Addressing Consumer Needs: Effects of Firms Remediation Strategies on Satisfaction and Brand Usage Intent in AI-Powered Voice Assistant Service Failures

Abstract

With the accelerating integration of AI-powered voice assistants into daily consumer interactions, effectively managing AI-driven service failures has become paramount for maintaining consumer trust, satisfaction, and sustained brand engagement. Despite extensive research on traditional service recovery mechanisms, existing frameworks fall short in addressing the distinct and complex nature of AI-driven failures. Motivated by the lack of systematic frameworks tailored explicitly to AI voice assistant contexts, this study introduces an integrated analytical framework grounded in Consistency Theory and Situational Crisis Communication Theory (SCCT) to address customer needs through strategic service failure remediation. Utilizing a mixed-methods research design and analyzing 5,894 consumer reviews, the study establishes a consistency relationship between service failures and remediation strategies. It delineates three innovative approaches to service recovery and examines their impact on consumer satisfaction and brand usage intent. The empirical findings reveal significant positive effects of strategically aligned recovery efforts on consumer satisfaction and brand usage intentions. By addressing the specialized nature of AI-driven failures, this research not only advances theoretical knowledge in AI service management but also provides actionable strategic guidance for businesses seeking to optimize consumer experiences and foster enduring customer relationships.

Keywords: AI-powered voice assistant; Firms remediation; Mixed-methods; Service failure; Consumer satisfaction.

1. INTRODUCTION

The proliferation of ***Artificial intelligence (AI)-powered Voice Assistants*** such as Amazon Echo and Google Assistant represents a significant paradigm shift in consumer interactions, fundamentally transforming daily activities from communication to commerce (Chen et al., 2022; Choi & Drumwright, 2021; Hu et al., 2022; Kamoonpuri & Sengar, 2023; Yuan et al., 2022). Their core strengths—natural interaction, increasingly autonomy, and contextual intelligence—enable more seamless user experiences (Chen et al., 2022; Hu et al., 2021;Schuetzler et al., 2020). Yet, as these systems grow more sophisticated, so too do the risks of service failures, including misinterpretation of intent, personalization errors, and privacy breaches (Easwara Moorthy & Vu, 2015). These failures not only frustrate users but also erode the trust and brand value firms aim to build.

Existing typologies of services failure (e.g., process vs. outcome failure; functional vs. non-functional failure; responsibility attribution frameworks) (Chen et al., 2021; Song et al., 2023; Gu et al., 2024; Leo & Huh, 2020) were designed for traditional or generalized AI contexts. They fail to fully capture the distinctive failure patterns of AI voice assistants in real-world use (Chopra et al., 2025), which often occur in multi-device, cross-platform, or real-time interaction scenarios. These failures are perceived by consumers not merely as technical glitches but as signals of unreliability or lack of intelligence - leading to dissatisfaction even when conventional recovery measures (e.g., refunds or apologies) are offered.

Moreover, evaluation systems remain narrowly focused on technical performance metrics like task accuracy or response time. This neglects user-centric aspects such as conversational flow, emotional tone, and contextual relevance—all crucial to perceived value. As a result, firms often adopt standardized recovery strategies that miss the mark, failing to address the nuanced expectations and emotions of users.

To address this gap, we propose a new integrated typology of AI voice assistant service failures, consisting of scenario adaptability (e.g., misunderstanding intent in complex situations), personalization capabilities (e.g., irrelevant recommendations), and value-based propositions (e.g., perceived lack of usefulness or privacy intrusions).

Our first research question thus emerges: **(1) How can firms strategically identify, categorize, and address the multifarious failures inherent in AI assistant services?**

Traditional recovery frameworks, such as equity theory or justice models, face limitations in AI contexts (Song et al., 2025). For example, compensation may not address non-financial dissatisfaction, and responsibility attribution becomes complex when the “service agent” is an algorithm. Additionally, unlike human agents, AI voice assistants lack the capacity for emotional remediation, such as empathetic listening or reassurance (Liu & Xu, 2023;Longoni et al., 2022; Wang et al., 2025).

Therefore, firms need strategic remediation approaches that go beyond technical fixes. This includes human interventions, better tone design, and employee training (Castillo et al., 2021; Meng et al., 2025) (Bagozzi et al., 2022; Lv et al., 2022). Drawing on the content-environment consistency perspective (Peng et al., 2020) and Situational Crisis Communication Theory (SCCT), this study examines how recovery efforts can be aligned with failure types to restore trust and engagement.

We thus ask a second research question: **(2) How can service remediation strategies be tailored to AI voice assistant failures, and how might they influence consumer satisfaction and brand usage intent?**

To answer these questions, this study adopts a mixed-methods approach. First, we analyze consumer reviews (N = 5,894) and conduct interviews to inductively construct our failure typology and identify remediation patterns. Then, through an empirical survey, we test how the alignment between failure types and recovery strategies influences consumer outcomes.

In doing so, our study makes three key contributions:

1. We propose a novel, empirically grounded typology of AI service failures that captures the complex, real-world challenges consumers face when interacting with voice assistants.
2. We extend SCCT to the domain of AI-powered services by introducing the concept of mirroring ability, interpret, and adapt to individual consumer expectations in high-tech, high-ambiguity scenarios. This enriches SCCT's applicability beyond human-to-human crisis contexts, bridging the gap between algorithmic service failures and strategic response mechanisms.
3. We offer a decision-making framework that guides firms in strategically aligning remediation strategies with specific types of AI service failures. Our findings demonstrate that this alignment significantly enhances consumer satisfaction and brand usage intent, providing both theoretical insight and practical direction for managing AI-enabled service breakdowns.

2. LITERATURE REVIEW

2.1 AI Service Failure

AI service failure refers to the inability of AI-powered voice assistants to meet user expectations during interactions owing to technical defects, functional limitations, or interaction barriers, resulting in suboptimal output or service experience (Leo & Huh, 2020; Alarcon et al., 2021). This failure encompasses both objective technical errors (e.g., execution mistakes, data omissions) and subjective experience gaps (e.g., insufficient emotional support, inaccurate recommendations) (Liu et al., 2023). In professional contexts, such as medical diagnosis or hotel booking, AI decision errors can lead to severe consequences (Chen et al., 2022; Lv et al., 2022), while functional failures in everyday interactions (e.g., misinterpreted voice commands) undermine user trust (Kim & Song, 2021). The core of AI service failure lies in the disparity between user expectations and actual experiences, rather than merely technical malfunctions (Newton et al., 2018). AI-powered voice assistants may struggle to meet rapidly changing customer needs, especially when high professional expertise is required (Huang & Rust, 2018). To gain a comprehensive understanding of the underlying causes of AI service failure, researchers have extensively explored its etiology. Studies indicate that the reasons for AI service failure can be attributed to service capabilities, service characteristics, and service lifecycle (Scherer et al., 2015), as well as non-anthropomorphized features (Fan et al., 2019), and service atmosphere issues (Fu et al., 2022).The existing literature categorizes AI service failure from four main perspectives (see Appendix A1). Appendix A1 summarizes existing literature on AI service failures, clearly illustrating the diverse typologies studied. Notably, prior research lacks a comprehensive typology tailored specifically for AI voice assistants.

From the service process perspective, some scholars distinguish between process failure and outcome failure (Chen et al., 2021; Liu et al., 2023). Process failure typically refers to issues encountered during service execution, while outcome failure is related to the results of the service or user satisfaction. However, such binary classification standards are relatively broad and fail to adequately reflect the complex issues AI voice assistants encounter across different interaction scenarios. For instance, in recommendation systems, if the AI cannot comprehend users' contextual information (Puntoni et al., 2020), it may generate irrelevant or outdated suggestions, resulting in a typical outcome failure (Rita

Gonçalves et al., 2025). These types of failures are linked not only to data update mechanisms but also to insufficient contextual understanding, making them difficult to be fully explained by a single classification framework.

Another point classifies failure based on functional attributes (Song et al., 2023) and service failure stages (Majeed et al., 2024), focusing on technical flaws or execution-level errors. However, such classifications are often confined to the technical dimension and overlook the diversity of users' subjective experiences. For example, there is still a lack of systematic categorization of AI-specific problems such as mis-triggering, poor contextual adaptation, and failure in emotion recognition (Chen et al., 2021; Liu et al., 2023). These issues are particularly prominent in intelligent voice services and differ significantly from traditional service logic. Relying on conventional service failure frameworks may obscure the structural characteristics of AI service failures, thereby impeding the effectiveness of targeted remedial strategies and weakening efforts in trust repair and user relationship management (Kramer & Lewicki, 2010).

From the perspective of responsibility attribution, AI service failures primarily stem from the responsibilities of service providers and external environmental factors (Castillo et al., 2024; Leo & Huh, 2020). Specifically, system responsibility usually involves AI algorithm defects, hardware malfunctions, and data issues (Barth & de Jong, 2017), while external environmental factors, often beyond the control of both service providers and users, also significantly contribute to failures. Additionally, issues related to algorithm interpretability (Chen, 2024; Chen et al., 2025), particularly ethical concerns such as morality, privacy, and fairness, as well as security risks like AI manipulation or attacks leading to inappropriate content (Bigman & Gray, 2018;Gu et al., 2024), warrant serious attention. The excessive collection and control of personal information by AI further exacerbate users' concerns about privacy breaches (Brandimarte et al., 2012). Meanwhile, traditional high-performance characteristics may result in users' adaptive difficulties within intelligent service environments (Hagtvedt et al., 2024). Although existing classification frameworks are valuable for clarifying sources of failure, they tend to concentrate on algorithmic and objective factors, while largely overlooking subjective failures that stem from users' cognitive biases in assessing risks and benefits. This oversight limits a comprehensive understanding of AI service failures and hinders the development of more precise and effective remedial strategies.

From the perspective of user needs and perceptions, research has examined factors such as users' tolerance for failure (Lv et al., 2021), the willingness to engage in negative word-of-mouth (Huang & Philp, 2020), and value creation and destruction (Hsu et al., 2021).Technological anxiety can further exacerbate users' negative perceptions of AI services (Yaou Hu et al., 2021). AI service failures can also induce frustration and insecurity among employees, as their job performance may be influenced by the reliability of technology (Yaou Hu et al., 2021).Some scholars have observed that while AI can provide basic functional services, it often fails to meet users' personalized needs or emotional expectations (Bagozzi et al., 2022; Kang et al., 2024). This is evident in phenomena such as algorithm aversion and perceived unfairness (Longoni et al., 2022), where users feel that the AI decision-making process lacks transparency and fairness. For example, content recommendation mechanisms can lead to filter bubble effects. Additionally, voice assistants may struggle with accent recognition, which hinders user experience and causes inconvenience (Castillo et al., 2021). These issues underscore the limitations of current AI systems in understanding and responding to users' personalized needs (Chen et al., 2025).

In summary, although existing research has explored AI assistant service failures from multiple perspectives, significant differences remain in classification criteria and understanding. This inconsistency hampers the effective implementation of service management and AI recovery strategies and obstructs the optimization of user experiences. Previous studies have largely classified service failures from the perspective of service processes and stages, neglecting the inherent attributes of services and the multidimensional challenges they face in practical applications. These challenges include issues related to voice wake-up, personalized needs, and user-technology adaptability, which go beyond mere task completion. The lack of a unified classification standard for service failures makes current research on AI service failures fragmented and disorganized. To effectively address these issues, this study fills that gap by introducing a three-dimensional framework addressing scenario-based, personalization-related, and value-oriented failures, thereby providing a clear structure for remediation strategies.

2.2 Strategies for AI Service Remedies

Given the inherent failure risks of AI systems across diverse application scenarios ((Vaerenbergh & Orsingher, 2016) and the technological limitations that hinder user task performance (Rzepka et al., 2020; Cukier, 2021; Hu et al., 2022), users tend to exhibit varied evaluations and recovery expectations in response to AI service failures (Huang & Lo, 2025; Song et al., 2023). Unlike traditional human-driven services, AI services are characterized by automation, efficiency, and limited emotional recognition.

Therefore, AI service recovery must integrate both conventional service theories and the distinct features of human–machine interaction to formulate adaptive and targeted recovery strategies (Huang & Rust, 2018; Tsarenko et al., 2019).

With the widespread adoption of AI in service contexts, the standardization of recovery processes has become a central research focus (Chen et al., 2021). When failures occur, firms must respond promptly through standardized communication and digital substitution mechanisms to restore user trust. Due to the lack of contextual awareness and emotional expression, AI systems rely on scripted templates and affective simulation, making it difficult to achieve emotional resonance or rebuild trust as human agents can (Wirtz et al., 2018). Structured recovery mechanisms are thus essential for improving service recovery outcomes (Harland et al., 2023). Standardized communication helps convey organizational accountability and attitudes toward failure (Vamplew et al., 2021). In practice, a complete apology that includes error acknowledgment, explanation, and commitment to improvement can enhance perceived sincerity and credibility (Harland et al., 2023). The act-evaluate-apologize model further provides a structured framework for managing dissatisfaction, and researchers advocate adjusting recovery priorities according to task importance to prevent trust deterioration (Vamplew et al., 2021). Humor, when applied appropriately, has also been shown to reduce user tension and enhance the recovery experience (Liu & Xu, 2023).

