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SERVICE FAILURE BY HUMAN, SERVICE RECOVERY BY AI CHATBOT: THE IMPACT OF JUSTICE, AI EFFICACY ON RECOVERY EFFORT

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Abstract. Artificial intelligence has led to significant innovation in the marketing field, with intelligent chatbots increasingly involved in both customer service provision and service failure recovery processes. While recent research on AI services and intelligent chatbots has been increasing, there has been little research on the collaborative efforts between AI chatbots and human agents for service failure recovery and users' perceptions of the process. Accordingly, the aim of this study is to assess the impact of AI chatbot intervention in recovering from service failures made by human agents on key service recovery outcomes. To achieve this, we model the influence of perceived justice in AI chatbot service recovery processes on outcomes such as customer forgiveness and post-recovery customer satisfaction mediated through efficacy towards AI chatbots. Additionally, drawing on anthropomorphism theory, we seek to verify the moderation effect of humanness, representing the degree to which AI chatbots resemble humans. To test the hypotheses, a total of 187 respondents who had experienced service failure by human agents and service recovery through AI chatbots were surveyed. The collected data were then validated for reliability and validity, and the hypotheses were tested using PLS analysis. Empirical analysis results confirm the significance of all hypotheses and moderation effects. The findings of this study hold academic significance as an exploration of the proactive role of AI chatbots in service recovery processes, providing both theoretical insights and practical implications for companies intending to implement chatbots in service settings in the future.

Keywords*:* artificial intelligence; chatbot; justice; chatbot efficacy; service recovery; forgiveness

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1. Introduction

Advances in artificial intelligence (AI) and natural language processing (NLP) technology have enabled chatbots to assist or replace humans in service work. Due to the advantages of technologies in the consistent and uninterrupted ability to work, companies increasingly use chatbots in the service industry [1]. Already, more than one out of four companies employs chatbot services to serve their customers [2], and many other companies believe that offering service through the assistance of chatbots will be important in the future [3].

A chatbot is a computer program that can communicate with humans through text and audio, simulating human interlocutors for information retrieval and entertainment [4,5]. By using chatbots, businesses can interact with customers at a reduced cost, addressing them in a relevant and personalised manner [6]. Chatbots have emerged as a new customer service application attempting to provide more efficient customer service. Furthermore, with the recent integration of advanced AI technology into chatbots, the pace of change by chatbots in the customer service domain is accelerating even further [7].

In response to the prevalence of chatbots, a growing body of research has explored the characteristics of chatbots that influence customer satisfaction [8-10]. This research stream has examined chatbots' service capabilities and performance [11]. Conversely, research on the capability of chatbots to recover service failures is rare. Service recovery is an essential effort needed to correct flaws in the service delivery process and turn service failure into favourable outcomes. Developing an effective service recovery strategy is critical to retaining consumers and building strong relationships. Genuine recovery, such as forgiveness and post-recovery satisfaction, is usually the ultimate goal of customer care service to comfort angry customers. However, few researchers have focused on service failure and chatbots' efforts to recover [10,12,13]. Existing research does not consider chatbots to be a serious recovery enabler that can deal with customer complaints and obtain forgiveness from the customers on behalf of the company. Also, as promising as it may seem, the ability of AI-driven chatbots compared to human customer service counterparts remains in question [8].

Given the importance of forgiveness and post-recovery satisfaction, this research focuses on answering the following questions. First, this study builds upon prior research on service failure recovery by extending its findings to underscore the potential for integrating AI capabilities to enhance service quality. Second, to evaluate the effectiveness of service chatbots in service failure recovery situations, this research assesses the perceived justice of chatbots and empirically identifies how AI chatbots' human-like characteristics affect the failure recovery process.

