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From Failure to Satisfaction: How AI Chatbot Language Affects Service Recovery in Chinese E-Commerce

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Abstract

In e-commerce service recovery, AI chatbots are increasingly replacing human agents, and their language style plays a key role in shaping consumer perceptions. This study investigates how anthropomorphic language style used by AI chatbots influences service recovery satisfaction among iGeneration (iGen) consumers in China. Drawing on service recovery theory and social cognitive theory, a moderated mediation model was tested using data from 312 participants with recent service failure experiences. The findings show that ALS has a positive effect on RS. This effect operates primarily through perceived warmth, whereas perceived competence does not play a mediating role. In addition, the mediator influence of perceived warmth weakens when the service failure is perceived as more severe, suggesting that the impact of anthropomorphic communication is contingent on failure severity. These finds highlight the significance of employing warm, human-like language when designing chatbot interactions, which helps improve service recovery outcomes and rebuild customer trust, especially among younger, digitally native consumers. However, companies should apply such strategies with caution in severe failure contexts, where their impact may diminish. This study advances theoretical understanding of emotional mechanisms involved in AI-mediated service recovery, offering practitioners seeking to make AI communication more human and optimize post-failure customer experience in e-commerce settings.

Keywords: AI Chatbot, Anthropomorphic Language Style, E-commerce, iGeneration, Service Recovery Satisfaction.

Introduction

China's e-commerce industry has grown rapidly, with online retail sales surpassing RMB 15 trillion in 2023 and expected to reach RMB 28 trillion by 2026 (1). This growth has brought a surge in customer interactions and service failures, making effective service recovery increasingly critical. The iGeneration (born 1997–2012) has emerged as a dominant consumer group in this dynamic market (2), characterized by high digital reliance and elevated expectations for instant support (3). To address the growing volume of online complaints (such as the 460,000 complaints in 2024), e-commerce platforms are rapidly adopting AI chatbots as the frontline of customer service, replacing human agents for service restoration (4). However, the emotionally sensitive nature of service recovery often conflicts with AI's limited human-like social capabilities, making it important to understand how chatbot communication can be designed to improve recovery satisfaction (4, 5).

Research shows that the way a chatbot talks is very important for how users like it. The way that AI talks called language styles can be formal or informal (5, 6), task-oriented vs. social-oriented (7, 8), empathetic (9-12), humorous (13-15), cute (16-18), or even anthropomorphism (19, 20), depending on their intended functions and audience (21, 22). Studies suggest that human-like language styles can strengthen emotional bonds, alleviate negative user sentiments, and restore consumers' trust (6, 15, 17). Specifically, Anthropomorphic Language Style (ALS) refers to the manner of speech used by a chatbot that exhibits human-like attributes, such as emotional expression, subjective judgment, and social engagement (19, 20). The essence of ALS lies in triggering a social response from the user by cueing the perception of human-like traits in the service agent (23). However, despite increasing interest in anthropomorphism, limited research has examined how ALS shapes consumer satisfaction in the emotionally charged context of service failures, especially within China's high-volume e-commerce environment (6, 17).

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This study draws on Social Cognitive Theory to explain how anthropomorphic language exerts its influence in service recovery. Prior research shows that when users encounter service agents, they engage in social evaluation processes and assess the agent along the two fundamental aspects of social cognition: perceived warmth (PW) and perceived competence (PC) (8, 23, 24). These friendliness and capability dimensions have been shown to be central evaluative criteria in both human–human and human–AI interactions (25, 26), and they shape users' trust, attitudes, and emotional responses toward service agents (27-31). While service recovery research traditionally emphasizes constructs such as fairness and interactional justice (32), these focus primarily on rational assessments. In contrast, perceived warmth and competence more directly capture the affective and social responses elicited by anthropomorphic communication, making them particularly relevant for understanding how AI language influences satisfaction following service failures (33). Additionally, extensive research has demonstrated that service failure severity significantly alters consumers' expectations, emotional reactions, and receptiveness to recovery strategies (6, 32–35). High-severity failures often heighten negative emotions and reduce sensitivity to socially oriented cues, potentially weakening the effectiveness of anthropomorphic language.

To integrate these perspectives, this research proposes that anthropomorphic language enhances PW and PC, which can lead to more satisfaction with recovery. PW (PC) is expected to weaken when service failure is seen as more severe. Building on the theoretical logic, a moderated mediation model is developed and tested to clarify when and why ALS improves service recovery outcomes among iGeneration consumers in China.

Theoretical Foundation: Service Recovery Theory and Social Cognitive Theory

Service recovery research requires a clear theoretical foundation to understand how organizations address service failures and rebuild customer satisfaction. In order to investigate how anthropomorphic language patterns of AI chatbots affect customer perceptions and satisfaction, the current study makes use of service recovery theory and social cognitive theory. The study offers a thorough framework for examining the emotional and cognitive aspects of AI-mediated service encounters by combining these two theoretical viewpoints.

In order to restore customer pleasure and cultivate enduring loyalty, service recovery theory offers insights into how businesses handle and overcome service problems (36, 37). The "service recovery paradox" (38, 39) refers to the idea that successful service recovery might reduce unfavorable consumer reactions and perhaps increase customer satisfaction above pre-failure levels. While prior studies primarily focused on human service providers (40, 41), emerging studies increasingly emphasizes how AI features affect service recovery outcomes (42, 43). Building on this shift, the study specifically examines how AI chatbots' anthropomorphic language style affects recovery satisfaction—a aspect that hasn't been well studied before (23).

