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ChatGPT and online service recovery: How potential customers react to managerial responses of negative reviews

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ABSTRACT

This study investigates the efficacy of generative artificial intelligence in online service recovery; specifically, the use of ChatGPT (vs. human employees) in preparing managerial response(s) (MR or MRs) to online hotel reviews is considered. ChatGPT could be used to generate human-like MRs for online service recovery but this could backfire due to algorithm aversion when an individual discounts algorithm decisions relative to human-made decisions. Data collected via interviews, a modified Turing test and an online experiment provide empirical support for this. Findings reveal that potential customers could not clearly differentiate between the two types of MR and could not clearly identify the 'better' of the two. Yet, when informed of the MR source, ChatGPT MRs led to lower affective, cognitive and conative outcomes. Findings also unveiled perceived authenticity and uncanniness as significant parallel mediating pathways in this algorithm aversion. Theoretical and managerial implications are discussed.

1. Introduction

"*Thank you for sharing your experience with us. We apologize for the cleaning issues you faced. Your feedback is being taken seriously, and we're working on enhancements to ensure a more satisfactory stay. We hope you'll give us another opportunity to provide you with an improved and comfortable experience.*" - Reply to a hotel review on TripAdvisor.

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Is this reply written by a hotel employee or by ChatGPT? Does it matter to potential customers whether this service recovery response was prepared by a human employee or by ChatGPT? (By the way, it was written by ChatGPT.) ChatGPT, a generative artificial intelligence (AI) chatbot (Abdullah et al., 2022), has gained tremendous attention worldwide since its introduction in November 2022 (OpenAI, 2022). Compared to its predecessors, generative AI chatbots are superior in their ability to better capture the context of a conversation, interact more naturally and converse using human-like responses (Abdullah et al., 2022). These attributes seemingly make generative AI chatbots suitable for online service recovery efforts as they can be used to generate replies to online reviews. Or do they?

To understand such potential use of generative AI first requires an appreciation of online service recovery. Online service recovery through the use of managerial response(s) (MR or MRs) to hotel reviews could yield a host of positive effects (Lopes et al., 2023), such as improving inferences made about a hotel (Sparks et al., 2016), restoring online reputation (Wei et al., 2013), enhancing service perceptions (Huang & Ha, 2020) and increasing purchase intention (Olson & Ro, 2020). With 69% of U.S. consumers always or regularly seeking out negative reviews and with this proportion increasing steadily over the years (Power Reviews, 2021), not posting replies to negative online reviews seems like a lost opportunity to recover from service failure. Consequently, there is a sizeable stream of literature, discussed below, emphasizing the importance of and recommending how to execute effective online service recovery via MRs.

Nevertheless, as generative AI is a recent technological advancement, research regarding its use in online service recovery is still limited. Past research on online service recovery via MRs has largely focused on MR attributes, e.g. designation of the employee who posted the reply, communication style, response speed and extent of personalization (Sparks et al., 2016; Zhang et al., 2020). This parallels service recovery research, both online and otherwise, which has likewise predominantly focused on recovery attributes, such as humor, empathy and empathetic accuracy (Lv et al., 2022; Xu et al., 2023; Xu & Liu, 2022), of encounters

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involving types of AI other than generative AI. Limited research has examined the use of generative AI in service recovery, likely because the technology that has existed in the past was not up to the task (Eshghi, 2023). Now, the conversational competency of generative AI chatbots would seem to make such usage a possibility. Therefore, our study is a timely effort, filling the gap in extant literature by examining the efficacy of generative AI in online service recovery.

Importantly, generative AI is based on conversational written text (Abdullah et al., 2022). Although research exists on the use of AI in technology-based service recovery, to the best of our knowledge, it predominantly focuses on interactions where it is obvious to the consumer that s/he is interacting with a non-human, such as chatbots (Agnihotri & Bhattacharya, 2023), virtual and augmented reality (Gonçalves et al., 2024), service robots (Choi et al., 2021; Hu et al., 2021) and self-service technology (Fan et al., 2020). Considering the conversational abilities of generative AI (Abdullah et al., 2022), it may not be obvious to consumers that they are interacting with a non-human. Therefore, to bridge the gap in existing literature, we consider the impacts of human likeness of generative AI on consumer responses.

Specifically, we propose that potential customers would demonstrate partiality for online service recovery efforts by human employees over those by generative AI, an effect known as algorithm aversion. By referencing algorithm aversion, i.e. a preference of human labor and a disinclination for robotic labor (Mahmud et al., 2022), we build upon the mind perception theory, which suggests that robots are generally seen has possessing little to no ability to feel mental or physical states (Gray et al., 2007). Presumably, this makes service recovery efforts by generative AI less relatable. Therefore, as informed by the expectations violation theory and uncanny valley theory, we further investigated perceived authenticity (Kim & Kim, 2020) and uncanniness (Mori et al., 2012) as explanatory pathways for algorithm aversion in online service recovery.

Overall, our study contributes to tourism and hospitality literature in three ways. Firstly, we bridge a theoretical gap in current literature on online service recovery delivered via generative AI. Secondly, by building on extant literature, we unveiled the roles of perceived authenticity and uncanniness as explanatory pathways in the efficacy of generative AI service recovery. Last but not least, we focus on the reactions of potential customers. The public nature of MRs means that individuals uninvolved in the preceding service failure are now observers of service recovery efforts and their reactions could be influenced as well. Yet, to date, limited attention has been paid to online service recovery from a third party perspective (Huang & Ha, 2020). To the best of our knowledge, our study represents a pioneering research effort that considers the perspective of potential customers on MRs generated using AI.

2. Theoretical foundation & hypotheses development

2.1. Managerial replies in service recovery

In writing and posting MRs, service providers are effectively targeting potential customers scanning through reviews and MRs prior to purchase decisions (Litvin & Hoffman, 2012). Although these potential customers were not directly involved in the service failure, their subsequent behavior can still be influenced by MRs. For instance, Olson and Ro (2020) revealed that potential customers display higher purchase intention towards restaurants that utilized MRs (vs. those that did not utilize MRs) in responding to negative online reviews. These findings were echoed by Le and Ha (2021) in the context of online shopping. By investigating the effects of MRs, Le and Ha (2021) showed that a high (vs. low) response rate leads to higher purchase intention among potential customers. Similarly, Darani et al. (2023) demonstrated that by mimicking wording in negatively-valence reviews, MRs increase purchase intention of potential customers.

The benefits of MR as a service recovery tool extend beyond behavioral or conative considerations such as purchase intention. MRs can also be used to elicit favorable affective outcomes (i.e. feelings or emotions evoked by marketing stimuli; Holbrook & Hirschman, 1982; MacKenzie & Lutz, 1989) and cognitive outcomes (i.e. memory, knowledge structure, beliefs, thoughts and protocols regarding the stimuli; Holbrook & Hirschman, 1982) among potential customers. For instance, MRs to negative reviews can help in customer relationship management and online reputation management (Wei et al., 2013). This was echoed by Sparks et al. (2016) who found that online MRs (vs. non-response) improved inferences that potential customers made about a hotel's trustworthiness and concern for its customers. Likewise, in analyzing data from TripAdvisor, Expedia, Hotels.com and Orbitz, Wang and Chaudhry (2018) showed that MRs that are customized to the contents of the corresponding negative review amplified the positive impact of MRs on subsequent online ratings, an indicator of customer satisfaction.