2. Literature Review

2.1. AI Chatbot in Service Failure

Customer complaints can be defined as the behavioural reactions of dissatisfied customers due to service failure [14]. When a consumer encounters service failure, they tend to retaliate against the responsible party [1]. Also, service failure has a high possibility of consumer dissatisfaction and negative word-of-mouth, leading to brand asset damage and customer churn [15]; as a result, companies strive to recover from service failures swiftly. Service recovery mitigates the losses caused by service failure to customers, improves the relationship with customers, and enhances customer trust in the firm [16].

Today's service industries provide opportunities for AI technology to engage in the service recovery process [17]. With the fast development of machine learning and natural language processing technology, several studies have explored issues with chatbots and AI technologies [2,18,19]. AI chatbots are digital service bots using advanced AI technology, such as natural language processing and machine learning in voice and text, to communicate with customers [2,20]. For effective and natural human-computer interactions, a chatbot must understand the customer′s questions in natural language and respond with a human-like response. In recent years, the development of AI technology has enabled chatbots to use natural language processing to engage in more sophisticated dialogue with humans, opening the door to extensive marketing, such as customer service [2].

AI chatbots are changing how businesses interact with customers to recover from service failure [21]. Chatbots are not restricted to routine operations but also help with service failure recovery processes [10]. Further, recent research argues that AI agents can be considered substitutes for human call centre workers and have the same role and responsibility as humans in service recovery [1,15].

Recent studies have increasingly focused on the effectiveness of AI chatbots in service failure recovery. When consumers perceive AI-based chatbots as trustworthy, they are more likely to forgive a company′s service failure and refrain from spreading negative word-of-mouth [22]. Specifically, the empathy demonstrated by chatbots during the service recovery process can elicit more favourable warmth evaluations from customers. Conversely, solution-oriented messages tend to enhance perceptions of the chatbot's competence [23]. Additionally, chatbot intelligence and perceived sincerity have been identified as critical attributes that enhance customer satisfaction with the recovery process [24].

However, these studies remain in their infancy, and the outcomes regarding the effectiveness of service failure recovery are far from conclusive. For instance, there is still no consensus on whether the integration of AI chatbots in the service recovery process ultimately enhances customer loyalty [25]. In this context, further research on perceived justice in interactions with AI chatbots could not only address the limitations of prior studies but also offer valuable insights into understanding the evolving role of chatbots as service recovery agents.

2.2. Perceived Justice and Service Recovery

The theoretical perspective of service recovery studies draws extensively on justice theory, which is adapted from social exchange and equity theory [26,27]. Equity theory is based on the literature in social psychology dealing with individuals' perceptions of fairness in situations. The concept of fairness in equity theory is relevant in any domain in which exchange takes place because it is conceivable that one or both parties will perceive inequity in the exchange process. According to equity theory, an individual will perceive inequity when comparing the ratio of their sacrifices to benefits with those of others and perceive the difference in the ratios [28].

Social exchange theory examines perceptions of justice influencing how people evaluate exchanges, including processes and outcomes. A three-dimensional view of justice includes decision outcomes, complaint-making procedures, and interpersonal behaviour in delivering outcomes and enacting procedures. Thus, a customer evaluates fairness in terms of various notions of justice: procedural, distributive, and interactional justice [29]. These kinds of justice influence customer satisfaction and customer forgiveness. In the existing literature on service recovery, the relationship between perceived justice facets and satisfaction is well discussed in academic research [30-32].

According to Muhammad (2020), distributive, interactional, and procedural justice affect customer forgiveness [33]. Customer forgiveness is a relevant process following service failure, leading to post-recovery satisfaction [34]. Forgiveness by customers reduces anger and obsession with the offender and offense and enhances compassion and generosity towards the offender [35]. According to del Rio-Lanza et al. (2009), emotions transfer perceptions of injustice to subsequent attitudes and behaviours [36]. Also, Schoefer and Ennew (2005) combine justice theory and cognitive appraisal theory and suggest that perceived justice indirectly affects positive behaviours and customer satisfaction [37].

