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When customers know it's AI: Experimental comparison of human and LLM-Based Communication in service recovery

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ABSTRACT

As generative AI (GAI) becomes increasingly integrated into customer service platforms, its ability to simulate human language raises new relational expectations, particularly in emotionally sensitive interactions. This study investigates how emotional intensity and identity disclosure shape user perceptions of GAI-authored service recovery messages. In a controlled experiment within the online food delivery context, participants evaluated identical service responses across two emotional conditions (routine vs. emotionally charged) and two identity conditions (AI vs. human, disclosed vs. undisclosed). Results reveal that while GAI is perceived as competent in low-emotion scenarios, its human-like language triggers negative reactions under high-emotion conditions, especially after its identity is disclosed. Users interpret simulated empathy as inauthentic, leading to what we term *identity-contingent trust violations*. Furthermore, participants with higher GAI familiarity were more critical, demonstrating a pattern of *critical familiarity*, where technical literacy heightens relational expectations. This study advances theories of human – AI interaction by integrating emotional context and identity perception into models of trust calibration. Practically, it highlights the need for role-appropriate GAI deployment and emotionally aware interaction design, where AI systems are matched to context-sensitive tasks and clearly framed as assistants, not surrogates, in situations requiring genuine emotional care.

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AI customer service; LLM-based service agent; identity disclosure; communication service recovery; User-generated reviews

1. Introduction

Service recovery has long been established as a critical site for repairing customer relationships (Nikhashemi, Kennedy, and Mavondo 2025), especially in industries like online food delivery where service failures are frequent, public, and emotionally charged (Line et al. 2024). These failures range from low-emotion logistical disruptions, such as late deliveries or app glitches (Ashraf and Bardhan 2024), to high-emotion relational breaches, such as repeated errors, unmet compensation

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expectations, or perceived rudeness (Gannon et al. 2022). While the former may elicit mild annoyance, the latter often triggers indignation, disappointment, or a perceived violation of fairness norms. In digital contexts, these emotional reactions are further amplified by user-generated reviews, where customers publicize not only the failure itself but their sense of being mistreated or invalidated (Akhoondnejad 2024).

Traditional, human-led service recovery methods, while often praised for their empathy and improvisational flexibility, are constrained by inconsistency, fatigue, and operational limits (Fürst et al. 2025). These limitations have prompted firms to adopt generative artificial intelligence (GAI), particularly large language model (LLM)-based agents, for managing frontline service interactions (Bhattacharyya 2024). These agents offer linguistic fluency, high availability, and procedural consistency, making them well suited for handling low-stakes, high-volume recovery tasks (Hu and Pan 2024). However, their growing use in emotionally consequential recovery scenarios, where customers expect rectification, and recognition, raises critical concerns about appropriateness and authenticity (McAlister, Alhabash, and Yang 2024; Yang, Zhou, and Yang 2023). As GAI becomes more adept at mimicking human conversational norms, customers shift their evaluative lens from procedural sufficiency to relational authenticity. What begins as an efficient exchange is reinterpreted, especially under high-emotion conditions, as a moral interaction (Lim et al. 2025). This creates a paradox: the more GAI sounds human, the more it is held to human relational standards (Hao, Demir, and Eysers 2024; Zhou, Lu, and Chen 2025). When users later discover that an emotionally resonant message, such as an apology or expression of concern, is generated by an AI, they often experience what we term an identity-contingent trust violation (Lee and Kim 2024; Yim 2024). Linguistic fluency alone becomes insufficient; instead, the absence of perceived intentionality or emotional investment can destabilize the interaction (X. Liu et al. 2025).

Despite the increased deployment of LLMs in customer service, existing research has yet to account for how emotional context moderates the relational consequences of AI identity disclosure. Prior studies largely evaluate GAI through functionalist lenses, focusing on speed, accuracy, or message clarity (Hsu and Lin 2023; Tan, Liu, and Litvin 2025; Yang, Zhou, and Yang 2023), without fully considering how users' trust and satisfaction are shaped by the perceived identity of the responder, especially in emotionally sensitive moments. Nor have they systematically examined how linguistic mimicry interacts with emotional expectations to either enhance or erode the effectiveness of AI-led service recovery. This gap is particularly salient in service recovery scenarios involving moral signals such as apologies, acknowledgment of faults, or expressions of regret, acts that are communicative, performative, and relational (K. Zhang and Hao 2024). When GAI delivers such messages via scripted templates, it may inadvertently trigger a deeper sense of alienation rather than resolution, especially when the customer interprets the gesture as inauthentic or manipulative (Ferreira et al. 2024).

This study addresses these theoretical and empirical gaps by examining how the emotional intensity of service failure contexts interacts with GAI's linguistic mimicry and identity disclosure. Specifically, we ask:

- RQ1: How does the disclosure of AI identity affect perceived relational authenticity, trust, and satisfaction in service recovery contexts?

- RQ2: Under what emotional conditions do linguistic mimicry by GAI amplify or undermine the effectiveness of service recovery?

To investigate these questions, we conducted a controlled experiment in the context of online food delivery, a sector where both low- and high-emotion service failures are frequent and consequential. Participants evaluated identical service recovery messages across two emotional conditions, routine (low-emotion) and emotionally sensitive (high-emotion), under two identity conditions: pre-disclosure and post-disclosure of the responder's nature (human or AI). This study contributes to theories of human – AI interaction by introducing identity-contingent relational trust, a form of trust shaped by message quality, and by perceived moral agency. We show that linguistic mimicry by GAI, while often beneficial, can backfire in high-emotion service contexts, especially after identity disclosure. This insight extends service recovery theory to account for the socio-emotional consequences of AI use. Practically, our findings call for role-sensitive deployment of GAI: firms should reserve AI for low-emotion, procedural tasks, and deploy human agents in emotionally charged cases. Moreover, transparent identity framing must be aligned with customer expectations to avoid relational breaches. Rather than replacing human empathy, GAI should act as a triage mechanism, escalating complex emotional interactions with human agents when needed.

2. Literature review

Service failures are defined as instances where service falls short of customer expectations and lead to a range of deficiencies from minor errors to substantial disruptions in service delivery (Salehi-Esfahani, Torres, and Hua 2023). In the digital age, there is a noticeable escalation in conflict as marked by dissatisfied customers utilizing social media channels for raising their complaints with service providers (Hwang and Mattila 2020). Online reviews have emerged as a pivotal form of user-generated reviews and revolutionized how customers communicate their service experiences (Serra-Cantallops, Ramón Cardona, and Salvi 2020). It is noteworthy that the impact of transparent complaint handling and recovery processes presents businesses with a two-fold opportunity: to effectively resolve customer complaints and to proactively transform negative complaints into positive opportunities (Allard, Dunn, and White 2020; Langaro et al. 2024). Service failures in the online food delivery industry stem from the inherent characteristics of services, namely intangibility, heterogeneity, inseparability, and perishability, which are more prominent due to the multi-layered nature and the need for continuous provider–customer interaction (Gansser, Bossow-Thies, and Krol 2021; Srivastava and Gosain 2020). Notably, it is the substandard and inefficient resolutions of these service failures, rather than the failures themselves, that most significantly drives customer dissatisfaction (Choi, Mattila, and Bolton 2021). In this scenario, embracing justice is crucial. Justice is perceived by customers through the lens of how equitably and justly service recovery is designed and offered, taking into full account the magnitude of the loss incurred from the service failure (Peinkofer et al. 2022).

2.1. Dimensions of justice in service recovery

The term of justice has been theorized as formed by three dimensions namely distributive, procedural, and interactional (Ali, El-Manstrly, and Abbasi 2023). Distributive justice is concerned with the perceived equity of the outcomes achieved through service recovery (Hornik and Rachamim 2023), reflecting in the tangible results, such as refunds, replacements, or other forms of compensation, and how these are weighed against the expectations of customers and the severity of the service failure (Kron et al. 2023). Procedural justice extends to the mechanisms and processes that lead to the recovery outcome and encompasses critical factors such as the timeliness, speed, and adaptability of the recovery process (Kim and So 2023). Interactional justice, the third dimension, emphasizes how service personnel communicate and handle relationships during the service recovery process, capturing the qualitative aspects of customer services, such as courtesy, empathy, and respect (Ali, El-Manstrly, and Abbasi 2023).

2.2. Operationalizing justice: six key recovery elements

Informed by the principles of justice theory, the construction of a robust framework is imperative for appraising the efficacy of service recovery efforts in addressing customer complaints. Accordingly, six methodological dimensions are widely recognized in service recovery efforts. These include timeliness, facilitation, redress, apology, credibility, and attentiveness (Davidow 2000, 2003). Each element is described as follows.

