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Language Styles, Recovery Strategies and Users' Willingness to Forgive in Generative Artificial Intelligence Service Recovery: A Mixed Study

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Abstract: As the prevalence of generative artificial intelligence (GenAI) in the service sector continues to grow, the impact of the language style and recovery strategies utilized during service failures remains insufficiently explored. This study, grounded in the theory of social presence and dual-process theory, employed a mixed-method approach combining questionnaire surveys and event-related potential (ERP) experiments to investigate the effect of different language styles (rational vs. humorous) and recovery strategies (gratitude vs. apology) on users' willingness to forgive during the GenAI service recovery process. It further delves into the chained mediating role of perceived sincerity and social presence in this process. The findings revealed that a humorous language style was more effective in enhancing users' willingness to forgive compared to a rational style, primarily through the enhancement of users' perceived sincerity and sense of social presence; recovery strategies played a moderating role in this process, with the positive impact of perceived sincerity on social presence being significantly amplified when the GenAI service adopted an apology strategy. ERP results indicated that a rational language style significantly induced a larger N2 component (cognitive conflict) in apology scenarios, while a humorous style exhibited higher amplitude in the LPP component (positive emotional evaluation). This research unveils the intricate relationships between language style, recovery strategies, and users' willingness to forgive in the GenAI service recovery process, providing important theoretical foundations and practical guidance for designing more effective GenAI service recovery strategies, and offering new insights into developing more efficacious GenAI service recovery tactics.

Keywords: generative artificial intelligence; service recovery; linguistic style; recovery strategies; event-related potentials

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1. Introduction

Generative Artificial Intelligence (GenAI) is rapidly gaining popularity and reshaping various domains such as content creation, customer service, and education, owing to its ability to generate text, images, and code that are almost indistinguishable from those produced by humans [1], as well as its significant enhancement of user productivity [2]. However, GenAI is not without flaws; it is still in its early stages of development and faces challenges such as "AI hallucinations" (the generation of inaccurate or misleading information) and service failures [3]. Completely avoiding these issues is currently unfeasible, as even the most advanced GenAI models can produce unpredictable errors, including erroneous text, images, or audio [4]. These service failures can lead to diminished user trust and even abandonment of the system [5]. Given the rapid growth and intense competition in GenAI applications, understanding how to effectively recover from service failures and maintain user trust in GenAI systems is crucial. Consequently, this research focuses on users' willingness to forgive after GenAI service failures, a critical factor for maintaining user satisfaction and long-term engagement [6].

The existing literature on service recovery mainly examines various recovery strategies (e.g., apologies, compensation) from the service provider's perspective, exploring their impact on user perceptions and behaviors [7]. On the other hand, some research emphasizes user characteristics, such as attribution style [5], sense of justice [8], or religious beliefs [9], to explain different reactions to service failures. However, the advent of GenAI introduces a unique challenge due to its highly sophisticated language capabilities and emotional expressiveness [10], which can enhance user experience by accurately modeling their emotions through interactive design [11]. This differentiates GenAI significantly from traditional rule-based and logic-based chatbots or virtual assistants [1]. The language style used by GenAI can significantly influence user trust, attitudes, and continued usage intentions [12]. For instance, a humorous language style can increase user tolerance and positive evaluations of the service provider [13], but if perceived as inappropriate or untimely, it can have the opposite effect [14]. Moreover, unlike traditional chatbots constrained by preset templates, the language style of GenAI, in theory, should not be limited by specific recovery strategies (e.g., apology or gratitude). However, existing research has largely examined language style or recovery strategies in isolation, lacking in-depth exploration of their interaction within GenAI contexts.

Past research on service recovery has predominantly relied on questionnaires and self-reports to understand users' subjective attitudes and evaluations of recovery measures [15]. Nonetheless, the use of GenAI involves a dynamic, real-time interactive process in which users often make judgments based on immediate emotions when assessing the quality, risk, or benefits [16]. Therefore, relying solely on retrospective recall and self-reports might not fully capture users' immediate experiences and psychological changes during the service recovery process, and may be subject to recall bias [17]. To gain a more comprehensive understanding of user reactions to GenAI service recovery, it is essential to employ a mixed-method approach that combines subjective evaluations with objective measures capable of capturing real-time responses, such as neurophysiological indicators [18]. Furthermore, earlier studies have paid little attention to the automated psychological processes involved in users' service recovery experiences. The dual-process theory [19] posits that human cognitive processes consist of both automated and conscious control pathways, whose roles in service recovery contexts warrant detailed investigation to uncover the cognitive mechanisms underlying users' willingness to forgive.

This study aims to explore the complex relationships between language style, recovery strategies, and users' willingness to forgive in GenAI service recovery processes, and to delve into the underlying psychological mechanisms. Specifically, this research seeks to answer the following questions: (1) Does the use of different language styles (rational vs. humorous) during service recovery affect users' willingness to forgive? (2) Do perceived sincerity and social presence mediate the impact of language style on forgiveness willingness? (3) Do recovery strategies (gratitude vs. apology) moderate the influence of perceived sincerity on social presence? (4) How do different language styles (rational vs. humorous) affect automated cognitive processes in GenAI service recovery, and how does this interact with recovery strategies (gratitude vs. apology)? To address these questions, this study integrates social presence theory and dual-process theory, employing a mixed-method approach comprising questionnaires and event-related potential (ERP) experiments. The questionnaires measure users' subjective perceptions and attitudes in simulated GenAI service recovery scenarios, while the ERP experiments capture users' immediate neural responses under different experimental conditions to reveal the underlying cognitive processing mechanisms. The contributions of this research are threefold: (1) it expands the research domains of service recovery and AI acceptance by incorporating language style and recovery strategies into the GenAI service recovery framework; (2) it utilizes a mixed-method approach, combining subjective evaluations and objective physiological indicators, to provide a more comprehensive understanding of users' willingness to forgive; and (3) it elucidates the chain-mediating role of perceived sincerity and social presence in the effect of language style on forgiveness willingness, and examines the moderating effect of recovery strategies, thus enriching the application of social presence theory in service recovery contexts. Theoretically, this research enhances the understanding of the cognitive and behavioral mechanisms underlying users' responses to GenAI service recovery, offering theoretical support for developing more effective service recovery strategies. Practically, the findings provide insights for the design and optimization of GenAI systems, improving user experience and satisfaction, and promoting the healthy development and application of GenAI technology.

2. Literature Review and Research Hypotheses

2.1. Research Related to the Failure of Artificial Intelligence or Robotic Services

Service failure refers to situations where service providers fail to meet user expectations or fulfill user needs [20], and such failures can have serious negative impacts [21], thus gaining extensive attention from scholars. Research in this area mainly focuses on investigating the severity and types of service failures, recovery strategies [22], customer attitudes [23], and personal characteristics [24] that influence the effectiveness of service recovery.

With the development of robotics and artificial intelligence (AI) technologies, service failure in the fields of human–computer interaction and service marketing has also drawn increasing attention. Existing research primarily explores several areas: firstly, the types of AI service failures [15] and recovery strategies [25]. For instance, Xing et al. (2022) examined the impact of different types of service failures (functional and non-functional) and recovery strategies (apology and compensation) on user trust and satisfaction [15]. Lv et al. (2022) found that in refusal-type service failures, gratitude strategies are more likely to gain user forgiveness compared to apologies [7]. When failures are caused by AI or robots, users expect more proactive recovery strategies [26]. In the tourism industry, robotic employee apologies can enhance senior travelers' satisfaction with service recovery [27]. Peng (2024) suggested that service failures in AI live e-commerce can be categorized into five dimensions from the perspective of inconsistent consumer expectations: information, functional, system, interactional, and aesthetic failures [28]. For chatbot service failures, recovery messages have a positive impact on service recovery, with solution-oriented messages eliciting stronger competence evaluations and empathy-seeking messages evoking stronger warmth evaluations [29].

Secondly, user attributions, psychology, and attitudes towards service failures are considered. For example, Meyer et al. (2022) indicated that users tend to attribute successful service to themselves and service failures to the providers, offering new insights for improving user acceptance [26]. Han et al. (2021) found that chatbot service failures induce consumer anger and negative cognition, which decreases competence perception and satisfaction [30]. Sun (2022) observed that cognitive load affects technology exhaustion and satisfaction [4]. The perceived security of chatbots can improve consumers' perceived competence and empathy, thereby increasing their willingness to forgive failures [31]. Robot design characteristics influence user attribution of failure, with competence-designed robots being more likely to be blamed for failures [26]. Users are less likely to attribute failures internally and to be more forgiving of service failures with less-anthropomorphized service robots [6]. The intelligence level of robots moderates the choice of recovery strategies for different types of service failures [15]. Chatbot self-recovery positively impacts consumer satisfaction with recovery, with perceived functional value and privacy risk serving as mediators [32].