Social cognitive theory emphasizes the dynamic interactions among individuals, behaviors, and external environmental factors (44). Central to this theory is reciprocal determinism, which explains how individuals continuously adapt their behaviors and perceptions based on environmental cues and social interactions (45). In this study, the anthropomorphic language style of AI chatbots represents an environmental factor influencing PW and PC, subsequently affecting service RS. Additionally, environmental aspect that influences these impressions and shapes the efficacy of anthropomorphic communication is the severity of service failure (33). Hence, social cognitive theory offers a strong framework for analyzing how customer perceptions and AI features interact to affect recovery satisfaction.

This study's theoretical base was built on a combination of service recovery theory and social cognitive theory. Service recovery theory emphasizes the significance of successful service recovery techniques and the service recovery process, while social cognitive theory elucidates the cognitive mechanisms through which consumers interpret and respond to AI-driven service interactions. Utilizing these theories collectively allows for a greater comprehension of how anthropomorphic language style impacts consumer perceptions and satisfaction within AI-enabled service recovery contexts.

Anthropomorphic Language Style and Recovery Satisfaction

The anthropomorphic language style of chatbots—defined as the use of human-like expressions and tones—can improve consumers' perceptions during interactions by making chatbots appear more empathetic, warm, and professional (5, 46). Drawing on the relational and emotional aspects of service interaction, ALS is particularly effective in post-failure settings (47). Such humanized communication helps consumers feel cared for and emotionally understood during service recovery, potentially reducing tension caused by service failures (47). This ability to effectively manage emotional fallout is directly tied to overall service recovery (48).

This communication style may also enhance consumers' acceptance of recovery outcomes by mitigating negative emotions. When chatbots use warm and gentle language in apologizing or problem-solving, customers feel listened to and respected, resulting in improved recovery satisfaction (12, 17, 48). Specifically, by conveying empathy and concern, ALS signals a willingness on the part of the firm to restore the relationship, which is a strong predictor of satisfaction in failure contexts (17, 48).

An increasing number of empirical research supports the notion that anthropomorphic language styles positively influence customer satisfaction and engagement (23, 49). Therefore, the hypothesis demonstrates:

H1: Anthropomorphic language style has a positive effect on consumers' service recovery satisfaction.

Perceived Warmth and Perceived Competence as Mediators

The ALS used by AI chatbots refers to a communication style that mimics human conversational cues, such as empathy, warmth, and professionalism. Prior research has suggested that this style can significantly shape users' psychological perceptions, particularly warmth and competence (50). Friendly and affectionate language increases consumers' perceived warmth, helping to build a sense of emotional connection and reduce tension after service failures (23, 31). Simultaneously, professional and precise language fosters perceived competence, enhancing consumers' trust in the chatbot's ability to handle issues effectively (30). Accordingly, the study suggests that anthropomorphic language style benefits both PW and PC. PW and PC are central in shaping consumers' responses to service recovery. Warmth reflects friendliness and care, which help ease consumers' negative emotions and foster emotional bonding with the service provider (29). Competence reflects the chatbot's efficiency and professionalism, which assures customers of the chatbot's capability to resolve the issue (25, 51). Both dimensions are critical in rebuilding customer satisfaction after a service failure. Consumers are more likely to express more satisfaction with their recuperation if they believe the chatbot is kind and knowledgeable. Therefore, this study proposes that recovery satisfaction is favorably influenced by both PW and PC.

While anthropomorphic language style may directly influence service recovery satisfaction, its effect is also likely to occur through PW and PC (16). As for social cognitive theory, individuals interpret social cues from interactional language and infer intentions (warmth) and ability (competence), which then shape their behavioral responses such as satisfaction (27, 51). Recent studies confirm that warmth and competence serve as key psychological mediators in chatbot-based service recovery (50, 52). Warmth helps reduce frustration, while competence enhances trust and confidence in problem resolution. Thus, this study hypothesizes that both PW and PC mediate the relationship between anthropomorphic language style and recovery satisfaction. Therefore, the hypothesis demonstrates:

H2a and b: Anthropomorphic language style has a positive effect on perceived warmth (competence).

H3a and b: Perceived warmth (competence) has a positive effect on service recovery satisfaction.

H4a and b: The effect of anthropomorphic language style on service recovery satisfaction is mediated by perceived warmth (competence).

The Moderating Role of Service Failure Severity

SFS is the consumers' subjective evaluation of how serious and disruptive a service problem is (53). It reflects how big the issue is seen to be and how it affects the customer's expectations, feelings, and actions (54). Unlike objective service errors, SFS captures the psychological weight consumers assign to a failure, which may vary across individuals even for the same incident. For example, a delayed delivery may be seen as trivial by one customer but severe by another who urgently needed the product. When it comes to service recovery, customers' perceptions of the failure's severity have a big impact on how they understand and react to recovery attempts. Therefore, SFS is a crucial moderating variable in determining how successful AI-driven service recovery techniques are.