Timeliness: The dimension of timeliness concerns how quickly an organization is perceived to address or manage a complaint (Li et al. 2023). In time-sensitive online food delivery services, any delays or errors can significantly reduce the perceived service value and negate the benefits of management responses aimed at customer satisfaction (Amoako et al. 2023). Consequently, customers have a heightened expectation for prompt action, anticipating procedural measures such as quick order replacement or immediate compensation, which are seen as standard service protocols rather than added courtesies (de Mesquita et al. 2023).

Facilitation: Effective communication systems are the linchpin in upholding procedural justice and ensuring that customers perceive a level of fairness and direct responsiveness in the event of service failures (Jacobs and Liebrecht 2023). Such systems are indicative of the deep-rooted dedication of organizations, serve as reactionary measures and proactive steps toward building a trust-based relationship with customers, fostering loyalty, and setting the stage for positive user-generated review promotions (Sengupta, Stafford, and Fox 2024).

Redress: Redress refers to compensatory measures such as refunds, vouchers, free products, or discounts provided to customers after a service failure to address their complaints and to uphold distributive justice (Ali, El-Manstrly, and Abbasi 2023). Within the online sector, the application of redress in distributive justice, is not straightforward due to the inability to provide immediate physical compensation (Rohden and Matos 2022). Despite this, the essence of distributive justice can still be preserved, for instance, when service providers address negative online feedback by proposing compensatory offers such as discounts or vouchers for future services, they are actively engaging in the principles of distributive justice (Bacile et al. 2020).

Apology: An apology acts as a form of psychological, non-monetary regret compensation (Kobel and Groeppel-Klein 2021). The role of apology can be multifaceted, serving as an admission of service fault and conveying a signal that the business takes the problem seriously and its commitment to proactive resolution (Shao et al. 2022). Furthermore, apologies carry more weight than tangible compensation in certain cultural contexts where saving face and emotional reconciliation are highly valued (Zoodma et al. 2021). This interpersonal aspect of service recovery is often associated with the perception of interactional justice, which assesses fairness in the way organizations treat customers during the complaint process (Ali, El-Manstrly, and Abbasi 2023).

Credibility: The credibility of a business is mirrored in its readiness to offer clear explanations for issues, an interactional act that underpins transparency integral to its reputation (Kharouf et al. 2020). When customers perceive this level of transparency and credibility, they tend to report more satisfying experiences with service recovery, which in turn significantly fortifies trust (Guo et al. 2023). Trust is an emotional, critical, and calculable asset in the customer–business relationship, cementing long-term loyalty and driving repurchase intentions (Taylor et al. 2020).

Attractiveness: Attentiveness emerges as a multifaceted construct encompassing respect, courtesy, empathy, and a genuine willingness to listen (Ampong et al. 2021; Luong, Wu, and Vo 2021). These dimensions collectively inform the quality and efficacy of the service failure response to customer complaints, transcending the mere resolution of the issue to consider the emotional state of customers and the tone of the meaningful dialogue (Huang and Ha 2020; Y. Zhang et al. 2021). This form of engagement often yields a greater impact on customer loyalty than traditional compensatory measures or restitution alone, suggesting that the psychological and relational aspects of customer service may indeed outweigh the benefits of mere transactional corrections in redress scenarios (Hao et al., 2025).

2.3. Service recovery dynamics in online food delivery

In the increasingly digitized ecosystem of online food delivery, where customer interactions are largely mediated through automated platforms, understanding how consumers evaluate AI-driven service recovery has become a pressing concern. A foundational theoretical framework to analyze this phenomenon is the Technology Acceptance Model (TAM), which posits that perceived usefulness and perceived ease of use are central determinants of technology adoption (Davis 1989). In scenarios involving low-complexity procedural failures, such as order tracking, incorrect deliveries, or refund processing, GAI systems are often positively evaluated due to their speed, consistency, and convenience. These capabilities allow GAI to outperform human agents in delivering rapid, standardized solutions in high-volume service environments (Wirtz and Stock-Homburg 2025). However, this functional efficiency does not translate seamlessly across all service recovery contexts. When service failures involve emotional dissatisfaction, perceived injustice, or relational breakdowns, customers often seek resolution, apology, empathy, and tailored engagement (Sahaf and Fazili 2024). In such emotionally salient interactions, the absence of social presence in AI systems significantly undermines their perceived usefulness (Khan et al. 2025), highlighting the limitations of TAM when applied in emotionally complex recovery scenarios.

To address these shortcomings, Commitment-Trust Theory offers a complementary perspective, emphasizing that customer trust in service recovery processes is shaped by outcomes and by transparency, credibility, and expectation alignment (Rashidi-Sabet and Bolton 2024). A key moderating factor is whether the identity of the service responder, human or AI, is made explicit. Research suggests that when customers are clearly informed that a response is AI-generated, they may recalibrate their expectations, resulting in greater tolerance of emotionally neutral or scripted interactions (Mogaji and Jain 2024). Conversely, undisclosed AI use may produce misattribution and perceived coldness, leading to a breakdown in trust. This aligns with the expectation-confirmation model in the trust literature, which asserts that trust and satisfaction are enhanced when perceived service experiences match adjusted expectations (Nguyen and Dao 2024). In this sense, disclosure operates as a trust-calibration mechanism, reducing the risk of misinterpretation and enabling more favorable customer evaluations of AI-assisted recovery, if framed correctly.

Adding another layer of nuance, the Service Recovery Paradox (SRP) posits that under specific conditions, customers may report higher satisfaction after a well-managed service failure than if no failure occurred at all (Rao, Suar, and Sahoo 2024). However, this paradox remains contentious in the online food delivery sector, where instant gratification, tight delivery windows, and multi-party accountability complicate both recovery implementation and consumer perception. While GAI may deliver procedural justice through speed and consistency, it often fails to convey interactional justice, the sense of fairness embodied in tone, empathy, and relational sensitivity (Yim 2024). Particularly in emotionally charged or high-stakes complaints, consumers may perceive even flawless AI responses as inadequate if they lack perceived sincerity or emotional acknowledgment. In these cases, human agents remain indispensable due to their capacity for contextual reasoning, emotional regulation, and sincere communication (Ryoo et al. 2025). These insights suggest the need for task-agent alignment: GAI should be deployed in functionally oriented, low-emotion cases, whereas human agents are better suited for complex or relationally sensitive issues. Despite a rich literature on service recovery strategies, limited attention has been paid to the interaction between response source identity and customer perception dynamics, a gap this study aims to address. As visualized in Figure 1, this research employs a two-stage experimental design, where participants evaluate service recovery responses both before and after learning whether the reply was generated by GAI or a human. This approach allows for the isolation of initial unbiased evaluations and the measurement of expectation shifts triggered by disclosure.

3. Research design

The research design of this study as shown in Figure 2 was methodically structured to examine the efficacy of LLM-generated responses to customer complaints in the context of online food delivery services. To begin, a set of 18 anonymized customer complaints and corresponding merchant responses was collected from publicly accessible sources on major food delivery platforms, including Meituan and Ele.me in China, and Deliveroo, Hungry Panda, and Fantuan in the UK. These platforms were selected based on two criteria: their dominant market presence in their respective regions and the availability of large volumes of open-access customer reviews and merchant responses, which offered

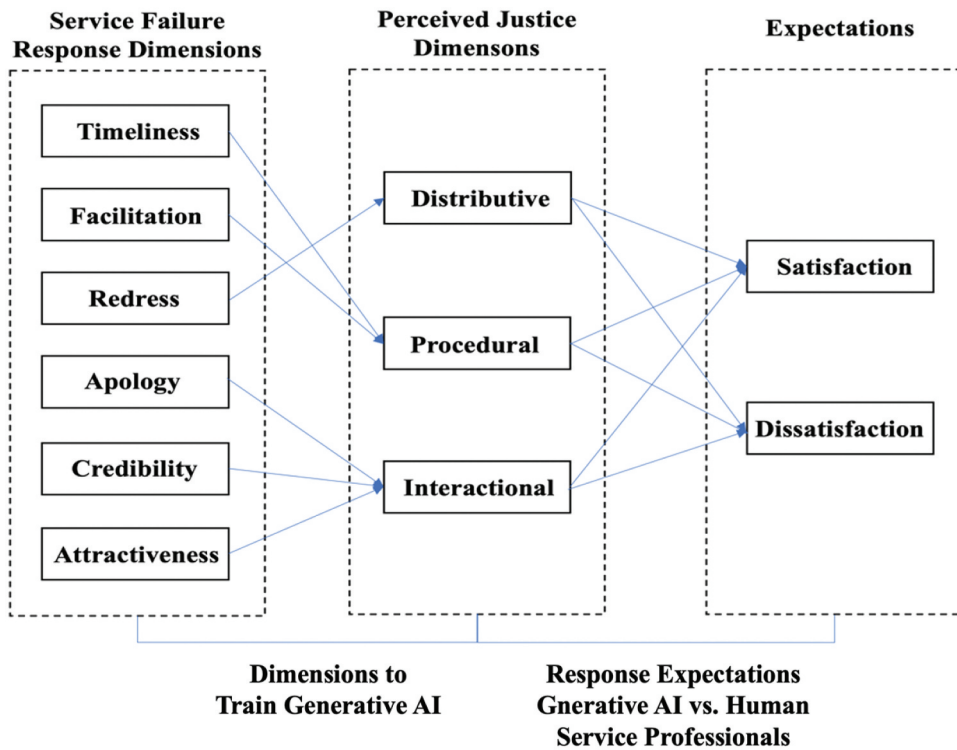


Figure 1. Service recovery dimensions and customer expectations.