2.3. The Moderating Role of Humaness

The chatbot operated by AI error-free interprets all human utterances and responds with relevant and precise human-like answers [38]. An AI-based chatbot is perceived as more human-like and more readily adopted than a conventional chatbot that contains errors in conversation. Also, according to Elicited Agent Knowledge (EAK), a person interacting with a non-human entity will examine the entity's features and behaviour to check for perceived similarity and human-like cues [39]. They argue that by anthropomorphising the non-human entity, a user can anticipate the entity's behaviour, increasing the likelihood of favourable outcomes. Anthropomorphism ties into motivations that are central to human experience. By anthropomorphising the AI chatbot, a user can anticipate the entity's behaviour, increasing the possibility of a favourable response [38]. Thus, we propose that the humanness of AI chatbots contributes to explaining the relationship between perceived efficacy towards AI chatbots and service recovery outputs.

3. Research Model
3.1. Hypothesis

The impact of distributive justice on efficacy can be confirmed through relevant studies. The efficacy perceived by voters in electoral contexts was investigated, with findings asserting that distributive fairness directly influences efficacy [40]. The impacts of perceived distributive justice and managerial respect on workplace meaningfulness have been investigated, revealing a significant relationship between distributive justice and self-efficacy [41]. Consequently, we propose the following hypothesis:

H1. Distributive justice positively affects chatbot efficacy.

Perceived justice significantly influences the efficacy of service recovery efforts by the service provider. The general public's efficacy regarding the police has been examined, with findings suggesting that perceptions of procedural justice positively influence collective efficacy [42]. Additionally, it has been demonstrated that procedures such as privacy protection foster favourable consumer sentiments towards service providers [43]. Consequently, we propose the following hypothesis:

H2. Procedural justice positively affects chatbot efficacy.

Adopting a friendly communication style reduces consumers' psychological distance, increasing their perception of warmth. This consequently positively impacts consumer sentiment and enhances their perception of the service provider's efforts to recover [44]. Each individual desires the service delivery process they experience to be fair and evaluates the fairness of the interactions within that process, which consequently leads to efficacy [45]. Consequently, we propose the following hypothesis:

H3. Interactional justice positively affects chatbot efficacy.

With the rapid proliferation of service chatbots, previous research has shown that the capability of service chatbots positively influences customer attitudes [46]. Additionally, empirical evidence from studies suggests that service providers equipped with both economic recovery capabilities and emotional recovery abilities in situations of service failure are more likely to receive forgiveness [47]. Consequently, we propose the following hypothesis:

H4. Chatbot efficacy positively affects forgiveness.

AI chatbots have been shown to possess service delivery, conversational skills, and service recovery capabilities, which can be leveraged to build customer satisfaction and loyalty [2]. Similarly, the capacity of chatbots to establish positive human-chatbot relationships has been examined, with findings indicating their influence on consumers' post-recovery satisfaction, drawing from politeness theory [13]. Consequently, we propose the following hypothesis:

H5. Chatbot efficacy positively affects post-recovery customer satisfaction.

It has been found that service quality and recovery efforts directly and significantly influence loyalty intentions within the e-business context [48]. Additionally, the impact of sincere and empathetic apologies for service failures in the banking industry on customers' genuine forgiveness and repurchase behaviour has been explored [49]. Consequently, we propose the following hypothesis:

H6. Post-recovery customer satisfaction positively affects forgiveness.

The impact of distributive justice on efficacy can be confirmed through relevant studies. The efficacy perceived by voters in electoral contexts was investigated, with findings asserting that distributive fairness directly influences efficacy [40]. The impacts of perceived distributive justice and managerial respect on work meaningfulness have been investigated, revealing a significant relationship between distributive justice and self-efficacy [41]. Consequently, we propose the following hypothesis:

3.2. Moderating Effect of Humanness

Understanding humanness is crucial to the AI chatbot’s conversational quality, leading to a customer’s satisfying experience [2]. To assess and understand humanness, three questions were utilised, drawing from established approaches in previous research [2,50]: ‘AI chatbot can accurately comprehend what I mean’, ‘AI chatbot is smart in understanding my intentions’, and ‘AI chatbot is similar to a human being’. This moderation hypothesis proposes that if AI chatbots have excellent and natural conversational quality, including understanding humanness, it will increase the positive impact of chatbot efficacy on post-recovery customer satisfaction and forgiveness (see Figure 1).