To further capitalize on their use of MRs in service recovery, service providers can leverage recent technological advancements in generative AI. Presently, AI in the form of chatbots is already in use in online service recovery (Agnihotri & Bhattacharya, 2023; Zhu et al., 2023). However, traditional chatbots are rule based and/or trained on predefined templates and training datasets (Eshghi, 2023). Conversely, chatbots that utilize generative AI, such as ChatGPT, rely on deep learning and large language models (Abdullah et al., 2022). This in turn means that generative AI chatbots are accorded unprecedented ability to better capture the context of a conversation, generate more creative answers and interact more naturally through more human-like responses (Abdullah et al., 2022). Such potential of generative AI to produce conversations using natural language and to better answer questions dovetails with consumers' preference for more human-like chatbots in online service recovery (Agnihotri & Bhattacharya, 2023). Hence, its productive use in generating MRs for online service recovery seems intuitive.

However, in some situations, consumers prefer human labor over robotic labor (Granulo et al., 2021). For instance, Zhu et al. (2023) found that service recovery efforts by chatbots (vs. human employees) led to lower customer satisfaction and revisit intention. This finding was consistent across the use of phone calls and cellphone text messages (Zhu et al., 2023). Similarly, Hu et al. (2021) revealed that consumers perceive service recovery efforts by human employees (vs. humanoid robots) as more sincere, thereby leading to higher recovery satisfaction. Notably, their research found no significant differences between text or voice apology generated by robots (Hu et al., 2021).

These differences in reactions to human and robotic service recovery could be explained by mind perception theory, which postulates that individuals perceive minds along the two dimensions of agency and experience (Gray et al., 2007). Agency covers the ability to employ self-control, to do and to plan while experience refers to the ability to feel mental and physical states, e.g. pain, pleasure and consciousness (Gray et al., 2007). Humans are generally perceived as possessing high agency and experience; in contrast, robots are typically seen as having moderate to high agency but low to no experience (Gray et al., 2007; Shank et al., 2021). When applied to service recovery, mind perception theory suggests that consumers could attribute lower experiential minds to robots by perceiving them as less capable of mental and physical sensations. Presumably, this lack of subjective experience by robots makes their service recovery efforts less relatable than those by humans.

Therefore, our research focuses on algorithm aversion, i.e. a preference for human labor and a disinclination for robotic labor (Mahmud et al., 2022). In algorithm aversion, an individual discounts algorithmic decisions (e.g. AI-generated decisions, mechanical decisions and forecasting support system) in comparison to his/her own decisions or other's decisions, whether consciously or unconsciously (Mahmud et al., 2022). For instance, Longoni et al. (2019) found that consumers prefer medical treatment from humans and are reluctant to use healthcare provided by AI in both real and hypothetical choices.

Similar findings were identified by Bellaiche et al. (2023) who investigated consumers' appraisal of visual art: they found that human-created artwork are judged more positively than those created by AI. At times, algorithm aversion can prevail even when robotic labor outperforms human labor (Castelo et al., 2019). In Yeomans et al.'s (2019) study of recommender systems, they compared consumer preferences in receiving joke recommendations from humans or via algorithms. They found that even though computer systems are more effective in predicting which jokes people will find funny, individuals are averse to computer recommender systems and prefer to rely on human recommenders (Yeomans et al., 2019).

Considering the possible influence of algorithmic aversion in the service recovery domain, we hypothesize that potential customers are predisposed towards efforts originating from a human employee. Service recovery is preceded by service failure, which means that service providers are attempting to restore instead of maintaining positive consumer perceptions. With a larger gap in service expectations to close, potential customers would arguably seek more human or less robotic interactions to experience greater engagement with and/or confidence in the service provider. As AI applications are typically perceived as possessing little, if any, experiential mind (Shank et al., 2021), potential customers are likely to feel cognitively obstructed when engaging with AI-generated contents (Bellaiche et al., 2023). Therefore, despite the humanness that generative AI applications could bring to MRs, we hypothesize (Fig. 1) that.

H1. Human-based (vs. AI-based) service recovery text is associated with higher levels of (a) affective, (b) cognitive, and (c) conative outcomes among potential customers.

2.2. *Perceived authenticity*

To explain the relationship hypothesized in H1, we adopt Kim and Kim's (2020) authenticity approach, which defines it as readers' subjective evaluation of the genuineness of online reviews. In reading online reviews, authenticity is conferred by potential customers (Beverland, 2005), as they can develop their own interpretation of authenticity even without subjective criteria (Lu et al., 2015). By extension, potential customers can also be expected to form their own interpretation of authenticity after reading MRs. These perceptions are "culturally contingent and historically situated" (Carroll, 2015, p. 3) and could also depend on perceived links with a person or place (Grayson & Martinec, 2004).

This focus on authenticity is guided by the expectancy violation theory. Originally proposed by interpersonal scholars and applied to various strategic communication settings of organizations (Park et al., 2021), the expectancy violation theory proposes that individuals employ expectations in their interactions with others (Burgoon, 1993). An expectation is a consistent pattern of anticipated behavior and is used by an individual to interpret the interaction, process information and subsequently behave (Burgoon, 1993). When someone behaves in a manner that deviates from what is anticipated, negative (or positive) violations occur when expectations failed to be met (or are surpassed), thus leading to less (or more) favorable outcomes than expectations conformity (Burgoon & Hale, 1988).

Arguably, in a service recovery context, consumers would expect service providers to be authentic, i.e. they are perceived as possessing genuineness, truthfulness and actuality (Alhouti et al., 2016). The authenticity of service employees is a service norm that consumers have come to expect in both in-person and offline service encounters (Turel et al., 2013), including service recovery. Service recovery involves actions to "resolve problems, alter negative attitudes of dissatisfied customers and to ultimately retain these customers" (Miller et al., 2000, p. 388). Presumably, these actions need to be authentic for them to be effective in restoring positive perceptions about the service provider. This is likely even more so considering how perceived service authenticity contributes to consumer satisfaction, service value and perceived quality (e.g. Bae, 2021; Grandey et al., 2005; Lu et al., 2015) in service delivery.

Nevertheless, as MRs could come from different sources, service recovery efforts could also vary in terms of whether they conform to or violate consumers' expectations of authenticity. In line with the expectancy violation theory, we propose that service recovery by human employees (vs. AI) would lead to more (vs. less) favorable outcomes as it conforms to (vs. fails to meet) consumers' expectations of authentic recovery efforts. Consumers generally perceive human-to-human interactions as more genuine and sincere than human-to-robot interactions (Shin & Jeong, 2020). After all, authenticity is "concerned with what it means to be human" (Steiner & Reisinger, 2006, p. 300) and robots, including chatbots, lack the personal touch that is present in humans (Agnihotri & Bhattacharya, 2023). Consequently, robot servers are perceived as less authentic and more superficial than human employees in rendering services (Lin & Mattila, 2021). They are also less effective in improving perceived service authenticity of core and facilitating products (Song et al., 2022). Overall, we hypothesize that.

H2. Perceived authenticity mediates the effect of service recovery entity (human-based text vs. AI-based text) on (a) affective, (b) cognitive, and (c) conative outcomes among potential customers.