rich, real-world data for analyzing complaint and response dynamics. China was chosen due to its position as the world's largest and most mature food delivery market (Y. Zhang et al. 2025), where Meituan alone holds nearly 70% of the market share, forming a duopoly with Ele.me (Jolly 2022). In the UK, Deliveroo is the second-largest food delivery platform by market share, controlling approximately 28% of the national market (Zego 2025). Hungry Panda and Fantuan, while more niche, have grown rapidly by catering to the UK's Chinese-speaking population, particularly international students, through a strong focus on Asian cuisine (He and Chan 2024). The decision to focus on China and the UK was further supported by the cross-national industry experience of one of the authors, who has worked extensively in the food delivery sector across both countries. This professional background enabled deeper contextual understanding and facilitated access to relevant user communities in both regions.

Each scenario was paired with two responses: one written by a human (sourced from actual food delivery platforms) and the other generated by a GAI. The GAI-generated responses were created using a standardized prompt to align with established service recovery theory: 'Please make a response to the following customer complaint by taking the three-justice dimension, distributive, procedural, and interactional, and the six customer service recovery dimensions, timeliness, facilitation, redress, apology, credibility, and attentiveness, into consideration'. All complaint scenarios were pre-classified into two distinct categories based on emotional intensity and resolution complexity: Routine and Emotionally Charged. Routine complaints referred to common, lower-intensity service

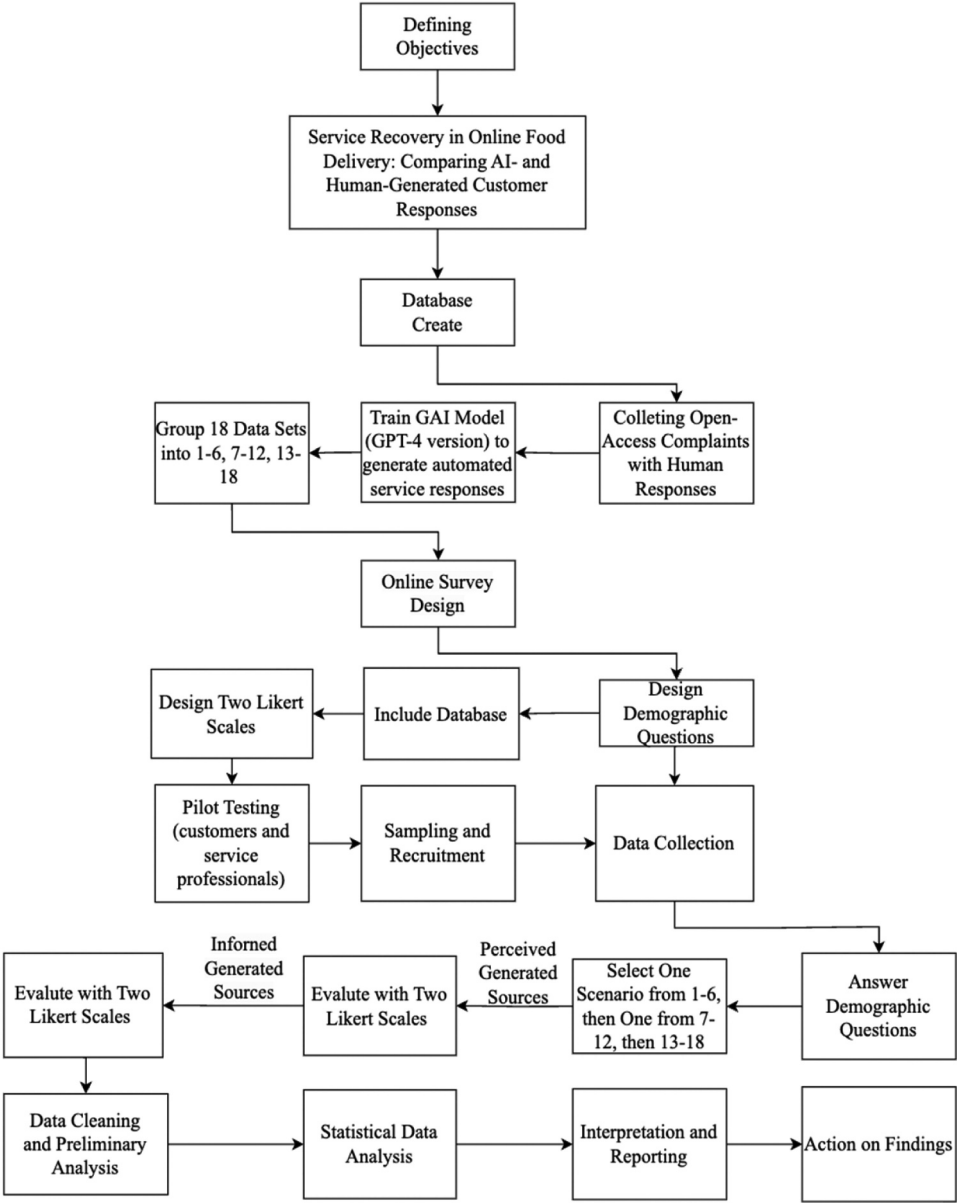


Figure 2. Research procedure.

issues (e.g., cold drinks, missing items, minor dissatisfaction) that could typically be addressed with standardized procedures. Emotionally Charged complaints involved strong negative emotions or perceived violations of trust (e.g., inedible food, illness, or experiences that provoke disgust or anger). The 18 scenarios were then grouped into three blocks (1–6, 7–12, and 13–18 shown in Table 1), each containing a mixture of both complaint types. The survey began with a screening question: ‘Have you ever either posted a review or read a customer review on a food delivery app or platform (e.g.,

Table 1. Scenario setting.

Scenario No.	Category	Scenario Title	Human Response Keywords	AI Response Keywords
Scenario 1	Routine	Milk Quality Complaint	apology, explanation, voucher	professional tone, structured escalation
Scenario 2	Emotionally Charged	Sushi Quality Decline	denial, voucher, handmade excuse	sincere apology, refund, future credit
Scenario 3	Routine	Missing Straw & Taste Issue	casual tone, refund mention	apology, customer care focus
Scenario 4	Emotionally Charged	Bad Sweet Potato Taste	personal excuse, empathy	refund, apology, quality assurance
Scenario 5	Emotionally Charged	Old Sashimi Complaint	deny problem, ingredient justification	apology, refund, complimentary meal
Scenario 6	Routine	Misleading Dish Photos	picture change explanation	visual accuracy, credit
Scenario 7	Emotionally Charged	Soggy Tempura & Sushi	delivery excuse, packaging fix	refund, apology, future meal
Scenario 8	Emotionally Charged	Disappointing Pork Knuckle	pricing defence, no apology	apology, refund, new offer
Scenario 9	Emotionally Charged	Vegetarian Misfit	defensive tone, vegan assertion	apology, refund, complimentary vegetarian meal
Scenario 10	Routine	Dry Chicken & Chips	monitoring, discount coupon	apology, process improvement
Scenario 11	Routine	Cold Coffee	coffee culture emphasis, invitation to revisit	apology, refund, hot drink replacement
Scenario 12	Routine	Wrong Drinks	driver fault, refund timeline	apology, replacement + voucher
Scenario 13	Routine	Flavourless Taro Milk Tea	sugar suggestion, melting ice	apology, replacement + voucher
Scenario 14	Emotionally Charged	Disappointing Food Appearance	defensive tone, process defence	apology, investigation, redress
Scenario 15	Routine	Wrong Combo Delivered	staff penalty, future free combo	apology, refund + voucher
Scenario 16	Routine	Missing Soup	blame delivery, sealed package emphasis	apology, fair resolution request
Scenario 17	Emotionally Charged	Disgusting Meal Experience	event excuse, raw material claim	apology, full refund, chef-prepared reoffering
Scenario 18	Emotionally Charged	Customer Vomiting After Meal	hotline deflection	apology, investigation, medical compensation, refund

Meituan, Deliveroo, Ele.me, etc.)? Only participants who responded ‘Yes’ were eligible to continue. After passing the screening, participants completed a brief demographic questionnaire before beginning the main experiment. The experiment followed a within-subject design and consisted of three sequential blocks. In each block, participants were randomly assigned to one of the six complaint scenarios. For each scenario, they read the customer complaint and one corresponding response, without being told whether the reply was authored by a human or AI. They were then asked to judge the identity of the responder (human or AI) and evaluate the response using two Likert-scale questions (e.g., perceived empathy and professionalism). After submitting these judgments, the true identity of the responder was revealed, and participants repeated the same Likert-scale evaluations to measure any changes in perception after disclosure. This procedure was repeated for all three blocks, with participants assigned a new scenario for each block.

