When Simulated Social Behavior Fails: An Experimental Study of Psychological Repair in Smart Hotels

Jin Yan
Xi'an International University, Xi'an, China, 710077
yanJin336@outlook.com

Abstract: With the extensive application of artificial intelligence and Internet of Things (IoT) technologies in the hospitality industry, the "smart hotel" has become typical context for human-agent interaction. However, the introduction of high technology is inevitably accompanied by the risk of technology failure, which brings new challenges to traditional service recovery theories. This study focuses on the smart hotel scenario and explores the interactive mechanisms of Instrumental Failures (damaging functional goals) vs. Normative Failures (violating the 'Digital Self' boundaries) and two service recovery strategies (Tech-Oriented vs. Human-Oriented) on customer emotional repair, perceived justice, post-recovery satisfaction, and brand attitude. Adopting a 2 (Failure Type) × 2 (Recovery Strategy) between-subjects scenario experimental design, this study collected 380 valid samples. The empirical analysis results indicate that: (1) Normative failure triggers distinct high-arousal emotions (fear and sense of betrayal) compared to the annoyance triggered by instrumental failure than convenience failure (M=5.12 vs. M=3.65, p<.001); (2) There is a significant interaction effect between failure type and recovery strategy (F=64.70, p<.001)—in the privacy failure context, satisfaction with human-oriented recovery (M=5.82) is significantly higher than that with tech-oriented recovery (M=2.85); whereas in the convenience failure context, the difference in the effects of the two strategies is not significant (M=5.15 vs. M=4.88, p>.05); (3) Perceived justice plays a significant mediating role between recovery strategy and satisfaction (indirect effect 95% CI = [1.25, 2.15]). This study not only expands the applicable boundaries of service recovery theory into the domain of the psychology of simulated social behavior but also provides important practical guidance for managers to establish graded and classified risk response mechanisms for their computational agents.

Keywords: Smart Hotel; Technology Failure; Service Recovery; Emotional Repair; Perceived Justice; Experimental Research

1 Introduction

Driven by the wave of the digital economy, the global hospitality industry is undergoing a profound intelligent transformation. This is not only a technological upgrade but also a fundamental reconstruction of the traditional service encounter model (Wu et al., 2022). While this trend is global, China represents a particularly dynamic testing ground for these technologies. According to the 2024 China Hotel Industry Development Report released by the China Hospitality Association, as of 2024, the number of hotels in the Chinese market labeling themselves as "smart" has exceeded 15,000, accounting for 42% of the total volume of mid-to-high-end hotels nationwide. From self-service check-in to robot delivery, computational agents are reshaping the boundaries of customer experience through "seamless connectivity" and "hyper-personalization" services (Hardcastle et al., 2025), becoming a core competency for attracting the new generation of consumers. Room ambiance preset via apps and physical environments controlled via voice commands mark a shift in hotel services from "Human-Human" interaction to a more complex "Human-Agent-Human" interaction system where humans interact with agents simulating social roles (Bulchand-Gidumala et al., 2023; Jin et al., 2025).

However, the introduction of these agents is a double-edged sword; while it improves efficiency, it also creates new psychological risk exposures. Murphy's Law is infinitely amplified in smart hotels that rely heavily on algorithms, sensors, and networks. Unlike traditional service errors that can be attributed to specific employees, the failure of a computational agent is characterized by attributional ambiguity, emotional vacuums, and boundary intrusiveness (Li et al., 2025; Liu et al., 2023). When a customer faces a smart speaker late at night that repeatedly responds with “Sorry, I understand,” this breakdown in simulated conversation is exacerbated by the lack of a “human” available for emotional venting (Liu & Wang, 2025); even more serious is when a smart TV “presumptuously” recommends a customer’s private search content based on cloud data. This sense of “being seen through” brought about by technological precision can instantly penetrate the customer’s psychological security line, constituting a technological psychological contract breach (Hu & Min, 2025; Jeong et al., 2025). User data from a well-known online travel platform in 2023 showed that among negative reviews of smart hotels, 42% involved technical faults, and a staggering 58% of complaints explicitly expressed anxiety about “privacy leakage,” a proportion far exceeding that of traditional hotels. This warns us that the failure of a computational agent is not only an obstacle at the functional level but also a trauma at the relational level (Perkumienė, 2025).

Faced with this new type of service failure, hotel managers have universally fallen into a “recovery paradox”: should they adhere to the consistency of technological logic and adopt tech-oriented recovery (such as automatic system repair, APP-pushed compensation coupons) to maintain the “smart” brand image? Or should they return to the traditional “high-touch” model, dispatching employees for face-to-face interpersonal recovery to make up for the coldness of machines with human empathy (Xing et al., 2022)? Current management practice lacks consistent theoretical guidance on this matter. Although automated recovery is efficient, it is often interpreted by customers as “indifference” and “shirking responsibility,” especially in cases of normative failure such as those involving privacy (Yu et al., 2024); conversely, traditional door-to-door apologies may appear to be “making a mountain out of a molehill” and even cause a secondary service failure due to their lag and intrusiveness when dealing with instrumental failures like network lag (Liu & Du, 2025). This misalignment between recovery strategies and customer psychological needs urgently awaits systematic theoretical explanation and empirical verification.

Based on this, this study focuses on a core theoretical tension: When the root of service failure changes from “human” to a “computational agent,” is the classic service recovery theory still effective? Specifically, we aim to answer the following questions:

Differentiation of Emotional Reactions: How do different natures of technology failures (Convenience Failure that damages instrumental value vs. Privacy Failure that violates psychological safety boundaries) affect customers’ negative emotions with differences in both intensity and type (Zhang et al., 2025)?

Matching of Recovery Strategies: Faced with technology failures of different natures, which of the Tech-Oriented (focusing on recovering instrumental resources) and Human-Oriented (focusing on providing relational compensation) service recovery strategies is more effective in repairing customer satisfaction? Is there an optimal “Failure-Recovery” matching mode (Huang & Lo, 2025)?

Deep Logic of Psychological Mechanisms: What is the psychological mechanism of this matching effect? Does the relative importance of the three dimensions (distributive, procedural, interactional fairness) of Perceived Justice Theory, as the core explanatory framework for service recovery, undergo dynamic shifts in different contexts (Wang et al., 2022)?