2.3. *Uncanniness*

Given generative AI's ability to converse like a human and the high level of human-likeness in their responses (Abdullah et al., 2022),

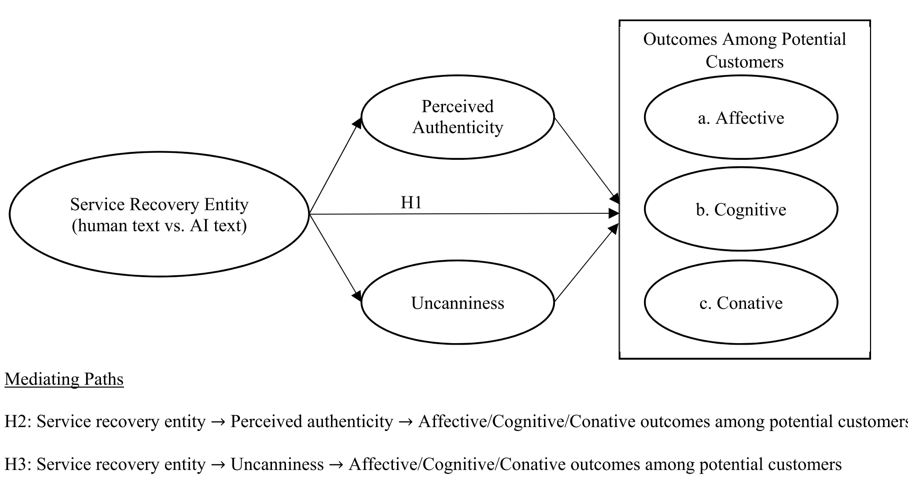

Fig. 1. Proposed research model.

generative AI applications could help to generate MRs that read like they are written by human employees. In such situations, the 'humanness' of generative AI applications could potentially fulfil or even consumers' expectations of authenticity in service recovery. However, we posit that the 'humanness' and learned ability of these applications would instead end up encumbering service recovery. By building on the uncanny valley theory (Mori et al., 2012), we propose that such human likeness is too much, such that it engenders eerie sensations, which users find to be uncomfortable and, as such, could potentially render service recovery ineffective.

According to the uncanny valley theory, human likeness in non-human replicas increases with increasing anthropomorphism or attribution of human traits/characteristics to the replica (Mori et al., 2012). However, this happens only up to a point, after which liking dips because the replica becomes unnerving for being too human-like (Mori et al., 2012). Replicas, such as machines and robots, typically lack attributes, e.g. the ability to sense, plan and act, that define what it is to be human (Gray & Wegner, 2012). Consequently, when consumers ascribe to robots the capacity to feel/sense, as opposed to just the capacity to act/do, feelings of uncanniness result (Gray & Wegner, 2012).

In line with the uncanny valley theory (Mori et al., 2012), Kim et al. (2019) found that as consumer-use robots became more human-like in their physical appearance and behavior, feelings of uncanniness emerge to negatively affect attitudes towards the robots. These findings are paralleled by Mende et al. (2019) and Shin and Jeong (2020) who investigated consumer responses to service robots. Through a series of experimental studies, Mende et al. (2019) revealed that human-looking robots elicited eeriness and a threat to human identity, which in turn stimulated compensatory consumption. Similarly, findings from Shin and Jeong (2020) demonstrated that unfavorable attitudes towards robot concierge were elicited when it highly resembled humans.

Based on the above discussion, we hypothesize that.

H3. Uncanniness mediates the effect of service recovery entity (human-based text vs. AI-based text) on (a) affective, (b) cognitive, and (c) conative outcomes among potential customers.

3. Methodology

Presently, empirical research regarding the use of generative AI in online service recovery by tourism and hospitality firms remains limited. Given this extant exploratory status of our research context, we employed a three-phase, mixed-methods approach. Phase 1 was designed to understand tourism and hospitality practitioners' current approach towards online service recovery and their insights regarding generative AI's potential for this purpose. This phase is deemed important given the unprecedented ability of generative AI compared to other types of conversational AI (Abdullah et al., 2022; Shen et al., 2023). To explore this new knowledge while capturing extensive explanations (Turner, 2010) based on participants' thoughts and experiences, in-depth semi-structured interviews were conducted with industry practitioners.

Meanwhile, phase 2 was designed to explore the viability of generative AI in online service recovery. Arguably, such specific application of generative AI is more viable if the MRs generated are – at the very least – of comparable quality vis-à-vis those written by humans. Hence, quantitative consumer responses were gathered via a modified Turing test (Mikulak-Klucznik et al., 2020) where participants attempt to distinguish between machine versus human outputs. Collectively, the results of phases 1 and 2 provided valuable inputs into phase 3, which involved the gathering of quantitative survey data via online experiments to test our research hypotheses.

In all three phases, ChatGPT was used as the focal generative AI application. ChatGPT was selected over other generative AI applications for three reasons. Firstly, its dialogue format facilitates its immediate use for generating MRs, as illustrated in Online Supplementary Materials A and B. Secondly, ChatGPT, per McKinsey & Company (2023), is generally considered to be the 'best' publicly available chatbot. Thirdly, in just two months after its launch, ChatGPT was estimated to have reached 100 million active users, thus making it the fastest growing consumer application in history (Hu, 2023). With this popularity level, our target respondents, which comprises tourism and hospitality practitioners and consumers, are more likely to be aware of ChatGPT than they may be of other generative AI applications.

4. Phase 1

4.1. Study design & sampling

An interview guide was designed to gather information about practitioners' current approach towards online service recovery and their insights regarding ChatGPT. Given the purpose of this phase, purposive sampling was adopted to ensure the inclusion of interviewees with the requisite experience and knowledge (Etikan et al., 2016). Specifically, we included practitioners in the U.S. who have at least two years of frontline service experience in the tourism and hospitality industry, and presently work for a tourism/hospitality business with a presence on at least one online review website.

A total of 11 interviews (Table 1) were conducted by two of the authors in May and June 2023. According to Myers (2013, p. 9), triangulation involves "more than one research method, use two or more techniques to gather data, or combine qualitative and quantitative research methods in the same study" so as to facilitate a more comprehensive understanding of the phenomenon. Hence, we recruited participants through two approaches: (i) the researchers' personal networks, and (ii) visitation of hotels and restaurants that are listed on online review websites, e.g. Yelp or Google. Triangulation via different recruiting resources helped ensure the trustworthiness of a study (Decrop, 1999). Data quality was further ensured through non-incentivized, voluntary participation with interviewees (seven males and four females; eight hotel and three restaurant practitioners) being assured of data confidentiality and participant anonymity.

Interviews were audio recorded with interviewees' permission and transcribed verbatim for further analysis. During the interviews, which lasted between 20 and 30 min, the researchers also documented their discussions via comprehensive field notes, thus providing extensive content. Data saturation, as no significant new themes emerged (Guest et al., 2006), was deemed to have been reached by the tenth interview, upon which time the researchers conducted an additional confirmatory interview.

4.2. Data analysis

Content analysis of the transcripts and field notes was then conducted. Firstly, two of the authors read the transcripts and field notes repeatedly to obtain a general understanding of the participants' responses (Rowlands, 2021). This step facilitated the search for merging

Table 1
Phase 1 – Profile of interviewees.