A central aspect of AI service recovery lies in identifying and responding to users' actual needs. Failure to do so may result in trust erosion caused by cognitive bias or expectation mismatch(Glikson & Asscher, 2023; Mahmood et al., 2022). Users often hold dual perceptions of AI, viewing it as both a functional tool and a quasi-human agent (Prahl & Goh, 2021). Recovery strategies must therefore address both functional repair and emotional reassurance, presenting higher complexity than traditional services. Studies show that rigid or unpredictable AI outputs can reduce user satisfaction (Kim & Song, 2023)and diminish perceived control and self-efficacy (Lv et al., 2022). The concept of mirroring capacity highlights the expectation-performance gap as a key source of failure (Prahl & Goh, 2021). Organizations that can identify and exceed user expectations through personalized recovery measures can strengthen brand performance and foster loyalty (Chen et al., 2025). However, whether firms should adopt over-responsiveness in recovery remains an open question, particularly when user expectations conflict with internal standards. The absence of clear theoretical frameworks and operational tools for identifying latent expectations and translating them into specific recovery strategies remains to be developed.

On the other hand, the core of AI service recovery strategies lies in accurately identifying and meeting users' genuine needs, thereby avoiding trust erosion caused by cognitive biases or expectation misalignment(Glikson & Asscher, 2023; Mahmood et al., 2022). Users hold a dual perception of AI: they view it both as a tool and as an entity with human-like interactive expectations (Prahl & Goh, 2021). Consequently, AI recovery must not only address functional restoration but also respond to user needs, making it far more complex than traditional human-driven services. Research indicates that when AI outputs are rigid or uncontrollable, user satisfaction decreases (Kim & Song, 2023), and users' sense of control over the process and self-efficacy are diminished (Lv et al., 2022). Prahl and Goh (2021) propose the concept of mirror capability, revealing that AI service failures often stem from a gap between user expectations and the system actual performance. To address this challenge, the mirror strategy emerges as an innovative crisis communication approach that attributes responsibility to broader social environments or human behaviors rather than directly admitting faults of the AI voice assistant (West, 2016). This strategy effectively shifts public attention by emphasizing the complex social context and diverse data sources underpinning AI systems, thereby alleviating user dissatisfaction.

If firms can accurately identify and proactively respond to user demands, even exceeding expectations by delivering highly personalized recovery services, it can strengthen brand performance and enhance user loyalty (Chen et al., 2025). Rejection of excessive demand refers to a firm's refusal to fulfill consumer requests that exceed reasonable boundaries due to resource constraints or operational efficiency considerations (Duhachek, 2005). From the consumer's perspective, such rejection is often interpreted as a signal reflecting the service quality or the firm's level of care, thereby influencing their overall service experience and emotional perception(Mousavi et al., 2020). However, academic research currently lacks systematic exploration of whether companies should over-respond to user demands during recovery, especially when user needs conflict with corporate standards, making strategy formulation more complex. Furthermore, existing theories remain insufficient to effectively identify users' implicit expectations and translate them into concrete recovery solutions.

Notably, AI service recovery is not solely performed by the system; the customer engagement and employees' attitudes also play a crucial role in relationship repair. Research shows that customer engagement is a multidimensional concept arising from the subjective experiences during interactions between customers and service providers(Yen et al., 2020). It encompasses not only customers' sharing of experiences in brand-related activities but also their conscious or unconscious attention to the company or brand, as well as their focused involvement during the interaction process(So et al., 2012). In this study, we further define customer engagement as users' perceptions of whether the firm enables and encourages their feedback and suggestions (e.g., The firm allows users to suggest improvements to the AI assistant).In the evolving landscape of service intelligence (Lv et al., 2022), firms often overlook the potential of customer engagement in optimizing algorithmic results while pursuing precision in services (Chung et al., 2018). This oversight leads to the neglect of authentic human insights (Huang & Lo, 2025). Although AI assistants can simulate complex human cognitive mechanisms (Montes & Goertzel, 2019), their functionality remains limited to specific domains (Čaić et al., 2019; McLean et al., 2021; Wirtz et al., 2018) and have not yet achieved full-spectrum intelligence (Cukier, 2021). Research indicates that customer co-creation of recovery is more effective in fostering emotional trust(Chen et al., 2022). Currently, firm strategies for addressing AI service failure are largely based on summarizing and correcting past mistakes (Clokie & Fourie, 2016; Jörling et al., 2019; Majeed et al., 2024). The effective integration of customer engagement and the development of a more comprehensive AI service recovery mechanism have emerged as key priorities in contemporary research.

In this context, service attitude (Bagozzi et al., 2022; Kang et al., 2024), service empathy (Kuo et al., 2012;Behnam et al., 2021), and the human–machine collaboration atmosphere (Liu et al., 2025) have emerged as key factors influencing service recovery performance. Research has shown that during the service recovery process, a high-warmth response from AI significantly enhances consumers' reuse intentions (Wang et al., 2025), with emotional perception playing a crucial mediating role (Li et al., 2023). The role of employees' service attitude in service experience has been demonstrated (Nguyen et al., 2022). Training employees' attitudes can further highlight the value proposition of firms (Khamitov et al., 2020).

In interactions with AI voice assistants, various types of failures can weaken the connection between individuals and the product (Cao et al., 2022), thereby impacting user satisfaction (Sohail & Syst, 2020). User satisfaction is essential for both measuring service quality and achieving effective management and sustained profitability, directly impacting the firm's long-term viability (Sands et al., 2022). After experiencing service failures, consumer attitudes play a significant role in shaping their subsequent behaviors (Badghish et al., 2024; Yoo & Donthu, 2001). Positive experiences with a firm's remedies increase the likelihood of continued use of AI voice assistants (Harrigan et al., 2018).Thus, this study aims to investigate satisfaction and brand usage intention as dependent variables within the framework of consistency theory, exploring how various service recovery resources can encourage further consumer engagement with the brand.

2.3 Consistency Theory Perspective and Situational Crisis Communication Theory

To meet evolving customer needs, firm solutions must innovate (Von Hippel & Kaulartz, 2021). We adopt the content-environment consistency perspective (Peng et al., 2020) to examine consistency between consumer needs and remediation solutions in AI-powered voice assistants' service resolution strategies (see Fig1). We argue that consistent service failure characteristics and remediation strategy lead to stronger satisfactory experience and brand usage intent.

[Fig 1. Theoretical framework Perspective]

To further explore this consistency, we introduce the Situational Crisis Communication Theory (SCCT). SCCT identifies coping strategies for crisis management (Coombs, 2006) , outlining crisis communication resolution paths and stakeholder actions to reduce threats. It comprises four main crisis response strategies: reconstruction, reduction/denial, and reinforcement (see Table 1).

[Table 1. Crisis Management Strategies and Contextualization]

Scholars have applied SCCT to analyze how coping strategies align with attribution of responsibility (Ma & Zhan, 2016) and crisis outcomes (Schneider et al., 2021). Service remediation can help repair consumer trust (Bagherzadeh et al., 2020; Bozic et al., 2019) and enhance perceived firm expertise (Chen et al., 2022). However, the quality of information provided during remediation still warrants further examination (Tronvoll & Edvardsson, 2019). To improve effectiveness, firms should implement clear apology protocols and resolution procedures (Prahl & Goh, 2021), which reflect their understanding of the failure and commitment to resolution. This study categorizes such measures as reconstruction strategies, which use apologies and solutions to restore reputation and rebuild trust.

Given the inherent limitations of AI assistant technology, firms often respond to service failures by denying system errors and clarifying that the AI is operating as intended. These failures frequently arise when consumers issue requests that exceed the AI's capabilities (Chen et al., 2021; Liu et al., 2023). In such cases, firms define the scope of service and emphasize functional boundaries (Prahl & Goh, 2021). This response represents a form of responsibility transfer, though it differs from traditional blame-shifting. Rather than avoiding accountability, firms contextualize the failure within broader societal mismatches-namely, the gap between user expectations and current technological capabilities (Tan et al., 2024). This approach introduces a new dimension of denial, one that highlights structural misalignments rather than individual fault. Accordingly, firms should continuously enhance their ability to identify consumer expectations, which this study classifies as mirroring capability. These responses are categorized as reduction strategies, designed to mitigate dissatisfaction through reasonable explanation and expectation management.

Beyond technical resolution, emotional factors and empathy are also crucial in service recovery (Lv et al., 2022). Consumers seek not only problem-solving but also warmth and understanding during service interactions (Gabbott et al., 2011b). As defined by (Ekinci, 2001), service attitude refers to consumers' perceptions of frontline employees' emotions, capabilities, and behavioral tendencies during the service process. Positive service attitude enhances recovery effectiveness and consumer perception, especially in the context of AI service recovery (Gabbott et al., 2011b). Moreover, peer feedback in online communities can prevent conflict escalation. When firms integrate consumer engagement and interaction, they facilitate co-creation and value enhancement (Chen et al., 2025;Yin et al., 2023). These are categorized as reinforcement strategies, focusing on interactive and emotional resolution.

3. MIXED METHODS INVESTIGATION

This study adopts a mixed methods to address the reality and diversity of AI service failure issues in complex technological environments (Liu et al., 2025) (see Appendix A2 for details). Compared to single-method approaches, mixed methods integrate the strengths of both qualitative and quantitative research, offering a more comprehensive and multidimensional insight (Califf et al., 2020; Venkatesh et al., 2016). Qualitative methods, which have been proven effective as tools for providing additional interpretive perspectives (Wolf & Maier, 2024), allow for the exploration of product flaws in AI assistants from user-generated reviews, thereby facilitating a deeper understanding of users' subjective experiences and failure perceptions. Quantitative methods, on the other hand, provide systematic and measurable empirical support. The complementarity of the two enhances the robustness and explanatory power of the research (Creswell & Plano Clark, 2018). This study employs a sequential explanatory design, initially identifying key issues and service recovery measures through qualitative interviews, followed by quantitative research to validate and expand on the preliminary findings. We summarize (1) nine service failure types from online user reviews and academic literature (Chen et al., 2022; Du et al., 2014) The literature mentions the concept of customer engagement and emotional contagion, which is also an important measure in the AI assistant environment, (2) derive a matching table from expert interviews and service remediation literature (Tronvoll & Edvardsson, 2019), and (3) link solution strategies to abstract concepts. The overall research design framework and specific methods are depicted in Fig 1.

[Fig 1. Theoretical framework and mixed methods]

3.1 Qualitative Research: Conceptualization Stage

3.1.1 Identifying Product Defects

We examine AI-powered voice assistant service failures by identifying product defects through three stages: sorting research subjects, initial classification basis, and identifying collection platforms. The first stage involves analyzing mainstream AI assistants, while the second stage examines negative user comments from official AI voice assistant brand communities. We extract critical characteristics about product defects and users' expectations for resolutions, comparing them with prior research (Urquhart et al., 2010).

In the early stages of the research, we reviewed multiple mainstream domestic AI voice assistant platforms, including Huawei Honor Club, Xiaomi Community, Tmall Genie, and Apple Siri, to assess the quality and themes of user reviews. However, most reviews on these platforms are fragmented and lack systematic themes. Moreover, user feedback is often unaddressed or un-followed up by the firms, making it difficult to construct a stable and reliable sample for analysis. Based on these observations, we ultimately selected the XiaoAi Community as the platform for data collection for the following reasons: (1) Representativeness of user-generated innovation: the Xiaomi Community is one of the most active user innovation communities in China. Users can freely discuss their product experiences, and the platform boasts a high level of user engagement and interactivity, reflecting the authentic voices of AI voice assistant users. (2) High interaction between officials and users: a large number of consumers actively engage in discussions through posts, while official personnel frequently intervene to offer unified responses and solutions to user feedback. This makes it one of the few platforms with a sustained "user-firm" interaction mechanism. (3) Data integrity and thematic concentration: Compared to the scattered user reviews on other platforms, feedback in the Xiaomi Community is more focused on the functionality, interactivity, and service experience of AI voice assistants. This provides clear and concentrated material for constructing a systematic framework for service failure classification.

This study collected 5,894 data with reviews spanning a year (April 2020 -April 2021). To ensure the relevance and quality of the analysis, clear inclusion and exclusion criteria were established during the data cleaning process. First, positive comments unrelated to service failure (e.g., "It's very useful" and "The experience is smooth") were excluded. Second, comments that were not related to the functions, interactions, or service experience of the AI voice assistant, such as those about new product releases and evaluations of other products, were also excluded. Third, comments that only described the hardware performance or system updates of Xiaomi mobile phones (e.g., This phone has good battery life) were removed. Finally, duplicate or highly similar comments were eliminated, with only one representative entry retained to avoid data bias. Finally, we imported 4040 reviews into Nvivo 12.0 software for manual coding, ensuring theoretical saturation (Birks et al., 2013) with 3900 open-coded data and 140 sample reviews.

3.1.2 Coding Scheme

Grounded theory, a systematic induction method, suits this study's extensive textual data for bottom-up analysis (Francis, 1999) better than natural language techniques (Zhu et al., 2021). The three-level coding process (Glaser, 1978)—open, axial, and selective coding—helps identify AI voice assistant service failure dimensions and relationships between categories for theoretical abstraction.