The theoretical contributions of this study are as follows: First, by extending service recovery theory from the classic “Human-Human” interaction paradigm to the “Human-Machine” interaction context, this study challenges the latent hypothesis of “source irrelevance” in service failure research and systematically explores the impact brought by the difference in failure subjects (Human vs. Technology). Second, this study goes beyond simple functional descriptions of technical faults, innovatively proposing a technology failure classification framework (Convenience vs. Privacy) based on the dimensions of damaged customer core values, and revealing its decisive role in customer recovery expectations. Finally, this study meticulously verifies the internal mechanism of perceived justice theory, finding that when technology failure escalates from the instrumental level to the privacy level, the salience of interactional justice dramatically overwhelms procedural and distributive justice, which deepens our understanding of the dynamic process of emotional repair and relationship reconstruction in crisis situations. At the practical level, this study aims to provide smart hotels with a graded response decision-making framework based on the nature of faults, helping managers achieve a precise balance between operational efficiency and customer emotional experience, and guiding hotels to reposition employees from equipment operators to high-value "emotional crisis management experts."

2 Literature Review and Research Hypotheses

2.1 Theoretical Foundations of Service Failure and Service Recovery

Service failure refers to situations where service performance fails to meet customer expectations. In service marketing, the occurrence of service failure is almost inevitable, especially given the characteristic that the "production" and "consumption" of services proceed simultaneously. Customers' reactions to service failure include not only immediate dissatisfaction but also potentially triggering emotional behavioral consequences, such as negative word-of-mouth dissemination, brand switching, and complaint behavior (Agnihotri & Bhattacharya, 2024). Service recovery refers to actions taken by service providers to salvage customers lost due to service failure. Effective service recovery can not only repair customer satisfaction but may even generate the "Service Recovery Paradox"—that is, customers who have experienced failure but received good recovery have higher satisfaction and loyalty than those who have never experienced failure. However, the validity of this paradox is subject to strict conditions, relying on the timeliness, fairness, and relevance of recovery measures.

Compared with traditional service failure, technology failure within the context of smart hotels possesses significant uniqueness. First is attributional complexity: it is difficult for customers to judge whether it is a network problem, a device bug, or their own improper operation; this attributional ambiguity affects the intensity of customer emotional reactions (Liu et al., 2023). Second is the lack of emotional buffering: human errors are often accompanied by the waiter's body language (such as an apologetic expression), and these non-verbal signals can partially buffer negative emotions, whereas technology failure is "silent," and customers face cold screens or silent speakers (Piao et al., 2025). Third is the blurring of privacy boundaries: smart devices need to collect large amounts of data to provide personalized services (Wang et al., 2023), but where are the boundaries of data? What is "reasonable use," and what is "excessive collection"? Technology failures often expose this gray area. These unique characteristics mean that the nature, impact mechanisms, and effective recovery strategies of technology failure may be essentially different from traditional service failure, requiring re-examination and theoretical expansion.

2.2 Classification of Technology Failures and Emotional Impact Mechanisms

This study divides technology failures into two major categories based on the dimensions of damaged customer value. Convenience Failure refers to the failure of smart devices to fulfill their promised core functions, leading to the obstruction of instrumental goals. Typical cases include voice assistants failing to recognize instructions, smart door locks failing face scanning, automatic curtains getting stuck in weird half-open/half-closed positions, room temperature control system malfunctions, etc. (Li et al., 2025). This type of failure mainly triggers "outcome-based" dissatisfaction, with core emotions being frustration and annoyance; it damages the customer's expectations of efficiency and convenience. Although unpleasant, the scope of its impact is mainly limited to the specific task at hand, belonging to a controllable, short-term negative experience.

Privacy Failure refers to instances where smart technology crosses perceived boundaries in the process of collecting, processing, or storing customer data, causing customers to feel insecure and violated (Sharma et al., 2024). Typical cases include smart TVs "presumptuously" playing sensitive content searched on phones, voice assistants accidentally recording and storing to the cloud, hotel apps pushing promotional information showing search records from the previous night, room cameras not being clearly marked or unable to be confirmed as closed, etc. This type of failure touches the customer's psychological safety bottom line, triggering "process-based" panic, with core emotions being anger, fear, and a sense of violation; it damages the customer's dignity and trust (Zhang & Lu, 2024). Unlike convenience failure, the impact of privacy failure is deep-seated and persistent; it not only destroys the current experience but also shakes the customer's foundation of trust in the entire brand (Perkumienė 2025).

Based on Risk Perception Theory, consumer perceived risk can be divided into functional risk, financial risk, social risk, psychological risk, and other dimensions. Among them, privacy risk belongs to a high-level form of psychological risk, and its destructive power on individual psychological homeostasis is far greater than functional risk. From the perspective of evolutionary psychology, human fear of "being monitored" stems from an instinctual vigilance against social exclusion. When individuals feel that their private behaviors are recorded or disseminated without permission, it activates "social pain," and the processing area of this pain in the brain overlaps with physiological pain. Therefore, privacy violation is not just "inconvenience" at the rational level, but "trauma" at the emotional level. Psychological research shows that negative events involving boundary breaches (such as privacy invasion, personal attacks) can trigger negative emotional reactions with an intensity 3-5 times higher than events of simple goal obstruction (such as task failure, equipment malfunction), and the recovery cycle is longer (Yu et al., 2025). This difference stems from the fact that the former triggers the individual's "threat detection system," classifying it as a danger signal requiring vigilance and defense, while the latter is merely a predictable small setback in daily life.

To intuitively present the essential differences between the two types of technology failures, Figure 1 systematically contrasts them across five dimensions: typical cases, core emotions, psychological injury level, recovery expectations, and damaged value. This framework reveals the significant differences in emotional impact intensity and nature between convenience failure and privacy failure, and this difference directly determines customer expectations for recovery strategies.