However, the aforementioned studies primarily focus on traditional AI and service robots, with relatively less attention paid to GenAI, a new emerging service provider. Compared to traditional service providers, GenAI has stronger content-generation capabilities and more flexible language styles, posing new possibilities and challenges for service recovery. For instance, GenAI can utilize different language styles and expressions tailored to users' personal characteristics and emotional states for apologies or explanations, thereby more effectively enhancing users' willingness to forgive.

2.2. Humor in Human–Computer Interaction Research

Humor, often manifested as self-deprecation or jokes, plays a significant role in interpersonal communication [33]. With the rapid development of AI and robotics, humor has increasingly been applied in human–computer interaction to improve user experience and satisfaction. Humor can effectively alleviate user tension following service failure and enhance their tolerance [13]. The use of humor by chatbots enhances user satisfaction through mechanisms of anthropomorphism and interactive fun [34]. Humorous responses can mitigate the negative effects of service failures, enhancing service recovery through mediators such as perceived competence, entertainment [35], perceived sincerity [36], and social presence [37]. However, the effectiveness of humorous language style varies depending on several factors, such as the severity of the service failure [38], robot attributes [36], and the service environment [39]. Yang et al. (2022) found that humor exacerbates user negative emotions when service failure is severe [38]. Additionally, robot attributes influence the effectiveness of humor strategies: warm-type service robots are better suited for humorous responses, while competence-type robots are better suited for rational responses [36]. Liu and Xu (2023) further noted that in hedonistic-dominant service environments, both self-deprecating and self-enhancing humor can improve user willingness, while in utilitarian-dominant environments, only self-deprecating humor has a positive impact [39].

The Benign Violation Theory (BVT) offers a theoretical perspective for understanding the mechanism of humor [40]. This theory posits that humor arises when an action violates social norms but does not cause real harm. Liu and Xu (2023), based on BVT, revealed that positive emotions and negative motive inference are key mechanisms influencing the interaction effects between types of humor and service contexts, further affecting user intention to use AI post failure [39]. However, existing research mainly focuses on the overall perception and behavioral intentions influenced by humor, with less attention on how humor impacts the specific cognitive processes of users concerning service failures, such as automatized cognition. Furthermore, there is a lack of exploration on how different recovery strategies, such as gratitude and apology, interact with humorous expressions.

2.3. Social Presence Theory

This study is grounded in Social Presence Theory, which posits that individuals develop a sense of the real presence of others while interacting with them through various media, a notion referred to as "social presence" [41]. The higher the social presence, the more likely individuals are to perceive others as genuine social actors and exhibit behaviors akin to face-to-face interactions, such as stronger adherence to social norms, higher trust levels, and increased willingness to engage [41]. Socially oriented communication by chatbots can significantly enhance users' sense of social presence, thereby affecting trust, empathy, and satisfaction [42]. In service recovery contexts, users expect to experience genuine care and understanding from service providers, and social presence is key to establishing such emotional connections [43].

Although AI lacks inherent social attributes in GenAI service recovery settings, its communication methods, such as language style, can convey various social cues, influencing users' perceptions and responses to AI. For example, humorous language styles may transmit more accessible and friendly social cues compared to rational language styles, thereby enhancing users' sense of social presence. Research has found that humorous communication by chatbots can enhance service recovery satisfaction through increased social presence [37]. Humorous expressions by chatbots can notably boost social presence, thereby improving customer service satisfaction [35]. According to Social Presence Theory, individuals develop a sense of real presence from their interactions (social presence), which then affects their behavior. Language style, as a social cue, can influence users' perceptions of AI's social presence, thereby affecting their willingness to forgive. We hypothesize that a humorous language style enhances users' sense of social presence, thereby increasing their willingness to forgive.

Perceived sincerity refers to the extent to which users perceive the service provider's genuine efforts to address problems during recovery [44]. A humorous language style might be perceived as a positive signal, indicating AI's sincere effort to resolve issues, thus enhancing perceived sincerity. Research has indicated that humorous responses in service recovery are linked to better service evaluations, with perceived sincerity acting as a mediator [36]. Perceived sincerity mediates the relationship between recovery strategies and service recovery satisfaction [45].

2.4. Recovery Strategies and Moderation Effects

Service recovery refers to the measures taken by businesses to restore customer satisfaction following service failures by striving to return customers to their pre-failure state [46]. Among numerous service recovery strategies, gratitude and apology are two fundamental communication strategies [47]. The gratitude strategy addresses service failures by emphasizing customer virtues and contributions, treating them as benefactors [47]. For instance, Magnini et al. (2009) found that expressing gratitude towards customers' understanding and support effectively enhances their satisfaction with service recovery [48]. You et al. (2020) further asserted that gratitude strategies can boost recovery satisfaction by enhancing consumers' self-esteem [47]. Lee and Lee (2022) discovered that gratitude enhances user experience [49]. These studies indicate that gratitude strategies can effectively mitigate the negative impacts of service failures, fostering positive customer responses. On the other hand, apology strategies have been a focal area in service recovery research. Apologies, defined as actions taken by service providers to acknowledge responsibility [47], help restore relationships by acknowledging responsibility and expressing the provider's regret [27]. Compared to monetary compensations, emotional recovery strategies such as apologies are more effective at eliciting consumer empathy and forgiveness [50]. Employee apologies effectively facilitate service reconciliation following failures [51].

Apologies can also be utilized as trust recovery strategies in social robots and positively affect those interacting with industrial robots [52]. The use of two robots (one main robot committing an error and apologizing, and a secondary robot also apologizing) yields better recovery outcomes than a single robot's apology, increasing users' willingness to forgive [53]. However, apologies are not always effective [54]. Apologies from chatbots lacking natural elements can diminish perceived sincerity, reducing customer satisfaction with the recovery [55]. For service failures, chatbots can repair trust through apologies [56]. The authenticity and timeliness of service robots' apologies influence users' forgiveness [45]. Both apologies (expressing regret, taking responsibility) and gratitude (providing compensation, showing appreciation) aim to restore stakeholder trust and satisfaction but differ in their focus on conveying sincerity and responsibility. Apology strategies emphasize expressing regret and assuming responsibility, highlighting service providers' faults and accountability, directly addressing the issue and assuming responsibility [47], which we believe better reflects the service provider's sincere attitude compared to gratitude strategies that emphasize customer virtues and contributions [47], thereby enhancing customers' social presence.

2.5. Application of EEG Technology in Human–Computer Interaction Research

Event-Related Potentials (ERPs), as a high temporal- and spatial-resolution non-invasive technology, enable real-time monitoring of user brain activity, revealing cognitive and emotional responses at the subconscious level [57]. This offers a new perspective and methodology for examining the impacts of human–computer interaction (HCI) on user psychology and behavior [58]. Existing studies have utilized EEG technology to delve into several key areas within human–computer interaction:

1. Emotional Responses: researchers have employed ERP technology to investigate the variance in emotional responses of users interacting with different types of artificial intelligence agents. For instance, Wang (2023) found that compared to real human interactions, users exhibit stronger negative emotion processing when interacting with chatbots, as indicated by increased P2 and LPP wave amplitudes [59]. This suggests that users' reactions to artificial intelligence agents are specific and necessitate further exploration into the underlying psychological mechanisms.
2. Cognitive Processing: EEG studies have also focused on the cognitive processing of users in human–computer interactions, especially in response to the social cues of artificial intelligence agents. For example, Caruana and McArthur (2019) discovered that users show stronger brain electrical responses to joint attention cues from human-controlled virtual characters [60], while Perez-Osorio et al. (2021) pointed out that even gaze cues emitted by robots can influence users' judgments of others' mental states [61]. These studies indicate that users spontaneously incorporate artificial intelligence agents into their social cognition framework and process their social cues accordingly.
3. Behavioral Decision-Making: some studies have utilized EEG technology to explore how human–computer interaction influences users' behavioral decision-making. For instance, Abubshait (2021) found that familiarity with robots affects users' learning performances and reward motivation [62], while Hinz and colleagues (2021) discovered that collaborating with robots alters users' action planning and outcome monitoring [63]. These studies provide neuroscientific evidence for understanding how human–computer interaction shapes user behavior decision-making.