Before the formal coding process commenced, the research team conducted systematic training to ensure that all members had a unified and thorough understanding of coding rules and conceptual definitions. Following a series of preparatory meetings to clarify the coding tasks, the research utilized an open coding approach, assigning descriptive and preliminary conceptual labels to each text comment, with the aim of identifying common research themes. This phase of work was carried out independently by two researchers, and inter-coder reliability was assessed using Cohen's Kappa coefficient to ensure objectivity and consistency. During this phase, the team held regular discussion sessions to address discrepancies, refine the coding strategy, and compare newly generated codes with existing categories to prevent conceptual over-generalization or fragmentation. To further validate the accuracy and reliability of the coding results, external experts, not involved in the coding process, were invited for review. Additionally, to illustrate the practical application of the coding framework, selected user comments are provided as examples in Appendix A3.

As our understanding of the field deepened, several intriguing themes emerged. We conducted axial coding to further analyze valuable comment content based on open coding. This study distinguishes these key categories from others and classifies them according to the coding themes and logical sequence. Through the coding of 49 initial categories, this study identified nine dimensions of AI voice assistant service failures (see Appendix TableA4). These nine thematic dimensions describe various contextual characteristics of service failures, allowing researchers to make comparisons across existing comment data, thereby enhancing the generalizability and comprehensiveness of the findings. Detailed classification can be found in Appendix A3. The next step involved selective coding, where the relationships between different categories were further abstracted at a higher theoretical level. This process, by analyzing the contextual connections between the initial and main categories, ultimately led to the formulation of the core categories of the theoretical framework (see Table 2).

[Table2. Thematic Dimensions and Main Category]

To systematically integrate the coding results of the above dimensions and deepen the theoretical understanding of service failure phenomena, this paper further consolidates these specific service failure characteristics into three core failure types. These categories reflect distinct ways in which AI voice assistants fail to meet user expectations based on technical limitations, interaction barriers, or functional shortcomings. "Scenario failure" refers to the inability of AI assistants to provide stable, contextually appropriate responses during core service interactions. It often involves fundamental breakdowns in essential functions. Based on consistent patterns observed in the data, we summarize the coding features of infrastructure, scene flexibility, voice interactivity, automated decision-making, and exceptional risk under this category. "Personalization failure" captures the assistant's inability to engage in individualized, adaptive communication and support. Users frequently express dissatisfaction with the lack of personalized conversation or extended service functionality. Therefore, conversation personalization and extended service are grouped under this failure type. "Value failure" reflects the tension users perceive between the functional benefits offered by AI services and the associated risks to privacy or perceived value. Consumers are increasingly aware of privacy trade-offs and potential economic exploitation. As such, we classify issues related to privacy security and profitability value under this dimension.

[Fig2. Coding Process]

3.2 Qualitative Research: Strategy Matching Stage

3.2.1 Ensuring Inquiry Quality

We adhere to the mixed-methods research guidelines proposed by (Venkatesh et al., 2013) and achieve theoretical saturation through systematic interviews, comparative analysis, and quantitative validation.

3.2.2 Data Collection and Analysis

We form an initial qualitative research set by combining five service remediation strategies (Tronvoll & Edvardsson, 2019) and firm solution measures from XiaoAi community's "Responsible person online" column. Modified Delphi (Hasson et al., 2000; van Looy et al., 2017) is used to derive a matching table of service remediation strategies (Fig3). According to the advice (Okoli & Pawlowski, 2004), three expert groups - posting consumer, product manager, and academic research - were set up and provide insights. The specific development details of the solution variables are provided in Appendix B1. SCCT categories further guide the selection of strategies for resolving issues. In terms of reconstruction strategy, it is important for the firms to enhance its knowledge and improve the quality of information. These are important processes for response standardization. Additionally, clear apology procedures and alternative solution should be incorporated into the service recovery (Prahl & Goh, 2021). This study classifies standardization of response and alternative solution measures as part of reconstruction strategy. In terms of reduction strategy, two approaches include denying AI system errors or clarifying failure reasons. Responsibility shifting, or 'mirroring capability,' in AI contexts reflects societal phenomena (Prahl & Goh, 2021), and firms can inform consumers of current technological limitations. This study classifies this aspect as a reduction strategy. Service remediation should consider emotional factors and empathy, as training service attitudes affect remedial measure effectiveness(Lv et al., 2022; Poushneh, 2021). Understanding online community comments is vital for conflict de-escalation, and consumer engagement facilitates resource integration (Chen et al., 2022; Gabbott et al., 2011a). We classify these strategies as reinforcement strategies.

3.2.3 Findings

Fig3(a) presents the scoring procedure, while (b) shows the top three resolution measures for each service failure category. Consumers value response content and alternative solution, especially for frequently occurring issues. Firms support, customer expectation identification, and engagement are crucial for personalized and extended service failures. Privacy security and profitability value failures necessitate high-quality alternative solution.

[Fig3. Score Calculation and Outcomes]

3.3 Quantitative Research: Model Analysis Stage

3.3.1 Research Model

Drawing from qualitative research results, this study abstracts product defects and firm remedial strategies into theoretical concepts, constructing a model based on key concepts (see Fig4). The model employs a consistency perspective to categorize AI voice assistant service failures into three feature sets. Remedial strategies are based on SCCT's three categories and previous qualitative finding.

[Fig4. Research Model]

3.3.2 Research Hypothesis

Scenario Failure: AI-powered voice assistant technologies need to interoperate with application scenario through certain types of hardware (wearables, mobile phones, smart speakers) (James et al., 2019). However, due to the unconstrained nature of real-world scenarios, such as changes in posture or light blockage, these can affect the AI assistant's ability to perform satisfactorily. Consumers experience a variety of interaction failures in real-time modified scenarios, which not only makes it difficult for individuals to engage with the system (McLean & Wilson, 2019), but also undermines the consumer experience (Animesh et al., 2011; Steuer, 1992).The execution of these different scenario tasks is inseparable from the comfort of AI-powered assistant language interaction(Knote et al., 2019). Consumers often communicate with the assistant in the form of voice wake-up. The AI-powered voice assistant also follows a pre-set program to automatically complete basic command tasks and messages. However, individual exceptions to the interaction process can easily occur, such as not being woken up. Based on the results of the previous qualitative study, this study found that the respondents' preferred solution strategies for problems with technical interaction features were reconstruction strategies and reinforcement strategies.

In the context of artificial intelligence, the configuration and optimization of firm resources to meet complex customer demands involve the firm value creation logic (Wixom Barbara H., 2017). Artificial intelligence has the capability to provide search results or anticipated value by understanding consumer needs and various task contexts (Henkens et al., 2022). In instances of failure in these scenarios, a standardized apology process becomes imperative, particularly in addressing routine conversational issues. Response standardization refers to a firm's efforts as perceived by consumers to regulate response behaviors during service delivery by relying on pre-established procedures, rules, and objectives(Kirsch et al., 2002). It aims to ensure consistency in addressing external environments and coordinating with multiple stakeholders. This ensures that consumers can promptly receive resolution commitments and compensatory solutions(Antonetti et al., 2018). AI products differ from ordinary products as they rely on the training and prediction based on specific datasets (Liao et al., 2020). Due to variations in the level of noise in data and the difficulty of signal extraction, the outcomes of human-machine conversations are inherently unstable. Consequently, firms face challenges in formulating resolution strategies. Research indicates that the pleasantness provided by organizational entities can positively influence satisfaction by reducing perceived uncertainty (Kuppelwieser et al., 2023). Adhering to a standardized apology process at such times has been shown to garner a higher degree of customer appreciation, thereby intensifying satisfaction with product recovery efforts (Hall & Hyodo, 2022).

Given the limited adaptability of AI voice assistants in non-standardized scenarios, firms often implement alternative support measures to mitigate service disruptions(Raju et al., 2021), reduce user dissatisfaction, and prevent customer attrition. Such measures reflect organizational capabilities in service recovery and problem resolution, and are widely adopted in system deployment and project collaboration (Aladwani, 2002). When scenario failures occur, alternative solutions can offer immediate and feasible operational pathways that align with the nature of the failure, thereby reducing user frustration during AI interactions (Chen et al., 2021). These failures often result from design limitations, such as reliance on specific wake-up conditions, and the use of substitute mechanisms is a key input for effective service recovery and improved customer satisfaction. Therefore, scenario failure is likely to positively drive the firm’s deployment of alternative resolution strategies to maintain overall service quality. We hypothesize:

H1a: Scenario Failure is positively associated with response standardization.

H1b: Scenario Failure is positively associated with alternative solution.

Since scenario failures are relatively common, consumers may frequently need to interact with firms or seek assistance (Liu et al., 2025). By training employees' attitudes, firms can effectively influence consumers' perceptions of the firm's responsiveness during failure situations (Ma & Ye, 2022). In the AI recovery process, consumers who encounter frontline service personnel with high empathy typically exhibit higher levels of trust and smaller psychological distance (Lv et al., 2022). This further underscores the positive correlation between scenario failures and employee attitude training.

Customer engagement is regarded as a key mechanism through which firms transform user insights into competitive advantage and enhance customer loyalty (Huang & Rust, 2018). Prior studies have shown its positive impact in AI-driven services (Castillo et al., 2021; Meng et al., 2025). Scholars suggest that customer engagement originates from consumers' interactive experiences with firms in specific service contexts(Brodie et al. 2011). In AI environments, customers provide feedback or participate in joint decision-making with the expectation of receiving a response from the firm, thereby facilitating service recovery (Behnam et al. 2021).When AI voice assistants experience scenario-related failures, firms often encourage customer engagement to identify root causes and improve service processes. Timely feedback and resource sharing during brand interactions can not only enhance user experience but also strengthen brand loyalty (Hollebeek et al., 2019). Through these interactions, customers derive perceived value and may share brand-related knowledge with others(Yen et al., 2020). Scenario failures are likely to prompt firms to foster customer engagement to enhance service recovery. We hypothesize:

H1c: Scenario Failure is positively associated with training employee attitude.

H1d: Scenario Failure is positively associated with customer engagement.

Personalization Failure: Research indicates that personalization is one of the core objectives of AI voice assistant applications (Ameen et al., 2022). However, failures in personalized services often arise from a firm's inability to effectively meet consumers' individual needs and preferences (Karwatzki et al., 2017), leading to consumer dissatisfaction (Wirtz et al., 2022). Studies have shown a positive correlation between personalization and consumer loyalty (Fang, 2019). Yet, when addressing specific or personalized needs, AI voice assistants sometimes provide misleading or incorrect answers, resulting in consumers receiving limited and generalized information (Chen et al., 2024), and even potentially violating their privacy expectations. Furthermore, AI voice assistant service providers may store or utilize data collected from devices to deliver targeted advertisements based on this information (Wirtz et al., 2022), which can raise consumer concerns about privacy breaches (Belk, 2021). Scholars have also proposed that the negative impact of failures in personalized information content is often more severe than that of system service failures (Bui & Kim Miyea, 2024). Research further suggests that over-satisfying consumers' personalized needs may lead to privacy violations and increase dependency on technology (Rust et al., 2002; Steinhoff & Martin, 2022).

Therefore, firms may opt to balance consumer expectations with reality by limiting excessive personalized demands and clearly defining the scope of problem resolution (Zuboff, 2015). While this strategy helps avoid vague responses and reduces the likelihood of inappropriate consumer behavior in the future (Kamran-Disfani et al., 2022), it could also heighten consumers' doubts about the firm's personalization capabilities. In situations of personalized service failure, if firms fail to fully consider the feelings and needs of customers when addressing excessive demands, negative consequences may arise (Chen et al., 2022). Thus, the rejection of excessive demand not only reflects technological limitations but may also lead consumers to perceive that the firm lacks attention to personalized care and human interaction in its remedial efforts (Chen et al., 2022).

Mirroring ability refers to a firm's capacity as perceived by consumers to accurately identify their needs and adjust its service delivery accordingly (Prahl & Goh, 2021). In the context of personalized services, failures in task execution by AI voice assistants can undermine consumers' sense of self-identity, leading to negative emotions and outcomes (Rita Gonçalves et al., 2025). Such failures typically reflect deficiencies in the firm's understanding of and responsiveness to consumer needs, meaning that consumers' core expectations are unmet, which further exacerbates doubts about the firm's service capabilities, especially regarding whether it truly comprehends their needs. Some scholars have noted that certain consumers tend to attribute errors to the robot rather than to humans (Tan et al., 2024). This perspective suggests that, in some cases, consumers may show greater tolerance for mistakes made by AI voice assistants. However, failures in personalized services are not solely technical issues; they also present an opportunity for firms to improve. If firms can enhance their ability to recognize customer expectations and align them with specific consumer needs, it may positively impact business performance (Kamran-Disfani et al., 2022). This process can also effectively mitigate negative consumer evaluations of the firm, such as dissatisfaction (Cai et al., 2024). Therefore, we aim to analyze how mirroring ability can address issues related to personalization. We hypothesize:

H2a: Personalization Failure is negatively associated with rejection of excessive demand.