No.	Gender	Job Role	Company type
1	Male	Event sales manager	Hotel
2	Male	Director of revenue management	Hotel
3	Female	Director of hotel intelligence	Hotel
4	Male	Assistant general manager	Hotel consultancy service
5	Female	Front desk agent	Hotel
6	Male	Event sales	Hotel
7	Female	Assistant general manager	Hotel
8	Female	Front desk manager	Hotel
9	Male	Restaurant manager	Restaurant
10	Male	Restaurant manager	Restaurant
11	Male	Operations staff	Restaurant

themes through repeated words or sentences across different participants. Secondly, the transcripts were analyzed using NVivo. In this, an inductive coding approach was used as it allowed data to lead the direction in order to develop themes (Chandra & Shang, 2019). Overall, our content analysis revealed the following three main themes.

Theme 1. Interviewees unanimously perceived the monitoring of online reviews – whether positive or negative – as something critical. Several described it as "*absolutely*" (Interviewees 8 & 10), "*definitely*" (Interviewee 3) or "*really*" (Interviewee 6) important. They believed that this was helpful in revealing customers' attitudes and satisfaction, regardless of how the monitoring was done. Their approaches ranged from engaging an external vendor to reply to all reviews (Interviewees 1 & 2) to designating it as the responsibility of a managerial level employee or the business owner (Interviewees 1, 3 to 7, 9 & 10).

Theme 2. Responding to negative online reviews was deemed necessary with evident partiality for selected service recovery strategies. Apologizing for the negative experience emerged as a strategy that was advocated by all interviewees. In fact, Interviewee 9 indicated that even if the issue was not caused by his company, they would still apologize in their MR. As explained by Interviewee 3, "*That [An apology] is an emotional thing. It does not matter what happened physically.*"

Similarly, interviewees predominantly felt that it was better to indicate in their MRs that the business would look or has looked into the issue raised in the online review, which represents procedural justice (Muhammad, 2020). An example of such an indication is, "*I will be addressing that for further educational purposes*" (Interviewee 8). This approach stems from the belief that customers would prefer to know how the issue was being resolved versus knowing why the issue happened (Interviewee 10).

Opinions on whether to include discounts or other forms of compensation in MRs were divided. Interviewees representing restaurants were receptive to this whereas those from hotels were reluctant. For instance, restaurant managers would offer discounts or complimentary small dishes for future visits (Interviewees 10 & 11) whereas hotel managers prefer to reward customers with loyalty points, in addition to issuing an apology, depending on the severity of the cases (Interviewee 7). Even if a hotel eventually provided some sort of compensation in selected cases, any mention of this was deliberately avoided in MRs as hotels "*don't want to encourage people to write bad reviews so that they can get a refund*" (Interviewee 8).

Theme 3. Interviewees recognized that while ChatGPT could potentially assist in generating MRs to negative online reviews, they were still not fully confident of its ability. The majority believed that it would still be necessary for a human employee to read each of ChatGPT's MR. Their concerns stemmed from ChatGPT's MRs potentially sounding "*like a computer*" (Interviewees 7 & 11) and hence, lack the human touch, which was especially important for smaller scale, local or family-owned businesses (Interviewees 9 & 11).

4.3. Discussion

Theme 1 points to the necessity of MRs, as perceived by tourism and hospitality practitioners. This provides justification for our study on understanding how generative AI can be appropriately utilized to produce MRs for service recovery. Phase 1's results further informed phases 2 and 3 in the following ways:

(i) Concerns about the 'humanness' of ChatGPT raise the question of its effectiveness in service recovery (theme 3). The use of ChatGPT in writing MRs would be justified only if its MRs are at least comparable, if not better than MRs prepared by human employees. This further justified our inclusion of phase 2 to investigate whether readers could differentiate between MRs written by human employees (vs. ChatGPT) and whether they perceive one to be better than the other.

(ii) Service recovery strategies identified during our interview stage informed phase 3's experiment stimuli and study design. The widely used strategies of an apology or an investigation into the issue at hand without any mention of compensation (theme 2) formed the narratives for phase 3's experiment stimuli. This approach recognizes the widely accepted conceptualization of service recovery as comprising three justice dimensions (Lopes et al., 2023), namely, interactional justice (e.g. an apology), procedural justice (e.g. an investigation into the issue) and distributive justice (e.g. compensatory discount) (Migacz et al., 2018). With such recognition in experimental stimuli, our study design featured only one justice dimension in each experimental scenario to avoid potential confounding effects (see section 6 and Online Supplementary Material B).

(iii) As we learned of the significant differences between the views of hoteliers and restauranteurs we interviewed (theme 2), we made the strategic decision to focus solely upon hotels in phases 2 and 3.

Phase 1 focuses on the insights of industry practitioners regarding online service recovery and ChatGPT. With these insights, we then proceeded with phase 2 to assess the viability of MRs by comparing those written by human employees versus ChatGPT.

5. Phase 2

5.1. Study design

The approach that guided phase 2 was a modified Turing test, which Mikulak-Klucznik et al. (2020) describes as an effective method for the study of AI when conducting a 'human versus machine' comparison study. Mikulak-Klucznik et al. (2020) used the method, which was first proposed by Turing and Haugeland (1950), to compare diagrams reflecting the synthesis of complex natural products prepared by human chemists versus the computer. Similarly, Candello et al. (2017) also employed a modified Turing Test to assess if participants could distinguish between financial advice provided by human or machine.

5.2. Sample, procedures & measures

To build up the corpus for the modified Turing test, we first extracted a TripAdvisor review and its corresponding MR from each of the top ten hotels in New York and Las Vegas. These two places were selected as they are among the top ten hotel markets in the U.S. in terms of hotel revenue (American Hotel & Lodging Association, 2022) while simultaneously representing locations with significantly different destination appeal. By including reviews from different hotels, the corpus also included MRs written by different people in different styles. The ten reviews for each location encompassed two from each level of reviewer rating, thus accounting for how hotel management and ChatGPT handled reviews of differing valence.

ChatGPT was then used to generate a MR for each extracted TripAdvisor review. Online Supplementary Material A details how ChatGPT was trained by the researchers to do this and provides a sample MR generated by ChatGPT. The final corpus comprised 20 TripAdvisor hotel reviews, 20 MRs written by the hotel and 20 MRs prepared by ChatGPT.

Our modified Turing test comprises two separately run surveys. In the first survey, i.e. a single text Turing test, participants were shown an original TripAdvisor hotel review and a MR written by either the hotel or ChatGPT. This setup parallels real-life settings where each review typically has only one MR. Participants of this single text Turing test were required to assess if they felt that the MR they read was written by the hotel or by a computer. The second survey, i.e. a paired text Turing test, paralleled the setup of Mikulak-Klucznik et al. (2020) and Candello et al. (2017). Participants were shown an original TripAdvisor hotel review and its corresponding pair of hotel and ChatGPT MRs. They were then asked to select the MR they felt was prepared by the hotel and which they felt to be 'better'.

Each participant of the single and paired text Turing tests viewed a total of five reviews and their associated MR(s). The reviews, MRs and itemized questions were randomly drawn from the corpus and randomly ordered. Participants were recruited via a panel company and their profile (Table 2) was balanced against the 2020 U.S. census. Participants were also screened for sample qualifications (i.e. >18 years old and having traveled for leisure in the previous 24 months or between 2017 and 2019).