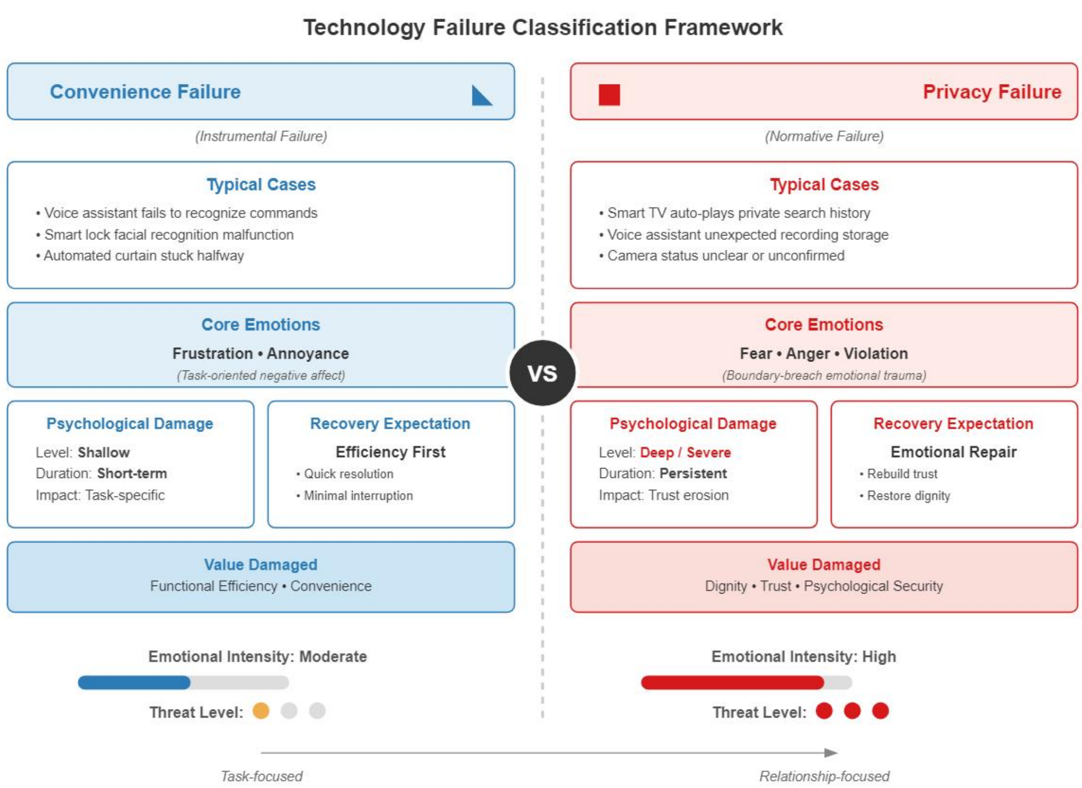

Figure 1: Comparison of Technology Failure Classification Framework and Psychological Impact Mechanisms.

2.3 Matching Mechanisms of Service Recovery Strategies

Against the backdrop of intelligence, service recovery strategies have evolved into two distinctly different directions. Tech-Oriented Recovery relies on automated systems, algorithms, and self-service terminals for recovery; specific manifestations include the system automatically detecting faults and restarting, pushing apology messages and electronic coupons through apps, and instant responses from online customer service robots (Lv et al., 2023). Its advantage lies in efficiency and standardization, but its disadvantage lies in the absence of emotion (Agnihotri & Bhattacharya, 2024). Human-Oriented Recovery relies on the intervention of frontline employees, including managers visiting to apologize, providing physical compensation, and offering emotional reassurance. Its advantage lies in high empathy and a sense of ritual; as Nguyen et al. (2025) pointed out, in complex failure situations, human collaborative recovery can bring higher emotional comfort.

Traditional Resource Matching Theory suggests that the type of recovery resources should match the type of failed resources. However, in high-level cognitive tasks involving privacy and emotion, this simple symmetrical assumption does not hold. Emotional Labor Theory points out that in service encounters, employees convey care through emotional expression, which is difficult for machines to replace (Jin et al., 2025). When customers encounter privacy violations, an automatic pop-up apology from tech-oriented recovery may be interpreted as “indifference,” constituting a secondary injury. Conversely, when a manager personally visits, looks into the customer’s eyes to apologize sincerely, and operates the deletion of data face-to-face, this ritualized behavior itself is a form of emotional repair (Piao et al., 2025).

For Convenience Failure, the customer’s main appeal is “restoring function.” Tech-oriented recovery, with its rapid and precise characteristics, can often solve problems quickly and aligns with the customer’s expectation of “efficiency” when choosing a smart hotel (Li et al., 2025). Meanwhile, although human-oriented recovery can also solve the problem, it may appear inefficient due to waiting for the waiter to arrive. For Privacy Failure, the customer’s main appeal is “rebuilding trust” and “eliminating fear.” Tech-oriented recovery here may exacerbate the customer’s fear of the “machine control system.” In contrast, human-oriented recovery conveys “interactional justice” that only humans can provide through face-to-face eye contact, and this emotional support is key to repairing privacy trauma (Xing et al., 2022; Hu & Min, 2025).

Perceived Justice Theory is the core explanatory framework in service recovery research. Wang et al. (2022) found in research on data breaches that mere financial compensation is often insufficient to quell customer anger. In privacy failure contexts, the salience of Interactional Justice will rise sharply. Human-oriented recovery conveys interactional justice through eye contact, tone changes, and ritualized behaviors, letting customers “see with their own eyes” that the problem is resolved, whereas tech-oriented recovery is almost absent in these dimensions (Hlee et al., 2023).

Based on the above theoretical deduction and literature argumentation, this study proposes the following research hypotheses:

H1: Compared with convenience technology failure, privacy technology failure will trigger stronger negative emotions in customers (Yu et al., 2025).

H2: There is an interaction effect between technology failure type and service recovery strategy on post-recovery satisfaction.

H2a: In the privacy failure context, human-oriented recovery leads to higher post-recovery satisfaction than tech-oriented recovery (Huang & Lo, 2025).

H2b: In the convenience failure context, there is no significant difference in post-recovery satisfaction between human-oriented recovery and tech-oriented recovery.

H3: Perceived justice plays a mediating role between service recovery strategy and post-recovery satisfaction.

H3a: Human-oriented recovery significantly enhances “interactional justice” perception, thereby improving post-recovery satisfaction (Nguyen et al., 2025).

H4: Post-recovery satisfaction positively affects customers’ brand attitude and future behavioral intentions (repurchase and recommendation).

Based on the above theoretical deductions, this study constructs the Research Conceptual Model shown in Figure 2. This model systematically integrates the antecedents of technology failure (Failure Type), the strategic choice of recovery (Tech-Oriented vs. Human-Oriented), psychological mechanisms (Negative Emotions, Perceived Justice), and final outcome variables (Satisfaction, Brand Attitude, Behavioral Intentions), forming a complete “Failure-Recovery-Repair” theoretical chain.