H2b: Personalization Failure is positively associated with mirroring ability.

Any failure encountered in the service process may damage the consumer's enthusiastic experience (Hsieh & Lee, 2021). It is therefore crucial to establish a good relationship between frontline workers and consumers during service remediation (Kuo et al., 2012). Research has shown that employees' ability to perceive and understand customer emotions and needs is a critical factor influencing service recovery performance (Bagozzi et al., 2022; Lv et al., 2022). In the context of personalized service failures, the service attitude is a key remedial measure. Employees' attitudes need to be optimized through targeted training when handling apologies, providing explanations, and facilitating team communication (Liu et al., 2025). This training helps employees adjust their external emotional expressions, enabling them to more effectively address consumer needs (Gong et al., 2020; Liu et al., 2025). However, when AI voice assistants experience personalization failures, employees often face challenging recovery tasks (Glikson & Asscher, 2023). These tasks can lead to feelings of unfairness and frustration, as employees may perceive them as beyond their responsibilities and role boundaries (Björk et al., 2013). Therefore, training employees' attitudes not only enhances service recovery quality but also helps firms better address personalized service failures.

Although customer engagement is widely recognized as a valuable mechanism in service recovery, different types of service failures may elicit divergent consumer responses. Unlike scenario-based failures, which are primarily technical in nature, personalization failures often involve unmet individual expectations or perceived violations of privacy (Lee et al., 2020), thereby triggering consumer distrust and psychological distancing (Longoni et al., 2023). Such failures are not typically perceived as system-level errors but are instead interpreted as a lack of attentiveness or ethical responsibility on the part of the firm (Huang & Lo, 2025), weakening users' trust in the firm's openness and receptiveness to feedback(Yen et al., 2020). In this context, personalization failures may violate the psychological contract consumers hold- an implicit set of expectations that firms should act with respect, transparency, and responsiveness during interactions(Raju et al., 2021). Perceived breaches of this contract can lead to erosion of trust and a decline in consumers' willingness to engage(Chung et al., 2018). Furthermore, the absence of effective engagement channels in current recovery strategies may exacerbate these effects, leaving consumers feeling ignored rather than respected or heard. Consequently, personalization failures are more likely to inhibit rather than encourage consumer feedback and interaction, ultimately leading to a decline in customer engagement. We hypothesize:

H2c: Personalization Failure is negatively associated with customer engagement.

H2d: Personalization Failure is positively associated with training employee attitude.

Value Failure: Technology value describes the consumer's perceived trade-off between applied perceptions and benefits (Venkatesh et al., 2012). Price is often linked to the quality of the product or service to determine the perceived value to the consumer (Zeithaml, 1988). The perceived effort and costs incurred by an individual in adopting a particular technology, including time, constitute the consumer's perceived investment(Farivar et al., 2018).The cost paid by the consumer may have a critical influence on the consumer's use of the technology. The information associated with a particular technology will be valued by consumers for different attributes of the product (McKnight et al., 2020). When firms delegate decision-making to artificial intelligence algorithm systems, the inherent unpredictability of complex technologies may lead to behaviors such as price fairness and inconsistent accessibility (Elliott et al., 2021; Zuboff, 2015). Unintended risk objectives (Rahwan et al., 2019) necessitate interventions through human-authenticated audits, which may hinder the perception of a satisfactory consumer experience. Moreover, some firms impose charges for certain services during consumers' use of AI voice assistants, such as cloud storage fees. These profit-driven practices may result in negative consumer attitudes, leading to service failures. For instance, voice assistants providing biased investment advice when simulating portfolio assets using algorithms (Hong et al., 2023) or failing to filter ideal recommended products (Marinova et al., 2016). In such cases, the reconstruction, reduction, and reinforcement strategies of the firms may all impact consumer perceived trust. Existing research indicates that standardized response processes have dual value in service recovery: on one hand, they clearly reflect the firm's service stance and problem-solving approach (Chen et al., 2023); on the other hand, standardized handling effectively compensates for user losses and helps form stable quality perceptions. Particularly in AI service contexts, where AI systems lack flexibility in perceiving product value (Lv et al., 2021), adopting standardized communication strategies becomes a key method for addressing service failures. Furthermore, given the potential risks in service processes, companies must establish contingency mechanisms (Tan et al., 2024). Such contingency plans not only enhance perceived service reliability (Song et al., 2023) but also effectively reshape consumer impressions through the implementation of alternative solutions (Rahwan et al., 2019). We hypothesize:

H3a: Value Failure is positively associated with firm response standardization.

H3b: Value Failure is positively associated with alternative solution.

Consumers hold diverse standards regarding the value proposition of technologies, making it difficult for firms to satisfy all expectations simultaneously. In AI service contexts, where consumer expectations are often ambiguous(Liu et al., 2025), rejecting excessive customer demands may be perceived as a lack of proactiveness or empathy, thereby intensifying the perception of value failure (Liu et al., 2023). Scholars have noted that while such avoidant coping strategies may reduce immediate pressure, they can hinder effective problem resolution for consumers (Duhachek, 2005). This creates a negative feedback loop in which consumers who already feel underserved become increasingly sensitive to any further negative responses, such as service rejection. As a result, under perceived value failure, firms may become less inclined to reject excessive demands to avoid further damaging the customer relationship. At the same time, value failure often reflects a mismatch between customer expectations and the firm's technological responsiveness. In applying AI models, firms must also be vigilant about potential risks such as lack of autonomy, discriminatory outputs, and covert tracking(Hunold et al., 2020; Shin & Park, 2019). These issues further heighten consumers' sensitivity to the trade-off between benefits and costs in technology-driven environments(Nguyen et al., 2023). Against this backdrop, firms can mitigate negative perceptions of value by enhancing their mirroring ability, defined as the capability to accurately identify and dynamically align with individual customer needs (Prahl & Goh, 2021). Enhancing this capability helps improve the consistency of service recovery(Nguyen et al., 2023), thereby effectively mitigating the value erosion caused by AI service failures. We hypothesize:

H3c: Value Failure is negatively associated with rejection of excessive demand.

H3d: Value Failure is positively associated with mirroring ability.

Existing service providers largely rely on voice assistants to deliver services, but evidently, these services have limited capabilities in addressing customer complaints (Huang & Rust, 2020). While artificial intelligence can learn preliminary relational cues from limited emotional data during the provision of AI services (McDuff & Czerwinski, 2018), it is confined to mechanical data analysis. In the dimension of value-benefit failure, proficient employees in firms still bear the responsibility for maintaining customer satisfaction and retention (Huang & Rust, 2017). Currently, in human-machine high-density interaction environments, artificial intelligence struggles to respond to emotions and sensations as humans do (Schuller, 2018). In the face of failure, a crucial prerequisite for offering emotional comfort is the training of employee attitudes, rendering it a vital enhancement strategy.

In the event of failures in artificial intelligence applications, customer engagement enables consumers to establish a genuine connection with the brand (Hollebeek et al., 2021). This robust interactive relationship is expected to lead to a higher customer lifecycle(Yen et al., 2020). When AI voice assistants experience value failure, it triggers consumers' perceptions of value imbalance, leading them to believe that the data privacy and operational costs incurred are grossly disproportionate to the service experience (Castillo et al., 2021). In such cases, although customer engagement is intended to repair brand relationships, the perception of algorithms as highly homogenized "black boxes" (Longoni et al., 2023) significantly weakens consumers' motivation to engage. Value failure causes consumers to view participation as ineffective in improving system performance. This reversal of participation in the context of value failure essentially reflects the unmet expectations for resource integration (Plé, 2017).When AI systems continually fail to meet value expectations, participation shifts from value co-creation to an additional burden (Castillo et al., 2021), ultimately leading customers to reduce their engagement or seek alternative services. We hypothesize:

H3e: Value Failure is negatively associated with customer engagement.

H3f: Value Failure is positively associated with training employee attitude.

Based on the service experience provided by firms, perceived consumer satisfaction is often regarded as a comprehensive emotional response (Schuetzler et al., 2020). Prior studies have confirmed a significant relationship between perceived service quality and customer satisfaction (Benlian et al., 2011). However, firms often lack standardized response mechanisms in their remediation processes, leading to frontline employees lacking the authority to resolve issues promptly. These delays are frequently cited as a major cause of customer dissatisfaction(Chopra et al., 2025). In contrast, when firms are able to provide clear and alternative solutions, consumers tend to temporarily suppress dissatisfaction by adhering to social norms and interpersonal expectations (Bonifield & Cole, 2007). At such moments, if firms can accurately identify customers' core expectations and demonstrate empathy, it can enhance consumers' perceived satisfaction. Moreover, when firms reject excessive customer demands, it often generates negative perceptions, thereby lowering satisfaction. By improving mirroring ability, firms can significantly enhance the perceived service experience (Prahl & Goh, 2021). In parallel, training employee attitudes is considered a crucial strategy for improving service recovery, particularly in situations requiring emotional support. Research also shows that when customers are granted opportunities to participate in the service remediation process, their sense of self-efficacy increases, leading to higher satisfaction (Dong et al., 2016). Therefore, balancing customer engagement with resource constraints is key to achieving win-win outcomes in service recovery. We hypothesize:

H4a: Response standardization is positively correlated with satisfaction experience.

H4b: Alternative solution is positively correlated with satisfaction experience.

H4c: Rejection of excessive demand is negatively related to satisfaction experience.

H4d: Mirroring ability is positively related to satisfaction experience.

H4e: Training employee attitude is positively related to satisfaction experience.

H4f: Customer engagement is positively related to perceived satisfaction experience.

Previous research has shown the positive outcomes when firms participate in problem solving, which promotes the relationship between consumers and brands (Hsieh & Chang, 2016). After consumers go through service remediation measures, it may help to strengthen the connection between consumers and brands, thus influencing brand usage intentions (Tronvoll & Edvardsson, 2019). When consumers experience service failures, if firms adopt standardized service remedies and know the key elements of problem resolution (Tronvoll & Edvardsson, 2019), consumer experiences will improve, which can positively influence their behavioral intentions. Especially in the complex service remediation process, it is difficult for firms to deal with all the issues raised at the same time. That means firms must identify the essence of customer expectations and prioritize reasonable and actionable solutions to problems. When firms adopt these strategies, consumers will think that the firm has coordinated and controlled the problems and opinions raised by users in the process of decision-making(Gunarathne et al., 2017), which positively influences brand usage intentions. If firms choose to reject excessive demands, consumers may further reduce their intention to use the brand (Badghish et al., 2024), perceiving the company as disregarding the limitations of the algorithm and the emotional needs of users.

In this context, the communication attitude shown by firms through organizing employees can be an important factor affecting customers' brand usage intention. Moreover, customer engagement can enhance customers' identification with and sense of belonging to the brand (Meng et al., 2025), thereby promoting their willingness to continue using the brand. Therefore, this paper hypothesized:

H5a: Response standardization is positively correlated with brand usage intent.

H5b: Alternative solution is positively correlated with brand usage intent.

H5c: Rejection of excessive demand is negatively correlated with brand usage intent.

H5d: Mirroring ability is positively related to brand usage intent.

H5e: Training employee attitude is positively associated with brand usage intent.

H5f: Customer engagement is associated with brand usage intent.

3.3.3 Research Method

This stage empirically tests the research model as part of a mixed research approach. The Credamo platform provided an independent sample, with a $5 questionnaire payoff and subject credit score (>80%) limit to ensure quality. Of the 302 distributed questionnaires, 221 were valid after excluding inattentive and non-AI assistant users. Table 3 displays descriptive statistics. A pilot study was conducted, and measurement scales were adapted from a seven-point Likert scale. Scenario failure adapted from (Animesh et al., 2011; Xiao et al., 2020), personalization failure adapted from (Ameen et al., 2022; Xiao et al., 2020), value adapted from (Venkatesh et al., 2012; Xiao et al., 2020).Response standardization adapted from (Kirsch et al., 2002), alternative solution adapted from (Aladwani, 2002)，rejection of excessive demand adapted from (Duhachek, 2005), mirroring ability adapted from (Oshri et al., 2019), customer engagement adapted from (Behnam et al., 2021), training employee attitude (Kuo, Chen, and Lu 2012).The dependent variables are adapted from McLean and Osei-Frimpong (2017). See Appendix B2 for details.