Customers' opinions of recovery attempts are significantly influenced by the severity of a service interruption. Previous research has shown that when an outage is perceived as severe, customers expect a more formal and effective recovery response (53, 54). Conversely, when severity is lower, consumers may respond more positively to softer, emotionally resonant communication styles (16). An anthropomorphic language style, which incorporates warm and humanized expressions, has been demonstrated to improve PW and PC (23). However, these effects may weaken when customers face high-severity failures, as they prioritize problem-solving over emotional interaction (55).

Based on the moderating effect of SFS, previous studies have shown that consumers' processing of chatbot conversation differs according to the severity of service failures (49). In cases of low-severity service failures, anthropomorphic features can enhance consumers' perceptions of warmth and professionalism, thereby promoting higher satisfaction with the recovery process (17). However, in cases of higher severity, consumers may question the authenticity of anthropomorphic language styles, which may weaken their effectiveness in shaping perceptions (25, 56). Therefore, the indirect influence of ALS on RS via PW and PC is expected to vary with the SFS. This moderated mediation framework suggests that the SFS determines how ALS affects RS through PC or PW. The research model is shown in Figure 1.

H5a and b: Severity of failure moderates the effect of anthropomorphic language styles on perceived warmth (competence).

H6a and b: Severity of failure moderate the effect of anthropomorphic language styles on perceived warmth (competence) toward AI chatbot, leading to different levels of recovery satisfaction.

Figure 1 presents the theoretical framework.

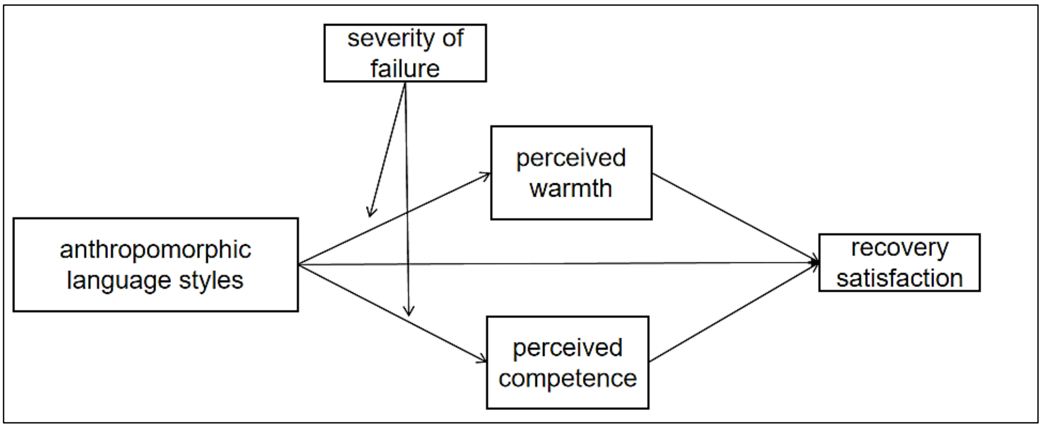

Figure 1: Research Framework

Methodology

Sample and Data Collection Strategy

A cross-sectional survey method was adopted in this study, with targeting iGen consumers (i.e. individuals who born between 1995 to 2012), who are highly engaged in online shopping and digital services (57). iGen consumers were chosen because they are digital natives who have grown up with AI-driven technologies and are highly engaged in online shopping and digital service interactions (57). Focusing on iGen is particularly appropriate for this research for two reasons. First, they are early-adopters and high-frequency users of AI-enabled customer service tools, making them more sensitive to variations in AI communication styles (58). Second, previous studies suggest that younger consumers tend to perceive anthropomorphism in technology differently from older generations, exhibiting higher expectations for human-like interaction and emotional resonance (59, 60).

To ensure conceptual clarity, a small-scale pretest (n = 15) was conducted via face-to-face interviews with participants representative of the target demographic. The pretest aimed to identify any items that were difficult to understand due to abstract wording or unfamiliar terminology. Results indicated that several respondents were confused by the term anthropomorphic language style. Accordingly, this study revised the questionnaire to include a brief explanation of anthropomorphism and provided relatable examples of anthropomorphized AI chatbots. This step helped improve the questionnaire's construct validity.

Data were collected by purposive sampling. Both online and in-person distribution methods were employed to ensure broad reach within the iGen demographic. After data cleaning, 312 valid responses were retained for analysis. All respondents were between the age from 13 to 29, confirming the sample's alignment with the definition of iGen consumers. In terms of gender distribution, 44.55% were male, with the remainder being female. The final sample size meets and exceeds established guidelines of Partial Least Squares Structural Equation Modeling (PLS-SEM).

Measurement of Variables

This study adopted 7-point Likert scales, anchored from 1 (strongly disagree) to 7 (strongly agree), to measure each of the key constructs. In order to maintain content validity and ensure theoretical consistency, the measurement items were adapted and refined from well-established instruments reported in prior literature. The scale for ALS is measured through six items modified from past research (61), which emphasize user perceptions of human-like characteristics in AI-generated communication. The scales for RS are measured with eight items, which integrates measurement indicators proposed by researchers in the past (62, 63), capturing users' post-recovery evaluations and service experience. Furthermore, the scales of PW and PC are measured using separate scales consisting of seven and eight items respectively, and they are all adapted from previous studies (27, 50, 64), focusing on users' affective and cognitive judgments of AI interactions. The scale of SFS is operationalized through a six items measure adapted from prior research (62, 65), which reflect respondents' perceived seriousness and inconvenience caused by service failure.