AI agents with human-like characteristics in the conversational process have been empirically shown to positively influence user satisfaction [51]. Moreover, interactions between users and chatbots are found to be more efficient when the chatbots are anthropomorphised [52]. Another piece of literature focuses on the role of the agent’s appearance and service failure recovery performance.

For example, a "cuteness effect" after service failure has been observed [12]. The cuter the chatbot’s appearance, the higher the customer’s tolerance for service failure [53], which suggests that chatbots with many human-like characteristics can reduce customer complaints and dissatisfaction caused by service failure.

Consequently, we propose the following moderator hypothesis:

H7. Humanness positively moderates the relationship between chatbot efficacy and forgiveness.

H8. Humanness positively moderates the relationship between chatbot efficacy and post-recovery customer satisfaction.

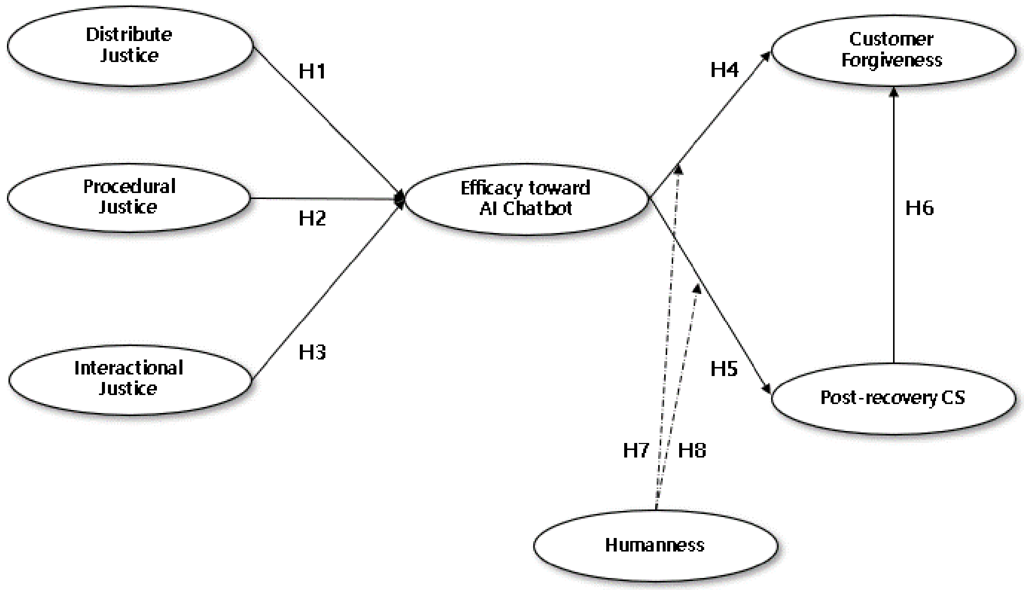

Figure 1. Research Model
Source: Developed by the author.

4. Research Process
4.1. Measurement Development

To ensure the initial validity of the measurement items, we utilized items from previous studies and subjected them to a face validity test by peer academicians. To mitigate common method variance, we implemented several preventive measures [54]. Specifically, we employed clear and concise wording, conducted a pretest, and included a reverse scale item to identify the acquiescence response style, following the approach outlined by prior research [55]. The measurement items were rated on a five-point Likert scale, ranging from '1. strongly disagree' to '5. strongly agree', as presented in the table below.