[Table 3. Descriptive statistics]

3.3.4 Model Testing

Smart PLS3.0 software was utilized for data analysis, following guidelines for second-order construct assessment (Wetzels et al., 2009). Construct reliability was assessed by calculating combined reliability (CR) and average variance extracted (AVE). CR values should exceed 0.7 and AVE values should be 0.5 or higher (Hair et al., 2014) Discriminant validity was established as the AVE square root surpassed all construct correlations. Research constructs were confirmed (see Appendix C1). Cross-loadings were lower than main loadings, supporting the paper's research constructs. To further solidify the validity of the constructs, we conducted covariance-based structural equation modeling (CB-SEM). The CFI was 0.801, the RMSEA was 0.069, and the SRMR value was 0.067. The GOF value are also presented in the appendix C1. From the Q^2 predict results, all values are greater than 0. This indicates that the prediction error of the PLS-SEM model is lower than the error obtained by simply using the means, demonstrating that the model has viable predictive capability. We employed the Cross-Validated Predictive Ability Test (CVPAT) to compare the average loss of PLS with the average losses of benchmark models such as the Indicator Average (IA) and Linear Model (LM). The results demonstrated that the predictive performance of the structural model significantly outperformed IA and LM, as evidenced by PLS-IA < 0 and PLS-LM < 0, thereby further confirming the practical predictive value (see Appendix C1, TableC2). Multicollinearity issues were assessed by examining first-order factor correlations and variance inflation factors. Convergent and differential validity of second-order constructs were evaluated using criteria from previous studies (Chin et al., 2003) (see Appendix C2). Antecedents explained 62.6% of consumer satisfaction and 50.8% of brand usage intent. The Harmon one-factor test revealed no significant common method bias. Control variables had no effect on dependent variables. Research model results are presented in Table 4 and Fig 5.

[Table 4. Hypothetical Results]

[Fig 5. Results of the Structural Model]

4. RESULTS AND ANALYSIS

4.1 Results

Most hypotheses were supported. Scenario failure positively correlated with response standardization ($\beta = 0.338$, $p < 0.01$), alternative solution ($\beta = 0.378$, $p < 0.001$), customer engagement ($\beta = 0.491$, $p < 0.001$), and employee attitude ($\beta = 0.359$, $p < 0.001$). This hypothesis further validates the findings from the initial qualitative research, indicating that when faced with scenario-based problems, consumers are more likely to adopt reconstruction and reinforcement strategies as solutions.

Personalization Failure had no significant relationship with rejection of excessive demand or customer engagement but positively correlated with mirroring ability ($\beta = 0.292$, $p < 0.01$) and training employee attitude ($\beta = 0.187$, $p < 0.05$). The lack of significant support for H2a may be attributed to a combination of factors, particularly users' tolerance for personalization failures and their subjective evaluation of the firms measures (Liu et al., 2023; Park, 2020). When users perceive these measures as aimed at improving the overall user experience or preventing resource misuse, they may not reject the restrictions due to personalization failures (Kim et al., 2023). As for the lack of support for H2c, it may be linked to users' attribution biases (Liu et al., 2023; Lv et al., 2021). Existing literature suggests that when users attribute personalization failures to the immaturity of AI technology rather than to the firm's failure to improve, they are less likely to engage in co-creation or provide suggestions for improvement (Castillo et al., 2021).

Value Failure positively correlated with response standardization, alternative solution, and mirroring capability ($\beta = 0.408$, $p < 0.001$). However, no significant relationship was observed between value failure and customer engagement (H3e), which may be attributed to several factors. First, if customers attribute value failures to uncontrollable factors, such as industry technological limitations or policy changes (Castillo et al., 2024), they may perceive that providing suggestions or engaging in co-creation would be futile, leading them to refrain from participating in the improvement process. Second, existing literature indicates that value-related failures are often difficult to explain, and firms frequently fail to offer robust explanations (Chen et al., 2025), which may further diminish customers' willingness to co-create. Additionally, some customers, after experiencing value failure, may opt to switch to competing products (Meng et al., 2025) rather than invest time in product improvement.

In reconstruction strategy, response standardization significantly correlated with consumer satisfaction, but alternative solution did not. Neither resolution measure correlated with brand usage intent. H4b, H5a, and H5b were not supported, which can be attributed to the following reasons. On one hand, the quality or timeliness of the alternative solution was insufficient, leading users to perceive these alternatives as unimportant(Zhang et al., 2022). On the other hand, users' expectations regarding the recovery offered by the alternatives were excessively high (Song et al., 2023). However, the actual effectiveness only met a basic level, making it difficult to achieve significant improvements in user satisfaction and brand usage intent. In reduction strategy, rejection of excessive demand negatively correlated with consumer satisfaction ($\beta = -0.134$, $p < 0.05$) and brand usage willingness ($\beta = -0.160$, p

< 0.05). Mirroring ability was unrelated to consumer satisfaction but positively correlated with brand usage intent ($\beta = 0.276$, $p < 0.001$).The lack of significant support for H4d may align with previous research findings(Liu et al., 2025). Some users, when the AI voice assistant accurately identifies their expectations, may experience privacy concerns or a sense of manipulation, which can diminish their satisfaction. Furthermore, in low-complexity tasks, users prioritize efficiency over being understood. In such cases, an increase in mirroring capabilities may not necessarily lead to a noticeable improvement in user satisfaction. In reinforcement strategy, employee attitude significantly correlated with consumer satisfaction ($\beta = 0.497$, $p < 0.001$) and brand usage intent ($\beta = 0.392$, $p < 0.001$), while customer engagement did not. This study posits that absent firm feedback or unresolved algorithmic issues may lead users to view their engagement as futile, thereby undermining its positive effect on satisfaction and brand usage intent. This explanation is also consistent with the findings of (Chen et al., 2025). Additionally, poor participation experiences (e.g., complex feedback mechanisms or limited incentives) can increase perceived burden and diminish users' engagement intention.

Overall, 62.6% of consumer satisfaction and 50.8% of brand usage intent were explained. For reconstruction strategies, response standardization and alternative solution accounted for 63.7% and 53.9% of explained variance, respectively. In reduction strategy, rejection of excessive demand and mirroring capability explained 38.3% and 38.7% of variance, respectively. For reinforcement strategy, customer engagement and training employee attitude accounted for 45.7% and 61% of explained variance, respectively. The results of the mediation analysis indicate that the attitude of training employee attitude mediates the relationship between scenario failure and satisfaction, as well as the relationship between scenario failure and brand usage intent. This indicates that adopting the approach of training employees' attitude can increase customer satisfaction and brand usage intent when facing scenario application issues. Mirror ability mediates the relationship between personalization failure and brand usage intent. The results show that adopting mirror ability can promote consumers' brand usage intent when facing issues related to technical personalization. Standardization of response and training employee attitude mediate the relationship between value failure and satisfaction. The mirroring capability and training employee attitude mediate the relationship between value failure and brand usage intent. This indicates that improving consumer satisfaction can be achieved through measures of response standardization and training employee attitude. Allowing consumers to perceive the good attitude of employees can strengthen the connection between the firms and consumers, as well as stimulate consumers' brand usage intent. In addition, mirroring capability is also beneficial for enhancing consumers' brand usage intent.

4.2 Comparative Analysis

We also posit that resolving AI voice assistant issues depends on consumers' relational norm orientation. Two types of relationship norm orientation theories exist: communal orientation, focusing on building strong customer relationships to address emotional needs, and task orientation, emphasizing task completion and communication efficiency (Verhagen et al., 2014). We devised two questionnaire scenarios based on these classifications (Aggarwal, 2004; Li et al., 2019), asking users to select their preference. With 93 choosing the first scenario and 128 the second, we conducted a comparative analysis (Table 5). The comparative analysis section was conducted to test whether distinct types of service failures (scenario-based, personalization-related, and value-oriented) produce differing consumer responses to the same remediation strategies. This approach directly supports hypothesis testing by examining interaction effects across failure categories, thereby validating whether certain strategies are universally effective or context-specific. For example, mirroring ability may be more effective in cases of personalization failure than scenario failure. The results indicate that three hypothetical paths exhibit significant variability between groups, suggesting that differing relationship norm orientations in service failure scenarios impact alternative solution and service attitudes' effects on consumer satisfaction and brand usage behavior. The comparative analysis contributes to the interpretation of certain hypotheses by offering additional insights into the results. Specifically, H5b did not pass the significance test in the overall model, and its effects were weak in both the task-oriented ($\beta = -0.044$) and community-oriented ($\beta = 0.021$) contexts. This suggests that the direct influence of alternative solutions on brand usage intent is limited. While the data does not support the significance of this path, significant inter-group differences were observed, implying that future research should explore the potential impact of this path further, particularly considering the role of other potential influencing factors. Conversely, both H4f and H5f received support within the research model. The comparative analysis further extends these results, revealing that in the task-oriented context, the influence of training employee attitudes on satisfaction ($\beta = 0.693$) and brand usage intention ($\beta = 0.652$) is notably stronger than in the communication-oriented context. This underscores the importance of prioritizing employee training to enhance service capabilities in task-oriented settings, thereby directly boosting user satisfaction and brand usage intent.

[Table 5. Comparative Analysis]

5. CONTRIBUTIONS

This research delves into the influence exerted by a firm's remediation tactics on customer satisfaction and brand usage inclinations in the context of service failure scenarios involving AI voice assistants. It succinctly outlines the problem dimensions and remediation approaches via qualitative research, scrutinizes customer preferences for firms' remediation tactics in different service failure scenarios using the Delphi expert interview technique, and employs a quantitative analysis to confirm the coherence of aligning technical problem traits with service solutions and their effects on consumer outcomes.

5.1 Theoretical implications

This study offers several crucial contributions to the realm of AI-empowered assistant studies concerning service failure scenarios. Firstly, we formulate a consistency theoretical model for AI voice assistant service solutions, which utilizes SSCT theory within AI voice assistant contexts for the first time. This model underscores that both the service failure process and the situational responses need to synchronize with the principal perspective. Should a service failure occur, it becomes incumbent on firms to allocate necessary resources to increase the likelihood of consumers interacting with their products (Hollebeek, 2011). We expand upon the original three categories of resolution strategies - reconstruction, reduction, and reinforcement - arguing that they can effectively address service failures. Moreover, we delve into the varying impacts of firm's remedies on consumers under task orientation and communication orientation, using norm orientation theories as our basis, thereby enriching and refining the theoretical framework of existing service recovery strategies.

Secondly, through a qualitative study of user reviews and product managers, this study not only responds to the limitations of the existing categorization framework for AI voice assistant service failures (Chen et al., 2022), but also extends and refines that framework. We propose a multi-dimensional classification system (Chen et al., 2022; Honig & Oron-Gilad, 2018) that not only serves as a valuable extension of traditional service theories in algorithm-driven contexts but also deepens the understanding of service failure types in AI voice assistants. To explore the underlying causes of service failures, this study systematically investigates user experiences across multiple service scenarios and identifies nine thematic dimensions. By employing a grounded theory approach, we offer a more comprehensive and structured analysis of the impacts of AI assistant service failures. Clarifying these key dimensions contributes to identifying and addressing barriers users face in adopting AI technologies, thereby offering valuable insights for future human-centric technological innovations.

Lastly, we extend the body of knowledge on service remediation literature (Vaerenbergh et al., 2018) by exploring consumers' favored resolution strategies within AI service contexts, providing directions for the development of firm strategies. This exploration uncovers the deep-seated effect of various strategies on consumer satisfaction and brand usage inclinations. More specifically, reconstruction strategies tie in with technical interaction aspects and bolster consumers' satisfaction experiences and brand usage intentions. Personality-related issues correspond to reduction strategies, with the enhancement of a firm's mirroring capabilities leading to a rise in consumer satisfaction and brand usage intentions. The matter of value failure pertains to all three strategies deployed by the firm, indicating the need for a multi-faceted response to address it.

This study introduces the innovative concept of mirroring capability within the service failure framework, addressing a theoretical gap in the research on AI voice assistant service recovery mechanisms. Unlike previous studies focusing on traditional response processes, economic compensation (Liu & Xu, 2023), and procedural justice, this study innovatively validates the role of mirroring capability in identifying users' intrinsic expectations and demonstrates its effectiveness in enhancing consumers' brand usage intentions. This finding expands the application boundaries of service recovery theory in the context of artificial intelligence. Notably, while previous literature has explored the direct impact of the AI environment (compared to traditional environments) on customer engagement (Yin et al., 2023), this study reveals a theoretical gap in understanding the mechanisms linking customer satisfaction and brand usage intention. We suggest that future research should delve deeper into the dynamic factors influencing customer engagement, thereby offering new insights for the development of related theories. Furthermore, this study empirically reveals the positive impact of employee training attitudes on consumers' response mechanisms when facing different types of service failures. These findings provide a fertile ground for the integration of disparate literature streams, and pave the way for future research into consumers' decision-making processes for service solutions.

5.2 Practical Implications

This research establishes a comprehensive framework of nine dimensions that characterize AI voice assistant service failure scenarios, offering a robust basis for firms to diagnose issues and define service failures accurately. The findings carry substantial relevance for AI voice assistant operators, furnishing strategic direction for rectifying product deficiencies, boosting sales, and enhancing corporate reputation. We have highlighted the causes of user dissatisfaction with the technology, such as subpar device learning capabilities and sporadic malfunctions.

Firms should adopt targeted and differentiated service recovery strategies based on the specific types of AI service failures, to enhance customer satisfaction and strengthen brand usage intention. For *scenario-based failures*, firms should prioritize the training of employees' service attitudes. When employees demonstrate a positive, empathetic, and professional attitude during interactions with users, it can effectively alleviate dissatisfaction caused by service disruptions. In addition, firms can pre-design a set of standardized voice prompts to guide users back to the correct usage context, thus avoiding confusion due to misoperation or unfamiliarity with the service scenario. Second, when facing *personalization-related failures*, firms should focus on enhancing their mirroring capability. This involves optimizing service processes and clearly defining service boundaries to help consumers set realistic expectations. For example, explicitly indicating the content and limitations of services in product manuals or service agreements can effectively prevent misunderstandings caused by information asymmetry. At the same time, firms should leverage multimodal technologies (such as voice and facial expression recognition) to capture user needs in real time and respond in ways that align more closely with user expectations. For instance, when signs of user anxiety are detected, AI voice assistants can adopt a softer and more empathetic tone to improve user experience and boost brand favorability.

