that it resembled a human. Though I knew it was not human, I felt confident about the bot's competency to solve my problem, just like a human agent" (Gender=Female; Age=31 years).

Anthropomorphism (benevolence): "The chatbot looked at me during the entire chat period. I felt it was dedicated to helping me with the wrong delivery I received. I liked the compassionate behavior and decided not bad mouthing the retailer. After all, mistakes happen!" (Gender=Female; Age=27 years).

Anthropomorphism (integrity): "When the chatbot looked at me while issuing a new delivery date, I felt the chatbot is less likely to be making false promises and is being honest. Though unsure if I would get my delivery at the revised time, I still felt like believing the chatbot and less angry after receiving the revised date" (Gender=Male; Age=26 years).

Perceived privacy concern (benevolence): "My friend told me that chatbots analyze every text detail we write while chatting. When the chatbot asked about my concern, it appeared more of spying and less of concern for my problem—not forgiving this attitude" (Gender=Female; Age=34 years).

Perceived privacy concern (ability): "When I conversed with the chatbot, I informed it about the product I was experiencing a problem with and wanted a refund. While issuing the refund, the chatbot asked if it should refund to my card. How did the chatbot know I paid with which card? Did it know my card number and other details? I am curious if my financial information is safe with this company. I am neither returning to the company which makes chatbots store my financial data nor encouraging my friends for the same. Anyways too many cyber threats these days!" (Gender= Male; Age=29 years).

Perceived privacy concern (integrity): "It was strange when the chatbot asked me if I had also lost a package earlier. How is that closely related to the issue of the package I lost this time? The status shows delivered, but actually, it was not delivered. Moreover, companies do have information on such aspects in their database. Not sure if the chatbot was interrogating me or was honestly trying to help me with my lost package. I have never ordered from that retailer since this incident, and neither have my friends based on my experience" (Gender= Female; Age=27 years).

6.3. Discussion

As can be observed from the interview excerpts, consumers emphasized how different traits of chatbots they had previous experience with influenced their willingness to forgive the firm and not spread negative word of mouth against the firm. For instance, when a chatbot asked if a customer had lost a package in the past, it made the customer believe the chatbot to be less integral. This happened as customers thought about how the past package failure delivery is associated with current service failure and made them doubt the intentions of the chatbot if it was there really to help. While appearing like humans, anthropomorphic chatbots increased customer willingness to trust the chatbot when it issued a new delivery date. Thus, qualitative findings also corroborate our empirical model. Thus, perceived empathy, anthropomorphism, and privacy concerns with chatbots influence different dimensions of their trustworthiness that affects the willingness of consumers to forgive the firm and not spread negative word of mouth.

7. General discussion

Across two studies covering utilitarian and hedonic product categories, we hypothesized the relationships between traits of chatbots (perceived privacy concerns, empathy, and anthropomorphic appearance) that enhanced chatbots' perceived trustworthiness (i.e., ability, integrity, and benevolence). We further hypothesized about the mediating role of these dimensions of trustworthiness on consumer willingness to forgive the firm and spread nWOM. Overall, we received evidence supporting most hypotheses excluding H1b and H1c, i.e., the influence of perceived privacy concerns on chatbots' perceived benevolence and integrity. The results remained consistent across both utilitarian and hedonic product categories. Thus, consumers' perception of chatbots' traits required in helping service recovery did not vary across product categories. Our findings regarding product categories align with extant research, where negative word of mouth did not vary across hedonic versus utilitarian product categories (Jin et al., 2023).

Our findings regarding the perceived empathy of chatbots and its influence on the perceived ability of chatbots to help with service recovery imply that even if chatbots are machines with no emotions, they can still exert similar types of social influence as humans with the choice of words and phrases they use during service recovery efforts. These words' choices can make chatbots perceived as able to solve customer problems through service recovery. Similarly, perceived empathy also increased the benevolence and integrity of empathetic chatbots.

The second subset of the third hypothesis suggested that the perceived empathy of chatbots enhances the perceived benevolence of chatbots. The path coefficient was positive and statistically significant. Thus, the perceived empathy of chatbots made them appear more benevolent to customers. Thus, the linguistic attributes of chatbots did influence the level to which they were perceived to have honest intentions of trying to resolve customers' issues.

For anthropomorphic chatbots also, our findings suggest that human-like appearance made consumers perceive chatbots as more integral, able, and benevolent. The findings are in congruence with CASA theory, where humans could also perceive machines as social agents, and anthropomorphism is likely to increase this social attribute of chatbots.

Information systems and marketing fields (Luo et al., 2019; Murtarelli et al., 2021) have shown an increasing interest in exploring the effectiveness of AI-based chatbots in improving service quality. Our findings are consistent with past service marketing literature that suggested customers are more likely to forgive a firm for service failure if the firm's perceived trustworthiness is high (Gannon et al., 2022; Xie & Peng, 2008). The present study's findings also corroborate previous findings on the significance of text messages that successfully generated customer forgiveness after a service failure. Li and Wang (2023) reported that when customer representatives conversed with customers on social media and their communication styles depicted empathy, the same generated customer forgiveness. Text-based empathy can help consumers gauge if a service provider is concerned about their affective state of mind when the customers do not receive service up to their expectations (Froehle, 2006). Our findings also suggest that if chatbots could leverage the same text-based communication principles, even they could, similar to humans, successfully generate forgiveness from consumers.

Our findings do not corroborate with studies in the service delivery context that reported anthropomorphic agents to have increased customers' perception of requiring extra effort to condescend with artificial agents (Ackerman, 2016). This happened because Ackerman's (2016) study's underlying mechanism differed from the present study. The human-like appearance of AI devices increased consumers' discomfort with AI due to beliefs of humans losing their unique identity to humanoids (Ackerman, 2016; Gursoy et al., 2019). Given that consumers' response to AI agents like chatbots depends on the context when service failure occurs, in the context of our study, consumers would prefer to perceive interacting agents as close to humans as possible, given human competency and ability to resolve problems (Teodorescu et al., 2021).

Furthermore, extant research in service recovery suggests that chatbot acceptance depends on the type of service failure, such as process vs. functional failure (Xing et al., 2022), giving customers a choice to interact with chatbot vs. humans (Huang & Dootson, 2022). Our findings shine a light on the traits of chatbots themselves rather than other attributes of service failure. Within the role of chatbots, our findings do not agree with the findings of Mozafari et al. (2021), who suggested that chatbot disclosure reduced consumer satisfaction with service recovery efforts due to reduced trust. However, the reason for reduced trust was failure caused by the chat agent or severe criticality of service failure. We tested our model for service failure caused by a company, such as late delivery. During the robustness test, our model stood well when we tested the double service failure model, where the chatbot could not resolve the issue. The difference may arise as we explore trustworthiness and not trust. As explained in the theory section, the difference between the two may result in different customer outcomes.

7.1. Theoretical contributions

By exploring the human-like traits of chatbots, we contribute to information systems and marketing literature. *First*, the present study leveraging CASA theory enhances understanding of how customers communicate with and experience quiescent agents like chatbots. In the online scenario, chatbots could emulate human behavior and persuade customers about their interactivity with humans (Blut et al., 2021). Brands can make chatbots achieve this imitation by making chatbots anthropomorphic, i.e., where customers perceive service chatbots as resembling humans. While researchers have found anthropomorphism to enhance product and brand liking in the marketing literature (Blut et al., 2021), we have limited knowledge of whether the anthropomorphism of chatbots in a service failure context can influence consumer decision to forgive the firm for service failure, once chatbots introduce recovery efforts. We thus extend the anthropomorphism literature of marketing to the information systems literature on AI-driven chatbots.

Second, we also shine a light on the limitations of CASA theory, where even after perceiving chatbots as social agents owing to their anthropomorphic appearance and empathetic communication, consumers are also aware that they will lose control over information if shared with chatbots, and this concern with privacy of information decreases trustworthiness of chatbots in the context of service failure. Although extant studies suggest that anthropomorphic chatbots could reduce privacy concerns, such concerns do remain and could adversely influence service recovery efforts through chatbots (Ischen et al., 2020).