5.3. Results & discussion

For the single text Turing test, 117 participants (Table 2) were retained following data cleaning, e.g. passing of attention check questions. This resulted in 585 observations (117 participants × 5 MRs), results of which are summarized in Table 3. Of the 286 hotel-based observations, 171 (59.8%) correctly identified that the response was posted by hotel, whereas 115 (40.2%) observations made an incorrect selection. Of the 299 AI-generated observations, 130 (43.5%) correctly identified that the response was prepared by AI, whereas 169 (56.5%) observations made an incorrect selection.

For the paired text Turing test, 115 participants totaling 575 observations were included in our analysis (Table 4). Of these 575 observations, 279 of them (48.5% of total) correctly identified the MR posted by hotel. Furthermore, 285 observations (49.6%) indicated that MRs posted by hotels were better while the remaining 290 observations (50.4%) selected the MR posted by ChatGPT as the better response.

Table 2
Phases 2 & 3 – Demographic profile of panel participants.

	Phase 2: Single Text Turing Test (n = 117)	Phase 2: Paired Text Turing Test (n = 115)	Phase 3[a]: Experimental Survey (n = 270)
Gender			
Male	52/44.4%	48/41.7%	118/43.7%
Female	65/55.6%	67/58.3%	152/56.3%
Age			
18–29 years	26/22.2%	23/20.0%	18/6.7%
30–39 years	24/20.5%	24/20.9%	40/14.8%
40–49 years	20/17.1%	21/18.3%	59/21.9%
50–59 years	27/23.1%	11/9.6%	44/16.3%
≥ 60 years	20/17.1%	36/31.2%	109/40.3%
Ethnicity			
Caucasian	75/64.0%	77/67.0%	220/81.5%
African American	17/14.5%	15/13.0%	19/7.0%
Hispanic/Latino/Spanish	12/10.3%	15/13.0%	11/4.1%
Asian	9/7.7%	7/6.1%	18/6.7%
Other/Prefer not to answer	4/3.5%	1/0.9%	2/0.7%
Educational level			
High school or less	24/20.5%	29/25.2%	41/15.2%
College	63/53.9%	68/59.1%	52/19.3%
Postgraduate	27/23.1%	17/14.8%	177/65.5%
Others/Prefer not to answer	3/2.5%	1/0.9%	–
Annual household income			
<$25,000	17/14.5%	12/10.4%	24/8.9%
$25,000–$49,999	15/12.8%	16/13.9%	35/13.0%
$50,000–$74,999	22/18.7%	27/23.5%	68/25.2%
$75,000–$99,999	13/11.1%	27/23.5%	44/16.3%
≥ $100,000	47/40.3%	31/26.9%	99/36.6%
Prefer not to answer	3/2.6%	2/1.8%	–

[a] Excludes pre-test sample.

Table 3
Phase 2 – Result of single text Turing test[a].

MR	Correct	Wrong	Total Observations
Prepared by hotel	171/59.8%	115/40.2%	286/100%
Prepared by ChatGPT	130/43.5%	169/56.5%	299/100%
Overall	301/51.5%	284/48.6%	585/100%

[a] N = 117.

Table 4
Phase 2 – Result of paired text Turing test[a].

MR	Correct	Wrong	Hotel	ChatGPT	Total Observations
Prepared by hotel	279/48.5%	296/51.5%	–	–	575/100%
Better	–	–	285/49.6%	290/50.4%	575/100%

[a] N = 115.

Overall, results indicated that participants held somewhat similar perceptions of hotel-generated and AI-generated MRs. In the single text Turing test, accuracy percentages for hotel and AI MRs are approximately 50%; that is, regardless of its source, each MR had about equal chances of being selected as a human-written response. When MRs written by the hotel and by ChatGPT were placed side-by-side as was the case in the paired text Turing test, there was only a 3 percentage point difference between correct and incorrect responses. When participants were asked which MR they felt was the better of the two, the results were similar as well. There was only a 0.5 percentage point difference between participants' perceptions of hotel-generated and AI-generated MRs.

Based on phase 2's results, we conclude that MRs generated by ChatGPT are of a reasonable quality level comparable to those prepared by hotel employees. The use of ChatGPT for online service recovery is therefore considered a viable application of generative AI. Having established this, we then proceeded with hypotheses testing in phase 3.

6. Phase 3

To test the hypothesized relationships in our research model, phase 3 included an online pre-test and an online experiment. The pre-test developed and tested experiment stimuli, including but not limited to the training and use of ChatGPT to generate MRs that featured only either interactional or procedural justice. By featuring only interactional or procedural justice in each MR, we controlled, as noted in section 4.3, for the potential effects of the specified justice dimension. This enabled us to focus on comparing the effects of AI- vs. human-based outcomes. For brevity, details of the pre-test are included in Online Supplementary Material B while those of the online experiment are presented below. Meanwhile, measurement items used in the online experiment are listed in Online Supplementary Material C.

6.1. Study design

The online experiment utilized a between-subject (service recovery entity: human-based text vs. AI-based text), scenario-based experiment in which participants viewed one of four text-based MRs (Table 5) to a TripAdvisor review. This scenario-based approach is widely used in service recovery research (Migacz et al., 2018). Moreover, the use of text-based stimuli in these scenarios parallel the current research context of MRs posted online.

Table 5
Phase 3 – MR stimuli[a] for online experiment.

Justice Type	Human-Based Service Recovery Text	AI-Based Service Recovery Text
Interactional justice	*Scenario 1:* Thank you for taking your time to write a review of your recent stay with us. We are sorry to hear that you were not fully satisfied with your overall stay. Please accept our apologies for any inconvenience caused. We aim to provide exceptional customer service and are extremely disappointed that the service you received fell below both your expectations and our standards. We greatly regret that we dropped the ball in several areas during your visit and hope that other aspects of your stay not mentioned in your review surpassed your expectations. Sincerely, Jessie Smith Pacific Hotel General Manager	*Scenario 3:* Thank you for sharing your experience with us. We genuinely appreciate your feedback and sincerely apologize for the extended wait during check-in, including the initial room mix-up. It is our responsibility to ensure a smooth and efficient process, and we deeply regret any inconvenience caused. We understand your disappointment and take full accountability for the issues you encountered. We apologize for falling short of your expectations and extend our gratitude for providing us with your valuable review. Your feedback is highly valued, and we appreciate your contribution to help us improve. Sincerely, ChatGPT (an artificial intelligence system), Pacific Hotel
Procedural justice	*Scenario 2:* Our team is concerned about your recent stay with us. We will share your feedback with all relevant departments and investigate the issues you raised, so that we can take appropriate actions to prevent them from happening again in the future. We endeavor to meet the room and service requirements of all our guests. However, during your stay, we were experiencing very high occupancy, which could have made this difficult to achieve. We hope that you will give us a second chance to welcome you back and restore your faith in us. Sincerely, Jessie Smith Pacific Hotel General Manager	*Scenario 4:* We are genuinely concerned about the issues raised in your review. The extended check-in time, initial room mix-up, subpar room conditions, and unacceptable service are concerning matters that will be thoroughly investigated. Your comments will be promptly directed to the relevant departments, and we will take appropriate actions to address the concerns you have raised. If you have any additional comments or would like to further discuss your experience, please feel free to contact the hotel directly. We hope to have the opportunity to serve you better in the future. Sincerely, ChatGPT (an artificial intelligence system), Pacific Hotel

[a] Each scenario has between 98 and 100 words. Scenario numbering is not shown to participants.