Lastly, in addressing *value-based failures*, firms should emphasize the construction and execution of standardized response mechanisms. When users misunderstand the functionality of paid services, for example, companies should promptly activate standardized explanatory scripts to clearly and accurately communicate the value of these services. Such process-based responses can not only improve response efficiency but also enhance the professional image of the firm, thereby increasing customer satisfaction. However, it is important to note that relying solely on alternative remedies may not significantly enhance consumers' brand usage intention, and may even have adverse effects. In particular, when users express overly high service expectations, a direct rejection by the firm may cause users to feel neglected, thereby weakening their trust and loyalty to the brand. Therefore, when dealing with value-based failures, firms should place greater emphasis on effective communication and proactive guidance rather than resorting to simple rejection or avoidance.

To mitigate service failures, firms should contemplate bolstering their capabilities instead of solely depending on traditional approaches. Our research affirms the efficacy of business interventions in resolving specific problems, while concurrently recognizing that some consumer apprehensions might surpass a firm's technological prowess. Firms ought to clearly articulate the capabilities of their technology and endorse each product enhancement as a unique selling proposition, thus assisting consumers in comprehending the limitations of AI assistants. It's also essential to underscore that innovations in fundamental technology ignite consumers' personalized needs. However, due to consumers' limited understanding of the distinction between big data computations and services, the expectations about the service are often not met. When issues such as low personalization and inadequate deep emotional interaction with AI voice assistants' surface, firms need to relentlessly upgrade their capability to discern customer expectations. Continuous enhancement of a firm's mirroring abilities emerges as the most promising strategy to boost brand usage intent.

We place significant emphasis on the role of positive communication attitudes during the service remediation process. Despite the psychological distance created by AI's multi-sensory stimuli (Lv et al., 2022), catering to fundamental consumer emotional needs can yield positive outcomes. Firms should focus on strengthening employees' attitude training in the service recovery process, enabling them to demonstrate a proactive service attitude when facing customer complaints or dissatisfaction. For instance, employees can learn to use empathy to perceive customers emotions and provide timely reassurance. This positive service attitude can not only effectively alleviate customers dissatisfaction but also significantly enhance their trust in the brand. This study also points out that when involving customers in service recovery, firms must fully recognize the complexity of this process. Although the results of this study have not yet found a significant role of customer engagement, many factors can indeed influence consumers final satisfaction and brand usage intention. Taking the feedback link for product improvement as an example, firms can invite some professional users to participate in it and obtain valuable suggestions by leveraging their profound professional knowledge and rich practical experience.

However, firms also need to avoid over-reliance on the non-professional opinions of ordinary users to prevent business decision-making mistakes.

Furthermore, from the standpoint of AI users with differing norm orientations, firms must exercise prudence when strategizing for diverse audience groups. For task-oriented consumers, the positive impact of training employee attitude on user satisfaction and brand usage intention is significantly higher than that in communication-oriented contexts. This highlights the importance of prioritizing employee training to enhance service capabilities in such contexts. Moreover, the direct impact of alternative solutions on brand usage intention is relatively limited. Therefore, firms should avoid over-reliance on alternative solutions and instead provide efficient and targeted solutions directly.

6. Limitation and Future Research

This study has limitations, primarily focusing on family and personal life aspects without considering other contexts. Future research could address this. Additionally, our data acquisition relied on secondary data from expert Q&A sessions rather than direct interviews with product managers, potentially causing subtle discrepancies in understanding during manual coding. Although we examined the relationship between service failure characteristics and firm remediation, we did not fully explore the underlying mechanisms. The inclusion of multiple variables in the study has increased its complexity, which may potentially lead to insufficiently in-depth explanations of certain relationships. Future studies might use a laboratory approach to address this gap. The relatively small sample size of this study has also limited the robustness and generalizability of the conclusions to some extent. Moreover, this research does not investigate social contextual and firm characteristic aspects of remediation, which could enrich our understanding of cutting-edge AI assistant services. While our study adopts a comprehensive, exploratory approach to capture multiple facets of AI voice assistant service failures and remediation strategies, we recognize that this broad scope introduces complexity in interpreting results clearly. We acknowledge this as a limitation and suggest future research could focus more narrowly, analyzing individual failure types or specific remediation strategies separately and in greater detail. Such focused studies can provide more nuanced insights into consumer reactions and remediation effectiveness. The findings may be shaped by platform-specific norms and user behaviors, with potential variation across Western contexts. Future research should pursue cross-platform and cross-cultural comparisons.

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TABLE

Table 1 Crisis Management Strategies and Contextualization

Strategy	Main Content	Contextualization
Reconstruction Strategy	Rebuild stakeholder relationships by redeeming the organization's reputation and apologizing to affected customers, especially if the organization has had similar negative crises in the past.	Response content, response quality, response time
Reduction/denial Strategy	Minimize liability to the organization by justifying and explaining the firm's actions. The strategy helps companies to minimize negative impacts while avoiding unnecessary faults. The latter aims to reassign responsibility or to deny the crisis. The situation is suitable when the organization is faced with non-objective allegations.	Rejecting excessive demand and identifying customer expectations
Reinforcement Strategy	Organize the face of the crisis through dedication and attitude of loyalty.	Customer engagement, communication attitude

Table2. Thematic Dimensions and Main Category

Main Categories	**Scenario Services**	**Personalized Services**	**Value-based Services**
Dimension	• Infrastructure • Scene Flexibility • Voice Interaction • Automated Decision Making • Exceptional Risk	• Conversation Personalization • Extended Services	• Privacy Security • Profitability Value
Conceptual Definitions	During the use of the AI assistant, consumers will encounter problems with the basic functionality of the product, and these services are not accessible for that product.	While AI assistants can meet basic tasks, there are still many personalized communication aspects that need to be improved, among others.	As AI smart assistant technology continues to improve, consumers are more focused on the trade-off between the benefits gained in that environment and privacy breaches.

Table 3. Descriptive Statistics

Type	Proportion
Gender	Male：42.1%; Female：57.9%
Age	1-20：1.4%; 21-30：57%; 31-40：36.2%; 41-50：4.1%; 51-60：1.4%
Education	General High School：3.6%; Specialties：11.3%; Bachelor’s degree：75.1% Master’s degree：8.6%; PhD：1.4%
Occupation	Student：10.9%; State-owned firms：26.2%; Public institution: 13.1% Civil servant:3.6%; Private firm:41.6%; Overseas-funded firm:4.1%; Other：5%

Table 4 Hypothetical Results

Hypothesis /path	P-Val.	T-Val.	Result
H1a：Scenario Failure -> Standardization of response	0.005**	2.787	Support
H1b：Scenario Failure -> Alternative Solution	0.000***	3.731	Support
H1c：Scenario Failure -> Customer Engagement	0.000***	5.234	Support
H1d：Scenario Failure -> Training Employee Attitude	0.000***	5.271	Support
H2a：Personalization Failure -> Rejection of excessive demand	0.942(n/s)	0.073	NO
H2b：Personalization Failure -> Mirroring Capabilities	0.002**	3.179	Support
H2c：Personalization Failure -> Customer Engagement	0.272(n/s)	1.098	NO
H2d：Personalization Failure -> Training Employee Attitude	0.015*	2.438	Support
H3a：Value Failure -> Standardization of Response	0.000***	7.481	Support
H3b：Value Failure -> Alternative Solution	0.000***	3.992	Support
H3c：Value Failure -> Rejection of excessive demand	0.000***	7.945	Support
H3d：Value Failure -> Mirroring Capabilities	0.000***	3.650	Support
H3e：Value Failure -> Customer Engagement	0.182	1.335	NO
H3f: Value Failure -> Training Employee Attitude	0.000***	5.152	Support
H4a：Response Standardization -> Satisfaction experience	0.039*	2.068	Support
H4b：Alternative Solution -> Satisfaction with the experience	0.954(n/s)	0.057	NO
H4c：Rejection of excessive demand -> Satisfaction experience	0.033*	2.133	Support
H4d: Mirroring capabilities -> Satisfaction experience	0.176(n/s)	1.354	NO
H4e: Customer engagement -> Satisfaction experience	0.411(n/s)	0.822	NO
H4f: Training Employee Attitude -> Satisfaction experience	0.000***	8.199	Support
H5a：Response Standardization -> Brand Usage Intent	0.727(n/s)	0.350	NO
H5b：Alternative Solution -> Brand Usage Intent	0.897(n/s)	0.130	NO
H5c：Rejection of excessive demand -> Brand Usage Intent	0.012*	2.514	Support
H5d：Mirroring capabilities -> Brand Usage Intent	0.000***	3.502	Support
H5e：Customer Engagement -> Brand Usage Intent	0.829(n/s)	0.216	NO
H5f：Training Employee Attitude -> Brand Usage Intent	0.000***	4.158	Support

Table5 Comparative Analysis

Assumptions	Task-oriented		Communal-oriented		
	Path coefficient	T-Value	Path coefficient	T-Value	P-value
Alternative Solution -> Brand usage Intent	-0.044	1.534	0.021	1.791	0.029
Training Employee Attitude -> Satisfaction	0.693	7.774	0.366	3.661	0.018
Training Employee Attitude -> Brand usage Intent	0.652	5.101	0.199	1.553	0.011