Data Analysis: PLS-SEM was employed in this study as the primary analytical tool, chosen for its distinct advantages in handling complex predictive models incorporating multiple mediators and a moderator. In the present analysis, SmartPLS 3 software was utilized to systematically conduct the data examination process, involving two sequential stages: 1) evaluating the measurement (outer) model was evaluated to confirm the reliability, internal consistency, and validity; 2) assessing the structural (inner) model to analyze the hypothesized causal relationships and estimate the path coefficients between latent constructs. Additionally, to establish statistical robustness, bootstrapping analysis with 5000 resamples was performed, providing evidence regarding the significance and stability of hypothesized relationships. We specifically utilized the specialized SPSS PROCESS macro (Model 7) as a robustness check to validate the index of moderated mediation, ensuring a comprehensive assessment of the full conditional indirect effect.

Results

Evaluation of Outer Model

Since all data in this study were collected using a single tool, common method bias (CMB) was carefully examined prior to further analysis. Harman's single-factor test was applied by loading all measurement items into an exploratory factor analysis with no rotation. The analysis revealed that the first factor approximately 32.863% of the total variance, which is well below the recommended threshold of 50%. Thus, it can be concluded that CMB is unlikely to threaten the validity of the results.

The measurement model evaluation is reported in Appendix A, which reports outer loadings, Cronbach's α, rho_A, CR, and AVE. All items exceeded the minimum loading criterion, so no items were deleted. The CR values exceeded critical value of 0.70, indicating satisfactory composite reliability. Similarly, both Cronbach's α and rho_A values were consistently above 0.70 across all constructs, further supporting internal consistency. Convergent validity was confirmed, as all AVE values surpassed the 0.50 threshold.

Furthermore, discriminant validity was further examined through the Heterotrait-Monotrait (HTMT) ratio, a relatively recent and increasingly preferred method (66). Table 1 summarizes the calculated HTMT values for each pair of constructs in this study. All obtained values are clearly below the conservative cutoff criterion of 0.85, indicating satisfactory discriminant validity.

Table 1: Results of Discriminant Validity Using HTMT

	ALS	PC	PW	RS	SFS	SFS*ALS
ALS						
PC	0.534					
PW	0.616	0.303				
RS	0.74	0.428	0.547			
SFS	0.111	0.121	0.068	0.053		
SFS*ALS	0.164	0.187	0.266	0.212	0.088	

Evaluation of Inner Model

After assessing the measurement model, the structural (inner) model was examined to test the hypothesized relationships among the latent constructs. Figure 2 displays the path coefficients along with the R^2 values for the endogenous variables. The path coefficients reflect the magnitude and direction of the proposed effects, whereas the R^2 values indicate the extent to which the model explains variance in each construct. According to established guidelines (66), R^2 values of 0.75, 0.50, and 0.25 are indicative of substantial, moderate, and weak explanatory power, respectively. As illustrated in figure 2, the R^2 values are 0.466 for RS, 0.359 for PW, and 0.267 for PC. According to these findings, the structural model has a moderate level of explanatory ability.

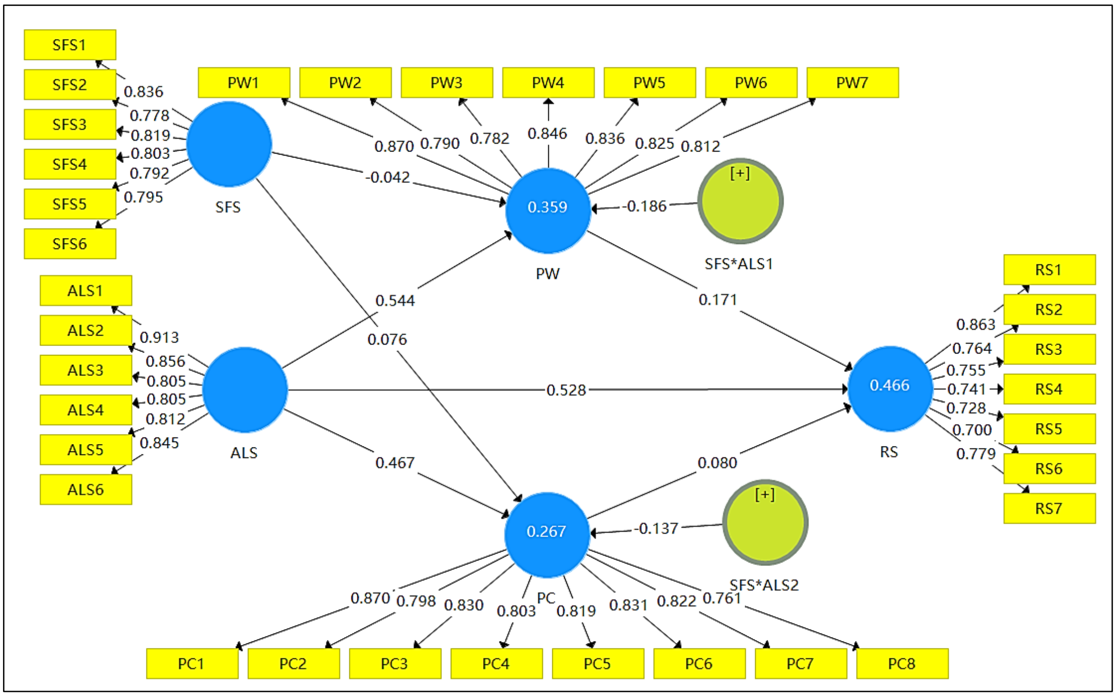

Figure 2: Path Model Mode via SmartPLS

Furthermore, a 5000-sample bootstrap is used in this study to confirm that the proposed connections are robust. Table 2 reports each route coefficient's statistical significance. All hypothesized paths are statistically supported ($p < 0.05$) (H1, H2a, H2b, H3a), except for the path from PC to RS, which does not reach significance ($p = 0.115$) (H3b).