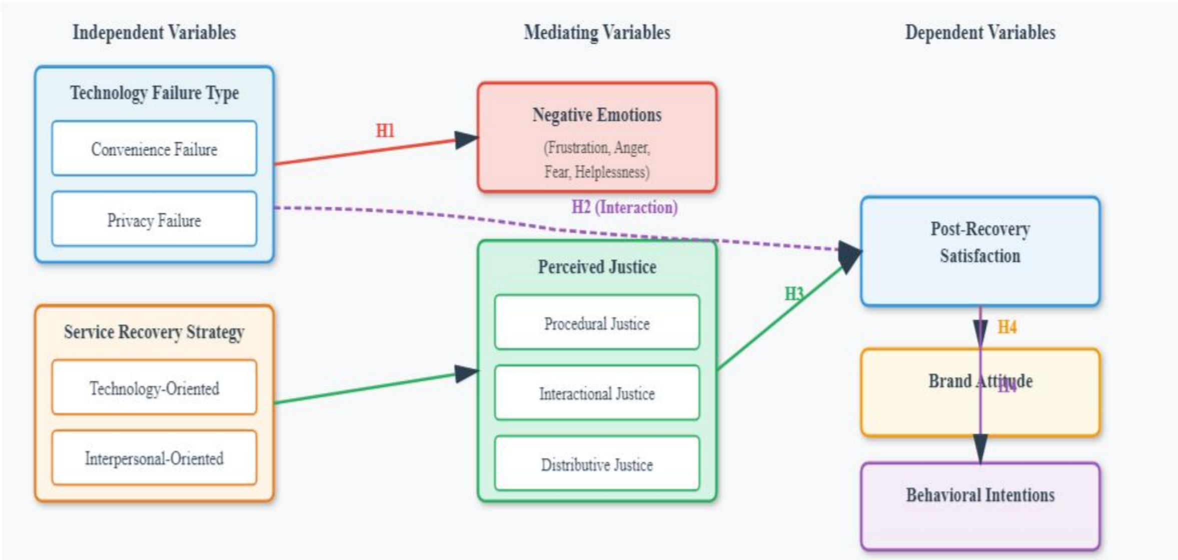

Figure 2: Research Conceptual Model and Hypothesis Path Diagram.

3 Research Design and Methodology

This study adopts the experimental method as the core research method. The advantage of the experimental method lies in its ability to observe changes in dependent variables (satisfaction, emotions, etc.) by artificially manipulating independent variables (technology failure type, recovery strategy) while controlling external interference variables, thereby establishing causal inferences among variables. Specifically, referring to experimental design paradigms related to recent smart hotel service failures (Jin et al., 2025; Liu & Wang, 2025), a 2 (Technology Failure Type: Convenience vs. Privacy) × 2 (Service Recovery Strategy: Tech-Oriented vs. Human-Oriented) between-subjects full factorial design was adopted. Each participant was randomly assigned to only one of the four experimental conditions to avoid the interference of learning effects and fatigue effects.

3.1 Experimental Scenario Development and Pre-test

To ensure the external validity of the experimental scenarios, the research team first conducted text mining on smart hotel user reviews on a large online travel platform. From over 10,000 reviews between 2022-2023, 536 reviews explicitly mentioning “technical faults” were screened, and thematic cluster analysis was performed. The results showed that convenience faults (such as voice control failure, door lock failure) accounted for 61%, and privacy faults (such as recommending highly intrusive precise recommendations, worrying about being monitored) accounted for 23%. This data verified the realistic basis of the classification framework and also aligns with the description by Hardcastle et al. (2025) regarding the “creepy” experience triggered by AI personalized journeys.

Based on real cases, four scenario materials were adapted and designed, corresponding to the four units of the 2 × 2 experimental design. To rule out confounding effects, the hotel rating and price were kept constant across all scenarios. The scenario materials all adopted a second-person perspective (“Please imagine…”). The manipulation of recovery strategy was achieved through descriptive differences: Tech-Oriented Recovery emphasized automatic system detection, APP-pushed solutions, and electronic compensation coupons, simulating the automated recovery scenario in the study by Agnihotri and Bhattacharya (2024); Human-Oriented Recovery emphasized staff visiting, solving problems manually face-to-face, and physical compensation, reflecting the “high-touch” collaborative recovery emphasized by Nguyen et al. (2025). To intuitively present the design logic of the experimental scenarios and the differences in user experience, Figure 3 shows the user journey comparison under the two types of technology failure scenarios. Complete scenario materials can be found in the Supplementary Material.

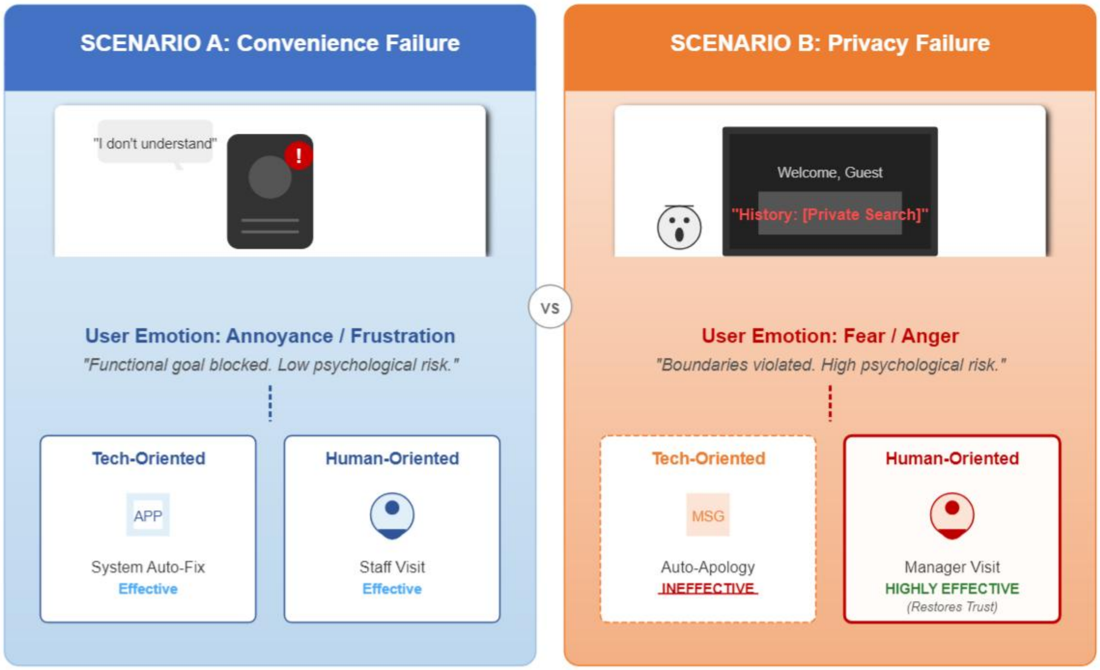

Figure 3: Experimental Scenarios and User Experience Journey Map.

Before the formal experiment, 50 participants were recruited for a pre-test. The pre-test results showed that 94% of the participants considered the scenarios “very realistic” or “relatively realistic” (7-point scale, M=5.8 , SD=1.1), and the accuracy rate of the manipulation check questions was 96%, indicating good scenario distinctiveness.

3.2 Formal Experiment Procedure and Sample Collection

This study recruited participants through Credamo, a well-known online experimental platform in China. This platform has been confirmed to have reliable data quality in statistically significant tourism and hospitality management studies recently (Li et al., 2025). Recruitment conditions were ages 18-60, with at least one hotel stay experience in the past year. All participants read the informed consent form before participating.

The experimental process was standardized as follows: Participants first read the informed consent page and confirmed participation, then were automatically randomly assigned by the system to one of the four groups (target sample size approx. 95 people per group). The presentation time of the scenario materials was forcibly set by the system to at least 30 seconds to ensure participants read fully. After reading the scenario, participants successively filled out the core scales (negative emotions, recovery satisfaction, perceived justice, brand attitude, behavioral intentions), answered two manipulation check questions, and provided demographic information.