6.2. Sample, procedures & measures

Participants were recruited from the same panel company used in phase 2. To ensure the feasibility of study protocol and address logistical considerations (Hassan et al., 2006), we conducted a pre-test with 23 participants. This pre-test facilitated checks for language, flow issues in the survey and measurement of initial scale reliability. For the full survey, demographics of the participants are census-balanced and shown in Table 2. Participants were screened for prior leisure travel experience in the last 24 months or between 2017 and 2019 before they were randomly assigned one of the four scenarios (Table 5). Following data cleaning, such as removal of participants who failed attention check questions, a total of 270 U.S. residents remained. This included 68 participants for scenario 1, 49 for scenario 2, 73 for scenario 3, and finally, 80 for scenario 4. These sample sizes adhered to the central limit theorem's recommendation, which suggests a minimum of 30 cases for each scenario (Kwak & Kim, 2017).

The survey included four sections: (i) screening questions to ensure the participant met sample requirements, (ii) display of text stimuli, (iii) measurement of focal constructs and our control variable, and (iv) collection of demographic information. All measurements utilized a seven-point Likert-type or semantic differential scale and are listed in Online Supplementary Material C together with item-specific descriptive statistics. No normality distribution problems were detected as skewness and kurtosis values were between −2 and 2 and -7 to 7 respectively (Hair et al., 2010; Online Supplementary Material C).

Uncanniness was measured by two items from Sullivan et al. (2022) with Pearson correlation of 0.76. *Perceived authenticity* was measured by four items from Kim and Kim (2020) with Cronbach's $\alpha = 0.95$. *Affective outcome* was measure by four items adapted from Litvin and Hoffman (2012), MacKenzie and Lutz (1989) and Dawar and Pillutla (2000) with Cronbach's $\alpha = 0.91$. *Cognitive outcome* was measured by two items adapted from Litvin and Hoffman (2012) and Spreng et al. (1995) with a Pearson correlation of 0.94. *Conative outcome* was measured with three items adapted from Litvin and Hoffman (2012) and Molinillo et al. (2018) with a Cronbach's $\alpha = 0.90$. All composite reliabilities were above the threshold of 0.70 (Hair et al., 1998), thus indicating high internal consistency. Correlations between the constructs are shown in Table 6.

In addition to the constructs of interest, we included a covariate of technology innovativeness. *Technology innovativeness* was measured with six items from Thakur et al. (2016) with a Cronbach's $\alpha = 0.97$. Technology innovativeness refers to "extent to which a consumer is motivated to be the first to adopt new technology-based goods and services" (Bruner & Kumar, 2007, p. 331). This was included as generative AI is a new form of technology and consumers have been shown to vary in their propensity towards the use of new applications of technology-based products (Bruner & Kumar, 2007).

Participants were kept hypothesis-blind at the beginning of the survey via incomplete disclosure of study purpose. Hence, they were debriefed about the study's full purpose upon survey completion. Consent to use their responses was then re-sought on the original basis of confidentiality and anonymity with assurance provided for full payment by the panel provider for their participation, regardless of their decision. Four participants did not assent; therefore, their responses were excluded.

6.3. Manipulation checks

Manipulation for service recovery text (human-based text vs. AI-based text) was checked using a binary question where participants had to identify if the MR they had read was written by the hotel's general manager or by AI. Also, as service recovery justice was controlled by manipulating the scenario text (Table 5), participants were asked to recall if the MR included an apology to the guest (i.e. interactional justice) or a promise to investigate the issues (i.e. procedural justice). Only participants who correctly answered both questions were retained in our analysis. Additionally, to assess realism of the scenarios presented, a seven-point scale (1 = highly unrealistic; 7 = highly realistic) was added. Across the four scenarios, perceived realism was acceptable ($M = 4.47$, $SD = 1.73$).

6.4. Results & discussion

H1 posited that human-based recovery text have higher levels of affective (H1a), cognitive (H1b) and conative (H1c) outcomes, compared to AI-based recovery text. A one-way ANOVA was conducted to compare the means of these two types of texts with results reported in Table 7. These results reveal that, firstly, human-based text ($M = 4.34$, $SD = 1.40$) has a significantly higher level of affective outcome compared with AI-based text ($M = 3.52$, $SD = 1.63$) among participants ($F (1, 168) = 17.71$, $p < 0.001$). Secondly, human-based text ($M = 4.68$,

Table 6
Phase 3 – Correlation of constructs.

Construct	*M*	*SD*	1	2	3	4	5	6
1. Uncanniness	2.54	1.68	–					
2. Perceived authenticity	3.91	1.83	−0.44*	–				
3. Affective outcome	3.88	1.58	−0.53*	0.81*	–			
4. Cognitive outcome	4.11	1.88	−0.50*	0.85*	0.89*	–		
5. Conative outcome	3.39	1.74	−0.48*	0.75*	0.85*	0.88*	–	
6. Technology innovativeness	3.17	1.81	0.06	0.19*	0.09	0.10	0.09	–

Note. *$p < 0.01$.

Table 7
Phase 3 – Results of one-way ANOVA.

Dependent Variables	Human-based Text		AI-based Text		F (1, 168)	*p* Value
	M	SD	M	SD		
Affective outcome	4.34	1.40	3.52	1.63	17.71	<0.001*
Cognitive outcome	4.68	1.78	3.69	1.85	18.92	<0.001*
Conative outcome	3.89	1.67	3.01	1.70	19.55	<0.001*

Note. *$p < 0.01$.

SD = 1.78) has a higher level of cognitive outcome compared with AI-based text (*M* = 3.69, *SD* = 1.85) among participants (F (1, 168) = 18.92, $p < 0.001$). Thirdly, human-based text (*M* = 3.89, *SD* = 1.67) has a higher level of conative outcome compared with AI-based text (*M* = 3.01, *SD* = 1.70) among participants (F (1, 168) = 19.55, $p < 0.001$). Hence, H1a, H1b and H1c are supported.

Two parallel mediation analyses were conducted using SPSS PROCESS model 4 to test H2(a, b and c) and H3(a, b and c) using bootstrapping based on 95% confidence intervals (CIs) and 5000 resamples. In these models, technology innovativeness was included as a covariate. The first parallel mediation analysis stream utilized responses for scenarios 1 and 3, which featured only interactional justice to examine H2 (a, b and c) and the second parallel mediation analysis stream utilized scenarios 2 and 4, which featured only procedural justice to examine H3 (a, b and c). To avoid potential issues regarding high correlations between affective, cognitive and conative outcomes, we refrained from analyzing them simultaneously in a model. This also complied with the restriction of model 4 in SPSS PROCESS to only one dependent variable at a time. Table 8 summarizes these results.

H2 posited that perceived authenticity mediated the effects of service recovery entity (human-based text vs. AI-based text) on participant's affective (H2a), cognitive (H2b) and conative (H2b) outcomes. Results from scenarios 1 and 3 revealed that, compared to human-based text, AI-based text leads to a lower level of affective (indirect effect = −0.37, 95% CI = [−0.5643, −0.1927]), cognitive (indirect effect = −0.49, 95% CI = [−0.7257, −0.2518]), and conative (indirect effect = −0.37, 95% CI = [−0.5553, −0.1938]) outcomes. Likewise, results from scenarios 2 and 4 also revealed that AI-based text (vs. human-based text) leads to lower levels of affective (indirect effect = −0.56, 95% CI = [−0.7843, −0.3430]), cognitive (indirect effect = −0.69, 95% CI = [−0.9468, −0.4445]), and conative (indirect effect = −0.57, 95% CI = [−0.8073, −0.3416]) outcomes. As the results reflect the expected direction and as the CIs do not straddle zero, H2a, H2b and H2c are supported for both interaction and procedural justice.