Third, we examine the mediating mechanisms between service chatbot traits and customer willingness to forgive and reduce nWOM in a service failure context. Considering mediators is significant as it assists

January 2, 2022
- 7:34
I am Russell. Tuple.com's chatbot. I keep a record of this conversation to allow me to keep improving the customer experience.
You can read our Privacy Notice for more details.
Connected with Russell (Chatbot)


Russell
- 7:34

Hello Customer. I'm Russell. Let me know how I can help you today!

You
-7:35
On December 5, 2021, I ordered two packs of Bambooee Tissue Toilet Rolls. Each pack contains six toilet rolls. Before placing the order, Tuple's website showed me that the delivery date would be December 16, 2021. It has been more than two weeks since the delivery date, and I have yet to receive the ordered items.


Russell
- 7:37

I am very sorry to know this!
I will try to help you in the best possible way. To proceed further, can you let me know, the Order Number?

You
-7:38
ORDER # 203-5359585-1433955


Russell
- 7:38

Thank you for providing the Order Number.
Let me quickly check this for you. Allow me a minute.

You
-7:39
Ok


Russell
- 7:40

Thank you for your patience. We had a technical difficulty in the last month, and this has interfered with the ordering system. Your order will be delivered by 4.00 pm on January 3, 2022. Please let me know if you prefer this delivery date or wish to cancel the order for a full refund.

You
-7:41
I am okay to receive the order by 3rd January 2022.


Russell
- 7:41

Thank you for understanding. I have now initiated the process to make the delivery by 4.00 pm on January 3, 2022.
Is there anything else I can help you with today?

You
-7:42
No, Thank you! That was all!


Russell
- 7:42

Have a good day!

End of chat
- 7:42

April 15, 2023
- 7:34
I am Russell. Tuple.com's chatbot. I keep a record of this conversation to allow me to keep improving the customer experience.
You can read our Privacy Notice for more details.
Connected with Russell (Chatbot)

Russell
- 7:34

Hello Customer. I'm Russell. Let me know how I can help you today!

You
-7:35
On March 17, 2023, I ordered Earvana earphones. Before placing the order, Tuple's website showed me that the delivery date would be Mach 28, 2023. It has been more than two weeks since the delivery date, and I have yet to receive the ordered items.

Russell
- 7:37

I am very sorry to know this!
I will try to help you in the best possible way. To proceed further, can you let me know, the Order Number?

You
-7:38
ORDER # 203-5359585-1433955

Russell
- 7:38

Thank you for providing the Order Number.
Let me quickly check this for you. Allow me a minute.

You
-7:39
Ok

Russell
- 7:40

Thank you for your patience. We had a technical difficulty in the last month, and this has interfered with the ordering system. Your order will be delivered by 4.00 pm on April 16, 2023. Please let me know if you prefer this delivery date or wish to cancel the order for a full refund.

You
-7:41
I am okay to receive the order by 16th April 2023.

Russell
- 7:41

Thank you for understanding. Is there anything else I can help you with today?

You
-7:42
No, Thank you! That was all!

Russell
- 7:42

Have a good day!

End of chat
- 7:42

scholars in avoiding overestimating or underestimating the significance of technology traits (Iyer et al., 2020; Tsai et al., 2021). The literature does not explore in detail the role of mediators. Where one stream of literature in marketing explores relational mediators, such as trust and satisfaction (Verma et al., 2016), another stream considers technology attributes from information systems literature. However, some studies do not consider mediators (Wirtz et al., 2018). We add to these underlying mechanisms of chatbot literature by exploring the role of their trustworthiness.

Fourth, marketing literature suggests several strategies to respond to service failure for effective customer emotion management through actions such as quick acts by management (Tax & Brown, 1998), rendering explanation (Liao, 2007), fair reception (Maxham & Netemeyer, 2002), effective complaint management procedures (Smith et al., 1999), and empowering employees to make decisions (Tax & Brown, 1998). However, the role of AI in SFR efforts is only scantly known. For consumer outcomes also, while extant studies have explored customer coping methods following service failure (Bose & Ye, 2015; Chen et al., 2021; Duhachek, 2005; Gelbrich, 2010), consumer forgiveness as a coping strategy has not been explored in-depth in the service settings, especially not in human-technology interface literature (Tsarenko & Tojib, 2011).

7.2. Implications for practice

Understanding the antecedents of chatbot trustworthiness and its influence on consumer forgiveness for service failure can help marketers and programmers adjust the chatbot systems' design. According to Invesp, a North American consulting firm specializing in conversion rate optimization, word-of-mouth marketing impacts USD 6 trillion of annual consumer spending. Thirteen percent of consumer spending decisions depend on feedback consumers get about service providers (O'Neill, 2022). In this context, nWOM can be detrimental to the business. Service failure increases the chances of nWOM. Our model helps managers to limit the chances of nWOM after the occurrence of service failure. Managers have primarily believed that consumer willingness to forgive or not after service failure depends on the personality traits of a consumer, such as how empathetic they are (Wei et al., 2022) or their spirituality (Tsarenko & Tojib, 2012), among other personality traits. However, our findings suggest consumer forgiveness depends on managers' trustworthy actions. Thus, firms using chatbots need to ensure that customers perceive these chatbots to be trustworthy. Once customers consider chatbots trustworthy as they make service recovery efforts, they are less likely to spread nWOM against the company and more willing to forgive it.

Firms must design text-based chatbots that can converse effectively through text and depict empathy even through nonverbal modes. Chatbots must use expressions like "I am very sorry to know this!" Nelson Mandela once said, "If you talk to a man in a language he understands, that goes to his head. If you talk to him in his language, that goes to his heart." Humans generally use exclamatory marks to reflect empathy. If a firm intends for customers to forgive them for service failure, it must follow human-based communication principles while deploying chatbots. Thus, words like "I am sorry" or linguistic style leveraging exclamations can make chatbots mimic human-like conversations. Thus, when chatbots, through texts, signal that they are being empathetic about customer loss incurred due to service failure, the customer's propensity to forgive the firm is likely to increase.

Our study also found that the anthropomorphic appearance of chatbots enhanced customers' likelihood to forgive the firm and lowered the probability of spreading nWOM against the company. This happened as human-like appearance enabled consumers to perceive chatbots as possessing human-like qualities. Although consumers' propensity to converse with human-like or machine-like agents varies with context, when service failure occurs, consumers display a proclivity to share their concerns with humans. Interacting with machine-like agents may increase skepticism among consumers regarding the ability of chatbots to resolve issues as efficiently as humans can. As our study suggests, anthropomorphism increases consumers' aptness to trust a chatbot for its service recovery efforts. Thus, firms should consider adopting anthropomorphic chatbots.

Overall, our findings affect how service providers and marketers should design customer service chatbots. The critical determinant of users' perceived trustworthiness of chatbots for forgiveness and reduced nWOM after service failures is the humanness of chatbots and their empathetic attitude apart from perceived security. By exploring traits of chatbots in computer-mediated communication, we suggest that chatbots must show empathy toward customers when they are text-based and make customers realize how the firm acknowledges the suffering or pain customer might have gone through when service delivery failed. Similarly, chatbots should depict anthropomorphic traits with human-like appearance. To reduce perceived risk and security concerns, firms should reduce their system vulnerabilities so that an attacker does not exploit them.

Finally, firms should try to make their data usage policy more explicit to customers so that consumers are aware of how their data can be used and feel more comfortable in sharing their personal details, purchase and payment histories, etc., in case of service failure (R. Hasan et al., 2021; M.K. Hasan et al., 2021).

7.3. Limitations and directions for future research

We did not consider any contingency conditions under whose impact the effect of chatbot traits on trustworthiness or consumer forgiveness could be attenuated or reduced. Future studies may also benefit from cross-cultural comparisons for chatbot traits. Mechanically intelligent chatbots, such as call center agents, can provide scripted responses to simple customer issues. Analytically intelligent AI-driven chatbots analyze customer problems (Huang & Rust, 2018), and intuitively intelligent AI-driven chatbots can understand customers' complaints, i.e., can understand human emotions (Huang & Rust, 2018). Thus, AI-driven chatbots are of multiple types, exhibit several aspects of human intelligence, and firms increasingly employ them in consumer service (Hwang et al., 2019). Their traits for trustworthiness may vary, and future research could explore this aspect. In the present study, we do not effectively answer the question of what traits of AI-driven chatbots can help in service recovery after a service failure is caused by AI (Lu et al., 2020), and research may explore this further in future research.