The spectrum of ERPs research is vast, with different ERP components reflecting various cognitive functions. The N2 component is an event-related potential (ERP) component that usually appears between 200 and 350 milliseconds after stimulus presentation, manifesting as a negative amplitude shift. Numerous studies have shown that the N2 component is a crucial neural indicator of cognitive conflict, reflecting the brain's detection and response to expectation violations [64]. When a stimulus conflicts with expectation, requiring additional cognitive control and conflict resolution, the N2 component's amplitude increases [64]. The Late Positive Potential (LPP) appears approximately 500–800 milliseconds after stimulus, mainly distributed over the central and parietal brain areas, and is related to emotional processing [65], offering a comprehensive reflection of the user's emotional experience towards products, services, or brands [66].

2.6. Hypotheses Formulation

Previous research methods in service recovery mainly relied on questionnaires and self-reports to understand users' subjective attitudes and evaluations of service recovery measures [15]. However, the use of GenAI is a dynamic, real-time interaction process, where user service evaluations often depend on immediate emotions [16]. In contrast, ERP, as a high temporal-resolution technology that can monitor users' brain activities in real-time, provides a more objective and in-depth perspective and method for exploring the psychology of users during GenAI service recovery. Therefore, this study will conduct Experiment 2 using Event-Related Potential (ERP) technology on the basis of Experiment 1, to explore the automated processes of users' reactions to GenAI service recovery, as shown in Figure 1. In situations of service failure, humor can effectively soothe angry users, earning their forgiveness [13], and avoid negative impacts [67]. Based on this, the present study hypothesizes that following service failure, GenAI's humorous responses can alleviate users' negative emotions and thus enhance their willingness to forgive. This is because emotionally soothed customers can view problems more positively and broadly, making them more likely to forgive mistakes. We hypothesize that a humorous language style can increase perceived sincerity during service recovery, thereby boosting willingness to forgive. Perceived sincerity and social presence are not isolated, but are closely connected. Perceptions of sincerity and honesty are strong predictors of social presence and user experience [68]. We hypothesize that when users perceive service providers as sincere, they feel more respected and valued, leading to a stronger sense of the provider's real presence, thereby enhancing social presence. We further propose that a more affable and easily perceived sincere humorous language style will enhance social presence, ultimately increasing users' willingness to forgive. Based on the literature on recovery strategies [47], we hypothesize that perceived sincerity has a stronger positive impact on social presence under apology recovery strategies than gratitude recovery strategies. To understand how language style affects users' willingness to forgive, this study integrates Dual-Process Theory, which postulates two pathways of human cognitive processing: automatic processing, which is unconscious, fast, and intuition-based, and controlled processing, which is conscious, slow, and requires cognitive effort [19]. A rational language style, particularly in apology scenarios, is more distant emotionally, likely triggering users' negative emotions and cognitive conflict, thereby enhancing the N2 component. In contrast, a humorous language style, being more acceptive, triggers less cognitive conflict, resulting in a smaller N2 component. The humorous style also tends to elicit a positive emotional experience in users, leading to increased LPP amplitude. Based on the theoretical framework above, this study proposes the following hypotheses:

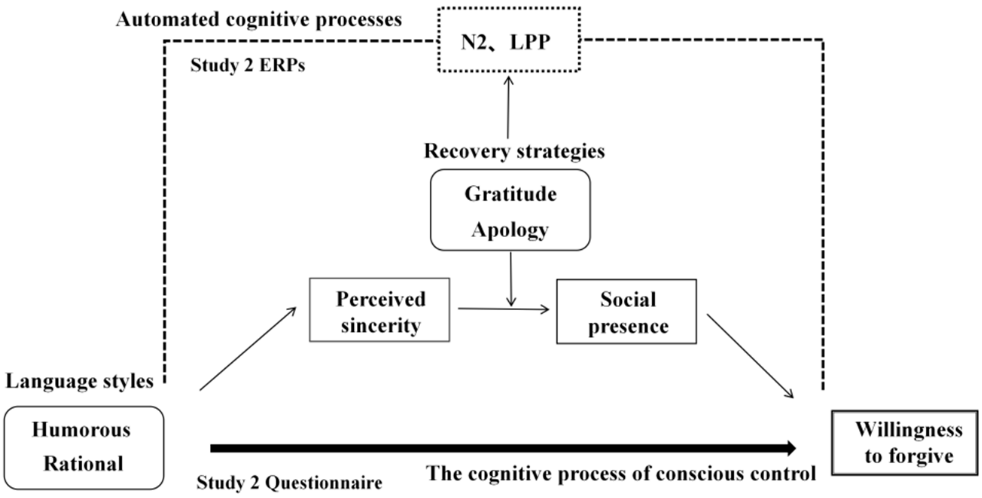

Figure 1. Theoretical model diagram.

H1. *During service recovery, compared to rational language styles, humorous language styles significantly enhance users' willingness to forgive.*

H2. *Perceived sincerity mediates the relationship between language style and willingness to forgive. Specifically, a humorous language style increases users' perceived sincerity, thereby enhancing their willingness to forgive.*

H3. Social presence mediates the relationship between language style and willingness to forgive. Specifically, a humorous language style enhances users' sense of social presence, thereby increasing their willingness to forgive.

H4. *Perceived sincerity and social presence act as a serial mediating pathway in the effect of language style on willingness to forgive. Specifically, a humorous language style enhances users' perceived sincerity, which in turn strengthens their social presence, thereby increasing willingness to forgive.*

H5. *Recovery strategy moderates the serial mediation effect of perceived sincerity on social presence. Specifically, compared to gratitude recovery strategies, apology recovery strategies show a stronger positive effect of perceived sincerity on social presence.*

H6. *Compared to humorous language style, a rational language style will induce a greater N2 component, especially in apology recovery strategies, where a rational language style compared to a humorous one will trigger a larger N2 component.*

H7. *Compared to a rational language style, a humorous language style will induce a larger LPP amplitude, indicating a more positive emotional evaluation of the humorous language style.*

3. Study 1

3.1. Experimental Design and Participants

This study employed a 2 (language style: humorous vs. rational) × 2 (recovery strategy: gratitude vs. apology) between-subjects experimental design to explore the impact of language style on users' willingness to forgive and to investigate the mediating roles of perceived sincerity and social presence, as well as the moderating effect of different recovery strategies on these relationships. With this experimental design, the study aimed to reveal the distinct effects of humorous and rational language styles in service failure scenarios, and the moderating effects of gratitude and apology strategies in users' forgiveness decisions. Participants were recruited through an online survey platform, with 279 participants completing the questionnaire experiment and receiving a reward for their participation. The experiment was conducted in Mandarin Chinese, and all materials, instructions, and communications were presented in this language. All participants were native Mandarin speakers or possessed native-level proficiency, ensuring that language comprehension did not impact the results. Two participants were excluded for failing an attention check question, yielding 277 valid participants (a validity rate of 99.3%). Among them, there were 69 males and 208 females, with the age distribution primarily 21–30 years old (41.5%) and 31–40 years old (41.2%). The majority of participants held a bachelor's degree (71.8%).

3.2. Experimental Procedure and Materials

The study utilized a 2 (language style: rational vs. humorous) × 2 (recovery strategy: apology vs. gratitude) between-subjects experimental design. Participants were randomly assigned to one of four conditions: gratitude + humor, gratitude + rational, apology + humor, and apology + rational. The specific experimental procedure was as follows: (1) Participants read and imagined a service scenario corresponding to their group, where GenAI responded with different language styles (rational vs. humorous) and recovery strategies (gratitude vs. apology) upon a service request. Scenarios included AI's response to the service request, user's feedback upon discovering a mistake, and AI's recovery response. (2) Questionnaire measurement: Perceived Sincerity was assessed by a 7-point scale evaluating participants' perception of the sincerity in GenAI's response to service failure, e.g., "I find GenAI's response to the service failure sincere". Social Presence was measured by a 7-point scale assessing the degree of social presence participants felt during the interaction with AI, such as "AI's response made me feel the contact between human beings". Willingness to Forgive was evaluated by a 7-point scale assessing participants' willingness to forgive the AI after a service failure, e.g., "After seeing GenAI's response, I choose to forgive this service mistake". Some items were scored in reverse, with an overall reliability of 0.784. Identification with the Scenario was measured by a 7-point scale assessing participants' degree of imagination into the experiment scenario, e.g., "To what extent can you imagine yourself as the user in the scenario". (3) Demographic information: participants' demographic information, such as gender and age, was collected. The experimental process strictly controlled for language style and recovery strategy, ensuring each participant was only exposed to the corresponding experimental condition. Through these components, this study sought to explore the interplay of language style and recovery strategy in GenAI service recovery on users' willingness to forgive and to examine the mediating role of perceived sincerity and social presence in this influence process. The gratitude and apology recovery strategies were designed referring to the study by Song et al. (2023), where the gratitude strategy begins with expressing great appreciation for the feedback, and the apology strategy starts with expressing sincere apologies for any confusion caused [69]. See Figure 2 for details. Operationalization measures included the following: language style measurement ("I think this AI's reaction is humorous" 1 = strongly disagree 7 = strongly agree); recovery strategy measurement ("I think this AI's recovery strategy is more of an apology or gratitude" 1=strongly towards apology 7 = strongly towards gratitude); the mediator variable of social presence (α = 0.892), referred to in the study by Lee et al. (2023), including items like "AI's response gave me a sense of communication and felt the conversation had substance" [70]; the mediator variable of perceived sincerity (α = 0.834), referred to in the study by Shan et al. (2024), including items such as "I find GenAI's response to the service failure sincere" [36]; and the dependent variable, willingness to forgive (α = 0.808), referred to in the study by Xing et al. (2022), including "After seeing GenAI's response, I choose to forgive this service mistake" [15], with some questions scored in reverse.