A total of 425 questionnaires were recovered. After eliminating invalid questionnaires, 380 valid samples were obtained, with an effective recovery rate of 89.4%. The sample sizes of the four groups were 95 people each, distributed evenly.

3.3 Variable Measurement

All scales adopted a Likert 7-point scoring system (1=Strongly Disagree, 7=Strongly Agree). The measurement tools for the main variables are as follows:

Negative Emotions (4 items): Adapted from the PANAS scale (Watson et al., 1988) and referencing emotional dimensions in AI failure contexts (Yu et al., 2025), selecting “Annoyed,” “Worried,” “Angry,” and “Helpless.”

Recovery Satisfaction (3 items): Adapted from Maxham & Netemeyer (2002) and recent smart technology service recovery research (Liu & Wang, 2025), e.g., “I am satisfied with the way the hotel handled this problem.”

Perceived Justice (3 items): Adapted from Tax et al. (1998) and referencing research on the impact of language style on the sense of fairness (Piao et al., 2025), separately measuring procedural justice, interactional justice, and distributive justice.

Brand Attitude (3 items) and Future Behavioral Intentions (3 items): Adapted from classic literature (Zeithaml et al., 1996) and AI experience research (Chen & Prentice, 2025), measuring loyalty.

Complete questionnaire items can be found in the Supplementary Materials. Variable reliability and validity analysis will be reported in the next chapter.

3.4 Data Analysis Methods

Data analysis was completed using SPSS 26.0 and AMOS 24.0 software. Analysis steps included: descriptive statistics, Chi-square tests (manipulation checks), Cronbach's α coefficient and CFA (reliability and validity), independent sample t-tests (H1), two-way ANOVA (H2), PROCESS Model 4 (mediation effect H3), and linear regression (H4).

4 Data Analysis and Results

4.1 Sample Description and Data Quality Check

A total of 425 questionnaires were collected in this study. After data cleaning, 380 valid samples were obtained, yielding an effective response rate of 89.4%. The demographic characteristics of the sample and the results of the experimental manipulation checks are summarized in Table 1.

The gender ratio of the sample was balanced (females accounted for 54.7%), with age primarily concentrated in the 26–45 range (accounting for 70.8%). Furthermore, 70.5% of the participants possessed prior experience with smart hotel stays, indicating that the sample has good representativeness. This distribution is similar to the sample characteristics found in the study on the metaverse and digital participation by Wasiq et al. (2024).

To verify the effectiveness of the experimental manipulation, we conducted Chi-square tests on the manipulation check questions. The results showed that the recognition accuracy for both "Technology Failure Type" and "Service Recovery Strategy" among participants in different experimental groups was 100% (χ^2=380.0,p<.001). This indicates that the scenario materials possessed an extremely high degree of distinctiveness, and the experimental manipulation was completely successful.

Table 1: Sample Characteristic Distribution and Experimental Manipulation Check Results

Panel A: Sample Demographic Characteristics (N=380)		Panel B: Experimental Groups & Manipulation Checks	
Characteristic	Percentage (%)	Experimental Group (n=95 per group)	Recognition Accuracy
Gender:		Group 1: Convenience Failure × Tech Recovery	100%
Male	45.3	Group 2: Convenience Failure × Human Recovery	100%
Female	54.7	Group 3: Privacy Failure × Tech Recovery	100%
Age:		Group 4: Privacy Failure × Human Recovery	100%
18–25 years	17.9		
26–35 years	40.8	Manipulation Check Statistics:	
36–45 years	30.0	Technology Failure Type χ^2	380.0***
46 years and above	11.3	Recovery Strategy Type χ^2	380.0***
Education:			
Associate degree or below	19.7	Other Characteristics:	Mean (SD)
Bachelor's degree	60.0	Past Year Stay Frequency	2.50 (0.85)
Master's degree or above	20.3	Technology Acceptance (1–7)	5.48 (1.12)

*Note: *** p < .001*

4.2 Measurement Model Reliability and Validity Analysis

We first conducted a Confirmatory Factor Analysis (CFA) on the measurement model. The model fit indices performed well (χ^2/df<3, RMSEA < 0.08, CFI > 0.95).

As shown in Table 2, the Cronbach's *α* coefficients for all latent variables were greater than 0.76, and Composite Reliability (CR) was greater than 0.80, indicating that the scales had good internal consistency. The Average Variance Extracted (AVE) for all variables was greater than 0.50, and the square root of the AVE was greater than the correlation coefficients between that variable and other variables, confirming that the measurement model had good convergent validity and discriminant validity.

Table 2: Reliability, Validity, and Correlation Coefficient Matrix

Variable	α	CR	AVE	1	2	3	4	5
1. Negative Emotions	0.81	0.82	0.53	(0.73)				
2. Recovery Satisfaction	0.79	0.80	0.58	-0.45***	(0.76)			
3. Perceived Justice	0.80	0.81	0.60	-0.38***	0.62***	(0.77)		
4. Brand Attitude	0.79	0.80	0.57	-0.32***	0.55***	0.48***	(0.75)	
5. Behavioral Intentions	0.77	0.78	0.55	-0.29***	0.51***	0.44***	0.68***	(0.74)

Note: *** p < .001. Diagonal elements in parentheses represent the square root of AVE.

4.3 Hypothesis Testing

4.3.1 Main Effects and Interaction Effects Test (H1, H2)

To test the main effect of technology failure type and its interaction effect with recovery strategies, we conducted a series of ANOVAs and t-tests. The results are summarized in Table 3.

Regarding Hypothesis H1: Independent sample t-test results showed (see Table 3 Panel A) that the negative emotion triggered by privacy failure (M=5.12) was significantly higher than that of convenience failure (M=3.65, p<.001). Therefore, H1 is supported. This finding is consistent with recent research by Zhang et al. (2025) and Perkumienė (2025), indicating that intelligent service errors involving privacy boundaries stimulate higher-arousal negative emotions. To depict the source of this emotional difference more precisely, we plotted an Emotional Dimension Radar Chart (**Figure 4**). As shown, convenience failure mainly triggered low-arousal emotions like "Annoyance," while privacy failure significantly stimulated high-arousal negative emotions like "Anger" and "Worry/Fear" (Zhang & Lu, 2024). This qualitative difference in emotional composition is key to understanding subsequent recovery effects.