We also considered a service failure scenario where service recovery efforts were successful, i.e., the chatbot could resolve the query (in robustness study 2). However, double service failure is also possible, i.e., where a chatbot cannot resolve the query (Zou & Migacz, 2022). Though we consider this scenario in a robustness test, future studies could explore the issue in detail.

In our theorization, we explain that trustworthiness rests on consumers' perception of efforts taken by the agent to resolve the issue rather than the actual resolution. So even if service recovery efforts fail, the chatbot's trustworthiness in terms of benevolence and integrity, and ability should not change, and our robustness study reports the same. However, a detailed theoretical and empirical investigation would be beneficial.

Finally, we considered a mixed-method approach in the present study. However, a single case study for service failure and recovery leveraging a grounded theory approach to uncover the role of chatbots in service recovery could also be helpful, as it gives a detailed version of an individual's experience.

8. Conclusion

To conclude the study, as predicted by CASA theory, chatbots can be effective in conducting service recovery efforts both across utilitarian and hedonic product categories. If chatbots are anthropomorphic,

empathetic and pose less privacy concerns, then these attributes of chatbots make them appear trustworthy through increased perceived ability, benevolence and integrity. The perceived trustworthiness of chatbots then increases consumers propensity to forgive the firm for service failure, and also spread negative word of mouth.

CRediT authorship contribution statement

Arpita Agnihotri: Conceptualization, Writing – original draft, Investigation, Formal analysis, Writing – review & editing, Supervision, **Saurabh Bhattacharya**: Methodology, Software, Validation, Data curation, Formal analysis, Visualization, Investigation, Supervision, Writing – review & editing.

Declaration of Competing Interest

None.

Appendix 1.1. : Study 1- Service Failure Recovery Scenario

Appendix section here.

Appendix 1.2. : Study 1- Service Failure Recovery Scenario

Appendix section here.

Appendix 2.1. : Robustness Study 1- Path Coefficients

Appendix section here.

	Hypothesized relationship	**Estimate**	t-value	**Conclusion**
H1	Perceived privacy concerns ——————— > Perceived ability	-0.121 * **	-3.75	Partially supported
	Perceived privacy concerns ——————— > Perceived benevolence	-0.005	-1.48	
	Perceived privacy concerns ——————— > Perceived integrity	-0.106	-1.24	
H2	Anthropomorphism ——————— > Perceived ability	0.132 * **	3.56	Supported
	Anthropomorphism ——————— > Perceived benevolence	0.124 * **	3.95	
	Anthropomorphism ——————— > Perceived integrity	0.141 * **	4.01	
H3	Perceived empathy ——————— > Perceived ability	0.155 * **	3.78	Supported
	Perceived empathy ——————— > Perceived benevolence	0.137 * **	4.05	
	Perceived empathy ——————— > Perceived integrity	0.154 * **	3.98	
H4	Perceived ability ——————— > Consumer forgiveness	0.102 * **	3.55	Supported
	Perceived benevolence ——————— > Consumer forgiveness	0.102 * **	4.26	
	Perceived integrity ——————— > Consumer forgiveness	0.144 * **	4.13	
H5	Perceived ability ——————— > nWOM	-0.083 * **	-4.25	
	Perceived benevolence ——————— > nWOM	-0.103 * **	-3.64	Supported
	Perceived integrity ——————— > nWOM	-0.215 * **	-3.59	

Appendix 2.2. : Robustness Study 1- Indirect Effects Mediation Models

Appendix section here.

Indirect effect	**1**	Indirect effect	**2**	Indirect effects	**3**
Perceived privacy concerns————— > Perceived ability ————— > Consumer forgiveness	(θ = −0.0123; LCI=−0.0157; UCI=−0.0089)	Perceived privacy concerns————— > Perceived ability ————— > nWOM	(θ = 0.0100; LCI=0.0038; UCI=0.0162)	Anthropomorphism————— > Perceived ability ————— > Consumer forgiveness	(θ = 0.0134; LCI=0.0066; UCI=0.0202)
				Anthropomorphism————— > Perceived benevolence ————— > Consumer forgiveness	(θ = 0.0126; LCI=0.0067; UCI=0.0185)
				Anthropomorphism————— > Perceived integrity ————— > Consumer forgiveness	(θ = 0.0203; LCI=0.0110; UCI=0.0296)

Indirect effect	**4**	Indirect effects	**5**	Indirect effects	**6**
Anthropomorphism————— > Perceived ability ————— > nWOM	θ = −0.0109; LCI= −0.0166; UCI= −0.0052)	Perceived empathy————— > Perceived ability ————— > Consumer forgiveness	(θ = 0.0158; LCI=0.0086; UCI=0.0231)	Perceived empathy————— > Perceived ability ————— > nWOM	(θ = −0.0128; LCI=−0.0187; UCI=−0.0069)
Anthropomorphism ————— > Perceived benevolence ————— > nWOM	(θ = −0.0127; LCI=−0.0207; UCI=−0.0047)	Perceived empathy————— > Perceived benevolence ————— > Consumer forgiveness	(θ = 0.0139; LCI=0.0051; UCI=0.0227)	Perceived empathy————— > Perceived benevolence ————— > nWOM	(θ = −0.0141; LCI=−0.0202; UCI=−0.0080)

(*continued on next page*)

(*continued*)

Indirect effect	4	Indirect effects	5	Indirect effects	6
Anthropomorphism————— > Perceived integrity ————— > nWOM	(θ = −0.0303; LCI=−0.0422; UCI=−0.0184)	Perceived empathy————— > Perceived integrity ————— > Consumer forgiveness	(θ = 0.0221; LCI=0.0097; UCI=0.0345	Perceived empathy————— > Perceived integrity ————— > nWOM	(θ = −0.0331; LCI=−0.0493; UCI=−0.0169)

Appendix 3.1. : Robustness Study 2- Path Coefficients

Appendix section here.

	Hypothesized relationship	Estimate	t-value	Conclusion
H1	**Perceived privacy concerns ————————— > Perceived ability**	**-0.119 * ****	**-3.99**	**Partially supported**
	Perceived privacy concerns ————————— > Perceived benevolence	**-0.018**	**-1.06**	
	Perceived privacy concerns ————————— > Perceived integrity	**-0.097**	**-1.19**	
H2	**Anthropomorphism ————————— > Perceived ability**	**0.147 * ****	**4.04**	**Supported**
	Anthropomorphism ————————— > Perceived benevolence	**0.106 * ****	**3.71**	
	Anthropomorphism ————————— > Perceived integrity	**0.139 * ****	**3.59**	
H3	**Perceived empathy ————————— > Perceived ability**	**0.111 * ****	**3.54**	**Supported**
	Perceived empathy ————————— > Perceived benevolence	**0.132 * ****	**3.81**	
	Perceived empathy ————————— > Perceived integrity	**0.118 * ****	**3.64**	
H4	**Perceived ability ————————— > Consumer forgiveness**	**0.126 * ****	**3.77**	**Supported**
	Perceived benevolence ————————— > Consumer forgiveness	**0.122 * ****	**3.71**	
	Perceived integrity ————————— > Consumer forgiveness	**0.102 * ****	**3.62**	
H5	**Perceived ability ————————— > nWOM**	**-0.091 * ****	**-3.82**	
	Perceived benevolence ————————— > nWOM	**-0.075 * ****	**-3.66**	**Supported**
	Perceived integrity ————————— > nWOM	**-0.158 * ****	**-3.94**	

Appendix 3.2. : Robustness Study 2- Indirect Effects Mediation Models

Appendix section here.