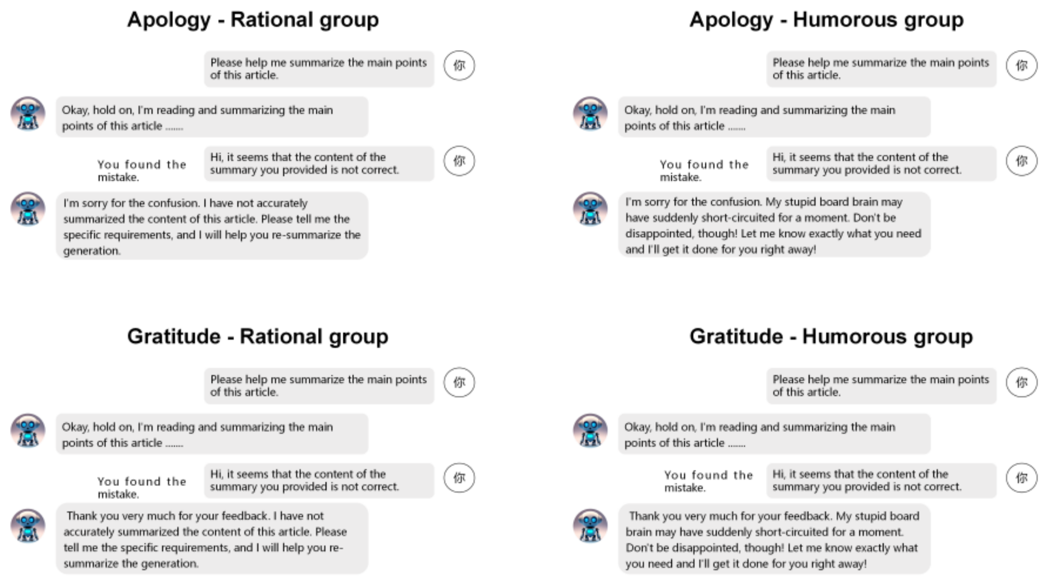

Figure 2. Experimental condition materials.

3.3. Experimental Results

The results from the independent samples t-test indicated that the humor group had a mean score of 5.35, with a standard deviation (SD) of 1.236; the rational group had a mean score of 2.68, with an SD of 1.324, revealing a significant difference between the humor and rational scores, t(275) = 17.306, $p < 0.001$. The apology group had a mean score of 2.04, with an SD of 1.099; the gratitude group had a mean score of 3.2, with an SD of 1.861, showing a significant difference between the apology and gratitude scores, t(275) = -6.360, $p < 0.001$. Therefore, the manipulation of experimental conditions was successful.

In this study, we employed the Bootstrap method within the Process macro in SPSS 27.0 software to examine the relationships among language style (IV), restorative strategy (Mod), perceived sincerity (M), social presence (M), and user forgiveness willingness (DV). We conducted two separate analyses using Model 6 and Model 91 to test our hypotheses.

We first ran Model 6 to test the effect of language style on forgiveness willingness, with perceived sincerity and social presence as mediating variables. The independent variable (IV) was language style (rational = 0, humor = 1). The mediators were perceived sincerity (M) and social presence (M), and the dependent variable (DV) was forgiveness willingness. The analysis of model 6, with 277 sample data and 5000 resamples for the 95% confidence interval (See Table 1), found that language style had a significant positive effect on perceived sincerity (β = 0.4647, p = 0.0003, 95% CI = [0.2180, 0.7115]), indicating that a humorous language style significantly enhances users' perception of sincerity. Language style had a significant positive effect on social presence (β = 0.2449, p = 0.0324, 95%

CI = [0.0206, 0.4692]). Perceived sincerity had a significant positive effect on social presence (β = 0.7971, p < 0.0001, 95% CI = [0.6918, 0.9024]). The direct effect of language style on forgiveness willingness was not significant (β = 0.0768, p = 0.4564, 95% CI = [−0.1258, 0.2794]). However, perceived sincerity had a significant positive effect on forgiveness willingness (β = 0.4191, p < 0.0001, 95% CI = [0.2921, 0.5460]), confirming H2. Social presence had a significant positive effect on forgiveness willingness (β = 0.2426, p < 0.0001, 95% CI = [0.1360, 0.3491]), confirming H3.

Table 1. Regression Analysis Results for Study 1.

Relationship	β (β)	*p*-Value	95% Confidence Interval
Language Style → Perceived Sincerity	0.4647	0.0003	[0.2180, 0.7115]
Language Style → Social Presence	0.2449	0.0324	[0.0206, 0.4692]
Perceived Sincerity → Social Presence	0.7971	<0.0001	[0.6918, 0.9024]
Language Style → Forgiveness Willingness (Direct)	0.0768	0.4564	[−0.1258, 0.2794]
Perceived Sincerity → Forgiveness Willingness	0.4191	<0.0001	[0.2921, 0.5460]
Social Presence → Forgiveness Willingness	0.2426	<0.0001	[0.1360, 0.3491]

The total effect model showed that language style had a significant positive total effect on forgiveness willingness (β = 0.4208, p = 0.0012, 95% CI = [0.1682, 0.6734]). The Bootstrap method's testing for multiple mediator effects indicated that language style's total indirect effect on forgiveness willingness through perceived sincerity and social presence was significant (indirect effect = 0.3440, BootSE = 0.0884, 95% CI = [0.1742, 0.5205]), confirming H1 and H5. Specifically, the indirect effect of language style on forgiveness willingness through perceived sincerity was significant (indirect effect = 0.1948, BootSE = 0.0631, 95% CI = [0.0850, 0.3309]), as was the indirect effect through social presence (indirect effect = 0.0594, BootSE = 0.0326, 95% CI = [0.0047, 0.1319]). Moreover, the indirect effect of language style on forgiveness willingness through perceived sincerity and then social presence was also significant (indirect effect = 0.0899, BootSE = 0.0405, 95% CI = [0.0208, 0.1793]).

Next, we ran Model 91 to examine the moderated mediation effect of restorative strategy on the indirect relationship between language style and forgiveness willingness. The IV was language style (rational = 0, humor = 1), the moderator was restorative strategy (apology = 0, gratitude = 1), the mediators were perceived sincerity (M) and social presence (M), and the DV was forgiveness willingness. Analysis of model 91, with 277 sample data and 5000 resamples for the 95% confidence interval, revealed that the restorative strategy moderated the indirect effect of language style on forgiveness willingness through perceived sincerity and social presence (Index = −0.0291, 95%CI = [−0.0865, −0.0019]), confirming H5. Specifically, when users received an apology as a restorative strategy, the indirect effect of language style on forgiveness willingness through perceived sincerity and to social presence was 0.1062 (95%CI = [0.0235, 0.2232]). When gratitude was the restorative strategy, this indirect effect was 0.0770 (95%CI = [0.0191, 0.1525]).