FIGURE

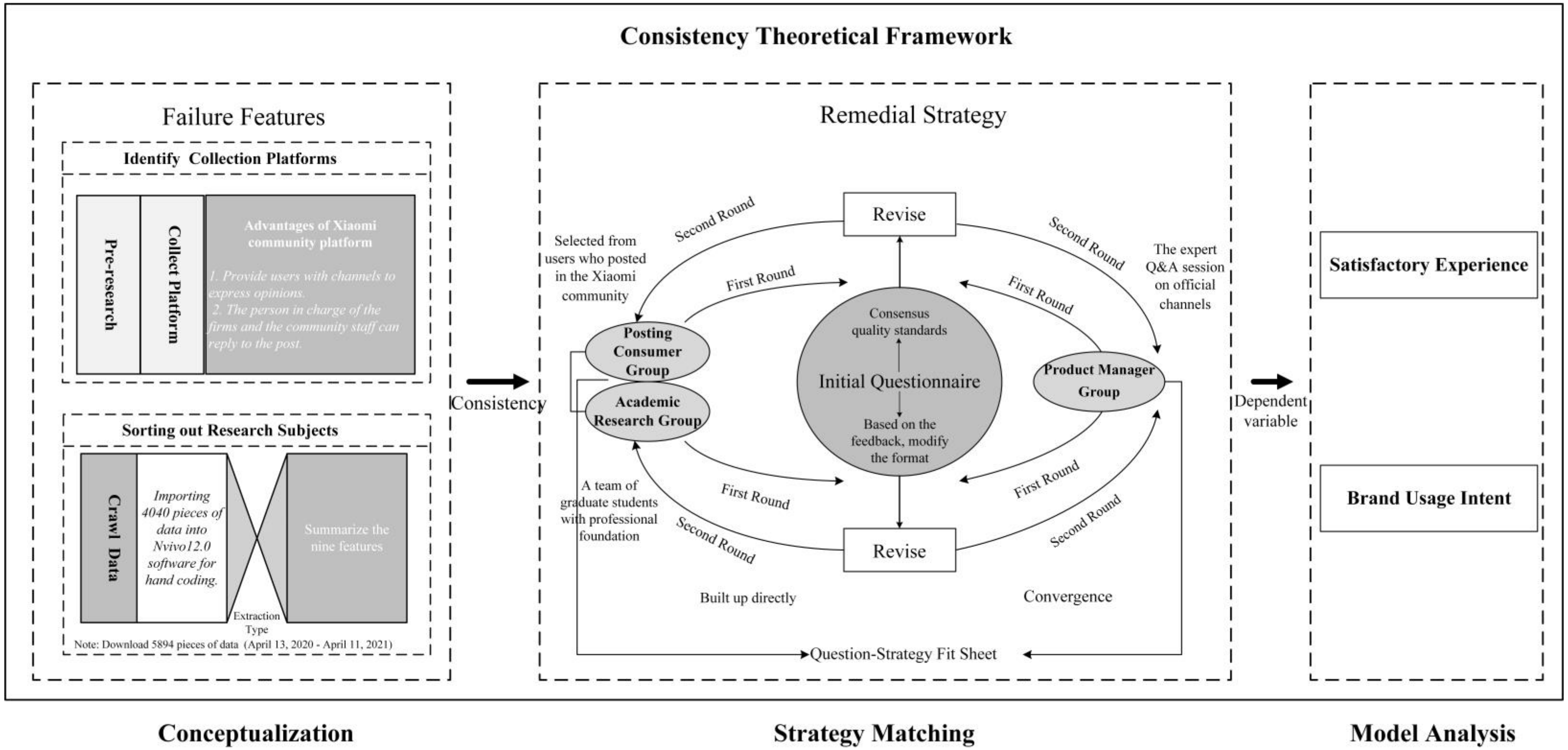


Fig 1. Theoretical framework Perspective

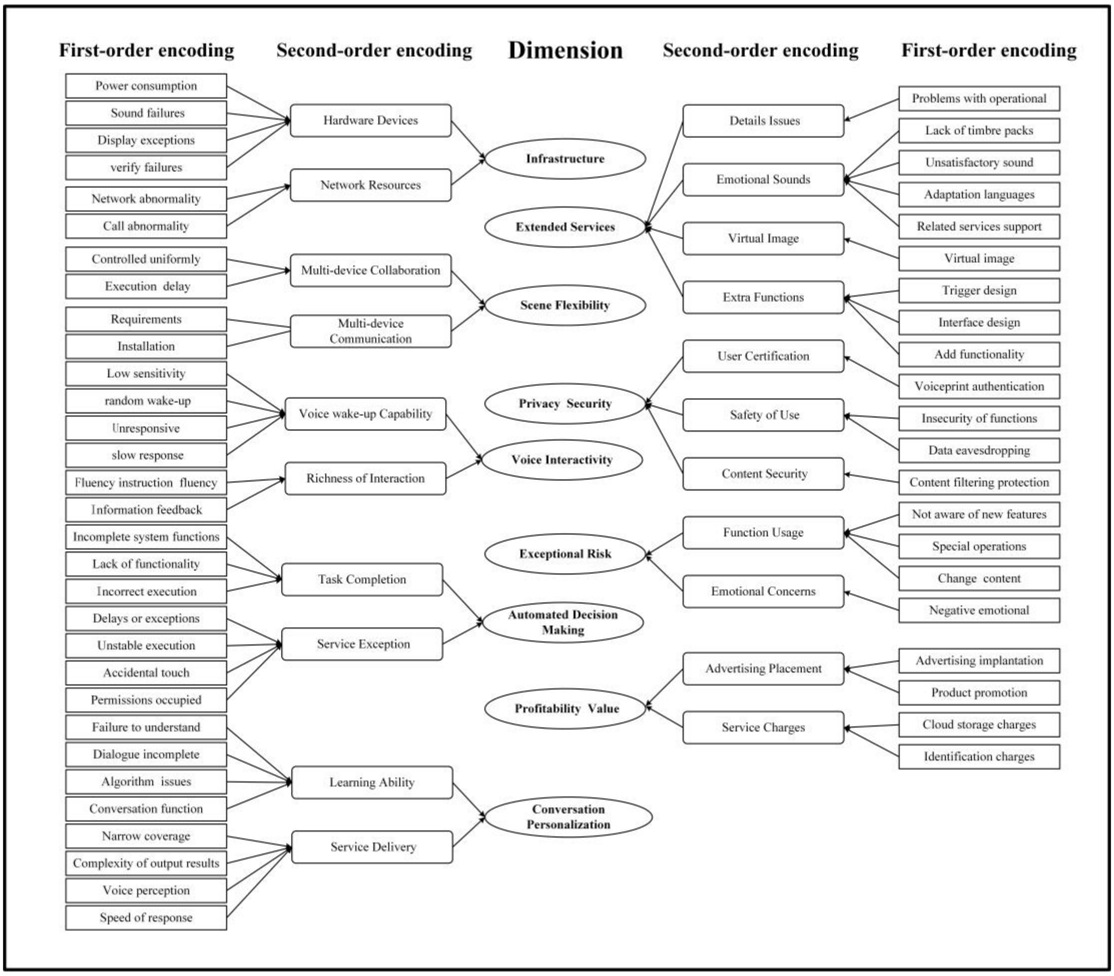


Fig 2. Coding Process

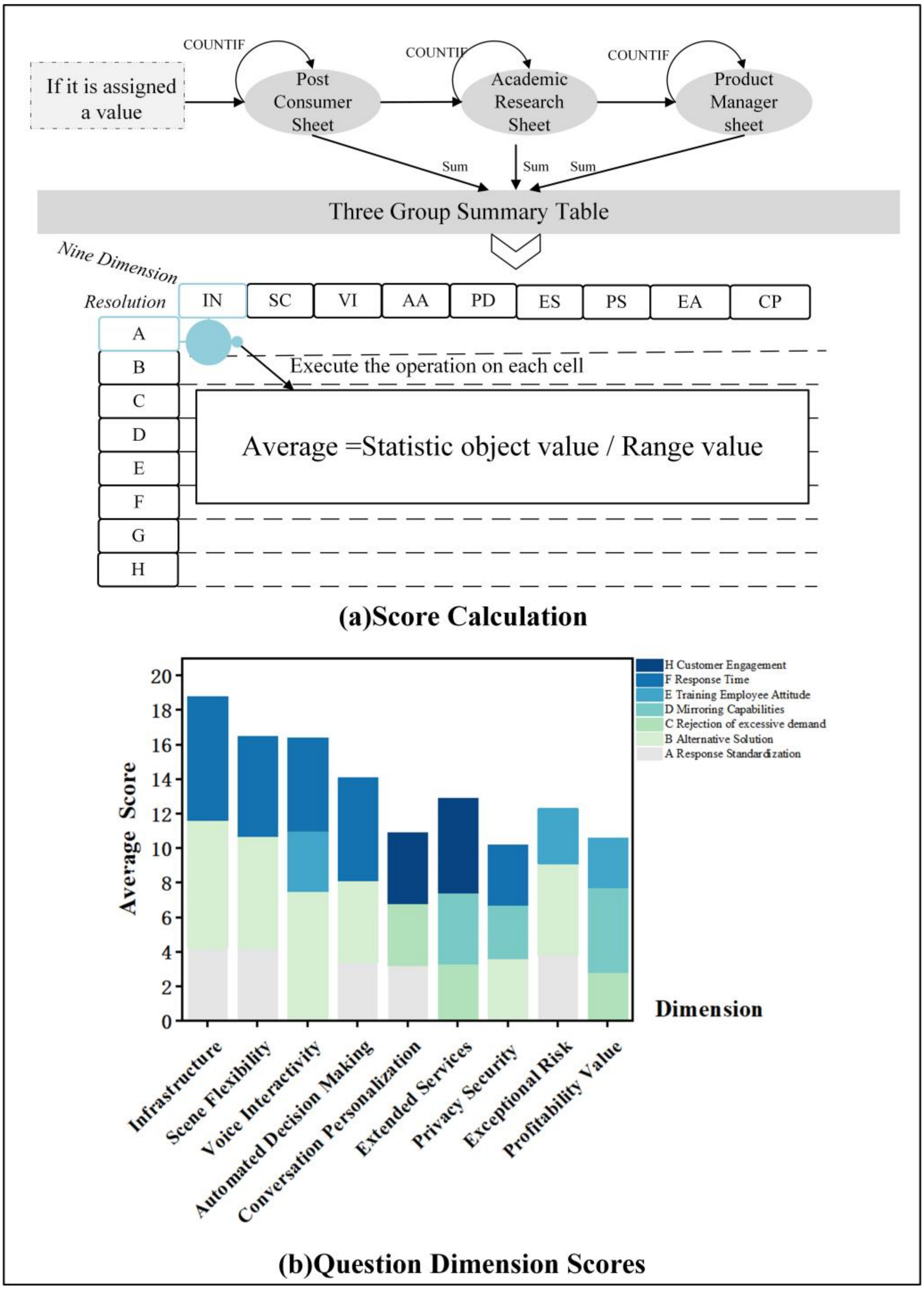


Fig 3. Score Calculation and Outcomes

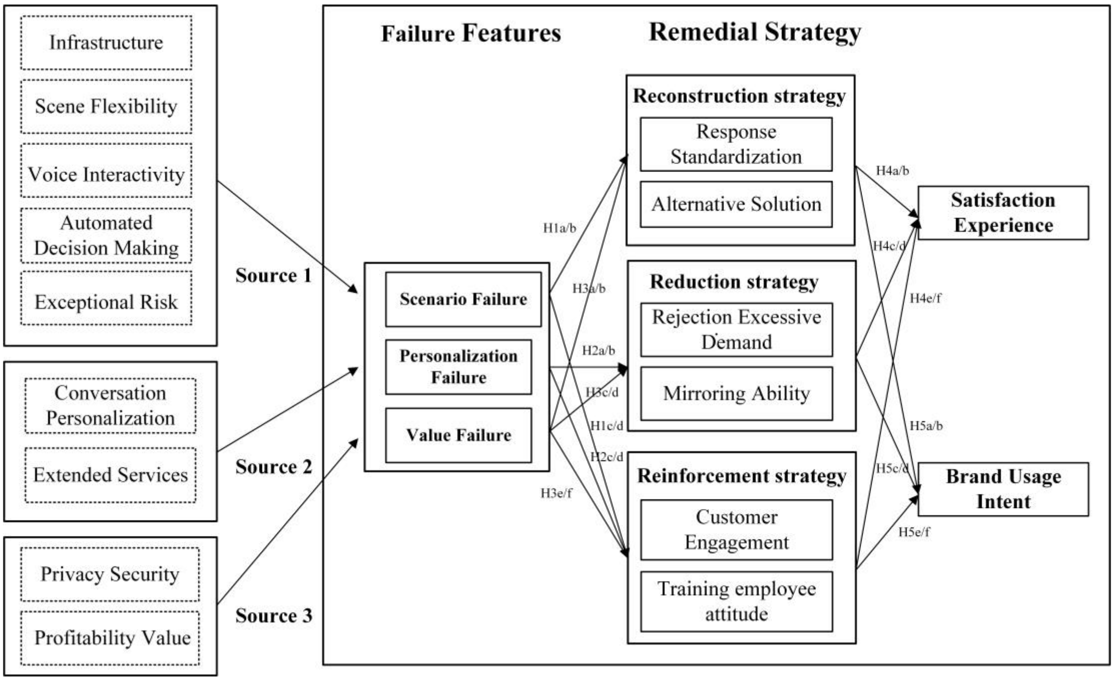


Fig 4. Research Model

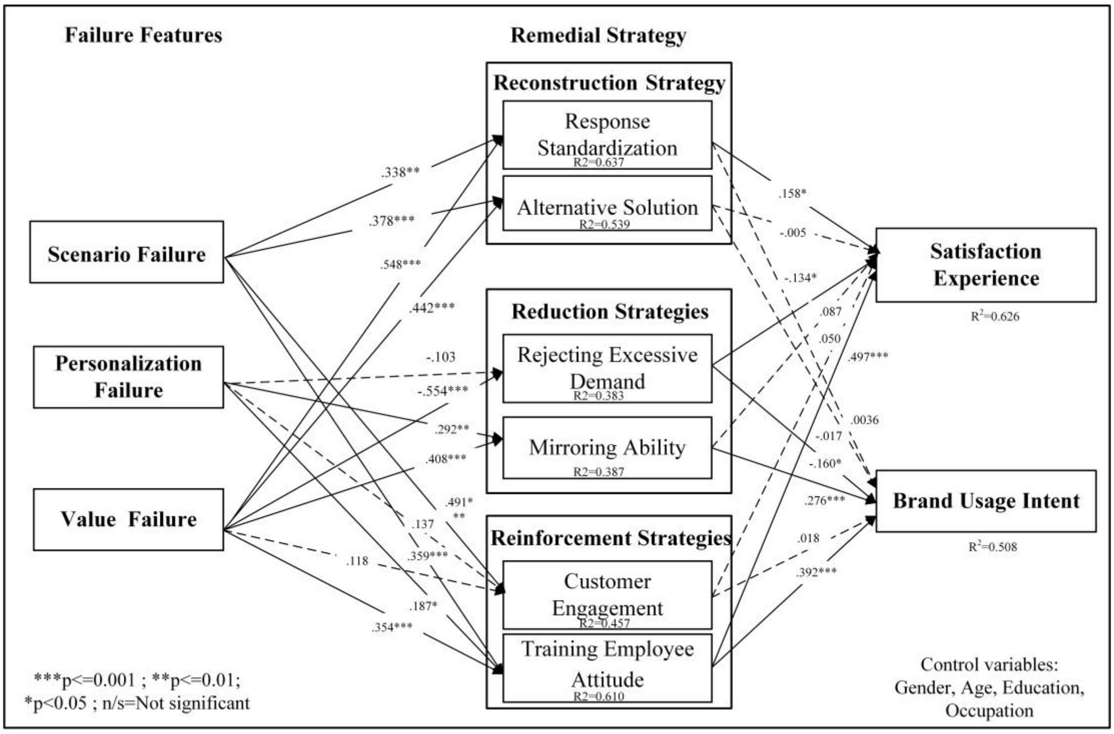


Fig 5. Results of the Structural Model

APPENDIX A

A1 Relevant literature on AI service failures

TableA1.Categorization of Research Perspectives

Perspective	Literature	Type of Failure	Findings	Summary
Service Process	(Chen et al., 2021; D. Liu et al., 2023)	Process failure and outcome failure	The former refers to defective or insufficient service delivery; the latter refers to the failure of the service to meet the basic needs of consumers.	The research literature is abundant, with extensive discussions in both traditional service and AI service fields.
	(Rita Gonçalves et al., 2025)	AI classification failure	AI classification failure can undermine consumers' self-identity and increase negative outcomes.	
	(Song et al., 2023)	Functional attributes and non-functional attributes (Non-functional failure)	The former is interpreted as the failure of machine personnel to provide basic services. The latter is the inability to provide services as expected.	
	(Honig & Oron-Gilad, 2018)	Communication failures and processing failures	The robot failure information processing model: communication failure; perception and understanding of failure; resolving failure. Technical failures are more focused on than interaction failures.	
	(Majeed et al., 2024)	Service failure stages; Service failure severity	Affect the cognitive responses and behaviors hotel of customers. The intensity of the tangible and intangible losses that customers perceive from the service failure affect their perceptions of and behavioral responses to the service provider.	
Information processing	(Zhang et al., 2024)	Information service failure	Information service failure is caused by inaccurate, incomplete, irrelevant, and incorrect information.	Despite the extensive discussions, the research perspectives are rather singular. There is a need to further explore the information issues that arise in different facilities and scenarios.
	(Song et al., 2025)	Incomprehensibility, lack of personalization, lack of capability, and lack of assurance	AI chatbot service failure positively impacts dehumanization and increases customers' perceptions of the severity of the service failure.	
	(Tan et al., 2024)	Stability and controllability	Stability refers to the persistence or transience of the factors causing the service failure. Controllability refers to the extent to which the service provider can change the causes of the failure. Perceiving that the service provider has the capability to avoid the failure but fails to do so increases the likelihood of negative emotions and behaviors.	
Responsibility Attribution	(Castillo et al., 2024)	Company responsibility, external environment	Advocating for control over subsequent interactions with the firm. The concept of attributing responsibility to external factors is rooted in self-serving bias, reflecting individuals' tendency to take more responsibility for success than for failure.	The literature is relatively scarce and fragmented. Particularly, there is a lack of in-depth discussion on the responsibilities for unexpected risks caused
	(Leo & Huh, 2020)	human service providers and service firms	When service failure occurs, if the service provider is a robot rather than a human, people are less likely to hold the robot itself accountable and more likely to blame the service company. This is because people perceive that robots have less control over the service outcomes than humans.	

	(Gu et al., 2024)	Internal and external	Internal attribution refers to attributing the failure of an AI chatbot to its capabilities, such as algorithms and NLP decision trees; whereas external attribution involves blaming environmental factors or human errors. Algorithmic errors can lead to service failures. Due to the "black box" nature of algorithmic decision-making, consumers are not only frustrated by the errors themselves but also by the lack of interpretability in algorithmic decisions.	by AI automated decision-making.
	(Chen, 2024)	Algorithm interpretability	Algorithmic failures are more widely generalized than human failures. Algorithmic empathy does not reflect a universal aversion to algorithms but is rooted in social categorization: it stems from how people perceive a group of AI systems compared to a group of humans.	
Customer Needs and Perception	(Longoni et al., 2022)	Algorithm empathy, procedural unfairness, and interactional unfairness	Algorithmic failures are more widely generalized than human failures. Algorithmic empathy does not reflect a universal aversion to algorithms but is rooted in social categorization: it stems from how people perceive a group of AI systems compared to a group of humans.	The literature has been moderately discussed but still needs further exploration. There is a gap in the research on personalized failure perception and the failure perception related to AI-enhanced services.
	(Castillo et al., 2021)	Authenticity issues, cognitive challenges, emotional issues, and integration conflicts	The covert presence during interactions, showing a lack of understanding, customers expect chatbots to display a certain degree of empathy. Integration conflicts lead to the loss of time and emotional resources.	
	(Peng et al., 2024)	Aesthetic failure	AI live-streaming aesthetic failure refers to the visual effects of the live-streaming environment, interaction design, virtual host image design, or interface layout being unattractive, and may even lead to consumer dissatisfaction.	
	(Lv et al., 2022)	Rejection and neglect	Claiming that consumers' service requests cannot be resolved due to a lack of flexibility (rejected by social AI). Due to a lack of common sense (ignored by social AI). Specifically, in the context of being rejected, individuals' social belonging needs are threatened.	

A2. Detailed Explanation of Mixed Methods

TableA2.Rationale and Steps for Selecting Mixed Methods Research

Guidelines	Rationale for the Study	Specific Considerations
(1) Suitability of Method	The data chain for evaluating the effectiveness of firm remedial measures cannot be collected on social platforms (i.e., firms post various solutions on platforms but do not know the level of user satisfaction).	· We first define the qualitative and quantitative research questions. · The qualitative research question is: In the context of AI assistant service failures, what remedial measures do consumers expect? · The quantitative research question is: How do different service failure issues faced by consumers influence the firm remedial measures?

		• The mixed research question is: How do different aspects of service failure affect the satisfaction and brand usage intentions? • Quantitative research further tests qualitative results, while the mixed research question relies on both qualitative and quantitative research results.
(2) Mixed Research Method Design	The qualitative study results will inform the subsequent quantitative research on a theoretical level, a sequential approach should be adopted.	• In sequential mixed-method design, qualitative and quantitative data collection and analysis are implemented at different stages, and each stage is integrated within its own separate phase.
(3) Data Analysis Strategy	Sampling Design Strategies	• The qualitative research sample and quantitative sample populations are not the same, but fit the same context of experiences of failing to use intelligent assistant services. • The qualitative research sample population originated from three categories: the academic researcher group, the product manager group, and the posting consumer group.
	Data Collection Strategies	• Qualitative research: using a pre-set interview schedule followed by open-ended questions. • Quantitative research: closed questions (questionnaire).