Table 1. Construct and Item

Construct (Source)	Operational Definition and Items
Distributive Justice [26]	"Perceived fairness of the outcome perceived in resolving the service failure by AI chatbot" 1. The outcome I received from the AI chatbot was fair 2. The outcome I received from the AI chatbot was right 3. In resolving the problem, the AI chatbot gave me what I needed
Procedural Justice [26]	"Perceived fairness of process employed in resolving the service failure by AI chatbot" 1. The length of time taken to solve my problem was not longer than 2. necessary 3. The AI chatbot showed adequate flexibility in dealing with my proble m 4. The AI chatbot solved the problem with the necessary procedure for m y convenience

Interactional Justice [26]	"Perceived fairness of how the customer is treated by AI chatbot" 1. The AI chatbot was appropriately concerned about my problem 2. The AI chatbot put the proper effort into resolving my problem 3. The AI chatbot's communication with me was appropriate
Efficacy toward AI chatbot [56,57]	"An individual's belief in AI chatbot's ability to effectively accomplish tasks and solve problems autonomously" 1. I have confidence in the AI chatbot's ability to effectively resolve service failures. 2. The AI chatbot is capable of independently troubleshooting service failure issues. 3. The AI chatbot possesses the necessary skills to address and resolve service failures. 4. I am confident that the AI chatbot can adeptly analyze and organize potential solutions to service failures.
Forgiveness [34,58]	"A customer's internal act of relinquishing anger and the desire to seek revenge against a firm as well as the enhancement of positive emotions toward the harm-doing firm" 1. I will allow the firm to make it up to me 2. I will make an effort to be more friendly in my future interactions with this firm 3. I will continue my relationship with this firm
Post-recovery [13]	"Level of satisfaction that a customer experiences after service failure has been resolved by the AI chatbot" 1. The AI chatbot's efforts to resolve the issue were satisfactory 2. I am content with the actions taken by the AI chatbot to rectify the service failure 3. Overall, I am satisfied with how the service failure was handled by the AI chatbot

Source: Developed by the author.

4.2. Sample and Data Collection

In April 2024, an online survey was conducted among service chatbot users in Korea to collect data. The survey lasted for ten days, during which participants were invited to complete a questionnaire. The sample was drawn from young consumers to ensure a representative sample of AI chatbot service users. To confirm that respondents had sufficient experience with AI chatbots, they were required to answer screening questions about their prior knowledge and usage of AI chatbots.

A total of 187 respondents completed the questionnaire, consisting of 26.2% male and 73.8% female participants, with an average age of 21.1 years. The survey findings indicated that respondents used AI chatbots in various service failure situations, with the following distribution: banking service failures (22.5%), e-commerce service failures (47.6%), online education service failures (5.9%), mobile communication service failures (7.5%), content subscription service failures (5.9%), and other cases (10.7%).

5. Empirical Result
5.1. Research Method

To ensure the internal consistency of the measurement items, we employed various statistical measures, namely Cronbach's alpha, composite reliability, and average variance extracted (AVE) [59]. Additionally, we conducted a confirmatory factor analysis to assess construct validity. The overall model was found to be satisfactory. The chi-square value was 321.231 with 137 degrees of freedom (p = 0.000). The major fit indices, including CFI (0.934), NFI (0.891), GFI (0.845), SRMR (0.060), and RMSEA (0.085), demonstrated an acceptable fit, indicating the goodness of fit of the model.

The Cronbach's alpha values for all items ranged from 0.696 to 0.944, and the composite reliability coefficients ranged from 0.706 to 0.946. These coefficients met the acceptable threshold of 0.60 [60], signifying that the measurement items exhibited high internal consistency.

Convergent validity was evaluated by examining the individual factor loadings of each construct item [61,62]. Most items surpassed the recommended threshold of 0.70, except for item C3. Additionally, the AVE values for each construct exceeded the recommended threshold of 0.5, indicating that the constructs demonstrated satisfactory convergent validity [60] (see Table 2).