4. Study 2

4.1. Participants

To ensure the scientific rigor and feasibility of the experimental design, this study conducted an a priori power analysis using G.Power 3.1 software. Given that this study aimed to explore the complex interactions among multiple variables, the statistical test power was set at 0.8, with an effect size of 0.25. Based on these parameters, it was calculated that at least 34 participants were needed to meet the experimental requirements. A total of 51 participants were successfully recruited through the decision laboratory's subject pool and social recruitment. To minimize the potential impact of individual differences and emotional states on the experimental results, participants were selected using a random sampling method. Four participants were excluded due to excessive ERP artifacts, leaving 47 valid participants (apology group 24 people, gratitude group 23 people; 22 males, 25 females; mean age 24.26 ± 3.23 years), including both undergraduate and graduate students, as well as individuals from the general population. All participants had normal or corrected-to-normal vision, were right-handed, and had no history of psychiatric disorders. Before the start of the experiment, all participants signed an informed consent form to ensure they understood the nature, purpose, and participation conditions of the experiment. After the experiment, participants received appropriate compensation as a token of gratitude. Moreover, this research project received approval from the Huaqiao University Ethics Committee, ensuring all experimental procedures complied with ethical standards.

4.2. Experimental Stimuli

The experimental materials of this study replicated mainstream GenAI dialogue designs, utilizing AI dialogue images to better immerse participants in the scenario. Recovery utterances following service failure were categorized into four types: rational apology, humorous apology, rational gratitude, and humorous gratitude. The gratitude and apology recovery strategies were designed referencing the study by Song et al. (2023) [69], where the gratitude strategy began with expressing thanks for the feedback, and the apology strategy involved acknowledging the mistake and expressing regret. An example scenario is as follows: during the end-of-semester course-paper writing phase, to gain a more comprehensive understanding of the object of study's history and the latest frontiers, you not only searched academic databases but also sought precise answers through GenAI. Based on your questions, GenAI provided you with some research and reference literature. After searching through major databases, you discovered the provided information was fictitious. Frustrated, you alerted GenAI, "The reference materials you provided do not exist". GenAI responded as follows: Rational Apology: "I'm sorry for the inconvenience caused; this was entirely due to my mishandling, and I will reflect on this earnestly to ensure improvement in the future". "I'm sorry for the inconvenience caused; the mistake you pointed out was caused by my negligence. I will be more careful and responsible in the future". Humorous Apology: "I'm sorry for the inconvenience caused; my brain went down while I was answering, so I'm going to refresh my cache and make sure I don't make any more stupid mistakes like this". "I'm sorry for the inconvenience caused; my brain short-circuited again today, answered the wrong question, let you laugh". Rational Gratitude: "Thank you for your feedback; the inconvenience caused was entirely due to my mishandling, and I will reflect on this earnestly to ensure improvement in the future". "Thank you for your feedback; you pointed out the problem in my answer, which made me realize my serious negligence". Humorous Gratitude: "Thank you for your feedback; I just lost my mind. I promise to remove the fluid from the brain, and there will be no such mistake again". "Thank you for your feedback; apparently, my artificial intelligence needs a bit more. . . well, intelligence. I appreciate your patience as I upgrade my knowledge base".

Each type of response included 20 sentences. Examples of the humorous responses include the following: "My brain had a temporary blue screen of death there! Rebooting now and promise to be less of a digital dodo next time." "My circuits got a little fried. Installing a conscience chip as we speak. I promise this won't happen again" and "I seem to have had a momentary lapse in judgment (or maybe coding). Working on fixing that now. Thanks for your understanding"! All responses were developed by the authors and reviewed by four experts to ensure appropriateness and humor. To adapt to the experimental needs in Mainland China, the number of characters in each reply was controlled, and the word length of each sentence was matched as closely as possible.

4.3. Experimental Procedure

The experimental stimuli were presented using the e-prime 2.0 software (PST, Psychology Software Tools, Pittsburgh, PA, USA). The entire experimental process consisted of 160 trials, with the experiment divided into apology and gratitude groups, each participating in 80 trials. The experiment used a 2 (language style: rational VS humorous) × 2 (recovery strategy: apology VS gratitude) mixed design. Participants sat comfortably in a dimly lit, sound-dampened electromagnetically shielded room, 100 cm from the computer screen. Each participant had 10 practice trials prior to the official experiment to familiarize themselves with the task. The official experiment was divided into four sets, with each set consisting of 20 trials. The specific process for each trial is shown in Figure 3. Initially, participants were guided into the experimental scenario through a scenario immersion paradigm. This was followed by a 500 ms fixation point presentation, and then a 5000 ms GenAI recovery response image appeared. During this period, participants were required to press the corresponding key to indicate forgiveness (f key) or non-forgiveness (j key) based on the AI response received. Before starting the official experiment, participants underwent comprehensive training to ensure familiarity with the experimental procedure. As the experiment was conducted on mainland China, a display time of 5000 ms was set to ensure subjects had sufficient time to read and understand each message. Throughout the experimental process, markers were placed on the GenAI service recovery response stimuli for subsequent analysis, focusing on exploring automated cognitive processes of users through 2ERPs, while subjective assessments were collected through situational questionnaires from Study 1, not focusing on behavior outcomes. Before the official experiment began, participants were required to sign a written informed consent form and agree to participate in the experiment.

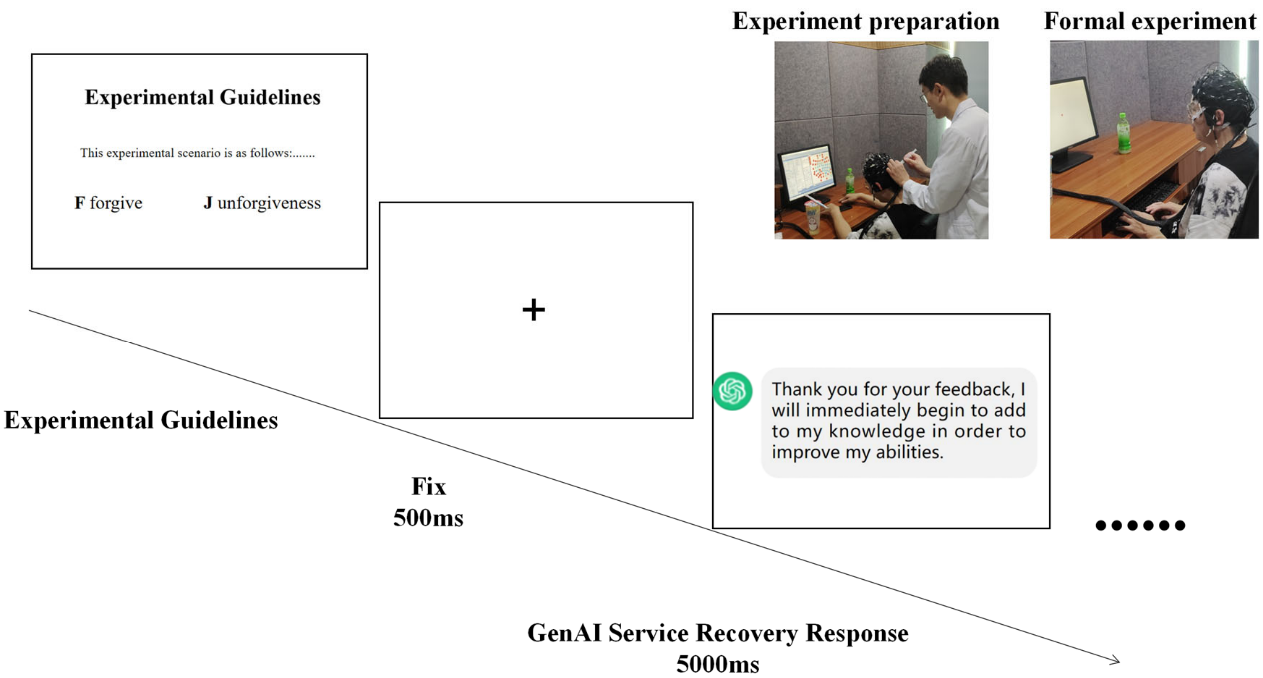

Figure 3. ERPs experiment flow chart.