Indirect effect	1	Indirect effect	2	Indirect effects	3
Perceived privacy concerns————— > Perceived ability ————— > Consumer forgiveness	(θ = - 0.0149; LCI=−0.0210; UCI=−0.0088)	Perceived privacy concerns————— > Perceived ability ————— > nWOM	(θ = 0.0108; LCI=0.0055; UCI=0.0161)	Anthropomorphism————— > Perceived ability ————— > Consumer forgiveness	(θ = 0.0185; LCI=0.0089; UCI=0.0281)
				Anthropomorphism————— > Perceived benevolence ————— > Consumer forgiveness	θ = 0.0129; LCI= 0.0071; UCI= 0.0187)
				Anthropomorphism————— > Perceived integrity ————— > Consumer forgiveness	(θ = 0.0141; LCI=0.0075; UCI=0.0208)

Indirect effect	4	Indirect effects	5	Indirect effects	6
Anthropomorphism————— > Perceived ability ————— > nWOM	θ = - 0.0133; LCI= −0.0185; UCI= −0.0081)	Perceived empathy————— > Perceived ability ————— > Consumer forgiveness	(θ = 0.0139; LCI=0.0065; UCI=0.0213)	Perceived empathy————— > Perceived ability ————— > nWOM	(θ = −0.0101; LCI=−0.0148; UCI=−0.0054)
Anthropomorphism ————— > Perceived benevolence ————— > nWOM	(θ = - 0.0079; LCI=−0.0142; UCI=−0.0016)	Perceived empathy————— > Perceived benevolence ————— > Consumer forgiveness	(θ = 0.0161; LCI=0.0059; UCI=0.0263)	Perceived empathy————— > Perceived benevolence ————— > nWOM	(θ = - 0.0099; LCI=−0.0153; UCI=−0.0045)
Anthropomorphism————— > Perceived integrity ————— > nWOM	(θ = - 0.0219; LCI=−0.0312; UCI=−0.0126)	Perceived empathy————— > Perceived integrity ————— > Consumer forgiveness	(θ = 0.0120; LCI=0.0042; UCI=0.0198)	Perceived empathy————— > Perceived integrity ————— > nWOM	(θ = - 0.0186; LCI=−0.0263; UCI=−0.0109)

References

Ackerman, E. (2016). Study: Nobody wants social robots that look like humans because they threaten our identity. *IEEE Spectrum*, 1–5.

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets, 31*, 427–445. https://doi.org/10.1007/s12525-020-00414-7

Akter, S., D'Ambra, J., & Ray, P. (2011). Trustworthiness in mHealth information services: An assessment of a hierarchical model with mediating and moderating effects using partial least squares (PLS. *Journal of the American Society for Information Science and Technology, 62*(1), 100–116. https://doi.org/10.1002/asi.21442

Al-Gahtani, S. S. (2011). Modeling the electronic transactions acceptance using an extended technology acceptance model. *Applied Computing and Informatics, 9*(1), 47–77. https://doi.org/10.1016/j.aci.2009.04.001

Ameen, N., Cheah, J. H., & Kumar, S. (2022). It's all part of the customer journey: The impact of augmented reality, chatbots, and social media on the body image and self-esteem of Generation Z female consumers. *Psychology & Marketing, 39*(11), 2110–2129. https://doi.org/10.1002/mar.21715

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior, 85*, 183–189. https://doi.org/10.1016/j.chb.2018.03.051

Asgari, P., & Roshani, K. (2013). Validation of forgiveness scale and a survey on the relationship of forgiveness and students' mental health. *International Journal of Psychology and Behavioral Research, 2*(2), 109–115.

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics, 54*, Article 101473. https://doi.org/10.1016/j.tele.2020.101473

Babin, B. J., Zhuang, W., & Borges, A. (2021). Managing service recovery experience: Effects of the forgiveness for older consumers. *Journal of Retailing and Consumer Services, 58*, Article 102222. https://doi.org/10.1016/j.jretconser.2020.102222

Baek, T. H., & Morimoto, M. (2012). Stay away from me. *Journal of Advertising, 41*(1), 59–76. https://doi.org/10.2753/JOA0091-3367410105

Baliga, A. J., Chawla, V., Ganesh, L. S., & Sivakumaran, B. (2021). Service failure and recovery in B2B markets–A morphological analysis. *Journal of Business Research, 131*, 763–781. https://doi.org/10.1016/j.jbusres.2020.09.025

Bell, C. R., & Zemke, R. E. (1987). Service breakdown: the road to recovery. *Management Review, 76*(10), 32–35.

Bickmore, T., & Schulman, D. (2007). Practical approaches to comforting users with relational agents. *CHI'07 extended abstracts on human factors in computing systems, CHI EA'07* (pp. 2291–2296). New York, NY, USA: Association for Computing Machinery.

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science, 49*(4), 632–658. https://doi.org/10.1007/s11747-020-00762-y

Bose, M., & Ye, L. (2015). A cross-cultural exploration of situated learning and coping. *Journal of Retailing and Consumer Services, 24*, 42–50. https://doi.org/10.1016/j.jretconser.2015.01.010

Brooks, A. W., Dai, H., & Schweitzer, M. E. (2014). I'm sorry about the rain! Superfluous apologies demonstrate empathic concern and increase trust. *Social Psychological and Personality Science, 5*(4), 467–474. https://doi.org/10.1177/1948550613506122

Casidy, R., & Shin, H. (2015). The effects of harm directions and service recovery strategies on customer forgiveness and negative word-of-mouth intentions. *Journal of Retailing and Consumer Services, 27*, 103–112. https://doi.org/10.1016/j.jretconser.2015.07.012

Castillo, D., Canhoto, A. I., & Said, E. (2021). The dark side of AI-powered service interactions: Exploring the process of co-destruction from the customer perspective. *The Service Industries Journal, 41*(13–14), 900–925. https://doi.org/10.1080/02642069.2020.1787993

Chen, N., Mohanty, S., Jiao, J., & Fan, X. (2021). To err is human: Tolerate humans instead of machines in service failure. *Journal of Retailing and Consumer Services, 59*, Article 102363. https://doi.org/10.1016/j.jretconser.2020.102363

Chenail, R. J. (2011). Interviewing the investigator: Strategies for addressing instrumentation and researcher bias concerns in qualitative research. *Qualitative Report, 16*(1), 255–262.

Cheng, J. W., & Mitomo, H. (2017). The underlying factors of the perceived usefulness of using smart wearable devices for disaster applications. *Telematics and Informatics, 34*(2), 528–539. https://doi.org/10.1016/j.tele.2016.09.010

Cheng, L., Craighead, C. W., Wang, Q., & Li, J. J. (2020). When is the supplier's message "loud and clear"? Mixed signals from supplier-induced disruptions and the response. *Decision Sciences, 51*(2), 216–254. https://doi.org/10.1111/deci.12412

Cheng, S. Y., White, T. B., & Chaplin, L. N. (2012). The effects of self-brand connections on responses to brand failure: A new look at the consumer–brand relationship. *Journal of Consumer Psychology, 22*(2), 280–288. https://doi.org/10.1016/j.jcps.2011.05.005

Cheng, Y., & Jiang, H. (2022). Customer–brand relationship in the era of artificial intelligence: Understanding the role of chatbot marketing efforts. *Journal of Product & Brand Management, 31*(2), 252–264. https://doi.org/10.1108/JPBM-05-2020-2907

Choi, B., & Choi, B. J. (2014). The effects of perceived service recovery justice on customer affection, loyalty, and word-of-mouth. *European Journal of Marketing, 48*(1/2), 108–131. https://doi.org/10.1108/EJM-06-2011-0299

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management, 60*, Article 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Croes, E. A., & Antheunis, M. L. (2021). Can we be friends with Mitsuku? A longitudinal study on the process of relationship formation between humans and a social chatbot. *Journal of Social and Personal Relationships, 38*(1), 279–300. https://doi.org/10.1177%2F0265407520959463.

Crolic, C., Thomaz, F., Hadi, R., & Stephen, A. T. (2022). Blame the bot: Anthropomorphism and anger in customer–chatbot interactions. *Journal of Marketing, 86*(1), 132–148. https://doi.org/10.1177/00222429211045687

Crowne, D. P., & Marlowe, D. (1960). A new scale of social desirability independent of psychopathology. *Journal of Consulting Psychology, 24*(4), 349–354. https://psycnet.apa.org/doi/10.1037/h0047358.