Table 2. Reliability and Validity

Construct	Item	Loadings	Cronbach Alpha	Composite Reliability	AVE
Distributive Justice (DJ)	a1	0.882	0.924	0.926	0.868
	a2	0.879			
	a3	0.931			
Procedural Justice (PJ)	b1	0.743	0.838	0.855	0.754
	b2	0.858			
	b3	0.796			
Interactional Justice (IJ)	c1	0.735	0.696	0.706	0.626
	c2	0.830			
	c3	0.571			
Perceive Efficacy toward A I chatbot (AE)	d1	0.842	0.922	0.923	0.810
	d2	0.877			
	d3	0.896			
	d4	0.842			
Forgiveness (FG)	e1	0.826	0.872	0.906	0.794
	e2	0.767			
	e3	0.906			
Post-recovery CS (CS)	f1	0.895	0.944	0.946	0.900
	f2	0.929			
	f3	0.943			

Source: Developed by the author.

In this study, the Fornell and Larcker test was employed to assess discriminant validity [60]. According to this test, a construct demonstrates discriminant validity if the square root of its average variance extracted (AVE) is more significant than its correlations with other constructs. The findings of this study indicate that each construct's AVE exceeds its correlations with other constructs. For example, the Forgiveness construct has an AVE of 0.891, which surpasses its correlations with other constructs (ranging from 0.380 to 0.581), demonstrating the presence of discriminant validity. The same pattern is presented for the other constructs in Table 3.

Table 3. Fornell-Larcker Test

Construct	(1) AE	(2) DJ	(3) FG	(4) IJ	(5) CS	(6) PJ
(1) Perceived (AE)	**0.900**					
(2) Distributive Justice (DJ)	0.482	**0.932**				
(3) Forgiveness (FG)	0.550	0.380	**0.891**			
(4) Interactional Justice (IJ)	0.501	0.416	0.581	**0.791**		
(5) Post-recovery CS (CS)	0.543	0.569	0.554	0.548	**0.949**	
(6) Procedural Justice (PJ)	0.569	0.548	0.493	0.537	0.571	**0.868**

Source: Developed by the author.

5.2. Hypothesis Test

This research used a Partial Least Squares (PLS) analysis to examine the causal relationships among constructs in the research model. PLS is a multivariate analysis technique well-suited for addressing interrelated causal research questions. Previous studies [61,63] have shown that PLS is particularly effective when dealing with small sample sizes, non-normal data, and limited prior theoretical foundations. Given that the area of service failure recovery by AI chatbots is relatively new, with limited prior research and few experienced users, PLS was considered an appropriate method for this study. Following the confirmation of the measures' reliability and validity, a bootstrapping sampling method was employed to test the hypothesised relationships. The results (see Table 4) demonstrate that all hypotheses were supported at a significance level of 0.05. Furthermore, the R-squared (R^2) scores indicate that the empirical model explains substantial variance in the endogenous variables. Specifically, chatbot efficacy, forgiveness, and post-recovery customer satisfaction have R^2 values of 0.405, 0.303, and 0.388, respectively.

Table 4. Test Result

Hypothesis	Path	S.D	t-value	p-value
H1. DJ → AE	0.201	0.080	2.524	0.012*
H2. PJ → AE	0.330	0.092	3.588	0.000*
H3. IJ → AE	0.241	0.089	2.701	0.007*
H4. AE → FG	0.354	0.093	3.806	0.000*
H5. AE → CS	0.543	0.072	7.521	0.000*
H6. CS → FG	0.361	0.093	3.876	0.000*

Source: Developed by the author.

An additional analysis was conducted to explore the potential moderation effect of humanness on the relationship between chatbot efficacy, forgiveness, and post-recovery customer satisfaction (CS). Moderation refers to a situation where the strength of the relationship between two constructs is contingent upon a third variable [61]. The results in Table 5 indicate that the moderation effect was found to be statistically significant.