The study was conducted entirely online, with participants recruited from both China and the UK. Between October 2023 and January 2024, purposive sampling was employed to recruit a total of 180 individuals, with direct experience using food delivery platforms. Recruitment was carried out through food-related online

communities, university mailing lists, and student-oriented social media channels. To ensure the relevance of participants' experiences, inclusion criteria specified that respondents must have either posted a complaint or read customer complaints on a food delivery app. Descriptive statistics were first conducted to summarize demographic characteristics (e.g., age and education). Associations between these variables and satisfaction with service recovery were tested using Pearson's chi-squared test and Cramer's V (Yap and Sim 2011). To evaluate the reliability of survey instruments, internal consistency was assessed using Cronbach's Alpha (α) and McDonald's Omega (ω) (Hayes and Coutts 2020). Given the ordinal nature of Likert-scale data, parametric methods such as the paired t-test or repeated-measures ANOVA were deliberately avoided due to their reliance on assumptions that are often violated in such contexts. These methods presume interval-level measurements, approximate normality, and homogeneity of variance, conditions rarely met by Likert-type responses (Norman 2010; Sullivan and Artino 2013). Treating ordinal data as intervals can lead to distorted inferences, especially in the presence of skewed distributions or ceiling or floor effects, which are common in attitudinal evaluations (Q. Liu and Wang 2021). Instead, the Wilcoxon signed-rank test was employed as a non-parametric alternative, offering a more appropriate approach for comparing paired ordinal data (Nussbaum 2024). Unlike parametric tests, the Wilcoxon test does not assume normality and is robust to violations of scale assumptions, thereby ensuring more reliable and valid insights into participants' perceptual changes when informed of the source of service responses (Erceg-Hurn and Miroseovich 2008). Visual representation tools, such as heat maps (Shen, Lever, and Joppe 2020) and alluvial diagrams (Paul and Roy 2023), were incorporated to effectively portray trends in feedback and demographic flows, enhancing the clarity of customer satisfaction determinants. Bar graphs complemented the statistical analyses to facilitate a clear and objective comparison of service dynamics.

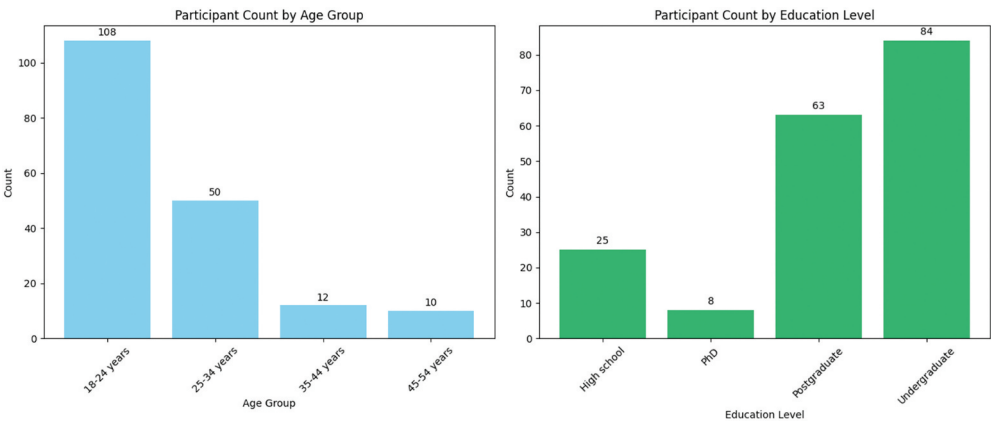


Figure 3. Demographic distribution of survey participants by age and education level.

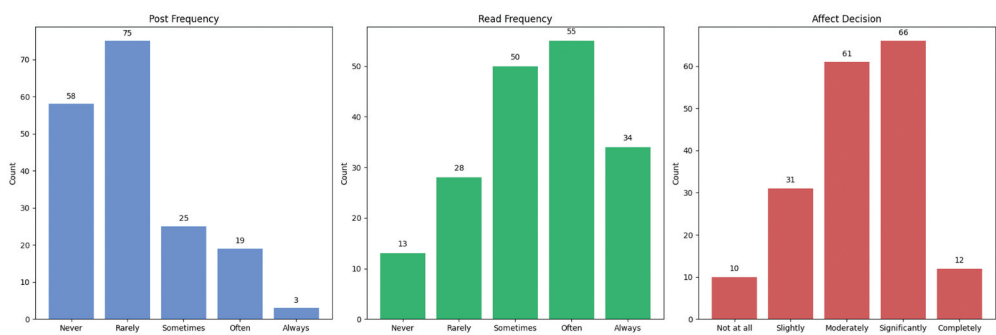


Figure 4. Participant engagement with online food delivery reviews: posting, reading, and decision Impact.

4. Results

4.1. Survey findings on the demographic variables

Figure 3 illustrates the demographic distribution of the 180 survey participants. The sample comprises 63% respondents from China and 37% from the United Kingdom, reflecting a diverse but predominantly Chinese participant pool. The left panel displays the age group distribution, with the majority (predominantly 18–24 years old) representing a younger cohort. The right panel depicts education levels, highlighting that most respondents hold either undergraduate or postgraduate degrees.

Figure 4 illustrates participants’ engagement with customer reviews in the context of food delivery platforms. The left panel shows that most participants rarely ($n = 75$) or never ($n = 58$) post reviews. In contrast, the middle panel reveals more active review

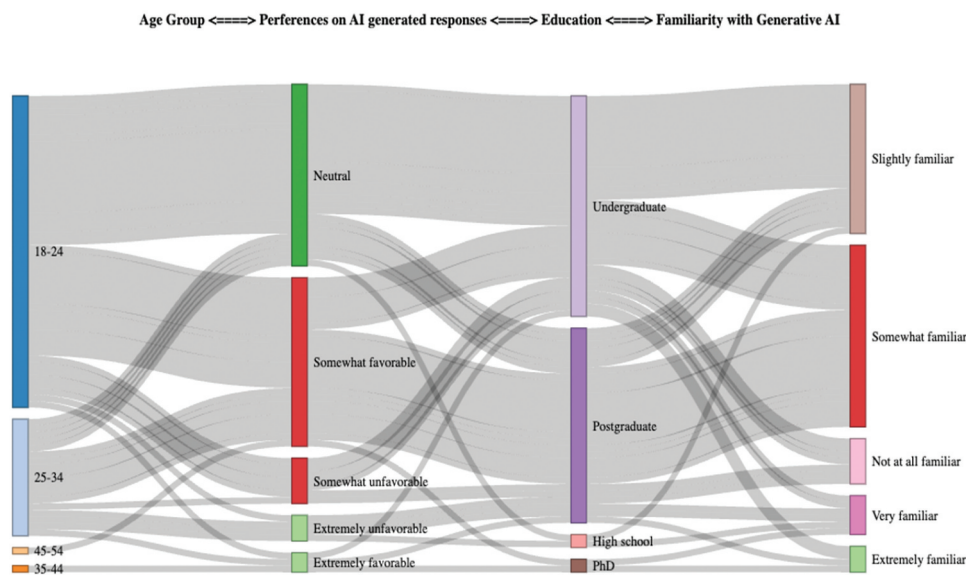


Figure 5. Customer preferences for GAI responses with demographic variables.

consumption, with ‘often’ ($n = 55$) and ‘sometimes’ ($n = 50$) being the most frequent responses. The right panel highlights the extent to which these reviews influence ordering decisions: 66 participants rated the influence as ‘significant’ and 61 as ‘moderate’, indicating that while few contribute content, a majority rely on reviews when making decisions.