H3 posited that uncanniness mediated the effects of service recovery entity (human-based text vs. AI-based text) on participant's affective (H3a), cognitive (H3b) and conative (H3c) outcomes. In examining the results for scenarios 1 and 3, AI-based text (vs. human-based text) leads to a lower level of affective (indirect effect = −0.07, 95% CI = [−0.1410, −0.0179]), cognitive (indirect effect = −0.07, 95% CI = [−0.1428, −0.0156]) and conative (indirect effect = −0.07, 95% CI = [−0.1462, −0.0186]) outcomes. Similarly, results for scenarios 2 and 4 reflected the same finding with AI-based text leading to a lower level of affective (indirect effect = −0.13, 95% CI = [−0.2368, −0.0500]), cognitive (indirect effect = −0.11, 95% CI = [−0.2109, −0.0453]), and conative (indirect effect = −0.11, 95% CI = [−0.2252, −0.0273]) outcomes. Given that these findings are in the expected direction and that the respective CIs do not include zero, H3a, H3b and H3c are supported for both interaction and procedural justice.

7. Overall results & discussion

7.1. Theoretical implications

In this study, we investigated the reactions of potential customers to MRs, a form of online service recovery. The reactions of potential customers matter because how they subsequently behave can be influenced by these MRs (Litvin & Hoffman, 2012), even if they are not part of the initial service failure. Moreover, with MRs written by generative AI

Table 8
Phase 3 – Results of parallel mediation analysis.

Independent Variable	Mediator	Dependent Variable	Indirect Effect	LLCI[a]	ULCI[b]	Hypothesis Validation
(i) Scenarios 1 & 3: interactional justice only						
Service Recovery Entity	Perceived Authenticity	Affective outcome	−0.37	−0.5643	−0.1927	H2a: Significant
		Cognitive outcome	−0.49	−0.7257	−0.2518	H2b: Significant
		Conative outcome	−0.37	−0.5553	−0.1938	H2c: Significant
	Uncanniness	Affective outcome	−0.07	−0.1410	−0.0179	H3a: Significant
		Cognitive outcome	−0.07	−0.1428	−0.0156	H3b: Significant
		Conative outcome	−0.07	−0.1462	−0.0186	H3c: Significant
(ii) Scenarios 2 & 4: procedural justice only						
Service Recovery Entity	Perceived Authenticity	Affective outcome	−0.56	−0.7843	−0.3430	H2a: Significant
		Cognitive outcome	−0.69	−0.9468	−0.4445	H2b: Significant
		Conative outcome	−0.57	−0.8073	−0.3416	H2c: Significant
	Uncanniness	Affective outcome	−0.13	−0.2368	−0.0500	H3a: Significant
		Cognitive outcome	−0.11	−0.2109	−0.0453	H3b: Significant
		Conative outcome	−0.11	−0.2252	−0.0273	H3c: Significant

Note. Confidence levels calculated through bootstrapping with 5000 resamples.
[a] LLCI = Lower-level confidence interval.
[b] ULCI = Upper-level confidence interval.

becoming almost indistinguishable from those written by human employees as determined in phase 2 of our study, generative AI's appeal to service providers is evident. Nevertheless, prior to the adoption of new technology, it is prudent to investigate the reactions of potential customers, which we did by measuring their affective, cognitive and conative responses. Considering the consistent results on these three outcome variables, we discuss our findings using a collective approach that indicates consumer preferences instead of focusing on each of affective, cognitive or conative outcome.

Specifically, we examine the effect of algorithm aversion in potential customers. This approach was guided by the mind perception theory, which posits that, unlike humans, robots are generally perceived as possessing little to no experiential mind (Gray et al., 2007; Shank et al., 2021). Indeed, as demonstrated in phase 3 when participants were informed of the source of MR text, AI-based text elicited lower positive feelings (i.e. affective outcome), lower expectation/satisfaction levels (i.e. cognitive outcome) and lower future purchase intentions (i.e. conative outcome). Not only does this finding align with the mind perception theory. It also corroborates past studies which demonstrate that human labor is preferred over robotic labor (Bellaiche et al., 2023; Longoni et al., 2019; Yeomans et al., 2019), especially in after-sales situations (De Keyser et al., 2015), thereby contributing to the broader literature on algorithm aversion.

Furthermore, to explain the effect of algorithm aversion, our study also investigated the parallel mediators of perceived authenticity and uncanniness. We adopted the expectancy violation theory to understand the role of authenticity and, in doing so, extend existing literature on expectancy violation theory to a consumer setting. Consumers expect service employees to be authentic (Turel et al., 2013) and the violation of such expectation in service recovery could lead to negative outcomes. Our findings from phase 3 indicate that service recovery text from a human employee is interpreted as more authentic than that from generative AI, thus resulting in more favorable affective, cognitive and conative outcomes. This finding resonates with research demonstrating robots as being perceived as less authentic than human employees in service delivery (Lin & Mattila, 2021; Song et al., 2022). Moreover, this finding also sheds light on authenticity beyond its role as a mediator. Service recovery entity – or more specifically, the human origin of the message source – is unveiled for its importance to potential customers in assessing authenticity. Even when robots can mimic human-likeness to a level indiscernible from a human, they continue to be perceived as less authentic; evidently, establishing authenticity is not as straight-forward as mimicking human-likeness. Given the importance of authenticity to consumers (Rickly-Boyd, 2012), we believe that further research is warranted to further investigate how authenticity can be effectively communicated in an online service recovery context as well as other automated or robotic contexts.

For the second mediator of uncanniness, we built upon the uncanny valley theory. Through this, our study extends online service recovery literature by empirically validating that being human-like versus, at least still today, being a human does not always facilitate recovery. Service recovery text generated by generative AI evoked higher levels of uncanniness to result in less favorable affective, cognitive and conative outcomes; clearly, not all human likeness is good or acceptable to potential customers. This finding corroborates research on human-looking consumer-use and service robots (Kim et al., 2019; Mende et al., 2019), which show that unpleasant feelings of uncanniness emerge when interactions with robots become too human-like (Sullivan et al., 2022). Notably, our finding contributes to the broader literature on the uncanny valley theory by demonstrating that uncanniness can be evoked using conversational text, thus extending past research which has focused predominantly on physical (Kim et al., 2019) or vocal (Mitchell et al., 2011) stimuli.

In addition to shedding light on consumer psychology underpinning online service recovery, our study also adds to research regarding the integration of AI – whether generative or otherwise – into tourism and hospitality service encounters. In our study, we focus on how the human-likeness of an AI application adversely impacts behavioral intentions. In comparison, current tourism and hospitality literature has focused predominantly on how anthropomorphism encourages favorable responses or technology acceptance in consumers (e.g. Agnihotri & Bhattacharya, 2023; Lin & Mattila, 2021). Yet, as shown in our study, it is the ability to converse like a human that has led to less favorable responses.