4.4. Data Acquisition and Analysis

This study utilized the Neuroscan system (Curry 8, Neurosoft Labs, Inc., Sterling, VA, USA) and its accompanying software for EEG data acquisition. The experiment employed a 64-channel Ag/AgCl electrode cap, placed at corresponding positions on the scalp according to the international 10–20 system, and used the Synamp2 amplifier for signal amplification. The data acquisition parameters were set as follows: sampling frequency was 1000 Hz, online bandpass filtering from 0.05 to 100 Hz, and online notch filtering at 50 Hz to effectively eliminate high-frequency noise and power line interference. During the experiment, the impedance of all electrodes was kept below 5 kΩ to ensure good signal quality. The FCz electrode was designated as the online reference electrode, with bilateral mastoids (M1, M2) recorded for offline re-referencing. After the collection was completed, the EEGLAB toolbox [71] was used to preprocess the raw EEG data. Initially, the data were re-referenced to the bilateral mastoids and downsampled to 500 Hz. Subsequently, the signal was filtered using a third-order Butterworth bandpass filter from 0.1 to 40 Hz to further eliminate high-frequency noise and low-frequency drift. To eliminate artifacts from eye movements, blinks, and muscle activity affecting the EEG signals, the Independent Component Analysis (ICA) method was used for data decomposition, in conjunction with the ICLabel plugin [72] for automatic artifact component identification (threshold set at 70%). The identified results were independently verified by two experienced researchers, with disputed components discussed and confirmed to ensure the accurate identification and removal of artifact components. Building on previous research, this study focused on two ERP components related to cognitive control and emotional processing: N2 and late positive potential (LPP). In this study, we selected 9 electrodes in the frontal and central parietal regions (FZ, F1, F2, FCZ, FC1, FC2, CZ, C1, and C2) for N2 component analysis [73], to examine the effects of different language styles and recovery strategies on users' early cognitive processing. For LPP component analysis [57], 9 electrodes in central, parietal, and occipital regions (C3, Cz, C4, CP3, CPz, CP4, P3, Pz, and P4) were selected to explore the impact of different language styles and recovery strategies on users' emotional responses and attitude changes. Statistical analyses of the extracted N2 and LPP components were conducted using repeated measures analysis of variance (ANOVA) to test the effects of language style (rational vs. humorous), recovery strategy (apology vs. gratitude), and their interaction on ERP amplitudes and latencies.

4.5. Results

Electrodes in the central brain region (Cz) and parietal brain region (Pz) were chosen to plot the EEG waveforms and topographic maps within a −200 to 1000 ms time window (see Figure 4). The N2-component time window was determined from the waveforms to be 150–200 ms, after which the mean amplitude of N2 across nine electrodes (FZ, FCZ, CZ, F1, F2, C1, C2, FC1, and FC2) underwent a 2 (recovery strategy) × 2 (language style) mixed ANOVA. The results of these analyses are presented in Table 2.

Table 2. ANOVA Results for N2 and LPP Components.

Component	Effect	F(1, 45)	*p*-Value	ηp^2	Significance
N2	Language Style	0.097	0.757	0.002	Not significant
	Recovery Strategy	0.642	0.427	0.014	Not significant
	Language Style × Recovery Strategy	7.644	0.008	0.145	**Significant**
LPP	Language Style	5.033	0.030	0.101	**Significant**
	Recovery Strategy	0.269	0.607	0.006	Not significant
	Language Style × Recovery Strategy	0.168	0.684	0.004	Not significant

As shown in Table 2, for the N2 component, the main effect of language style was not significant ($F(1, 45) = 0.097$, $p = 0.757$, $\eta p^2 = 0.002$). The main effect of recovery strategy was not significant ($F(1, 45) = 0.642$, $p = 0.427$, $\eta p^2 = 0.014$). The interaction effect between language style and recovery strategy was significant ($F(1, 45) = 7.644$, $p = 0.008 < 0.05$, $\eta p^2 = 0.145$). Simple effects analysis revealed that under the gratitude recovery strategy, language style had no significant impact on the N2 component ($p = 0.086$). Under the apology recovery strategy, rational language style ($M = -1.878$, $SE = 0.891$) elicited significantly larger N2 components than humorous language style ($M = -1.124$, $SE = 0.953$, $p = 0.037 < 0.05$).

As shown in Table 3, for the LPP-component time window was identified from the waveforms as 500–600 ms, and the mean amplitude of LPP across nine electrodes (PZ, CPZ, CZ, P1, P2, C1, C2, CP1, and CP2) underwent a 2 (recovery strategy) × 2 (language style) mixed ANOVA. For the LPP component, the main effect of language style was significant ($F(1, 45) = 5.033$, $p = 0.030 < 0.05$, $\eta p^2 = 0.101$), the main effect of recovery strategy was not significant ($F(1, 45) = 0.269$, $p = 0.607$, $\eta p^2 = 0.006$), and the interaction effect between language style and recovery strategy was not significant ($F(1, 45) = 0.168$,

p = 0.684, ηp^2 = 0.004). Post hoc comparisons revealed that the humorous language style (M = −0.014, SE = 0.624) induced significantly higher LPP components than the rational language style (M = −0.899, SE = 0.568, p = 0.030 < 0.05).

Table 3. Simple Effects Analysis for N2 Component.

Recovery Strategy	Language Style	Mean (μV)	SE (μV)	*p*-Value
Apology	Rational	−1.878	0.891	
	Humorous	−1.124	0.953	0.037 *
Gratitude	Rational			
	Humorous			0.086

* Note: p < 0.05 indicates statistical significance.

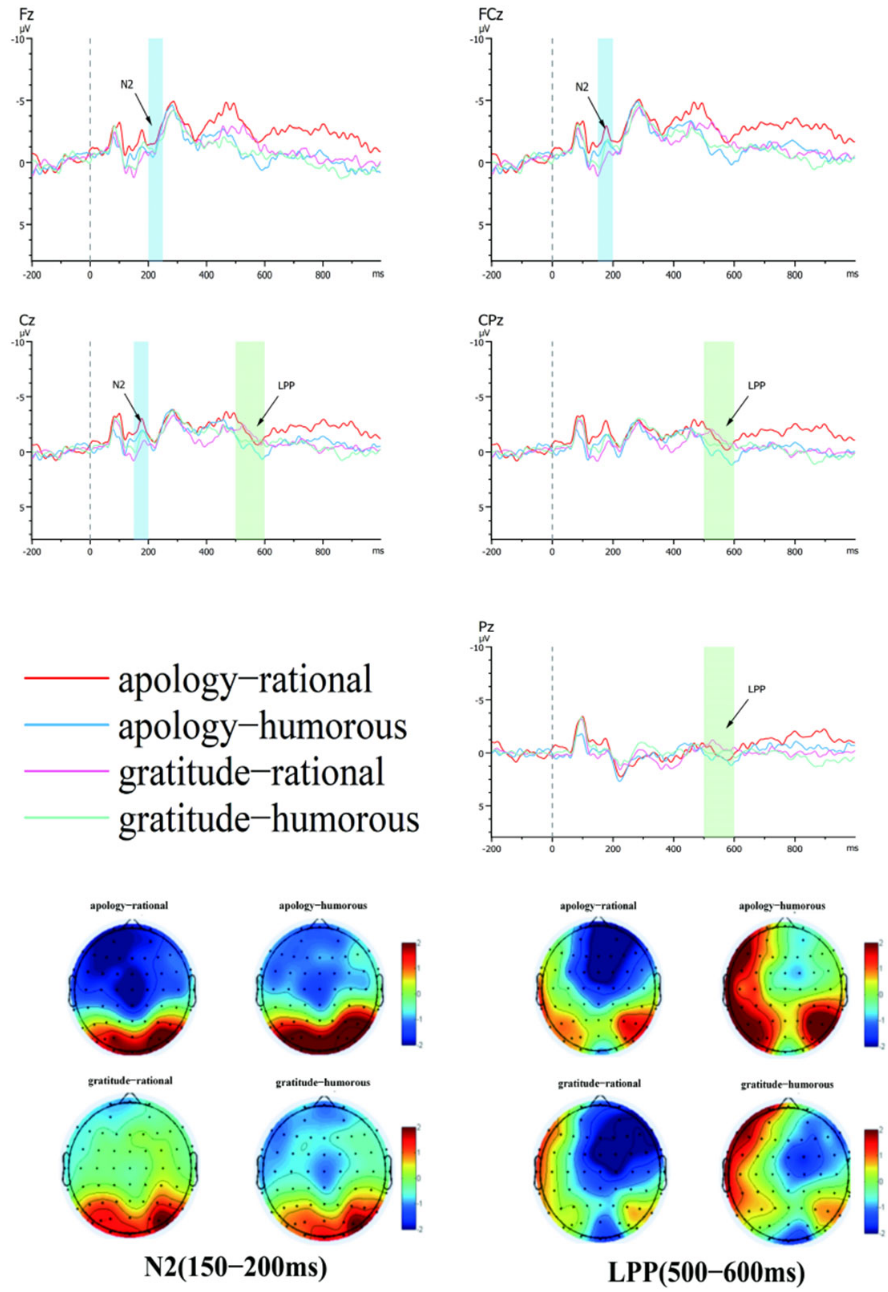

Figure 4. ERP waveform map and ERP topographic map for each condition.