Figure 5 maps the associations among age groups, preference for AI-generated responses, education level, and familiarity with GAI, revealing multifaceted and non-linear patterns. The dominant age groups represented are 18–24 and 25–34, who collectively form the core demographic of GAI users. Within both age groups, ‘neutral’ remains the most frequently reported attitude toward AI-generated content, accounting for the largest single category of preference. However, among 25–34-year-olds, there is a notably stronger flow toward ‘somewhat favorable’ responses compared to the 18–24 group, which skews more heavily toward neutrality. Favorable sentiment is more prominent among participants aged 35–44 and 45–54, albeit in smaller sample sizes, suggesting that receptivity may increase slightly with age. Conversely, even within the younger groups, ‘somewhat unfavorable’ and ‘extremely unfavorable’ responses are not negligible, indicating that youthful exposure to GAI does not universally translate into approval. The divergence across age brackets indicates that preferences are shaped by more than generational familiarity, possibly including expectations of professionalism, prior exposure to AI failures, or contextual use cases. Highest levels of education and familiarity with GAI further stratify these preferences. Among participants with postgraduate degrees, responses are widely distributed across all preference categories, from ‘extremely unfavorable’ to ‘extremely favorable’. This educational group also reports the highest levels of GAI familiarity, with strong flows toward ‘somewhat familiar’ and ‘very familiar’. However, notably, familiarity with GAI does not uniformly correlate with positive attitudes. Several

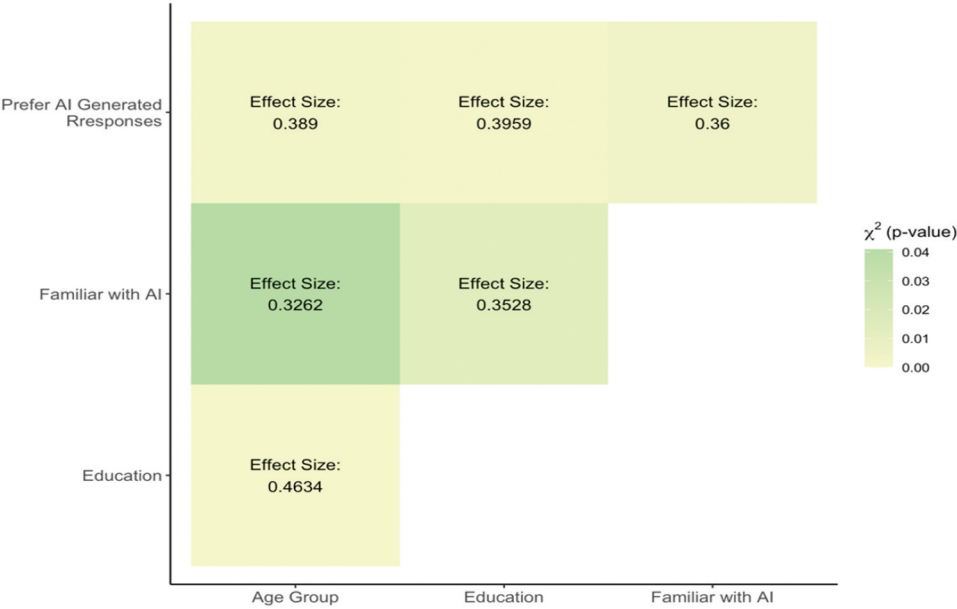


Figure 6. Analysis of customer preferences using Cramer’s V and Pearson’s χ^2 tests.

participants who report being 'very familiar' or even 'extremely familiar' still express 'somewhat unfavorable' or 'extremely unfavorable' preferences. This suggests a potential for disillusionment or critical awareness that emerges with deeper understanding. In contrast, undergraduate and high-school participants tend to cluster in the middle familiarity ranges ('slightly familiar' or 'somewhat familiar'), and their preferences mostly fall between 'neutral' and 'somewhat favorable'. Notably, few respondents at any educational level express 'extremely favorable' views, highlighting a general atmosphere of cautious acceptance rather than enthusiasm.

Specifically, the data presented in Figure 6 employs both Cramer's V and Pearson's chi-squared tests (χ^2) with a significance level of $p \leq 0.05$, revealing notable associations. Education emerges as the predominant factor influencing GAI familiarity, with an effect size quantified at 0.3582. The age group follows, demonstrating a slightly diminished effect size of 0.3262 in the same context. When considering the preference for GAI responses, the data reveals a hierarchy of influences: education is the most influential (effect size of 0.3959), closely succeeded by age group (effect size of 0.389) and familiarity with GAI (effect size of 0.36).

The structured seven questions were designed specifically to elucidate the frequency of usage of various platforms by consumers, their propensity to post reviews (categorized into positive or negative feedback), and the extent to which these reviews influence their decision-making process before placing an order. Additionally, the questionnaire sought to understand the familiarity of customers with GAI technologies and how their own experiences or observations of complaint responses affect their ordering behaviors. Figure 7 illustrates key findings from our analysis, indicating that while only 9% of the customers regularly post reviews, a substantial 53% consider these reviews crucial in their decision-making, highlighting the significant impact a minority of active reviewers has on

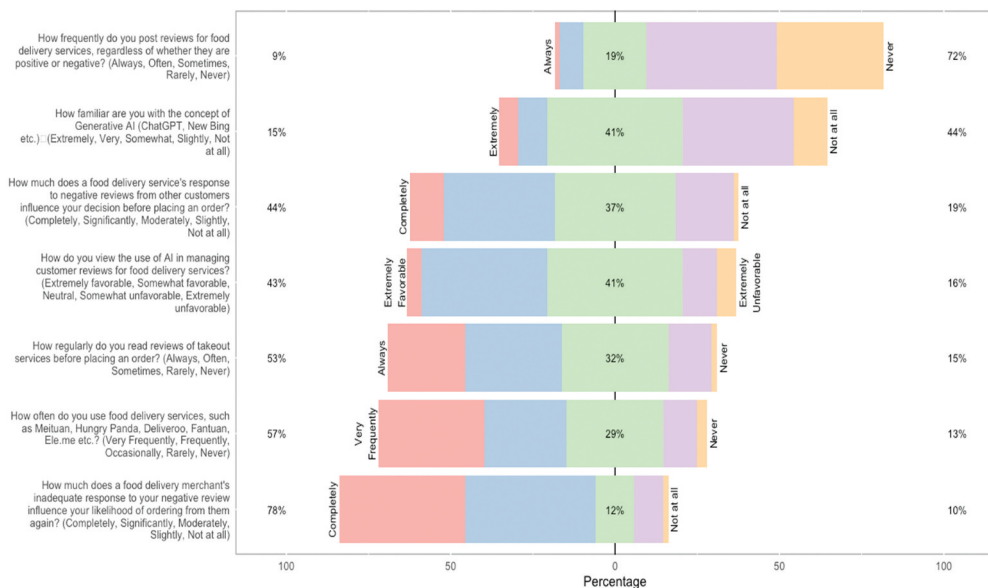


Figure 7. Customer behaviour and preferences when using food takeaway delivery services.

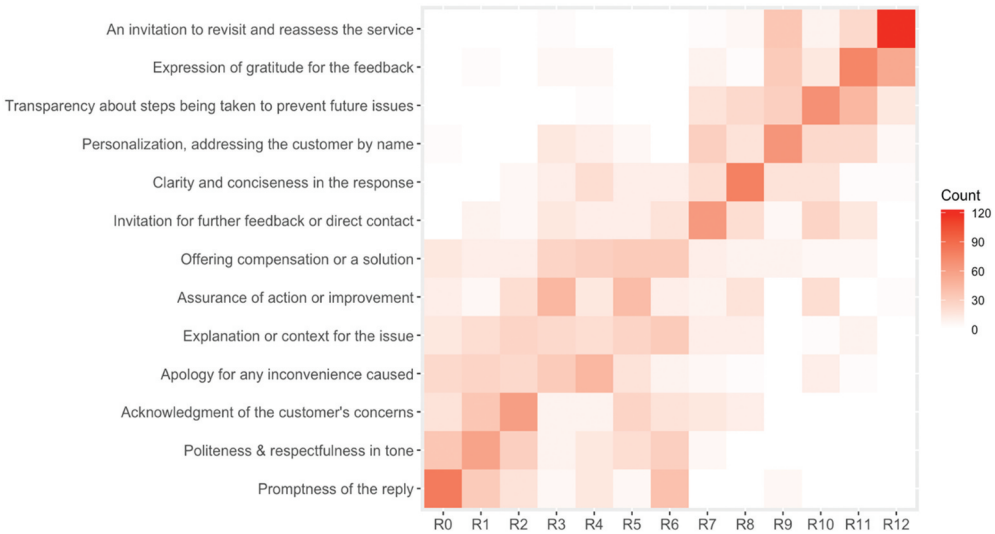


Figure 8. Determinants of customer satisfaction in complaint responses.

potential customers. The influence of negative feedback from others affects 44% of respondents’ ordering decisions, and 78% of the respondents reported that their own negative experiences, if not adequately addressed, affect their future choices. Additionally, the data reveals a moderate openness (43%) towards the incorporation of GAI in customer service although 44% of the respondents are unfamiliar with these technologies. These findings provide a baseline for understanding preferences regarding the use of GAI in addressing their issues.