Table 5. Moderation Effect

Moderation Effect	Path	S.D	t-value	p-value
H7. (Humanness * AE) → FG	0.150	0.064	2.329	0.020*
H8. (Humanness * AE) → CS	0.101	0.050	2.010	0.045*

Source: Developed by the author.

The results of the moderator analysis are often visually represented using simple slope plots, a commonly used approach. Figure 2 below shows a simple slope plot illustrating the relationships moderated by humanness.

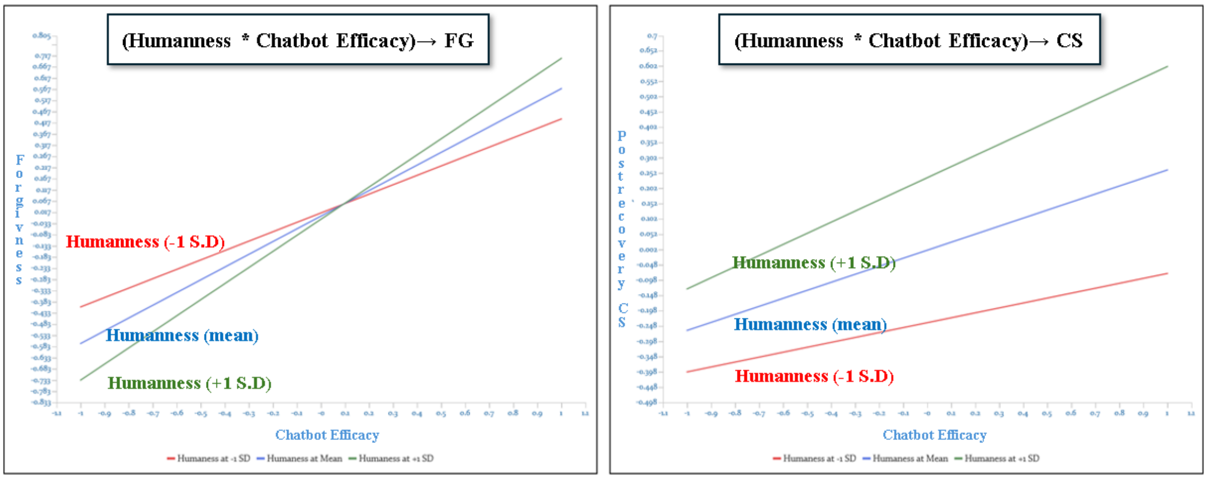

Figure 2. Slope Slot
Source: Developed by the author.

The findings regarding Moderation Effect 2 indicate that customers who perceive AI chatbots with high levels of humanness, as measured at +1 standard deviation above the mean, demonstrate a stronger association between chatbot efficacy and post-recovery customer satisfaction compared to individuals who perceive low levels of humanness, as measured at -1 standard deviation below the mean.

On the other hand, the results for Moderation Effect 1 reveal an inverse relationship between humanness and its moderating effect in the low chatbot efficacy group and the high chatbot efficacy group. In the low chatbot efficacy group, a weaker association between chatbot efficacy and forgiveness was observed when humanness was perceived as high. Conversely, an opposite outcome was found in the high chatbot efficacy group.

6. Conclusion
6.1. Research Implications

The results of this study have various academic and practical implications. First, this study raises the fundamental question of whether AI chatbots can address failures caused by human service providers.

Many studies have focused on how human service workers address service failures caused by their colleagues. Recently, some studies have examined service failures caused by chatbots [1]. However, this study examines the potential collaboration between humans as service providers and AI chatbots as recovery agents. This research perspective is a rare approach that, to the best of the author's knowledge, has not yet been explored as an academic subject.

Second, regarding academic implications, users perceive ‘efficacy’ regarding AI chatbots as increasingly significant, as the replacement of traditional service personnel, such as call centre agents, is rapidly advancing. While previous studies have discussed concepts like PC efficacy and mobile efficacy, there is a lack of research on efficacy perceptions specifically related to AI services or chatbots. Therefore, this study suggests the necessity of applying the concept of efficacy to AI, which could serve as a foundation for future research topics.