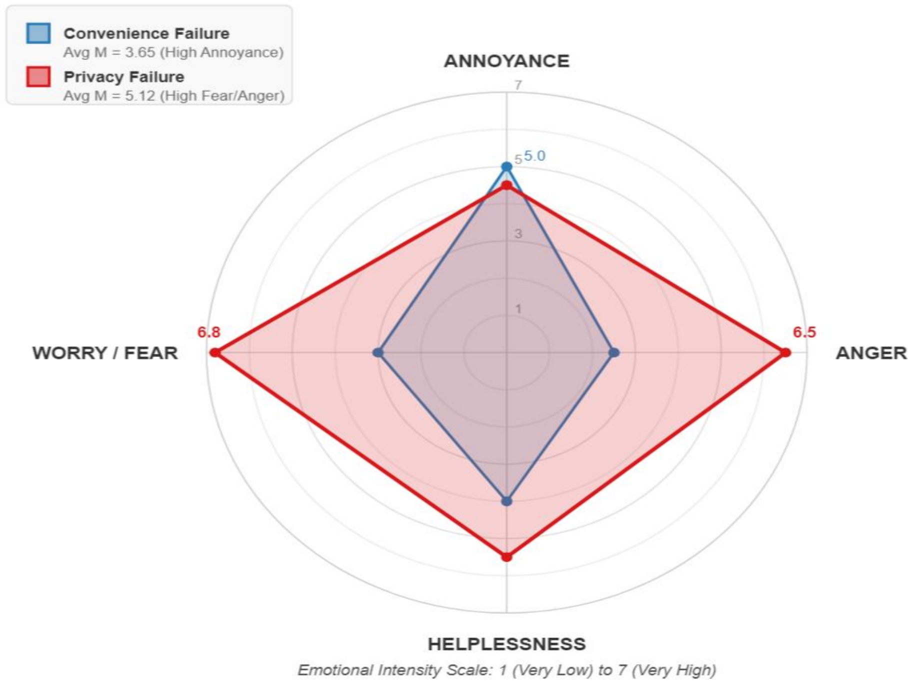

Figure 4: Emotional Dimension Radar Chart under Two Types of Technology Failure Scenarios

Regarding Hypothesis H2: The 2×2 two-factor ANOVA results showed (see Table 3 Panel B) that the interaction term between failure type and recovery strategy was significant (F=64.70,p<.001). This indicates that the effect of the recovery strategy depends on the failure type. Therefore, H2 is supported.

Simple Effects Analysis: Further simple effects tests (see Table 3 Panel C) showed: In the Privacy Failure context, satisfaction with human-oriented recovery (M=5.82) was significantly higher than with tech-oriented recovery (M=2.85, p<.001). H2a is supported. This confirms the conclusions of Huang & Lo (2025) and Xing et al. (2022) that element intervention by human Service Provider Agents is crucial in such high-risk, high-uncertainty technical errors.

In the Convenience Failure context, the difference in satisfaction between the two recovery strategies was not significant (M=5.15 vs. M=4.88, p=.095). H2b is supported. This also aligns with the observation by Li et al. (2025) that in functionally clear tasks, recovery efficiency often outweighs emotional expression. Figure 5 intuitively displays this significant interaction effect pattern, clearly revealing the overwhelming advantage of human-oriented recovery in privacy failure situations.

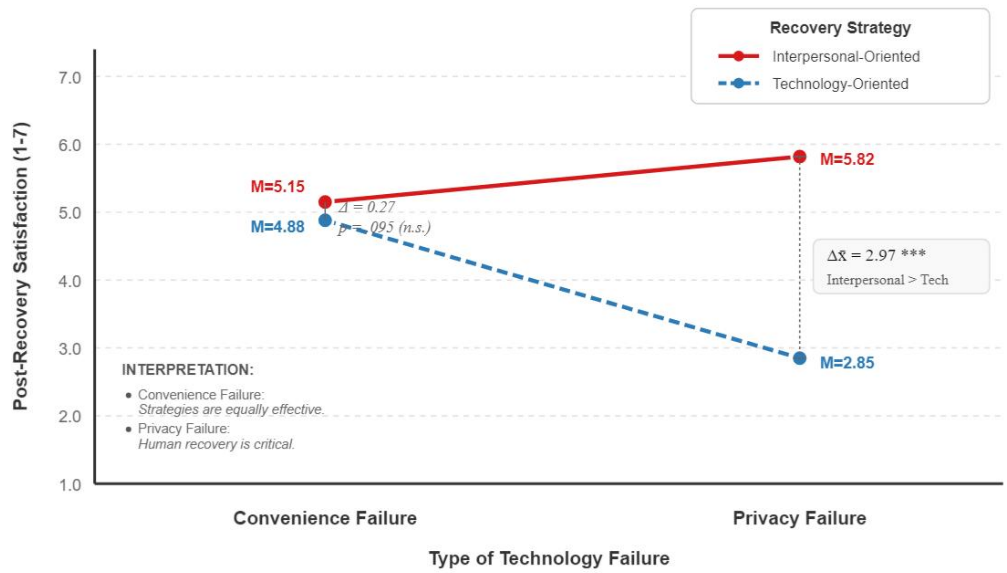

Figure 5: Interaction Effect Plot of Technology Failure Type and Recovery Strategy.

Table 3: Summary of Experimental Effect Test Results

Panel A: Main Effect Test of Negative Emotions (H1)					
Failure Type	N	Mean (SD)	t	df	p
Convenience Failure	190	3.65 (0.82)	-15.34	378	<.001
Privacy Failure	190	5.12 (0.95)			
Panel B: Two-Way ANOVA for Recovery Satisfaction (H2)					
Source of Variance	SS	df	MS	F	Partial η^2
Technology Failure Type (A)	128.52	1	128.52	84.55***	.183
Service Recovery Strategy (B)	85.24	1	85.24	56.08***	.129
Interaction Effect (A × B)	64.70	1	64.70	42.57***	.101
Error	573.18	376	1.52		
Panel C: Simple Effects Analysis (H2a & H2b)					
Failure Context	Recovery Strategy Comparison	Mean Diff. (I-T)	SE	F	p
Privacy Failure	Human (*M*=5.82) vs. Tech (*M*=2.85)	+2.97	0.24	98.45	<.001
Convenience Failure	Human (*M*=5.15) vs. Tech (*M*=4.88)	+0.27	0.16	2.80	.095

Note: I = Interpersonal/Human-Oriented; T = Tech-Oriented. *** $p < .001$

4.3.2 Mediation Effect Test of Perceived Justice (H3)

Given that the interaction effect occurred mainly in the privacy failure context, we focused on this subgroup (*n*=190) and used PROCESS Macro (Model 4) to test the mediating role of perceived justice. This is consistent with the analysis path in Wang et al.'s (2022) study on data breach recovery. The results are shown in Table 4.