The intensity of the colors in [Figure 8](#) reflects the frequency count of positive feedback associated with specific response elements. Notably, ‘Promptness of the reply’ denoted by R0, stands out as the most critical determinant, receiving the highest count of positive responses. This underscores the urgency customers place on swift responses. Adjacent to this, ‘Politeness & respectfulness in tone’ and ‘Acknowledgment of the customer’s concerns’ denoted by R1 and R2, respectively, although not as heavily weighted as R0, still present significance of establishing a respectful and empathetic dialogue. Other elements such as transparency about steps being taken to prevent future issues and the expression

Table 2. ω -coefficient and Cronbach’s α tests for internal consistency of questions regarding customer satisfactions, fairness, and effectiveness with GAI- and human-generated responses.

	Customer Satisfaction (Credibility, Apology, Attentiveness, Redress, and Facilitation)				Justice of Fairness and Effectiveness (Distributional, Interactive, and Procedural)			
	Perceived AI		Perceived Human		Perceived AI		Perceived Human	
	CQ	CSRQ	CQ	CSRQ	CQ	CSRQ	CQ	CSRQ
ω (Total):	0.85	0.88	0.87	0.88	0.75	0.79	0.78	0.79
Cronbach’s α (std):	0.82	0.83	0.85	0.85	0.75	0.78	0.77	0.74
G6 (smc)	0.79	0.81	0.82	0.83	0.67	0.71	0.70	0.69
Positive Correlations:	100%	100%	100%	100%	100%	100%	100%	100%

Note: CQ indicates the questions for customers; CSRQ: denotes the questions for customer service representatives.

of gratitude for the feedback, indicated by lighter shades, still play a considerable role in shaping overall customer satisfaction.

4.2. Initial perceived assessment outcomes

Initially, to garner impartial feedback, respondents were not informed of the origin of responses, with subsequent disclosure intended to assess the effect of source awareness on their satisfaction levels. The survey data, as illustrated in Table 2, exhibits excellent internal consistency in gauging customer satisfaction, as well as perceptions of fairness and effectiveness regarding GAI- and human-generated responses. Both the ω coefficient and α tests yielded high scores, with ω results ranging from 0.75 to 0.88 and α scores from 0.74 to 0.85 across different categories. These results are supported by strong G6 (smc)

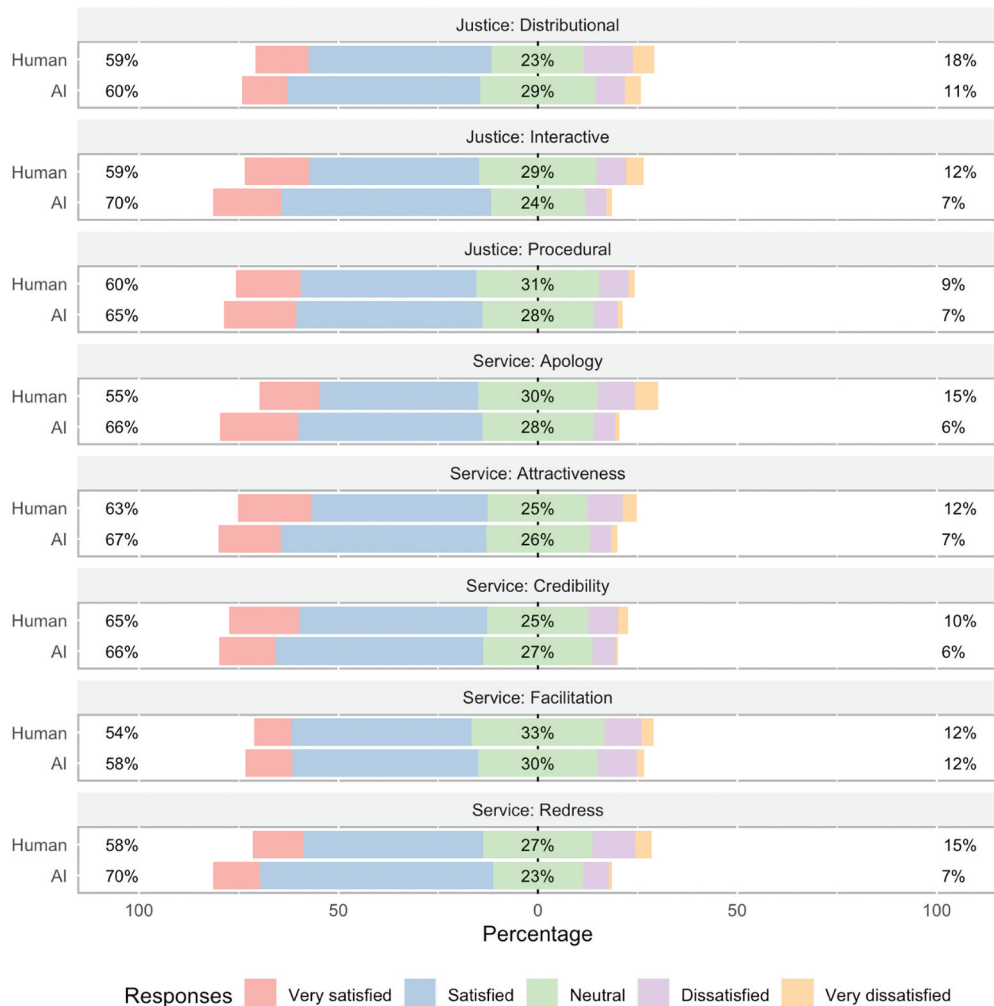


Figure 9. Customer perceptions of three justice principles and five service dimensions.

values and a 100% rate of positive correlations, confirming the reliability of the questions designed for both customers and customer service representatives.

From the obtained results (Figure 9), GAI is demonstrating superior performance across various justice and service dimensions. It boasts a higher satisfaction rate in interactive justice at 70%, surpassing humans by 11%. For procedural justice, GAI again leads with a satisfaction rate of 65% over humans' 60%, and fewer customers are dissatisfied at 7% versus 9%. When delivering apologies, GAI achieves a satisfaction rate of 66%, significantly higher than the human rate of 55%. GAI also edges out in attractiveness, deemed more satisfying at 67% compared to 63% for human interactions. Credibility is closely contested; both GAI and humans are nearly tied in satisfaction at 66% and 65%, respectively, but GAI has a narrower margin of dissatisfaction at 6%, less than humans' 10%. Facilitation efforts are slightly more satisfying with GAI at 58%, as opposed to 54% for human services, with dissatisfaction standing evenly at 12%. In terms of redress, GAI's performance is notably stronger, with a 70% satisfaction rate, a marked improvement over the human satisfaction rate of 58%, coupled with a dissatisfaction rate of 7%, which is less than half that of human agents.

Customers increasingly prefer GAI-generated responses, appreciating their unbiased and equitable treatments across diverse demographics. Such responses are characterized by politeness, respect, patience, and professionalism, essential qualities that ensure customer satisfaction regardless of the GAI's inherently mechanical tone. GAI systems excel in following procedures, explaining decisions, and inviting further feedback, thus maintaining a high level of accuracy and credibility comparable to human representatives. GAI-generated responses are 'warmer' by 11% of that written by humans. More interestingly, GAI tends to be more generous in that it never forgets to provide solutions or compensation for any problems faced by the customer, which can greatly enhance satisfaction levels. In facilitating a smooth and efficient interaction with customers, GAI seems to have done as well as human customer service representatives.

4.3. Comparative analysis of perceived and informed results

In Table 3, the p-values derived from the paired sample Wilcoxon tests predominantly exceed the established significance threshold ($\alpha = 0.05$). This indicates that the differences in median ratings based on perceived versus informed information are not statistically significant. Such results lend credence to the equivalence in quality between GAI-generated and human-authored customer service responses. It underscores an increasing receptivity toward the adoption of GAI technologies in customer service roles by participants. Notable exceptions to this trend were observed in the domains of Apology (Human, $p = 0.002$), Distributional Justice (Human, $p = 0.007$), Interactive Justice (Human, $p = 0.004$), and Procedural Justice (AI, $p = 0.03$; Human, $p = 0.01$), where the p-values fell below the significance level.