Table 2: Bootstrapping Results

	Path Coefficient	Observed T-Statistics	Standard Deviation	Effect size (f2)	Bias	Confidence Intervals (2.5%)	Confidence Intervals (97.5%)	P value	Results
ALS -> PC	0.467	9.949	0.047	0.288	-0.005	0.376	0.556	0.000	Supported
ALS -> PW	0.544	13.187	0.041	0.446	-0.004	0.462	0.623	0.000	Supported
ALS -> RS	0.528	9.789	0.054	0.291	0.000	0.421	0.629	0.000	Supported
PC -> RS	0.080	1.578	0.050	0.009	0.000	-0.020	0.178	0.115	Not Supported
PW -> RS	0.171	3.057	0.056	0.037	0.000	0.061	0.283	0.002	Supported
SFS*ALS1 -> PW	-0.186	4.990	0.037	0.053	-0.013	-0.248	-0.104	0.000	Supported
SFS*ALS2 -> PC	-0.137	3.476	0.040	0.025	-0.027	-0.186	-0.025	0.001	Supported

Moderating Effects

The study hypothesized that the ALS-PW and ALS-PC relationships are moderated by the presence of SFS (H5a and b). Table 2 shows the interaction effect between ALS and SFS on PW is significant and negative ($\beta = -0.186$, $\rho = 0.000$), indicating that the effect of ALS on PW depends on the SFS (H5a). Specifically, as illustrated in Figure 3, the slope for ALS is steeper when SFS is low, suggesting a stronger positive relationship between ALS and PW under low failure severity. Conversely, under high SFS, the relationship is much weaker. Similarly, a significant negative interaction effect is observed between ALS and SFS on PC ($\beta = -0.137$, $\rho = 0.001$), as depicted in Table 2 (H5b). This suggests that when SFS is strong, the beneficial impact of ALS on PC decreases, as seen in Figure 4. These results thus offer empirical support for the moderating effect of service failure severity, showing that the impact of ALS on perceived competence and warmth is much greater when failure severity is low but diminishes as severity rises.