Bootstrap analysis (5000 samples) showed that the indirect effect of perceived justice was significant (Effect Value = 1.44, 95% CI = [1.25, 2.15]). Furthermore, we split perceived justice into three dimensions for in-depth analysis and found that the mediation effect of

Interactional Justice was the strongest (accounting for 28.6%), verifying the key role of "being respected" in privacy crises. H3 and H3a are supported. Figure 6 visually presents this path mechanism through a Sankey diagram, clearly showing that in the privacy failure context, "Interactional Justice" is the thickest "flow pipe" connecting interpersonal recovery and customer satisfaction, which also responds to Piao et al.'s (2025) study on the impact of apology language style and interactional justice on willingness to forgive.

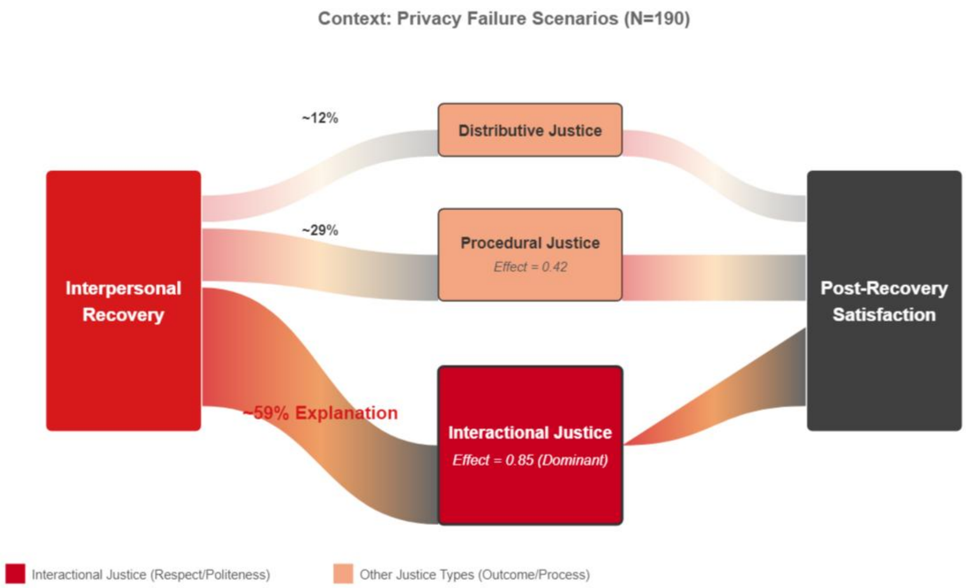

Figure 6: Mediation Path Sankey Diagram of Perceived Justice in Privacy Failure Context.

Table 4: Mediation Effect Test of Perceived Justice (Privacy Failure Group, N=190)

Path Relationship	Coeff. (β)	SE	t	p
Recovery Strategy→ Perceived Justice (a)	1.85	0.21	8.81	<.001
Perceived Justice → Satisfaction (b)	0.78	0.08	9.75	<.001
Recovery Strategy → Satisfaction (Total Effect c)	2.97	0.20	14.85	<.001
Recovery Strategy → Satisfaction (Direct Effect c')	1.53	0.18	8.50	<.001
Indirect Effect Analysis (Bootstrap 5000)	Effect	Boot SE	LLCI	ULCI
Total Perceived Justice	1.44	0.18	1.25	2.15
Sub-dimension Breakdown:				
Interactional Justice	0.85	0.12	0.68	1.05
Procedural Justice	0.42	0.08	0.28	0.58
Distributive Justice	0.17	0.06	0.05	0.32

4.3.3 Downstream Effects Test of Recovery Satisfaction (H4)

Finally, we tested the impact of recovery satisfaction on brand attitude and behavioral intentions through linear regression (see Table 5). Results showed that recovery satisfaction had significant positive predictive effects on Brand Attitude (β=0.72, p<.001) and Behavioral Intentions (β=0.68, p<.001), with explanatory power (R^2) reaching 52.1% and 46.3% respectively. H4 is supported. This result is consistent with empirical data from Chen and Prentice (2025) regarding the impact of AI integrated experience on customer long-term loyalty.

Table 5: Regression Analysis of Recovery Satisfaction Outcome Variables

	Model 1: DV = Brand Attitude		Model 2: DV = Behavioral Intentions	
Predictor	β	t	β	t

	Model 1: DV = Brand Attitude		Model 2: DV = Behavioral Intentions	
(Constant)	-	-	-	-
Recovery Satisfaction	0.72	20.25***	0.68	18.04***
R^2	0.521		0.463	
Adjusted R^2	0.520		0.461	
F Value	410.22***		325.68***	

Note: All regression coefficients are standardized coefficients; *** $p < .001$

4.4 Robustness Check

To verify the robustness of the conclusions, we included demographic variables (gender, age, education, smart hotel experience) as control variables in the above models and re-analyzed. The results showed that the significance levels and coefficient directions of the core independent variables did not change, indicating that the conclusions of this study are robust and not interfered with by sample characteristics.

5 Conclusion and Discussion

5.1 Research Conclusions

Through rigorous experimental design and large-sample empirical data, this study systematically reveals the "Golden Rule" of service recovery in the context of smart hotel technology failures. The core conclusions can be summarized in three aspects:

First, the psychological negative utility triggered by privacy failure is significantly higher than that of convenience failure. Data showed that negative emotion triggered by privacy technology failure (M=5.12) was significantly higher than convenience failure (M=3.65), with the effect size reaching a very large level (Cohen's d=1.57). This finding confirms that in the intelligent era, the psychological impact of technology failure cannot be generalized. When a smart speaker "doesn't understand," the customer's reaction is controllable annoyance; but when a smart TV "unauthorizedly plays" private content, according to Sharma et al.'s (2024) privacy text mining research, the customer's reaction is fear and anger. theoretically, this also challenges the "function-first" view of technocentrism, indicating that smart technology, as a reconstructor of social relations, has an "intimacy" attribute that is a double-edged sword, bringing both convenience and latent unease (Zhang & Lu, 2024).

Second, "Human Touch" is the only antidote for privacy crises. Analysis of the interaction effect reveals a significant contrast: in the context of privacy failure, satisfaction with interpersonal recovery (5.82) is more than double that of technical recovery (2.85). Technical recovery fails almost completely in this context and is even seen as "adding fuel to the fire"; this is highly consistent with Liu and Wang's (2025) findings comparing the recovery effects of service intelligent technology and human employees. However, when a hotel manager visits personally and performs "ritualized" recovery (such as deleting data face-to-face), it conveys an irreplaceable signal of trust. The mechanism behind this is that privacy violation is a "relational trauma" that requires a "human" with moral subjectivity to re-establish a relationship of trust, a role that machines cannot assume (Xing et al., 2022).