Dao, H. M., & Theotokis, A. (2021). Self-service technology recovery: The effect of recovery initiation and locus of responsibility. *Journal of Interactive Marketing, 54*, 25–39. https://doi.org/10.1016/j.intmar.2020.09.001

De Vellis, R. F. (1991). *Scale Development: Theory and Application*. Thousand Oaks, CA: SAGE.

DeWitt, T., & Brady, M. K. (2003). Rethinking service recovery strategies: The effect of rapport on consumer responses to service failure. *Journal of Service Research, 6*(2), 193–207. https://doi.org/10.1177%2F1094670503257048.

Dong, B., Sivakumar, K., Evans, K. R., & Zou, S. (2016). Recovering coproduced service failures: Antecedents, consequences, and moderators of locus of recovery. *Journal of Service Research, 19*(3), 291–306. https://doi.org/10.1177%2F1094670516630624.

Dörnyei, K. R., & Lunardo, R. (2021). When limited edition packages backfire: The role of emotional value, typicality and need for uniqueness. *Journal of Business Research, 137*, 233–243. https://doi.org/10.1016/j.jbusres.2021.08.037

Duhachek, A. (2005). Coping: A multidimensional, hierarchical framework of responses to stressful consumption episodes. *Journal of Consumer Research, 32*(1), 41–53. https://doi.org/10.1086/426612

Dwivedi, Y. K., & Wang, Y. (2022). Guest editorial: Artificial intelligence for B2B marketing: Challenges and opportunities. *Industrial Marketing Management, 105*, 109–113. https://doi.org/10.1016/j.indmarman.2022.06.001

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: a three-factor theory of anthropomorphism. *Psychological Review, 114*(4), 864–886. https://psycnet.apa.org/doi/10.1037/0033-295X.114.4.864.

Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: Evidence from a banking application in Turkey. *International Journal of Bank Marketing, 39*(2), 294–311. https://doi.org/10.1108/IJBM-02-2020-0056

Fan, H., Han, B., & Gao, W. (2022). Im)Balanced customer-oriented behaviors and AI chatbots' Efficiency–Flexibility performance: The moderating role of customers' rational choices. *Journal of Retailing and Consumer Services, 66*, Article 102937. https://doi.org/10.1016/j.jretconser.2022.102937

Fehr, R., Gelfand, M. J., & Nag, M. (2010). The road to forgiveness: a meta-analytic synthesis of its situational and dispositional correlates. *Psychological Bulletin, 136*(5), 894–914. https://psycnet.apa.org/doi/10.1037/a0019993.

Fetscherin, M., & Sampedro, A. (2019). Brand forgiveness. *Journal of Product & Brand Management, 28*(5), 633–652. https://doi.org/10.1108/JPBM-04-2018-1845

Fitzsimmons-Craft, E. E., Chan, W. W., Smith, A. C., Firebaugh, M. L., Fowler, L. A., Topooco, N., & Jacobson, N. C. (2022). Effectiveness of a chatbot for eating disorders prevention: A randomized clinical trial. *International Journal of Eating Disorders, 55*(3), 343–353. https://doi.org/10.1002/eat.23662

Folkman, S., & Moskowitz, J. T. (2000). Stress, positive emotion, and coping. *Current Directions in Psychological Science, 9*(4), 115–118. https://doi.org/10.1111/1467-8721.00073

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177%2F002224378101800104.

Froehle, C. M. (2006). Service personnel, technology, and their interaction in influencing customer satisfaction. *Decision Sciences, 37*(1), 5–38. https://doi.org/10.1111/j.1540-5414.2006.00108.x

Furner, C. P., Drake, J. R., Zinko, R., & Kisling, E. (2022). Online review antecedents of trust, purchase, and recommendation intention: A simulation-based experiment for hotels and AirBnBs. *Journal of Internet Commerce, 21*(1), 79–103. https://doi.org/10.1080/15332861.2020.1870342

Gambetti, E., & Giusberti, F. (2009). Dispositional anger and risk decision-making. *Mind & Society, 8*(1), 7–20. https://doi.org/10.1007/s11299-008-0052-z

Gannon, M., Taheri, B., Thompson, J., Rahimi, R., & Okumus, B. (2022). Investigating the effects of service recovery strategies on consumer forgiveness and post-trust in the food delivery sector. *International Journal of Hospitality Management, 107*, Article 103341. https://doi.org/10.1016/j.ijhm.2022.103341

Gaudine, A., & Thorne, L. (2001). Emotion and ethical decision-making in organizations. *Journal of Business Ethics, 31*, 175–187. https://doi.org/10.1023/A:1010711413444

Gelbrich, K. (2010). Anger, frustration, and helplessness after service failure: Coping strategies and effective informational support. *Journal of the Academy of Marketing Science, 38*(5), 567–585. https://doi.org/10.1007/s11747-009-0169-6

Giebelhausen, M., Robinson, S. G., Sirianni, N. J., & Brady, M. K. (2014). Touch versus tech: When technology functions as a barrier or a benefit to service encounters. *Journal of Marketing, 78*(4), 113–124. https://doi.org/10.1509%2Fjm.13.0056.

Gilchrist, K. (May 9, 2017). Chatbots expected to cut business costs by $8 billion by 2022. *CNBC*. https://www.cnbc.com/2017/05/09/chatbots-expected-to-cut-business-costs-by-8-billion-by-2022.html.

Grégoire, Y., Tripp, T. M., & Legoux, R. (2009). When customer love turns into lasting hate: The effects of relationship strength and time on customer revenge and avoidance. *Journal of Marketing, 73*(6), 18–32. https://doi.org/10.1509%2Fjmkg.73.6.18.

Grégoire Y., Van Vaerenbergh Y., Orsingher C., & Gelbrich K. (2022). CfP JSR: Smart service failure-recovery. *Journal of Service Research*. https://www.servsig.org/wordpress/2022/08/cfp-jsr-smart-service-failure-recovery/.

Gronroos, C. (1988). Service quality: The six criteria of good perceived service quality. *Review of Business, 9*(winter), 10–13.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Hallikainen, H., Hirvonen, S., & Laukkanen, T. (2020). Perceived trustworthiness in using B2B digital services. *Industrial Management & Data Systems, 120*(3), 587–607. https://doi.org/10.1108/IMDS-04-2019-0212

Harrison-Walker, L. J. (2001). E-complaining: A content analysis of an Internet complaint forum. *Journal of Services Marketing, 15*(5), 397–412. https://doi.org/10.1108/EUM0000000005657

Harrison-Walker, L. J. (2019). The critical role of customer forgiveness in successful service recovery. *Journal of Business Research, 95*, 376–391. https://doi.org/10.1016/j.jbusres.2018.07.049

Hasan, M. K., Kamil, S., Shafiq, M., Yuvaraj, S., Kumar, E. S., Vincent, R., & Nafi, N. S. (2021). An improved watermarking algorithm for robustness and imperceptibility of data protection in the perception layer of internet of things. *Pattern Recognition Letters, 152*, 283–294. https://doi.org/10.1016/j.patrec.2021.10.032

Hasan, R., Shams, R., & Rahman, M. (2021). Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri. *Journal of Business Research, 131*, 591–597. https://doi.org/10.1016/j.jbusres.2020.12.012

Haugeland, I. K. F., Følstad, A., Taylor, C., & Bjørkli, C. A. (2022). Understanding the user experience of customer service chatbots: An experimental study of chatbot interaction design. *International Journal of Human-Computer Studies, 161*, Article 102788. https://doi.org/10.1016/j.ijhcs.2022.102788

Hayes, A. F. (2018). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. New York, NY: Guilford Publications.