5. Discussion

This study aims to explore the impact of different linguistic styles (rational vs. humorous) and recovery strategies (gratitude vs. apology) on users' willingness to forgive during the GenAI service recovery process, and to delve deeply into the chain mediation role played by perceived sincerity and social presence in this process. Moreover, the research investigates the interactive effects of recovery strategies on the relationship between linguistic style and cognitive processes (through N2 and LPP components). Specifically, we attempt to answer the following research questions: (1) Does the use of different linguistic styles (rational vs. humorous) during service recovery affect users' willingness to forgive? (2) Do perceived sincerity and social presence mediate the effect of linguistic style on willingness to forgive? (3) Does the recovery strategy (gratitude vs. apology) moderate the effect of perceived sincerity on social presence? (4) Do different linguistic styles (rational vs. humorous) in the GenAI service recovery process have an effect on the automated cognitive process? How does this effect interact with the recovery strategy (gratitude vs. apology)? These research questions aim to reveal the complexity of the psychological mechanisms in the service recovery scenario and provide both theoretical and practical guidance for developing more effective AI service strategies. To address these questions, this study combines social presence theory and dual processing theory, employing a mixed-method research approach of surveys and ERPs experiments to explore the impact of rational versus humorous linguistic styles under different recovery strategies (gratitude vs. apology) on users' willingness to forgive. Surveys were used to measure users' subjective perceptions and attitudes in simulated GenAI service recovery scenarios, while ERP experiments aimed to capture users' immediate neural responses under different experimental conditions, revealing underlying cognitive processing mechanisms.

5.1. Humorous Linguistic Style Promotes Forgiveness: The Chain Mediation Role of Perceived Sincerity and Social Presence

The research findings support our core hypothesis that the humorous linguistic style, compared to the rational linguistic style, can more effectively enhance users' willingness to forgive. The humorous linguistic style can indirectly promote forgiveness by boosting users' perceived sincerity and a sense of social presence. This finding aligns with social presence theory [41], which posits that when users perceive a sense of social presence from service providers, they are more likely to exhibit positive emotional and behavioral responses. A humorous linguistic style can be seen as a social cue that narrows the distance between users and GenAI service providers, enhancing users' perception of social presence, and thereby increasing their willingness to forgive. Although this study confirms that a humorous linguistic style can effectively enhance perceived sincerity and social presence, an unexpected finding is that the direct impact of humorous linguistic style on willingness to forgive was not significant. This suggests that the formation of users' willingness to forgive is a more complex psychological process that is influenced by multiple factors, not just linguistic style alone. Previous studies on service recovery have also shown that when chatbots employ a humorous linguistic style for recovery, users perceive higher sincerity [36] and a greater sense of social presence [37], thereby enhancing the effectiveness of service recovery. However, these studies only examined these two mediating mechanisms in isolation. Building on prior research, this study takes a step further by finding that the humorous linguistic style affects willingness to forgive through the chain-mediating mechanisms of enhancing perceived sincerity and social presence. This study extends this finding to the context of GenAI service recovery, indicating that advanced GenAI agents can also enhance users' social presence and willingness to forgive by adopting suitable linguistic styles, and their superior language text and emotional capability may yield even better results. The findings not only enrich the application of social presence theory in the service recovery scenario, but also provide a theoretical basis for designing more effective GenAI service recovery strategies. Specifically, in practice, this means that GenAI service providers should consider integrating humorous elements into the linguistic style of GenAI service agents to enhance users' perceived sincerity and social presence, thereby promoting forgiveness, and enhancing user experience and satisfaction.

5.2. The Moderating Role of Recovery Strategies on Humorous Language Style: Enhancement of Social Presence

A more in-depth analysis has revealed that recovery strategies play a significant moderating role in this process. When GenAI services employ apology strategies, the positive impact of perceived sincerity on social presence is significantly amplified. This implies that, in an apologetic context, users' perception of the GenAI service provider's sincerity more strongly translates into social presence, thereby enhancing the willingness to forgive. This study not only explores the role of language styles, but also emphasizes the importance of recovery strategies, particularly in shaping users' perceptions of social presence.

The apology strategy itself conveys an attitude of taking responsibility and expressing regret [74], which enhances users' perceived sincerity of the GenAI service provider. As a powerful means of expressing sincerity, a sincere apology can effectively facilitate forgiveness [75]. Enhanced perceptions of sincerity, in turn, lead users to view the GenAI service as a more socially present entity, making them more willing to accept the apology and grant forgiveness [37]. These findings suggest that forgiveness is a complex psychological process dependent on contextual factors, with the forgiveness process for service failures being influenced not only by direct factors, but also by contextual ones such as recovery strategies [7]. Consistently, the moderating role of recovery strategies revealed in this study provides new perspectives for the practice and formulation of service recovery strategies. Previous studies on the impact of apologies on perceived sincerity focused on differences between human and robotic service providers [45], whereas this study delves deeper into the effects of apologies and gratitude on perceived sincerity and social presence. However, unlike Lv et al. (2022), who suggested that gratitude strategies might more easily elicit forgiveness compared to apologies [7], this study's findings indicate that, within the GenAI service context, users prefer sincere apologies when faced with errors rather than rejected services. This further confirms the critical role of recovery strategies in modulating the effects of perceived sincerity and social presence on forgiveness willingness. This study not only enriches the literature in the field of service recovery, but also extends the application of social presence theory within the context of AI service recovery. Developers should consider the effects of different recovery strategies when constructing GenAI service agents, focusing not only on the choice of language style but also on the adaptability of recovery strategies to maximize users' willingness to forgive and optimize user experience.

5.3. ERP Experiment Results: Exploring Cognitive Processing Mechanisms

The ERP experiment results provide robust neural support for our research model, elucidating how language style and recovery strategies interact to influence users' automated cognitive processes. The findings from ERP experiments validate the previously discussed insights at a neural level. Under apology strategies, the N2 component induced by rational language style is significantly greater than that induced by humorous language style, indicating that rational language style in apologetic contexts elicits greater cognitive conflict. Conversely, the LPP amplitude induced by humorous language style is significantly higher than that of rational language style, suggesting that users have a stronger motivational relevance and more positive emotional evaluation towards humorous language style. These results further support the theory of social presence, and unveil the neural mechanisms through which language style affects users' willingness to forgive.

Further analysis revealed an interaction between recovery strategies and language styles on users' willingness to forgive. Specifically, under apology strategies, the influence of language style on the N2 component is not significant. However, under gratitude strategies, the N2 component induced by humorous language style is significantly smaller than that induced by rational language style, suggesting that rational language in apology contexts elicits greater cognitive conflict or requires more attentional resources for processing [64]. In the context of gratitude strategies, humorous language style reduces users' cognitive conflict and is more easily accepted. This may be due to the positive emotions conveyed by gratitude strategies, as research has shown that gratitude can induce higher positive emotions [76] and humorous language style can further enhance these positive emotions, reducing negative perceptions of service failures. This finding indicates that users' automatic cognitive processes are jointly affected by language style and recovery strategies. Additionally, the significantly higher LPP amplitude induced by humorous language style compared to rational language style underscores users' stronger motivational relevance and more positive emotional evaluation towards humorous language style [66]. This consistent finding, together with the survey results, highlights the fact that humorous language style can enhance perceived sincerity and social presence. According to the benign violation theory, minor deviations from established norms and expectations constitute essential elements of humor [77]. In this framework, humorous GenAI can effectively subvert users' inherent perceptions of AI as rational and objective entities, minimizing negative emotions arising from unmet service expectations through a humorous tone [78], thus achieving a benign form of expectation violation. Research by Hajcak et al. (2010) indicates that the LPP is highly sensitive to emotional stimuli, with more emotional stimuli eliciting stronger LPP responses [79]. When combined with survey results, this finding further supports the notion that humorous language style, compared to rational style, can effectively improve service recovery outcomes in GenAI service failure contexts. These ERP experiment results demonstrate that users' automated cognitive processes are not static, but are influenced by the interplay of language style and recovery strategies. Apology strategies tend to evoke more rational cognitive processing in users, while humorous language style under apology strategies reduces cognitive conflict and elicits more positive emotional evaluations, fostering forgiveness. This discovery complements our primary findings from the survey and offers new insights for developing more comprehensive and precise GenAI service recovery strategies. By combining subjective perception and neural response data, our research provides a novel perspective and empirical support for understanding the psychological mechanisms underlying users' responses in the GenAI service recovery process.