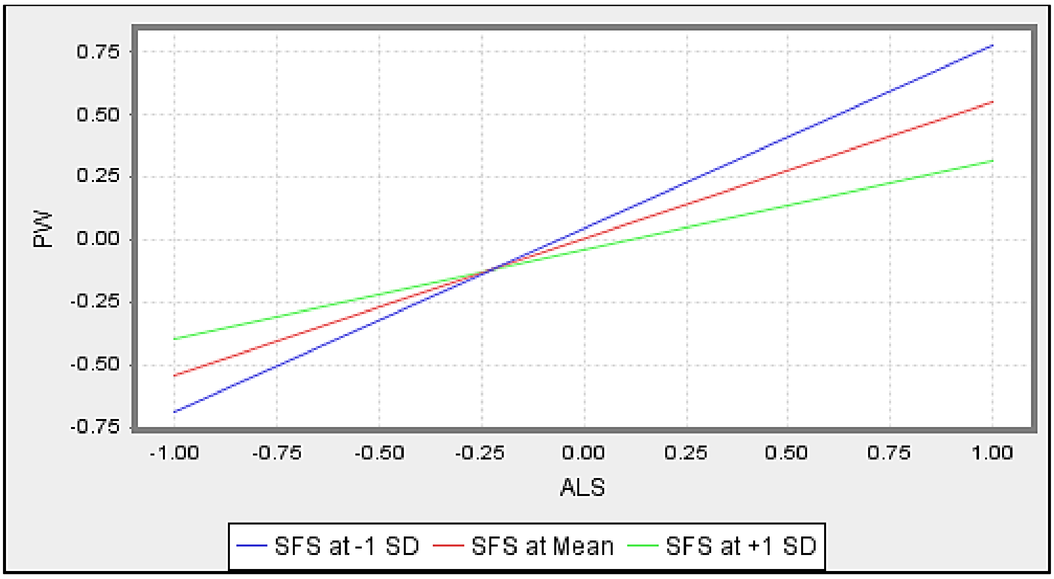

Figure 3: Moderating Effect of SFS on the ALS-PW Relationship

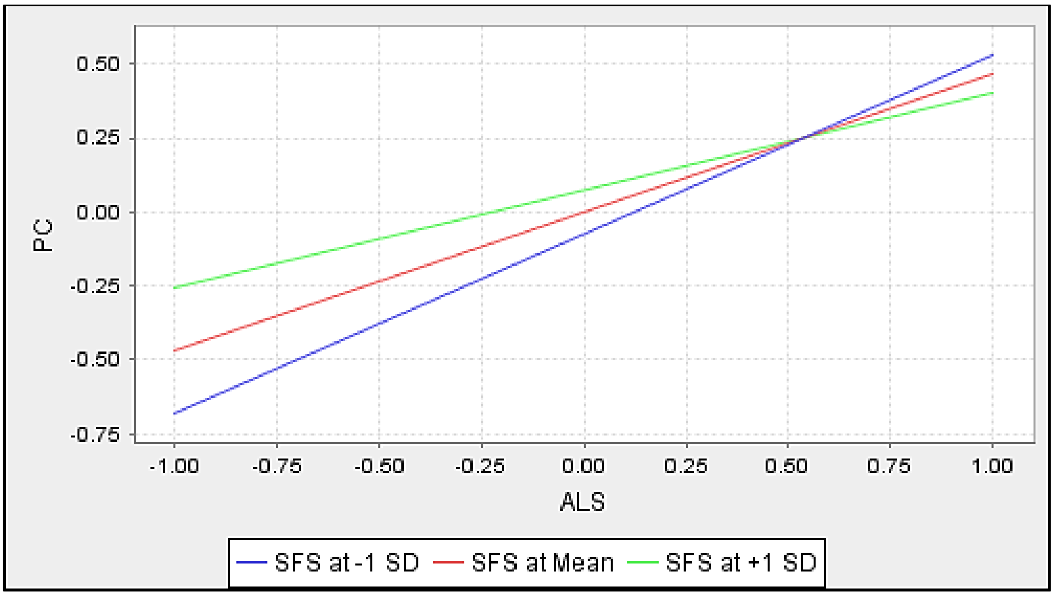

Figure 4: Moderating Effect of SFS on the ALS-PC Relationship

Mediating Effects

Furthermore, the study tested the indirect effects to examine whether PW and PC mediate the relationship between ALS and RS. As shown in Table 3, the indirect effect of ALS on RS via PW is significant (β = 0.093, p = 0.003), indicating that this link is mediated by PW (H4a). Nevertheless, the indirect impact of ALS on RS via PC does not reach statistically significant (β = 0.037, p = 0.128) (H4b). Therefore, the findings support that PW, but not PC, plays a mediation role in the association between ALS and RS.

Moderated Mediation Effects

Then, using a bootstrap analysis with 5,000 resamples, the researchers tested the moderating mediation model using SPSS PROCESS MODEL 7 software. Table 4 shows that the negative and significant index of moderated mediation (Index = -0.0172, 95% CI [-0.0312, -0.0054]) confirms that SFS moderates the mediating role of PW (H6a). The conditional indirect impact of the ALS→PC→RS pathway is minor and not significant at all SFS levels, according to the PC moderated mediation index (Index = -0.0065, 95% CI [-0.0196, 0.0043]) (H6b).

Regarding conditional indirect effects, Table 5 indicates that the indirect effect of ALS on RS mediated by PW is significant across all levels of SFS, but the effect decreases as SFS increases (e.g., at low SFS, effect = 0.1239, 95% CI [0.0454, 0.2027]; at high SFS, effect = 0.0523, 95% CI [0.0168, 0.0995]). The results confirm that SFS has a moderating effect on the mediating role of PW.

Table 3: Indirect Effects Analysis

	Path Coefficient	Observed T-Statistics	Standard Deviation	Bias	Confidence Intervals (2.5%)	Confidence Intervals (97.5%)	P value	Results
ALS -> PW -> RS	0.093	2.946	0.032	0	0.035	0.16	0.003	Supported
ALS -> PC -> RS	0.037	1.524	0.024	0	-0.007	0.089	0.128	Not Supported

Table 4: Moderated Mediation Effect of SFS

	Index	BootSE	BootLLCI	BootULCI	Result
ALS → PW → RS	-0.0172	0.0066	-0.0312	-0.0054	Supported
ALS → PC → RS	-0.0065	0.0061	-0.0196	-0.0043	Not Supported

Table 5: Moderated Mediation Effect of PW

SFS Level	Effect	BootSE	BootLLCI	BootULCI	Result
at -1 SD (low)	0.1239	0.0401	0.0454	0.2027	Supported
at Mean (medium)	0.1038	0.0337	0.0380	0.1717	Supported
at +1 SD (high)	0.0523	0.0215	0.0168	0.0995	Supported

Discussion

With the rapid expansion of the e-commerce industry, service failures have become increasingly frequent, prompting platforms to adopt AI chatbots as frontline agents for handling customer complaints. iGen consumers, as digital natives, not only drive the growth of online shopping but also demonstrate a high degree of acceptance and reliance on AI-based customer service solutions. Understanding how AI chatbots' communication style influences customers' recovery satisfaction is therefore crucial for both theory and practice. While prior researches has emphasized the significance of anthropomorphic design in digital interfaces, the mechanisms and boundary conditions by which chatbot language style shapes consumer perceptions and satisfaction in service recovery contexts remain underexplored, especially among iGen users.