Third, it was confirmed that justice is perceived between AI chatbots and humans during the service process, and this perception can influence service performance. While some concerns about the morality or ethics of AI have been raised in previous research on AI services, there has been little scholarly discussion on how such concerns may impact the AI service environment. This study argues that fairness is essential for AI chatbots to successfully interact with customers, suggesting that this research represents an early contribution advocating for ethical standards in the commercialisation of AI.

Fourth, it was empirically verified that AI chatbots can not only listen to customer complaints and provide counselling but also induce customer forgiveness and satisfaction. This result suggests that the phenomenon of human resource replacement by AI in service marketing will accelerate in the future, highlighting the need for additional research prioritising AI as a key research agenda.

The research results also provide important implications for practitioners. First, it was confirmed that AI chatbots can generate customer forgiveness and satisfaction in the post-recovery process without the intervention of human service providers. This indicates the possibility of fully automating the customer service recovery process. By introducing advanced customer consultation services, companies will be able to reduce costs, such as labour expenses, and simultaneously improve the process of handling customer complaints.

Second, it was confirmed that introducing AI chatbots could alleviate challenges caused by emotional labour among employees and mitigate job stress among customer service workers. The escalation of demanding customer requests and increased emotional burnout among workers have negatively impacted company activities, such as higher worker stress and turnover rates. Companies should prioritise the introduction of AI chatbots in tasks that require high levels of emotional labour.

Third, it was found that the greater the extent to which AI chatbots resemble humans, the more quickly they are forgiven by customers, and the higher the customer satisfaction in the post-recovery process after service failure. This relationship was confirmed to have a moderating effect through the ‘humanness’ variable. Therefore, companies should make AI chatbots feel more human-like. Specifically, efforts such as changing the user interface of the customer contact system to be more user-friendly, introducing virtual avatars resembling humans, assigning human names to chatbots, and refining large-scale language models (LLMs) to implement more natural sentence structures and conversational styles will be essential.

6.2. Limitations and Further Research

Despite its academic and practical implications, this study has limitations as empirical research, and further research is needed.

First, the sample of this study primarily consisted of university students in their twenties. This age group represents early adopters of information technology and internet services, and they are valuable as an active source of word-of-mouth marketing. Considering that the spread and adoption of AI chatbots will also start with this generation, the validity of the sample selection is justified. However, the digital divide may influence service adoption across generations. Therefore, efforts are needed to ensure the generalizability of research results by including a more diverse range of age groups in the study.

Second, previous studies differ in their classification of the sub-dimensions of perceived justice. In this study, three dimensions—distributive justice, procedural justice, and interactional justice—were included as exogenous variables. However, some researchers argue that justice consists of four dimensions, while others claim that interactional justice is merely a sub-dimension of procedural justice. Future research should consider various perspectives on justice dimensions and examine potential improvements to the research model.

Third, AI services, the focus of this study, are undergoing rapid technological advancements. Consequently, the potential of AI technology is also expanding rapidly, and scholarly research on the relationship between AI and marketing is evolving at a similar pace. Therefore, continuous and periodic research is needed to understand what innovations emerging AI technology brings to customer service.

Fourth, the impact of service chatbots on service recovery may vary depending on factors such as the type of service failure, the severity of the failure, and the type of service provided. For example, depending on whether the service failure results from technical or human factors, customers may make different judgments about the recovery efforts of the AI chatbot, potentially exhibiting a stricter attitude toward human failures. Additionally, the more severe the service failure, the less likely customers are to forgive the issue resolved by the AI chatbot. Future research should include these contextual factors as moderating variables for further investigation.

Future research should expand to address the limitations of this study and explore new possibilities.

Data Availability Statement: Data cannot be shared due to ethical or privacy constraints.

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

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