The analysis of Figures 10 highlights some of the most pronounced differences in customer satisfaction with service recovery responses, focusing on the shifts observed when customers were informed of the response origin (human or GAI). Before disclosure, customer evaluations primarily reflected the content of the service itself, with human responses generally perceived as empathetic and personalized. This is particularly evident in distributive and interactive justice, where human-generated responses showed high levels

Table 3. Two-tail paired sample Wilcoxon test for median differences in the quality of ratings between perceived GAI/Human generated responses and informed GAI/Human generated responses.

	Customer Service Dimensions						Justice Dimensions					
	Facilitation		Redress		Apology		Credibility		Attractiveness		Distributinal	
	GAI	Human	GAI	Human	GAI	Human	GAI	Human	GAI	Human	GAI	Human
Participants	0.42	0.19	0.83	0.08	0.35	0.002	0.07	0.07	0.99	0.12	0.05	0.007
											0.57	0.004
											0.03	0.01

Use a 0.05 level of significance.

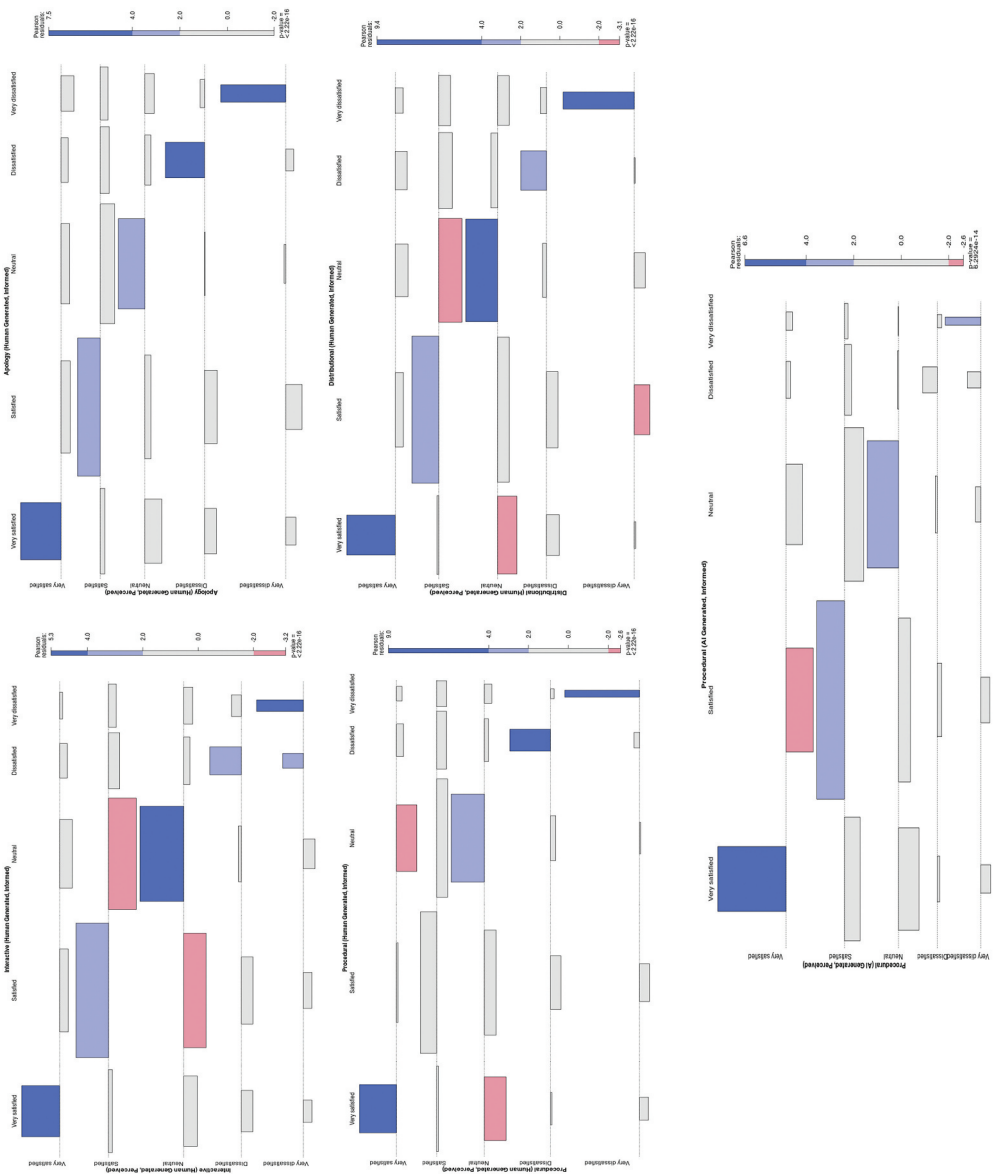


Figure 10. Comparison of satisfaction with human/GAI-generated before and after disclosure.

of satisfaction in the 'Very Satisfied' category and lower dissatisfaction rates. However, GAI responses also performed well in certain aspects, particularly in procedural justice, where the efficiency and objectivity of GAI seemed to resonate positively with customers prior to disclosure. Customers often exhibited balanced responses, with moderate satisfaction levels, indicating that initial evaluations tended to focus on the effectiveness of the service, irrespective of its origin. After the disclosure of the response origin, noticeable differences emerged in how customers reassessed their satisfaction. Human-generated responses saw a significant increase in satisfaction, especially in scenarios requiring apologies and personalized interaction, as evidenced by the rise in positive Pearson residuals in the 'Very Satisfied'

category. This suggests that transparency regarding the human origin of the response enhanced perceptions of empathy and trustworthiness, aligning well with customers' expectations for personalized service. In contrast, GAI-generated responses had mixed effects post-disclosure. While some customers appreciated GAI's efficiency in procedural justice, transparency also led to increased dissatisfaction, particularly when the GAI's performance fell short. The significant negative residuals in the 'Very Dissatisfied' category underscore the heightened sensitivity to GAI errors, likely due to the perceived lack of empathy in GAI responses.

5. Discussion

This study offers compelling evidence that familiarity with GAI does not linearly lead to greater acceptance, indeed, it often sharpens scepticism. Rather than validating the promise of frictionless AI integration, our results suggest that individuals who are most literate in GAI technologies become more exacting in their assessments, particularly when the interaction occurs in emotionally consequential contexts. Within the sphere of online food delivery, where errors are frequent and frustrations immediate, the emotional stakes are non-trivial. Participants with the highest self-reported familiarity and education, those likely to understand GAI's functional design, were also those who most readily perceived its relational inadequacy. For them, GAI's procedural fluency was insufficient. They scrutinized not what was said, but what was not conveyed: warmth, contrition, acknowledgment. This response reflects a shift from evaluating interaction quality in terms of information provision to evaluating it in terms of emotional attunement. What has emerged is a powerful mismatch: the more GAI approximates human interaction linguistically, the more it is held accountable for failing to meet human relational expectations (Kasirzadeh and Gabriel 2023).

What appears on the surface to be a linguistic problem is, in reality, a matter of perceived intentionality. Before users know the source of the message, they often evaluate it based on efficiency, how quickly it resolves an issue, whether the tone is polite, whether it aligns with the norms of customer service discourse. But once the source is revealed, their interpretive frame shifts entirely. Messages previously regarded as 'clear' or 'sufficient' become suspect, even irritating, when users realize that no real person has authored them. The same apology that feels adequate when imagined to be from a human suddenly reads as hollow when attributed to AI. This re-evaluation reflects an instinctive awareness that emotional meaning is embedded in the assumed social relationship between speaker and recipient (Guinrich and Graziano 2024). People extend trust and grace to humans because they infer effort and care; they withhold it from AI because there is no underlying intent. And while GAI is designed to simulate the emotional labour of human service agents, its responses, lacking embodied presence, moral accountability, and personal investment, remain emotionally weightless (Hao and Demir 2024). Thus, GAI's mimetic success becomes its relational undoing: the more convincingly it sounds like a person, the more jarring it becomes when it fails to feel like one.

This explains why the emotional 'contract' between customer and platform ruptures more severely when GAI is revealed as the source in high-stakes service interactions. When customers are dealing with a misplaced order or a late delivery, they are not merely resolving a transaction, they are asserting dignity, fairness, and sometimes even basic need. In these moments, they seek not just restitution, but recognition (Brännström,

Wester, and Nieves 2024). When GAI attempts to fulfil that need by using templated apologies or performative empathy, it can produce a deeper sense of alienation. The scripted nature of AI responses betrays their lack of emotional grounding. Unlike human agents, who are understood to be capable of genuine care, even when poorly expressed, GAI has no 'self' to extend in the exchange. It cannot exhibit hesitation, vulnerability, or remorse (George et al. 2023). And customers know this. For experienced users especially, GAI's 'empathy' reads as an impersonation of connection. In these cases, the customer is not simply dissatisfied with the answer, they are unsettled by the pretence (Zhao et al. 2025). This creates a subtle but powerful breach: not of accuracy or logic but of relational authenticity.