The findings reveal that the anthropomorphic language style of chatbots significantly enhances consumer recovery satisfaction, supporting the primary hypothesis. PW significantly mediates the relationship between chatbot language style and service RS, and this mediation impact is weakened under high service failure severity—highlighting the boundary condition posed by perceived failure severity. Interestingly, while perceived competence has also been proposed as a mediator, the results indicated that its mediating impact was not substantial, especially as failure severity increased. Moreover, perceived warmth and competence were both influenced by anthropomorphic language style, but only warmth consistently translated into higher recovery satisfaction. These results partially diverge from some prior expectations and literature, which often emphasize the dual function of warmth and professional competence, suggesting that in emotionally charged service recovery situations, warmth may outweigh competence in driving customer satisfaction.

Theoretical Implications

This study advances research in the field of AI-driven service recovery by focusing on AI agents rather than human service providers (67-69). First, by centering on recovery satisfaction as the key outcome, our study fills a vacuum in existing research, by focusing on recovery satisfaction as the primary objective. The majority of previous research has concentrated on AI design elements and outcomes, such as customer tolerance (17), failure acceptance (70), or repurchase intention (24). While valuable, these outcomes do not directly capture the effectiveness of service recovery itself (71). This study offers a more useful and straightforward perspective for assessing the effects of AI anthropomorphic language styles in service failure settings by focusing on recovery satisfaction.

Second, the study clarified the psychological mechanisms through which ALS influences RS. Although previous studies generally suggested that both PW and PC could serve as mediating variables in AI-consumer interactions (16, 27, 50), the present findings reveal that only PW played a significant mediating role between ALS and RS, while the mediating path of PC was not support. The finding provides evidence for the academic debate regarding the relative roles of PW and PC in AI-consumer interactions. The results indicate that, in actual e-commerce service recovery scenarios, consumers place greater importance on emotional care (29, 72). It clarifies the psychological processes behind successful AI service recovery and enhances theoretical talks on how AI's anthropomorphic language style affects customer reactions.

Finally, this study broadens the contextual understanding of anthropomorphic language style effectiveness by incorporating service failure severity as a moderating variable. Few studies have thoroughly investigated failure severity's moderating effect in the ALS–outcome link, despite earlier research briefly acknowledging its contextual significance (32, 56). Findings reveal that the positive effects of ALS on PW and recovery satisfaction diminish as the service failure severity increases. This suggests that while enhancing the human-like language style of chatbots typically helps improve consumer satisfaction, its impact is limited in scenarios of severe service failures. Therefore, the study refines the service recovery theory and emphasizes the need for AI language styles in digital service environments to be context-specific and precisely adjusted.

Practical Implications

First, the results offer practical advice for designers of AI systems and e-commerce platforms. Because anthropomorphic language style and recovery satisfaction are positively correlated, platforms should make investments to create AI chatbots that communicate more like humans. Rather than focusing solely on efficiency, designers should incorporate warmth, empathy, and natural conversational cues into chatbot responses. Particularly in low-severity service failure situations, enhancing anthropomorphic features can improve customers' emotional experience and service recovery satisfaction.

Second, customer service managers should leverage AI chatbots as a key touchpoint in service recovery processes. The results indicate that anthropomorphic language mainly increases satisfaction through perceived warmth, while the mediating impact of PC is not significant. Therefore, training and optimizing AI responses to convey friendliness and emotional understanding may be more effective than emphasizing technical competence, especially when the goal is to restore customer trust after minor issues. For more serious service failures, it may be necessary to transition seamlessly from AI to human customer service immediately, as the advantages of human-like language are not as evident in such situations.

Third, e-commerce platforms are encouraged to implement dynamic adjustment strategies for chatbot language styles based on failure severity. Since the moderator role of perceived failure severity was supported, platforms can develop adaptive dialogue systems that respond differently depending on the severity of customer complaints. For minor issues, chatbots should employ a warmer, more friendly style, while for major issues, they should adopt a direct, efficient, and respectful communication style, with human intervention when necessary.

Limitations and Implications for Future Studies

There are a number of limitations to this study that present possibilities for further investigation. First, the sample was composed exclusively of Chinese iGen consumers recruited through a self-administered online survey. Therefore, the findings may not be representative of other generational groups or cultural backgrounds. Future investigations are encouraged to adopt more diverse sampling strategies that span different regions, age groups, and socio-cultural contexts to enhance external validity. Second, the cross-sectional study design and reliance on self-report measurement tools increase the risk of CMB and limit the establishment of causal relationships; therefore, longitudinal or experimental studies are recommended to strengthen causal inferences. Third, this study focuses solely on e-commerce service recovery scenarios and may not fully reflect the complexity of service failures in other contexts; future studies could extend this research framework to include other industries or more complex real-world service environments (10). Fourth, while we demonstrate the effectiveness of ALS, its implementation raises significant ethical considerations (42). Future research must explore the ethical implications of using anthropomorphic language, including issues of transparency (i.e., whether the chatbot's AI nature is clearly disclosed), consumer privacy risk regarding emotionally driven data collection, and the potential for emotional language manipulation, particularly when targeting vulnerable consumer groups like iGen. Integrating ethical discourse will be crucial for the responsible design and deployment of AI agents. Finally, this study only considered a limited number of mediating and moderating variables; Future studies should pursue a more comprehensive model by integrating Justice Theory (e.g., procedural/ distributive justice) with our social cognitive framework. Furthermore, exploring the influence of external factors, such as prior AI experience (73), consumer characteristics (74), and the dynamic changes in the connection between consumers and AI (17, 49). A more thorough grasp of how anthropomorphic language styles operate in dynamic service interactions may result from these enhancements.