Therefore, from a theoretical perspective, our results provide support for the presence of an upper limit on favorable responses engendered by anthropomorphism. This observation is not novel, as it reflects the part of Mori's (2012) uncanny valley theory where liking, as inspired by human likeness, eventually dips when a replica becomes too human-like. However, our finding remains relevant and pertinent as anthropomorphism has drawn an emerging stream of literature in our field (Fan et al., 2020). Moreover, the tourism and hospitality industry continually seeks to incorporate emerging technologies, e.g. generative AI, into different forms and facets of service encounters. With AI increasingly integrated into customer-facing interfaces, including but not limited to service recovery, and with AI becoming progressively more intelligent, more research needs to be conducted to understand its aversion/acceptance by consumers.

7.2. Practical implications

Our research shows that ChatGPT (vs. human) can write comparable MRs and others have shown that it can do so with high efficiency (Koc et al., 2023). In other words, by integrating generative AI into online service recovery, service providers could most likely benefit in terms of time and labor savings. Nevertheless, findings from our study indicate that the adoption of generative AI could instead backfire with unfavorable affective, cognitive and conative outcomes potential customers. Therefore, we advocate a cautious approach, as most potential customers seemingly prefer interacting with a human employee for service recovery even if it is via a text interface.

One such approach would be the employment of generative AI to supplement or augment online service recovery executed by human employees instead of using it to fully automate service recovery. For instance, ChatGPT could be used to write MRs. However, these MRs could be reviewed and amended as appropriate by a human employee. Doing so could help to bring the human touch to the recovery process and hence, maintain perceived authenticity in the service encounter. Simultaneously, with a human employee involved in the process, feelings of eeriness might be decreased. If a service provider proceeds with the full integration of generative AI in writing and posting MRs without oversight from a human employee, the findings of our research suggest that the organization should consider decreasing the human likeness of the responses. This could be achieved by using programmatic or robotic speech that makes the MR less conversational. While this approach may attenuate the purpose and contribution of generative AI, it could allow the service provider to strike a better balance between efficiency in dealing with online reviews and desired outcomes. Alternatively, the organization could also consider making the human touch more salient in their MRs. For instance, this could be achieved by programming interfaces with the option to easily get in touch with service employees.

At this juncture, it is important to note that the practical implications we have discussed are based on the premise that the service provider discloses the source of the MR. Without this information, potential customers may not correctly identify if a MR is written by a human employee or by generative AI. After all, our findings point to how they are virtually indistinguishable. While such non-disclosure would remove concerns on how potential customers would react to AI-driven service recovery efforts, it in turn brings about practical concerns regarding the ethics of such actions.

Notably, our study also holds practical implications that relate to the use of generative AI beyond online service recovery. In extending our findings beyond online review platforms to other company-consumer interfaces, organizations should assess if a particular service encounter should be performed by AI technology or if it would be better off being handled by a human employee. For service encounters where the human touch matters, the use of generative AI may be less appropriate. However, it is possible that for selected types of service encounters, the human touch may not be as critical as in the case of service recovery. An example would be frequently asked questions (FAQ) chatbots that handle more mundane or lower risk tasks, such as responding to queries about opening hours of a hotel's dining outlet. Potential customers in such encounters are likely to have fewer concerns about the human touch and hence, be less averse towards the use of generative AI-generated responses. Generative AI could thus be tapped in such encounters, thus enabling the judicious use of technology and human employees by organizations.

Additionally, instead of relying on anthropomorphism to encourage potential customers to be more comfortable with generative AI, organizations could consider emphasizing the human origin of the application. Based on our findings, generative AI is already engendering a high level of human-likeness to the point of eliciting eeriness. This implies that additional anthropomorphic features, such as a human-like voice or body, may not be as helpful in eliciting favorable outcomes among target clientele. Nevertheless, an emphasis on the human origin of the application could be helpful in maintaining a human touch and remaining connected with potential customers despite the use of generative AI. For this purpose, strategic communications by the organization could be leveraged, such as the use of background stories, taglines or marketing plans, so as to encourage greater acceptance of generative AI.

7.3. Limitations

Our study faces several limitations despite its contributions. We exclusively used hotel reviews and hotel MRs. Hence, our findings are limited to online service recovery in the hotel industry. To increase results generalizability, future studies could replicate our study in other tourism and hospitality sectors, e.g. restaurants and theme parks, and also, in other service industries, e.g. healthcare and banks. This is because the nature and/or different technological level of each industry might impact how potential customers perceive recovery efforts.

In our experimental design, we controlled for the potential confounding effects of interactional justice and procedural justice, which are two of the three most widely considered service recovery dimensions. We did not include distributive justice, e.g. discounts for subsequent patronage. Future studies could consider this, especially since phase 1 of our study indicated that selected sectors (e.g. restaurants) could be utilizing this more than hotels.

Given the recency of generative AI, we included technology innovativeness as a covariate to account for personal consumer traits. Nevertheless, as indicated by literature on service failure and service recovery (Bae et al., 2021; Hu et al., 2021), other consumer attributes, e.g. travel experience and status in customer loyalty programs, could likewise impact reactions to MRs written by generative AI. Future studies should investigate these consumer attributes as potential moderators of our research model.

Finally, we focused on potential customers who observed the online service recovery process despite not being part of the original service failure. Future studies could consider the perspective of hotel guests directly involved in the preceding service failure and, in doing so, investigate the effect of hybrid (i.e. AI- and human-based) service recovery. Arguably, hotels, particularly those of luxury positioning, could combine AI-generated MRs with human-based recovery efforts (e.g. an apology phone call from a human employee), the latter of which may not be disclosed in MRs.

8. Conclusion

By focusing on the use of generative AI, this study represents a pioneering effort in understanding reactions of potential customers to MRs, a form of online service recovery. With expanding application of and continual advancements in generative AI, this form of technology is markedly different from its predecessors. Hence, an investigation of how potential customers could react to MRs is important. Findings from our study demonstrate that potential customers are unable to clearly differentiate MRs written by generative AI from those written by humans, and do not distinctively rate one type of MR as being 'better' than the other. Despite this, findings from our study further unveiled that potential customers are averse to MRs prepared by generative AI due to lower perceived authenticity and higher uncanniness, leading to lower levels of affective, cognitive and conative intentions.

During the preparation of this work the authors used ChatGPT in order to generate experimental stimuli (see Table 5, Online Supplementary Material A and Online Supplementary Material B). After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Impact statement

Recent advancements in the conversational abilities of generative artificial intelligence (AI) means that this form of technology, e.g. ChatGPT, can now be considered for online service recovery. Indeed, as demonstrated by our research, consumers could not clearly distinguish between managerial responses to online reviews prepared by ChatGPT and by human employees. Considering this and the potential time and labor savings that ChatGPT could yield, it would seem that service providers should adopt its use as soon as possible.

However, these potential benefits of ChatGPT need to be balanced against how potential consumers feel about ChatGPT. As further unveiled by our research, at present, consumers are not too receptive to its use in online service recovery. This means that even though business processes could become more effective and efficient through ChatGPT, the use of ChatGPT still needs to be carefully weighed and considered.

Declaration of interest

None.

CRediT authorship contribution statement

Karen Pei-Sze Tan: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Yi Vanessa Liu:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Stephen Wayne Litvin:** Writing – review & editing, Methodology, Conceptualization.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tourman.2024.105057.

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