Hinds, J., Williams, E. J., & Joinson, A. N. (2020). "It wouldn't happen to me": Privacy concerns and perspectives following the Cambridge Analytica scandal. *International Journal of Human-Computer Studies, 143*, Article 102498. https://doi.org/10.1016/j.ijhcs.2020.102498

Ho-Dac, N. N., Carson, S. J., & Moore, W. L. (2013). The effects of positive and negative online customer reviews: do brand strength and category maturity matter. *Journal of Marketing, 77*(6), 37–53. https://doi.org/10.1509%2Fjm.11.0011.

Hoffman, K. Douglas, & Bateson, John E. G. (1997). *Essentials of Services Marketing*. TX: Dryden: Fort Worth.

Hong, I. B., & Cho, H. (2011). The impact of consumer trust on attitudinal loyalty and purchase intentions in B2C e-marketplaces: Intermediary trust vs. seller trust. *International Journal of Information Management, 31*(5), 469–479. https://doi.org/10.1016/j.ijinfomgt.2011.02.001

Huang, D. H., & Chueh, H. E. (2021). Chatbot usage intention analysis: Veterinary consultation. *Journal of Innovation & Knowledge, 6*(3), 135–144. https://doi.org/10.1016/j.jik.2020.09.002

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172. https://doi.org/10.1177%2F1094670517752459.

Huang, Y. S. S., & Dootson, P. (2022). Chatbots and service failure: When does it lead to customer aggression. *Journal of Retailing and Consumer Services, 68*, Article 103044. https://doi.org/10.1016/j.jretconser.2022.103044

Hwang, S., Kim, B., & Lee, K. (2019). A data-driven design framework for customer service chatbot (July). *International Conference on Human-Computer Interaction* (pp. 222–236). Cham: Springer, (July).

Ischen, C., Araujo, T., Voorveld, H., van Noort, G., & Smit, E. (2020). Privacy concerns in chatbot interactions. *Chatbot Research and Design: Third International Workshop, CONVERSATIONS 2019, Amsterdam, The Netherlands, November 19–20, 2019, Revised Selected Papers 3* (pp. 34–48). Springer International Publishing,.

Iyer, G. R., Blut, M., Xiao, S. H., & Grewal, D. (2020). Impulse buying: a meta-analytic review. *Journal of the Academy of Marketing Science, 48*(3), 384–404. https://doi.org/10.1007/s11747-019-00670-w

Jin, Y. H., Ueltschy Murfield, M. L., & Bock, D. E. (2023). Do as you say, or I will: Retail signal congruency in buy-online-pickup-in-store and negative word-of-mouth. *Journal of Business Logistics, 44*(1), 37–60. https://doi.org/10.1111/jbl.12322

Johnson, D. S. (2007). Achieving customer value from electronic channels through identity commitment, calculative commitment, and trust in technology. *Journal of Interactive Marketing, 21*(4), 2–22. https://doi.org/10.1002/dir.20091

Joireman, J., Grégoire, Y., & Tripp, T. M. (2016). Customer forgiveness following service failures. *Current Opinion in Psychology, 10*, 76–82. https://doi.org/10.1016/j.copsyc.2015.11.005

Jones, C. L. E., Hancock, T., Kazandjian, B., & Voorhees, C. M. (2022). Engaging the avatar: The effects of authenticity signals during chat-based service recoveries. *Journal of Business Research, 144*, 703–716. https://doi.org/10.1016/j.jbusres.2022.01.012

Karakas, F., & Sarigollu, E. (2013). The role of leadership in creating virtuous and compassionate organizations: Narratives of benevolent leadership in an Anatolian tiger. *Journal of Business Ethics, 113*, 663–678. https://doi.org/10.1007/s10551-013-1691-5

Khamitov, M., Grégoire, Y., & Suri, A. (2020). A systematic review of brand transgression, service failure recovery and product-harm crisis: integration and guiding insights. *Journal of the Academy of Marketing Science, 48*, 519–542. https://doi.org/10.1007/s11747-019-00679-1

Kim, Y., & Sundar, S. S. (2012). Anthropomorphism of computers: Is it mindful or mindless. *Computers in Human Behavior, 28*(1), 241e250. https://doi.org/10.1016/j.chb.2011.09.006

Knox, G., & Van Oest, R. (2014). Customer complaints and recovery effectiveness: a customer base approach. *Journal of Marketing, 78*, 42–57. https://doi.org/10.1509%2Fjm.12.0317.

Konya-Baumbach, E., Biller, M., & von Janda, S. (2023). Someone out there? A study on the social presence of anthropomorphized chatbots. *Computers in Human Behavior, 139*, Article 107513. https://doi.org/10.1016/j.chb.2022.107513

Kopalle, P. K., Gangwar, M., Kaplan, A., Ramachandran, D., Reinartz, W., & Rindfleisch, A. (2022). Examining artificial intelligence (AI) technologies in marketing via a global lens: Current trends and future research opportunities. *International Journal of Research in Marketing, 39*(2), 522–540. https://doi.org/10.1016/j.ijresmar.2021.11.002

Kosiba, J. P. B., Boateng, H., Okoe Amartey, A. F., Boakye, R. O., & Hinson, R. (2018). Examining customer engagement and brand loyalty in retail banking: The trustworthiness influence. *International Journal of Retail & Distribution Management, 46*(8), 764–779. https://doi.org/10.1108/IJRDM-08-2017-0163

Lankton, N. K., McKnight, D. H., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. *Journal of the Association for Information Systems, 16*(10). https://aisel.aisnet.org/jais/vol16/iss10/1.

Lauer, T., & Deng, X. (2007). Building online trust through privacy practices. *International Journal of Information Security, 6*, 323–331. https://doi.org/10.1007/s10207-007-0028-8

Lee, S., & Choi, J. (2017). Enhancing user experience with conversational agent for movie recommendation: Effects of self-disclosure and reciprocity. *International Journal of Human-Computer Studies, 103*, 1–35. https://doi.org/10.1016/j.ijhcs.2017.02.005

Li, M., & Wang, R. (2023). Chatbots in e-commerce: The effect of chatbot language style on customers' continuance usage intention and attitude toward brand. *Journal of Retailing and Consumer Services, 71*, Article 103209. https://doi.org/10.1016/j.jretconser.2022.103209

Liao, H. (2007). Do it right this time: The role of employee service recovery performance in customer-perceived justice and customer loyalty after service failures. *Journal of Applied Psychology, 92*(2), 475–489. https://doi.org/10.1037/0021-9010.92.2.475

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121. https://psycnet.apa.org/doi/10.1037/0021-9010.86.1.114.

Liu, R., Gupta, S., & Patel, P. (2021). The application of the principles of responsible AI on social media marketing for digital health. *Information Systems Frontiers Advance Online Publication*. https://doi.org/10.1007/s10796-021-10191-z

Lu, V. N., Wirtz, J., Kunz, W. H., Paluch, S., Gruber, T., Martins, A., & Patterson, P. G. (2020). Service robots, customers and service employees: what can we learn from the academic literature and where are the gaps. *Journal of Service Theory and Practice, 30*(3), 361–391. https://doi.org/10.1108/JSTP-04-2019-0088

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947. https://doi.org/10.1287/mksc.2019.1192

Lutz, C., & Tamó-Larrieux, A. (2020). The robot privacy paradox: Understanding how privacy concerns shape intentions to use social robots. *Human-Machine Communication, 1*, 87–111. https://search.informit.org/doi/10.3316/INFORMIT.097053479720281.

Machneva, M., Evans, A. M., & Stavrova, O. (2022). Consensus and (lack of) accuracy in perceptions of avatar trustworthiness. *Computers in Human Behavior, 126*, Article 107017. https://doi.org/10.1016/j.chb.2021.107017

Malhotra, N. K., Kim, S. S., & Patil, A. (2006). Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research. *Management Science, 52*(12), 1865–1883. https://doi.org/10.1287/mnsc.1060.0597

Martin, K. D., Borah, A., & Palmatier, R. W. (2017). Data privacy: Effects on customer and firm performance. *Journal of Marketing, 81*(1), 36–58. https://doi.org/10.1509/jm.15.0497

Maxham, J. G., III, & Netemeyer, R. G. (2002). A longitudinal study of complaining customers' evaluations of multiple service failures and recovery efforts. *Journal of Marketing, 66*(4), 57–71. https://doi.org/10.1509%2Fjmkg.66.4.57.18512.