Conclusion

This study demonstrates that anthropomorphic language style significantly enhances recovery satisfaction in AI-driven e-commerce service recovery, primarily through perceived warmth rather than competence. The findings reveal that the effectiveness of anthropomorphic communication diminishes under high service failure severity, highlighting the importance of contextual adaptation. The results contribute to theory by clarifying the psychological mechanisms underlying AI-consumer interactions and refining the understanding of boundary conditions. Practically, they suggest that e-commerce platforms should design chatbots capable of delivering warm and human-like communication, adjusting their linguistic style according to failure severity. These insights not only deepen academic knowledge of AI's function in service recovery but also offer actionable guidance for developing more empathetic and effective AI customer service systems.

Abbreviations

ALS: anthropomorphic language style, iGen: iGeneration, PC: perceived competence, PW: perceived warmth, RS: recovery satisfaction, SFS: service failure severity.

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Author Contributions

Yujie Chen: conceptualization, data collection, data analysis, wrote the manuscript, Norkhazzaina Salahuddin: conceptualization, review, editing, supervision, Munirah Khamarudin: review, editing, supervision.

Conflict of Interest

The authors declare no conflict of interest.

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this work, no generative artificial intelligence tools were used to write or generate text. Standard AI-assisted tools such as grammar and spell checkers were used solely to improve language clarity and readability, and all intellectual contributions are those of the authors.

Ethics Approval

This study did not involve vulnerable populations, sensitive personal data, or any procedures that could cause harm or distress. As such, formal ethical approval was not required in China. Nevertheless, the research was conducted in accordance with the university's ethical guidelines. Participation was entirely voluntary, informed consent was obtained, and all responses were anonymous and confidential.

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Appendix A: Constructs and Their Responding Measures

Construct		Item	Loading	α	rho_A	CR	AVE
Anthropomorphic Language Style (61)	ALS1	I personally feel the language of the chatbot is: Artificial – lifelike	0.913				
	ALS2	I personally feel the language of the chatbot is: Machinelike – Humanlike	0.856				
	ALS3	I personally feel the language of the chatbot is: Fake - Natural	0.805				
	ALS4	I personally feel the language of the chatbot is: Unconscious - Conscious	0.805	0.916	0.918	0.935	0.706
	ALS5	I personally feel the language of the chatbot is: Emotionless – Emotional	0.812				
	ALS6	I personally feel the language by the customer service chatbot is: Programmed – Autonomous	0.845				
Recovery Satisfaction (62, 63)	RS1	I am satisfied with how the customer service chatbot handled this particular service problem.	0.863				
	RS2	I believe the customer service chatbot provided a satisfactory resolution to this issue.	0.764				
	RS3	I am satisfied with the service recovery quality of customer service chatbot.	0.755				
	RS4	I am satisfied with the service recovery of the seller, regarding this particular event (most recent e-shopping problem)	0.741	0.879	0.882	0.907	0.582
	RS5	I am satisfied with my overall experience with the [seller name].	0.728				
	RS6	The chatbot responded quickly and resolved my issue in a timely manner.	0.700				
	RS7	I felt confident in the chatbot's knowledge and ability to resolve my issue.	0.779				
Perceived Warmth (50, 75)	PW1	I personally feel this customer service chatbot looks: Unfriendly – Friendly	0.87				
	PW2	I personally feel this customer service chatbot looks: Bad-intentioned – Well-intentioned	0.79				
	PW3	I personally feel this customer service chatbot looks: Untrustworthy –Trustworthy	0.782				
	PW4	I personally feel this customer service chatbot looks: Cold –Warm	0.846	0.921	0.922	0.936	0.678
	PW5	I personally feel this customer service chatbot looks: Bad-natured – Good-natured	0.836				
	PW6	I personally feel this customer service chatbot looks: Fake – Sincere	0.825				
	PW7	I personally feel this customer service chatbot looks: Intolerant –Tolerant	0.812				
Perceived Competence (50, 64, 75)	PC1	I personally feel this customer service chatbot looks: Incompetent – Competent	0.87				
	PC2	I personally feel this customer service chatbot looks: Unconfident – Confident	0.798				
	PC3	I personally feel this customer service chatbot looks: Incapable – Capable	0.83				
	PC4	I personally feel this customer service chatbot looks: Inefficient – Efficient	0.803				
	PC5	I personally feel this customer service chatbot looks: Unintelligent – Intelligent	0.819	0.929	0.930	0.941	0.668
	PC6	I personally feel this customer service chatbot looks: Unskilled – Skillful	0.831				
	PC7	I personally feel this customer service chatbot looks: Uncompetitive – Competitive	0.822				
	PC8	I personally feel this customer service chatbot looks: Disorganized – Organized	0.761				
Service Failure Severity (62, 65)	SFS1	This service failure of e-commerce incident was very serious to me.	0.836				
	SFS2	I felt angry because of this service failure of e-commerce.	0.778				
	SFS3	I felt unpleasant because of this service failure of e-commerce.	0.819				
	SFS4	The service failure of e-commerce caused significant inconvenience to my shopping process.	0.803	0.892	0.900	0.916	0.646
	SFS5	The service failure of e-commerce was a big problem for me.	0.792				
	SFS6	The service failure of e-commerce was a major aggravation for me.	0.795				