5.4. Theoretical Implication

This study's theoretical contributions manifest across five primary dimensions: first, it expands the application of the theory of social presence within the context of service recovery in GenAI, exploring how GenAI can enhance perceived sincerity through language style, thereby bolstering social presence and influencing users' willingness to forgive. This not only enriches the application scenarios of the theory of social presence, but also offers a new perspective on understanding the social cognitive mechanisms in human–computer interaction. Second, it reveals the formation mechanism of user forgiveness willingness during the GenAI service recovery process. Perceived sincerity [36] and social presence [37] serve as two critical mediating variables linking language style to users' forgiveness willingness, rather than language style directly affecting forgiveness. This discovery deepens the understanding of the psychological process of user forgiveness, providing a theoretical basis for building more effective service recovery strategies. Moreover, it underscores the moderating role of recovery strategies in GenAI service recovery, where an apology strategy, compared to a gratitude strategy, can enhance the impact of perceived sincerity on social presence, thereby increasing users' willingness to forgive. This indicates the importance of selecting appropriate recovery strategies for different service failure scenarios, where the choice of language style needs to match the specific recovery strategy. Additionally, by integrating the theory of social presence with the dual processing theory, this study constructs an integrative theoretical framework to explain the complex relationships among language style, recovery strategies, user cognition, and behavioral response during the GenAI service recovery process, offering new insights into understanding the psychological mechanisms of users in GenAI service recovery scenarios.

Lastly, introducing neuroscience methods in research methodology reveals the impact of different language styles and recovery strategies on users' cognitive processing from a neuroscience perspective, demonstrating the effectiveness of interdisciplinary approaches in understanding users' psychological mechanisms during the service recovery process, and providing new thoughts and methods for research in this field.

5.5. Managerial Implication

The managerial contributions of this study are reflected in several aspects: firstly, this study provides guidance for the design of GenAI systems. The results found that humorous language styles and sincere apology strategies can effectively enhance users' willingness to forgive. This offers a clear direction for the design of GenAI systems; that is, during the service recovery process, priority should be given to adopting humorous language styles and sincere apology strategies to alleviate users' negative emotions and rebuild trust. In designing service recovery strategies, it is necessary to consider not only the content of the information, but also the impact of the way it is conveyed. The results discovered that perceived sincerity and social presence are key factors affecting users' willingness to forgive. This suggests that developers and service providers, in formulating service recovery strategies, need to focus on how to enhance users' perceptions of sincerity and social presence. For example, this can be achieved through personalized apologies, timely responses, and proactive assistance. Secondly, it provides reference for AI ethics governance: this study focuses on users' emotional experiences during the GenAI service recovery process, emphasizing that AI design should be human-centric. This offers new ideas for AI ethics governance; that is, while pursuing technological progress, it is also important to focus on the social impact of artificial intelligence, ensuring the development of AI technology aligns with human values and ethical standards. In designing GenAI systems, cultural sensitivity is crucial. While this study suggests humorous language and apologies can be effective, these strategies need to be adapted to specific cultural contexts. Directly applying the findings from this study, which focused on Chinese users, to other cultures, such as Japan, where more formal and apologetic approaches are often preferred, may not yield the desired results. Therefore, future development should prioritize creating culturally adaptable GenAI systems that can tailor their service recovery strategies based on the user's cultural background. This could involve incorporating cultural knowledge into the GenAI's training data and developing algorithms that can detect and respond appropriately to cultural cues in user interactions. Furthermore, the gender distribution in our sample may not be fully representative of the general population. Future research should investigate the potential influence of gender on user perceptions and responses to GenAI service recovery strategies. Lastly, this study advocates that user experience design should pay attention to neuroscience indicators. The research found that humorous and rational language styles triggered different responses in the brain, indicating varied psychological activities and emotional responses of users to these communication methods. This means companies can use these neuroscience findings to more finely tune and test their service recovery strategies, thereby more effectively guiding users' emotional and cognitive responses. In designing GenAI service agents, taking into account users' cognitive processing characteristics in different scenarios can effectively optimize service recovery strategies.

5.6. Research Limitations and Future Directions

Despite the significant insights this study offers into the roles of language style and recovery strategies in the context of GenAI service recovery, it has several limitations. Firstly, this research employed simulated GenAI service recovery scenarios. Although experimental controls were applied to enable observation of the impact of specific factors, a gap exists between the experimental environment and the complex and diverse service scenarios present in real-world situations. The simulated environment, while designed to mimic real-world interactions, may not fully capture the complexities and nuances of actual user experiences. For example, the emotional investment of users in a real-world service failure situation might be higher than in a simulated scenario, potentially influencing their reactions to the GenAI responses. Our findings suggest that a humorous apology from the chatbot might be more effective than a rational apology in mitigating negative customer reactions. Similarly, in an online shopping context, a GenAI-powered customer service agent might offer a humorous gratitude message after resolving a delivery issue, potentially enhancing customer satisfaction. However, the effectiveness of humor might depend on factors like the severity of the service failure and the individual customer's personality. Future research should prioritize collecting data from real-world interactions with GenAI systems. This could involve analyzing user logs from GenAI-powered customer service platforms, conducting field studies observing user interactions with GenAI applications, or developing interactive experiments that more closely resemble real-world service encounters. By combining data from real-world interactions with controlled experiments, we can gain a more comprehensive understanding of how to design GenAI systems that effectively navigate service recovery situations and enhance user satisfaction. Secondly, the subjects of this study were primarily from a single cultural background (mainland China), which may not be sufficient to generalize across all user groups. For example, while humor was found effective in this study with Chinese participants, different cultural backgrounds may have varying interpretations and acceptance of humor in service recovery. In Japanese culture, for instance, where formality and elaborate apologies are often expected, a humorous approach might be perceived as insincere or inappropriate, especially in situations involving significant service failures. Future research could broaden the sample range, investigating differences in responses to language styles and apology strategies among users of different ages and cultural backgrounds, such as comparing the effectiveness of humor in service recovery between Chinese and Japanese users. Individual differences in personality traits, such as agreeableness, conscientiousness, and neuroticism, could potentially influence participants' responses to different recovery strategies and language styles. For example, individuals high in agreeableness might be more inclined to forgive, regardless of the recovery strategy employed. Future research should incorporate personality assessments, such as the Five-Factor Model Inventory (FFI), to explore the mediating role of personality in the relationship between recovery strategies, language style, and forgiveness willingness. In addition, this study mainly focuses on users' immediate responses after service recovery. In the long run, different language styles and apology strategies may have varying effects on user loyalty, trust building, and corporate image. Future studies could adopt a longitudinal design to examine the impact of different service recovery strategies on long-term user trust, satisfaction, and loyalty, focusing on their influence on long-term user behavior and attitudes. Finally, besides recovery strategies, other factors such as GenAI anthropomorphism, service type, and severity of service failure could also impact users' reactions to GenAI service recovery strategies. Furthermore, this study primarily concentrated on written language style. If future generative models advance through voice communication, future research could consider including non-verbal elements such as tone and speech rate. Future studies might also focus on other user-experience metrics, such as user trust, satisfaction, and referral intention, to construct a more comprehensive GenAI service evaluation system.

6. Conclusions

Through surveys and ERP experiments, this study comprehensively explored the complex relationships among language style, recovery strategies, and users' willingness to forgive during the GenAI service recovery process, revealing the mechanisms of perceived sincerity, social presence, and the cognitive process of automatization involved. Key findings include the following: a humorous language style can enhance users' perceived sincerity and sense of social presence, thereby increasing their willingness to forgive; apology strategies can modulate the impact of language style on willingness to forgive, specifically showing that apology strategies significantly amplify the positive impact of perceived sincerity on the sense of social presence, thereby enhancing users' forgiveness.

The ERPs results further indicate that different language styles result in distinct brain processing levels; a rational language style under apology conditions elicited a larger N2 component, whereas a humorous language style caused a larger LPP amplitude. These findings not only deepen our understanding of the psychological mechanisms within users during the GenAI service recovery process, but also provide rich empirical evidence and theoretical guidance for designing more effective GenAI recovery strategies, emphasizing the fact that developers should consider the interactive effects of different language styles and recovery strategies when building GenAI service agents, to improve user experience and satisfaction.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by Ethics Committee of Huaqiao University(M2023009).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: All relevant data generated and/or analyzed in this study are publicly available on the Open Science Framework (OSF) platform DOI:10.17605/OSF.IO/5JVFM.

Conflicts of Interest: The authors declare no conflicts of interest.

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