As this breach occurs, the nature of the trust itself begins to bifurcate. In routine, low-stakes service situations, such as confirming an order's arrival or explaining a delivery delay, GAI can be highly effective. It performs procedural tasks efficiently and consistently, generating trust through predictability. But in emotionally charged moments, affective trust becomes central. Customers are no longer measuring the system's competence; they are measuring its capacity to care. Here, GAI falls short (Sahoh and Choksuriwong 2023). Even when the message contains the right words, it cannot generate the feeling that someone truly understands the problem. In many cases, the customer does not want the quickest solution, they want the slow, deliberate confirmation that their frustration matters (Ozuem et al. 2024). Human agents, despite occasional lapses, can provide this through tone, pacing, hesitation, or improvisation (Yang, Zhou, and Yang 2023). These are affective signals that AI, however advanced, cannot convincingly reproduce. As a result, customers begin to differentiate between good and bad service, and between acceptable and unacceptable forms of service. Procedural trust may still be extended to GAI, but relational trust is withdrawn.

This interpretive divide is intensified by the social dynamics of identity disclosure. Once the customer knows whether the agent is human or machine, the entire interaction is socially recategorized. A response once perceived as efficient becomes cold; a delay once considered annoying becomes forgivable. Human fallibility is granted leeway; machine perfection is not (Sison and Redín 2023). This asymmetry reveals a deeper normative schema shaping service interaction. Humans are expected to try, even when they fall short. AI is expected to succeed, precisely because it does not 'try'. This creates a peculiar injustice in how GAI is judged, but it is a revealing one: it shows that judgments of service quality are deeply moral and relational (Bilgihan et al. 2024). Customers bring expectations about identity, agency, and social accountability into the interaction. When these expectations are violated, when the machine assumes a role it cannot substantively inhabit, trust falters not because of what the AI did, but because of what it could never be (Hao and Demir 2025).

GAI systems, when designed to replace rather than supplement human service roles, risk alienating the very customers they aim to serve (Hao et al., 2025). It is not enough to generate grammatically correct responses or offer timely refunds. In moments of failure, customers want to feel that their frustration is felt, not merely processed. Until GAI systems can establish credible markers of emotional investment, or until they clearly delineate the boundary between procedural efficiency and relational care, they will continue to disappoint in contexts that demand more than logic. For delivery platforms, this means thinking beyond automation. It means reimagining AI not as a replacement for

empathy, but as a mechanism for triage, escalation, or augmentation. True service recovery is about repairing a relationship. Until AI can do that its role in these emotionally textured moments must remain secondary.

6. Conclusion

This study fundamentally reorients how we understand consumer responses to GAI in service recovery, especially in the emotionally charged domain of online food delivery. The prevailing assumption that familiarity breeds acceptance is shown to be overly simplistic. Instead, we observe a more complex evaluative pattern, what we term critical familiarity, wherein users with greater exposure and technical literacy in GAI are more discerning, more demanding, and ultimately more critical when AI fails to meet relational expectations. GAI performs well when customers seek instrumental resolution: correcting a wrong charge, tracking a late order, or reissuing a voucher. However, when the interaction involves emotional stakes, frustration over repeated mistakes, perceived disrespect, or an unresolved complaint, the absence of embodied moral agency becomes glaring. Customers do not merely assess the content of responses; they evaluate the perceived presence behind those responses. In such moments, GAI's linguistic competence is not enough. In fact, the closer GAI mimics human tone and structure, the more unforgiving the backlash when users realize that empathy, understanding, or effort were simulated, not sincere. This dissonance, between human-like surfaces and machine-like substances, is precisely what erodes trust.

From a strategic standpoint, food delivery platforms must reconfigure how GAI is embedded within customer service architectures. Automation cannot be treated as a one-size-fits-all solution. Instead, platforms must design differentiated interaction pipelines, wherein GAI is deployed for low-stakes, high-volume queries, while human agents are reserved for cases requiring emotional engagement or normative judgment. Crucially, GAI should not be tasked with emotionally significant tasks like apologizing for poor service, explaining repeated failures, or offering consolation. These are far more than communicative acts, they are relational performances that presuppose intentionality and moral authorship, both of which GAI lacks. Thus, the system should include robust escalation triggers, semantic, emotional, or behavioral that detect when a user's concern is functional and existential. Platforms should treat service recovery as the tail end of logistics, and as a core site of brand trust maintenance. When service interactions fail at the emotional level, they create churn, they also actively damage the platform's ethical standing in the eyes of the consumer.

In terms of implementation, design considerations must go far beyond conversational fluency. Our findings suggest that disclosure of agent identity is not neutral, as it fundamentally shapes how customers interpret the same message. Knowing that a response comes from GAI doesn't just lower expectations; it reconfigures the interactional frame. What might appear professional when assumed to be human becomes emotionally sterile when known to be machine-authored. As such, transparency must be carefully framed. Platforms should communicate AI identity explicitly but respectfully, positioning GAI as a capable assistant rather than a substitute for human care. GAI messages should embody bounded humility: acknowledging limitations, avoiding emotional overreach, and

inviting escalation where appropriate. Additionally, platforms must abandon the illusion that AI can ‘perform empathy’ through formulaic phrases. Instead, investments should be made into context-aware response systems, AI agents that adjust tone, timing, and escalation based on real-time cues, such as user word choice, tone intensity, or issue repetition frequency. This would allow GAI to serve as a triage function, efficiently filtering and routing interaction types, rather than carrying the emotional burden of the service relationship itself.

Theoretically, this research extends and complicates existing understandings of human-AI service interaction by focusing not merely on comparative performance, but on the shifting dynamics of customer judgment before and after identity disclosure. While prior studies have examined the functional equivalence of human and AI agents in delivering service tasks, they have largely treated customer responses as stable or invariant. Our findings suggest the opposite: customer evaluation is deeply contingent on the perceived identity of the responder. Once the AI identity is revealed, customers do not simply reassess the quality of the interaction, they reinterpret its entire moral and relational framing. This reveals a critical blind spot in both traditional service recovery models and mainstream human-computer interaction frameworks. These models emphasize rational utility, perceived usefulness, efficiency, and ease of use, but neglect the identity-based expectations triggered by AI’s mimicry of human behavior. Our study suggests that GAI’s ability to simulate human-like responses does not produce straightforward acceptance. Instead, it activates a different, more demanding layer of evaluation rooted in relational legitimacy and perceived sincerity. We thus argue for an expansion of existing theories to incorporate identity-sensitive, post-disclosure effects, where trust and satisfaction depend on what is said or done, and on who is believed to be spoken. This reconceptualization is especially urgent in the age of generative AI, where the line between human and synthetic interactions is intentionally blurred.

Future research should further examine the ways in which customers interpret and adapt to AI identity over time and across contexts. One important avenue is to explore how trust and satisfaction evolve in longitudinal interactions, does repeated engagement with GAI agents, particularly in emotionally charged situations, lead to expectation recalibration or cumulative frustration? Additionally, future studies could investigate how the timing and framing of identity disclosure, for instance, early vs. delayed revelation, or neutral vs. emotionally framed disclosure, affect user perception, particularly in high-stakes service scenarios like complaint resolution or refund denial. Cross-cultural comparisons would also enrich our understanding of whether expectations of empathy, formality, or agency differ across sociocultural settings. Another key direction is to segment users by demographics or GAI familiarity but by psychological traits, such as need for emotional reassurance, anthropomorphism tendency, or expectations of fairness. This would help explain why some users are more likely to reject or accept AI-led service recovery after identity disclosure. Finally, future work should focus on developing role-sensitive service models, where AI is not just evaluated by performance metrics but by its capacity to fulfill roles that match user expectations, informational, procedural, or relational. This shift would contribute to a more adaptive and socially intelligent integration of AI into service ecosystems.

Ethics statement

This study was reviewed and approved by the Cardiff University Business School Research Ethics Committee under approval number 812, dated 6 July 2022. All participants were informed about the purpose of the study and provided their consent before participation. The study ensured the confidentiality and anonymity of all participants, and they were given the option to withdraw from the study at any point without penalty. No personal identifying information was collected during the study to ensure the privacy and security of the data.

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