McCullough, M. E., Fincham, F. D., & Tsang, J. A. (2003). Forgiveness, forbearance, and time: the temporal unfolding of transgression-related interpersonal motivations. *Journal of Personality and Social Psychology, 84*(3), 540. https://psycnet.apa.org/doi/10.1037/0022-3514.84.3.540.

McKnight, D. H. (2005). Trust in information technology. In G. B. Davis (Ed.), *The Blackwell Encyclopedia of Management* (Vol. 7, pp. 329–331). Maiden, MA: Blackwell.

Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems (TMIS), 2*(2), 1–25. https://doi.org/10.1145/1985347.1985353

Migacz, S. J., Zou, S., & Petrick, J. F. (2018). The "terminal" effects of service failure on airlines: Examining service recovery with justice theory. *Journal of Travel Research, 57*(1), 83–98. https://psycnet.apa.org/doi/10.1177/0047287516684979.

Mostafa, R. B., & Kasamani, T. (2022). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing, 56*(6), 1748–1771. https://doi.org/10.1108/EJM-02-2020-0084

Mozafari, N., Weiger, W. H., & Hammerschmidt, M. (2021). Trust me, I'm a bot–repercussions of chatbot disclosure in different service frontline settings. *Journal of Service Management, 33*(2), 221–245. https://doi.org/10.1108/JOSM-10-2020-0380

Murtarelli, G., Gregory, A., & Romenti, S. (2021). A conversation-based perspective for shaping ethical human–machine interactions: The particular challenge of chatbots. *Journal of Business Research, 129*, 927–935. https://doi.org/10.1016/j.jbusres.2020.09.018

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues, 56*(1), 81–103. https://doi.org/10.1111/0022-4537.00153

Nass, C., & Steuer, J. (1993). Voices, boxes, and sources of messages: Computers and social actors. *Human Communication Research, 19*(4), 504–527. https://doi.org/10.1111/j.1468-2958.1993.tb00311.x

Nguyen, Q. N., Sidorova, A., & Torres, R. (2022). User interactions with chatbot interfaces vs. Menu-based interfaces: An empirical study. *Computers in Human Behavior, 128*, Article 107093. https://doi.org/10.1016/j.chb.2021.107093

O'Neill, S. (April 22, 2022). Word of mouth marketing: Stats and trends for 2023. LXA. Retrieved from https://www.lxahub.com/stories/word-of-mouth-marketing-stats-and-trends-for-2023.

Park, J., & Ha, S. (2016). Co-creation of service recovery: Utilitarian and hedonic value and post-recovery responses. *Journal of Retailing and Consumer Services, 28*, 310–316. https://doi.org/10.1016/j.jretconser.2015.01.003

Park, N., Jang, K., Cho, S., & Choi, J. (2021). Use of offensive language in human-artificial intelligence chatbot interaction: The effects of ethical ideology, social competence, and perceived humanlikeness. *Computers in Human Behavior, 121*, Article 106795. https://doi.org/10.1016/j.chb.2021.106795

Pica, G., Jaume, L. C., & Pierro, A. (2022). Let's go forward, I forgive you! On motivational correlates of interpersonal forgiveness. *Current Psychology, 41*, 6786–6794. https://doi.org/10.1007/s12144-020-01180-7

Pelau, C., Dabija, D. C., & Ene, I. (2021). What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. *Computers in Human Behavior, 122*, Article 106855. https://doi.org/10.1016/j.chb.2021.106855

Plank, R. E., Minton, A. P., & Reid, D. A. (1996). A short measure of perceived empathy. *Psychological Reports, 79*(3), 1219–1226. https://doi.org/10.2466/pr0.1996.79.3f.1219

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://psycnet.apa.org/doi/10.1037/0021-9010.88.5.879.

Press, G. (November 25, 2019). AI stats news: Chatbots increase sales by 67% but 87% of consumers prefer humans. Forbes. Retrieved from https://www.forbes.com/sites/gilpress/2019/11/25/ai-stats-news-chatbots-increase-sales-by-67-but-87-of-consumers-prefer-humans/?sh=2eee137948a3.

Przegalinska, A., Ciechanowski, L., Stroz, A., Gloor, P., & Mazurek, G. (2019). In bot we trust: A new methodology of chatbot performance measures. *Business Horizons, 62*(6), 785–797. https://doi.org/10.1016/j.bushor.2019.08.005

Qiu, L., & Benbasat, I. (2010). A study of demographic embodiments of product recommendation agents in electronic commerce. *International Journal of Human-Computer Studies, 68*(10), 669–688. https://doi.org/10.1016/j.ijhcs.2010.05.005

Rabbani, M. R. (2022). Fintech innovations, scope, challenges, and implications in Islamic Finance: A systematic analysis. *International Journal of Computing and Digital Systems, 11*(1), 1–28.

Rajaobelina, L., Prom Tep, S., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. *Psychology & Marketing, 38*(12), 2339–2356. https://doi.org/10.1002/mar.21548

Ramesh, A., & Chawla, V. (2022). Chatbots in marketing: A literature review using morphological and co-occurrence analyses. *Journal of Interactive Marketing, 57*(3). https://doi.org/10.1177/10949968221095549

Rapp, A., Curti, L., & Boldi, A. (2021). The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots. *International Journal of Human-Computer Studies, 151*, Article 102630. https://doi.org/10.1016/j.ijhcs.2021.102630

Reeves, B., & Nass, C. (1996). *The media equation: How people treat computers, television, and new media like real people*. New York, NR: Cambridge University Press.

Richins, M. L., & Dawson, S. (1992). A consumer values orientation for materialism and its measurement: Scale development and validation. *Journal of Consumer Research, 19*(3), 303–316. https://doi.org/10.1086/209304

Riyanto, Y. E., & Jonathan, Y. X. (2018). Directed trust and trustworthiness in a social network: An experimental investigation. *Journal of Economic Behavior & Organization, 151*, 234–253. https://doi.org/10.1016/j.jebo.2018.04.005

Roggeveen, A. L., Tsiros, M., & Grewal, D. (2012). Understanding the co-creation effect: When does collaborating with customers provide a lift to service recovery. *Journal of the Academy of Marketing Science, 40*, 771–790. https://doi.org/10.1007/s11747-011-0274-1

Roy, R., & Ng, S. (2012). Regulatory focus and preference reversal between hedonic and utilitarian consumption. *Journal of Consumer Behaviour, 11*(1), 81–88. https://doi.org/10.1002/cb.371

Ruan, Y., & Mezei, J. (2022). When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. *Journal of Retailing and Consumer Services, 68*, Article 103059. https://doi.org/10.1016/j.jretconser.2022.103059

Rye, M. S., Loiacono, D. M., Folck, C. D., Olszewski, B. T., Heim, T. A., & Madia, B. P. (2001). Evaluation of the psychometric properties of two forgiveness scales. *Current Psychology, 20*(3), 260–277. https://doi.org/10.1007/s12144-001-1011-6

Schiemann, S. J., Mühlberger, C., Schoorman, F. D., & Jonas, E. (2019). Trust me, I am a caring coach: The benefits of establishing trustworthiness during coaching by communicating benevolence. *Journal of Trust Research, 9*(2), 164–184. https://doi.org/10.1080/21515581.2019.1650751

Schuetzler, R. M., Grimes, G. M., Giboney, J. S., & Rosser, H. K. (2021). Deciding whether and how to deploy chatbots. *MIS Quarterly Executive, 20*(1), 1–15. https://doi.org/10.17705/2msqe.00039

Sheehan, B., Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research, 115*, 14–24. https://doi.org/10.1016/j.jbusres.2020.04.030

Shiota, M. N., Keltner, D., & John, O. P. (2006). Positive emotion dispositions differentially associated with Big Five personality and attachment style. *The Journal of Positive Psychology, 1*(2), 61–71. https://doi.org/10.1080/17439760500510833

Shukairy, A. (May 4, 2018). Chatbots in customer service – Statistics and trends [infographic]. Invespcro. Retrieved from https://www.invespcro.com/blog/chatbots-customer-service/.