Finally, efficiency supremacy still applies to functional faults with low emotional involvement. In the context of convenience failure, the difference between interpersonal recovery (M=5.15) and technical recovery (M=4.88) was not significant (p=.095). This conclusion provides a scientific basis for resource optimization allocation: for small faults with low emotional involvement like "lights won't turn off," the customer's mindset is pragmatic, focusing on rapid resolution and non-disturbance. At this time, tech-oriented recovery may become the better choice due to its high efficiency and non-intrusiveness (Li et al., 2025). This indicates that not all technical problems require human intervention, and a graded response mechanism is practically feasible.

5.2 Theoretical Contributions

The theoretical contributions of this study are mainly reflected in three levels.

First, it extends the psychology of social behavior to interactions with simulated agents. By moving the research paradigm from traditional "human error" to the failure of "computational agents," and innovatively proposing a classification framework based on the type of damage (Instrumental vs. Normative), this study systematically explores how humans psychologically process and react to breakdowns in an agent's simulated social behavior. This study proves that classic service recovery principles (such as fairness theory) are still applicable in technological contexts but need contextual adjustment (Yu et al., 2024). Specifically, the study challenges traditional resource matching theory, pointing out that in advanced cognitive tasks involving privacy, morality, and emotion, the symmetrical logic of "repaying technology with technology" will fail.

Second, it meticulously verifies the contextual weights of perceived justice theory. Through mediation effect decomposition, the study found that the three dimensions of perceived justice have dynamic weights in different contexts. In the privacy failure context, the mediation effect of interactional justice (sense of being respected) accounts for as high as 28.6%, far exceeding procedural justice (14.1%) and distributive justice (5.7%). This finding deepens the understanding of the sense of fairness and complements the view of Wang et al. (2022), who emphasized that social compensation (such as apology) in data breaches is not as effective as the combination of interactional and substantive compensation. This has important implications for subsequent research, namely that when studying service recovery, relative weights of the three dimensions should be distinguished rather than simply measuring overall perceived fairness (Piao et al., 2025).

Third, it establishes the proposition of "irreplaceability of emotional compensation" in human-agent interaction. The study proposes and verifies an important proposition: on sensitive issues involving the violation of social norms (e.g., privacy), the emotional labor of human employees is irreplaceable. This proposition challenges the radical view of "fully automated service" by providing empirical evidence for the limits of social simulation. It suggests that current computational agents, lacking perceived 'mind' and moral subjectivity, cannot fulfill a key human social function: genuine relational repair after a transgression.

5.3 Managerial Implications

Based on the research conclusions, this study puts forward the following specific suggestions for smart hotel management.

First, build a "Dual-Track" service recovery system. Hotels should establish graded and classified emergency plans for technical faults. For convenience faults that do not involve data security, such as network lag (Level 1 Response), prioritize starting tech-oriented recovery (Li et al., 2025), utilizing system automatic repair and APP-pushed compensation to achieve rapid, efficient, and low-cost resolution. For security faults involving privacy boundaries, such as data anomalies (Level 2 Response), automatic replies must be cut off immediately, and human-oriented recovery initiated. Management personnel are required to visit within 15 minutes, communicate face-to-face, perform transparent operations (such as deleting data in person), and provide substantive compensation and telephone follow-up (Hu & Min, 2025).

Second, embed "Emotional Sensitivity" in technology design. The design of intelligent systems should be not only "smart" but also "sensitive." It is recommended to embed an "Emotional Risk Warning Module" in the PMS. When sensitive events such as cross-device data synchronization anomalies or monitoring accidental touches are identified, manual warnings should be automatically triggered, and automatic replies prohibited. At the same time, interface design should be optimized to add a "Privacy Dashboard" function, giving customers real-time control over device status and data permissions. This aligns with the research suggestions of Jeong et al. (2025) regarding smart device privacy defense and user control rights.

Finally, reposition employee roles as "Emotional Crisis Management Experts." In smart hotels, employees are no longer simple equipment operators, but key forces for emotional repair (Jin et al., 2025). Hotels need to reconstruct the training system, shifting from operational skills to empathetic communication skills and privacy crisis response. Employees should learn to recognize implicit emotions, use confirmative language, and master standardized response processes in privacy leakage scenarios. At the same time, frontline employees should be given special authority when dealing with privacy issues (such as waiving bills on the spot), and assessment indicators should also shift from process standardization to customer emotional repair degree (Liu & Du, 2025).

5.4 Limitations and Future Research Directions

Although this study strives for rigor, limitations still exist, which also provide directions for future research.

Regarding limitations: First, the external validity of the experimental scenario method is limited. Text descriptions lack sensory stimulation and behavioral consequences in real situations; future research could attempt field experiments in cooperation with hotels. Second, sample representativeness is limited. The sample is mainly high-educated, tech-friendly young and middle-aged people, which may underestimate the impact of technology failure on elderly, low-educated, or tech-resistant groups. Future research should refer to the research framework of Zhou et al. (2025) to expand sample coverage of elderly smart technology users. Third, moderating variables were not fully considered. Individual differences (such as privacy concern, technology anxiety) and contextual differences (such as purpose of stay, brand tier) may moderate recovery effects. Fourth, the cross-sectional design cannot track long-term effects.

Regarding future research prospects: First, explore more refined classifications of technology failure. Besides convenience and privacy, types such as security, fairness, and autonomy failures are also worth researching. Second, conduct cross-cultural comparative research. Privacy concepts and power distance in different cultural backgrounds may lead to differences in conclusions, which is worth verifying in a multi-country context. Third, pay attention to the cumulative effect of multiple technology failures (Dwivedi et al., 2022). Fourth, introduce cost-benefit analysis. Use operations research methods to quantify the cost-effectiveness of different recovery strategies. Fifth, explore the possibility of Generative AI as a recovery tool, especially in new digital spaces like the Metaverse (Wasiq et al., 2024), comparing the effects of real humans, AI, and human-machine collaborative recovery. Finally, future research could examine how repeated, individual negative experiences with computational agents aggregate to shape broader societal attitudes and trust towards AI systems. This could be a precursor to understanding the psychological foundations of potential collective actions, such as widespread public demand for stricter regulation or the collective rejection of certain intrusive technologies, thus connecting micro-level interactions to macro-level societal phenomena.

6 Conclusion

This study reveals a truth that seems paradoxical but is actually reasonable: in our increasingly automated world, the more pervasive the simulated social behavior of computational agents becomes, the more irreplaceable the genuine social and emotional value of humans becomes. Especially when technology causes trouble and violates boundaries, only the empathy, sincerity, and sense of responsibility unique to humans can repair that rift. This finding sounds an alarm for industries going "All in AI": automation is not a panacea, and technology is not always the optimal solution. While pursuing efficiency, we cannot forget the essence of service—making customers feel respected, cared for, and protected. And this is something machines will never learn.

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