Singh, J., & Crisafulli, B. (2015). Customer responses to service failure and recovery experiences. In S. Sahadev, K. Purani, & N. Malhotra (Eds.), *Boundary Spanning Elements and the Marketing Function in Organizations* (pp. 117–135). Cham: Springer. https://link.springer.com/chapter/10.1007/978-3-319-13440-6_8.

Sinha, J., & Lu, F. C. (2016). "I" value justice, but "we" value relationships: Self-construal effects on post-transgression consumer forgiveness. *Journal of Consumer Psychology, 26*(2), 265–274. https://doi.org/10.1016/j.jcps.2015.06.002

Smith, A. K., Bolton, R. N., & Wagner, J. (1999). A model of customer satisfaction with service encounters involving failure and recovery. *Journal of Marketing Research, 36*(3), 356–372. https://doi.org/10.1177%2F002224379903600305.

Song, Y., Luximon, A., & Luximon, Y. (2021). The effect of facial features on facial anthropomorphic trustworthiness in social robots. *Applied Ergonomics, 94*, Article 103420. https://doi.org/10.1016/j.apergo.2021.103420

Stiff, J. B., Dillard, J. P., Somera, L., Kim, H., & Sleight, C. (1988). Empathy, communication, and prosocial behavior. *Communication Monographs, 55*(2), 198–213. https://doi.org/10.1080/03637758809376171

Suhaili, S. M., Salim, N., & Jambli, M. N. (2021). Service chatbots: A systematic review. *Expert Systems with Applications, 184*, Article 115461. https://doi.org/10.1016/j.eswa.2021.115461

Talwar, S., Dhir, A., Scuotto, V., & Kaur, P. (2021). Barriers and paradoxical recommendation behaviour in online to offline (O2O) services. A convergent mixed-method study. *Journal of Business Research, 131*, 25–39. https://doi.org/10.1016/j.jbusres.2021.03.049

Tax, S. S., & Brown, S. W. (1998). Recovering and learning from service failure. *Mitosz Sloan Management Review, 40*(1), 75–88. https://sloanreview.mit.edu/article/recovering-and-learning-from-service-failure/.

Teodorescu, M. H., Morse, L., Awwad, Y., & Kane, G. C. (2021). Failures of fairness in automation require a deeper understanding of human-ML augmentation. *MIS Quarterly, 45*(3). https://doi.org/10.25300/MISQ/2021/16535

Tsai, C. T., & Su, C. S. (2009). Service failures and recovery strategies of chain restaurants in Taiwan. *The Service Industries Journal, 29*(12), 1779–1796. https://doi.org/10.1080/02642060902793599

Tsai, W. H. S., Liu, Y., & Chuan, C. H. (2021). How chatbots' social presence communication enhances consumer engagement: The mediating role of parasocial interaction and dialogue. *Journal of Research in Interactive Marketing, 15*(3), 460–482. https://doi.org/10.1108/JRIM-12-2019-0200

Tsarenko, Y., & Tojib, D. R. (2011). A transactional model of forgiveness in the service failure context: A customer-driven approach. *Journal of Services Marketing, 25*(5), 381–392. https://doi.org/10.1108/08876041111149739

Tsarenko, Y., & Tojib, D. (2012). The role of personality characteristics and service failure severity in consumer forgiveness and service outcomes. *Journal of Marketing Management, 28*(9–10), 1217–1239. https://doi.org/10.1080/0267257X.2011.619150

Vázquez-Casielles, R., del Río-Lanza, A. B., & Díaz-Martín, A. M. (2007). Quality of past performance: Impact on consumers' responses to service failure. *Marketing Letters, 18*(4), 249–264. https://doi.org/10.1007/s11002-007-9018-x

Venkatesh, V., Brown, S. A., & Sullivan, Y. (2016). Guidelines for conducting mixed-methods research: An extension and illustration. *Venkatesh, V., Brown, SA, and Sullivan, YW'Guidelines for Conducting Mixed-methods Research: An Extension and Illustration,'Journal of the AIS, 17*(7), 435–495. https://ssrn.com/abstract=3958485.

Verhagen, T., Nauta, A., & Feldberg, F. (2013). Negative online word-of-mouth: Behavioral indicator or emotional release. *Computers in Human Behavior, 29*(4), 1430–1440. https://doi.org/10.1016/j.chb.2013.01.043

Verma, V., Sharma, D., & Sheth, J. (2016). Does relationship marketing matter in online retailing? A meta-analytic approach. *Journal of the Academy of Marketing Science, 44*(2), 206–217. https://doi.org/10.1007/s11747-015-0429-6

Voss, K. E., Spangenberg, E. R., & Grohmann, B. (2003). Measuring the hedonic and utilitarian dimensions of consumer attitude. *Journal of Marketing Research, 40*(3), 310–320. https://doi.org/10.1509/jmkr.40.3.310.19238

Wang, W., & Benbasat, I. (2007). Recommendation agents for electronic commerce: Effects of explanation facilities on trusting beliefs. *Journal of Management Information Systems, 23*(4), 217–246. https://doi.org/10.2753/MIS0742-1222230410

Wang, X., Lin, X., & Shao, B. (2022). How does artificial intelligence create business agility? Evidence from chatbots. *International Journal of Information Management, 66*, Article 102535. https://doi.org/10.1016/j.ijinfomgt.2022.102535

Wang, Y., Zhang, M., Li, S., McLeay, F., & Gupta, S. (2021). Corporate responses to the coronavirus crisis and their impact on electronic-word-of-mouth and trust recovery: Evidence from social media. *British Journal of Management, 32*(4), 1184–1202. https://doi.org/10.1111/1467-8551.12497

Wangenheim, F. V. (2005). Postswitching negative word of mouth. *Journal of Service Research, 8*(1), 67–78. https://doi.org/10.1177%2F1094670505276684.

Wei, C., Liu, M. W., & Keh, H. T. (2020). The road to consumer forgiveness is paved with money or apology? The roles of empathy and power in service recovery. *Journal of Business Research, 118*, 321–334. https://doi.org/10.1016/j.jbusres.2020.06.061

Wei, J., Wang, Z., Hou, Z., & Meng, Y. (2022). The influence of empathy and consumer forgiveness on the service recovery effect of online shopping. *Frontiers in Psychology, 13*, Article 842207. https://doi.org/10.3389%2Ffpsyg.2022.842207.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management, 29*(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Wu, K. W., Huang, S. Y., Yen, D. C., & Popova, I. (2012). The effect of online privacy policy on consumer privacy concern and trust. *Computers in Human Behavior, 28*(3), 889–897. https://doi.org/10.1016/j.chb.2011.12.008

Xie, Y., & Peng, S. (2009). How to repair customer trust after negative publicity: The roles of competence, integrity, benevolence, and forgiveness. *Psychology & Marketing, 26*(7), 572–589. https://doi.org/10.1002/mar.20289

Xing, X., Song, M., Duan, Y., & Mou, J. (2022). Effects of different service failure types and recovery strategies on the consumer response mechanism of chatbots. *Technology in Society, 70*, Article 102049. https://doi.org/10.1016/j.techsoc.2022.102049

Yan, Y., Gupta, S., Licsandru, T. C., & Schoefer, K. (2022). Integrating machine learning, modularity and supply chain integration for Branding 4.0. *Industrial Marketing Management, 104*, 136–149. https://doi.org/10.1016/j.indmarman.2022.04.013

Zafar, A. U., Qiu, J., Li, Y., Wang, J., & Shahzad, M. (2021). The impact of social media celebrities' posts and contextual interactions on impulse buying in social commerce. *Computers in Human Behavior, 115*, Article 106178. https://doi.org/10.1016/j.chb.2019.106178

Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C: Emerging Technologies, 98*, 207–220. https://doi.org/10.1016/j.trc.2018.11.018

Zou, S., & Migacz, S. J. (2022). Why service recovery fails? Examining the roles of restaurant type and failure severity in double deviation with justice theory. *Cornell Hospitality Quarterly, 63*(2), 169–181. https://doi.org/10.1177/1938965520967921