	Data analysis strategies	• Utilizing the Delphi method for the qualitative study: The first round of expert consultation is conducted, and then the ideas newly proposed by the experts are incorporated to modify and integrate the findings. Subsequently, a second round of expert interviews is carried out until theoretical saturation is achieved. • Analyzing qualitative data first, followed by quantitative data.
(4) Meta-analysis	Transitioning from specific observations to broader generalizations and theories.	• The rationality of content extraction. • Hypotheses are proposed in the interviews of this paper, and then the hypotheses are tested.
(5) Quality Assessment and Validation	Quality of analytical reasoning	• Compliance with reliability coefficients for qualitative and quantitative research standards.

A3. The Coding Scheme and Data

TableA3. Open Coding

Num	Categories	Raw Data
1	Power Consumption Issues	"Xiao Ai is too power-hungry; it tops the list."
2	Sound Malfunctions	"Unable to play sound, device makes static noise. Audio stuttering, microphone issues."
3	Display Anomalies	"Life progress bar malfunctions, font changes abnormally"
4	Submission or Verification Failures	"Xiao Ai, for example, shows device verification failure during voice package customization."
5	Network Issues	"Server busy, no network connection, network anomaly pop-ups."
6	Call Anomalies	"Bluetooth headphones Air2 have intermittent call issues."
7	Inability to Control Devices Uniformly	"Both phone and speaker wake up simultaneously and respond."
8	Execution Delays	"Xiao Ai takes over ten seconds to turn on the bedroom light via voice command."
9	Excessive Communication Requests	"After operating home appliances via Xiao Ai, Mi Home keeps popping up to ask for likes. Is there a way to turn this off?"
10	Communication Device Installation	"Xiao Ai for Xiaomi Notebook shows 'Your account does not seem to be associated with any applicable devices.'"
11	Low Sensitivity	"Xiao Ai is not very responsive; it doesn't answer when called!"
12	Unintended Wake-ups	"Why does Xiao Ai start talking so easily?"
13	No Response After Wake-up	"Xiao Ai wakes up but doesn't respond to subsequent commands when continuous dialogue is enabled."
14	Inconvenience in Command Conveyance	"I have to unlock my phone every time I call Xiao Ai. What's the point then?"
15	Lack of Feedback	"Xiao Ai only shows subtitles instead of speaking after being called up. It no longer shows detailed information about the headphones in the status bar."
16	Incomplete System Functions	"Xiao Ai can't stop music playback. The microphone remains occupied even after the music stops."
17	Lack of Important Features	"When will Xiao Ai get voiceprint recognition wake-up? It was proposed last year, but it's still not available in the stable version. Don't tell me it's due to hardware limitations. If that's the case, why is it available in the development version?"
18	Failure to Execute Functions Correctly	"Without location turned on, asking Xiao Ai for the weather gives information for another city."

18	Failure to Execute Functions Correctly	"When I call Xiao Ai on WeChat and ask her to exit, WeChat also closes."
19	Delays or Anomalies Caused by Service Provider Review	"I accidentally shared my Xiao Ai training, and now it's been in review for weeks. I can't cancel it. What should I do?"
20	Unstable Function Execution	"Frequent crashes, unable to load class schedules."
21	Accidental Execution of Specific Functions	"The 'Where is Xiao Ai' function triggers automatically."
22	Occupation of Relevant Permissions	"Xiao Ai occupies the recording permissions of other apps."
23	Failure to Understand User Needs	"I say a sentence in English, and Xiao Ai opens KuGou music."
24	Incomplete Dialogue	"Xiao Ai sometimes stops responding mid-sentence when called via voice command."
25	Algorithm Performance Issues	"Xiao Ai needs to improve its arithmetic. Division and 'divided by' are different."
26	Insufficient Detail in Dialogue Functions	"After saying goodnight to Xiao Ai, the music she plays can't be set to stop automatically. I have to get up and turn it off manually. Can't this be improved?"
27	Limited Service Chain Coverage	"Can book domestic flights but not international ones." "Can it answer FAQs related to air travel?"
28	Complexity of Output Results	"It just shows a string of plain text. Why can't it provide a direct link to the desired page?"
29	Voice Perception and Speech Rate	"The biggest drawback of Xiao Ai is its poor handling of text emotions and corresponding word rates. For example, the word 'hάo heng' (arrogant), Xiao Ai pronounces it as 'h άo hēng,' which lacks the right flavor."
30	Operational Details	"I hope Xiao Ai can be added to the negative one screen for quick access."
31	Limited Voice Packs	"Can we add a voice pack like JARVIS, something with a strong tech feel?"
32	Unnatural or Inaccurate Voice	"The Jasmine voice sounds odd, like speaking with a mask on."
33	Addition of More Languages	"Can we add Cantonese to Xiao Ai's language options?"
34	Support for Custom Services	"The AI call function doesn't support my custom voice. I set it, but it doesn't use the custom voice after exiting. What's going on?"
35	Virtual Avatar	"When will Xiao Ai get a live2D avatar like the Black Shark phone? It would feel more interactive."
36	Trigger Design	"I'd love to set certain triggers for automatic reading. For example, when charging starts, it could say 'Charging

		started, estimated 38 minutes to finish.' When charging ends, it could say 'Charging complete. Have a nice day.'"
37	Interface Design	"Simplicity, color scheme, floating window style, etc."
38	Addition of Functions	"Wouldn't it be better if Xiao Ai had a reading function like Siri?"
39	Voiceprint Authentication	"I strongly support voice encryption for privacy and security."
40	Function Insecurity	"Please fix a bug in Xiao Ai. She can bypass app locks and open hidden apps directly, which is a privacy risk. I hope the official team can fix this."
41	Data Eavesdropping	"Can smart devices eavesdrop on my calls?"
42	Content Filtering Protection	"I hope smart assistants can add child content filtering."
43	Unfamiliarity with New Functions or Special Operations	"I had this feature when I first bought my phone, but I accidentally turned it off. Now I want to use the multi-function keyboard with Google Pinyin Input. How can I do that? The voice I added in the voice store is not showing up in the voice settings."
44	Inability to Customize Content	"Why can't I change Xiao Ai's name?"
45	Pure Negative Emotion Expression	"Xiao Ai is being rebellious."
46	Ad Insertion	"Have you noticed that Xiao Ai is starting to show ads? Is it necessary for a voice assistant to insert ads into conversations? It feels like she's a salesperson for others. This only prolongs the time it takes for me to get the main information."
47	Product Promotion	"Sometimes ads include a lot of product promotion content."

This part discusses how different types of comments are associated with service failure categories (see TableA4). Hardware and network resources, as foundational elements in the implementation of AI assistant systems, are categorized under the infrastructure dimension. Considering that consumers interact with AI assistants to perform tasks in various contexts, but that environmental factors often contribute to service failures, we conceptualize this as the scene flexibility dimension. Recent algorithmic optimizations aim to enable smart assistants to autonomously complete tasks, thus issues related to this are grouped under automated decision making. Human-machine interaction, a key feature of smart assistant applications, requires further consideration of user sensory experiences and operational convenience. However, the current maturity of AI voice assistant services remain limited, leading to consumer complaints about their perceived lack of intelligence. These issues are encapsulated in the Voice Interaction dimension. Some consumer comments also refer to occasional or individual-specific failures, which we classify under Exceptional Risk. A frequent issue highlighted by consumers is the inability of smart assistants to provide personalized responses and recommendations based on diverse user needs and commands. Consumers particularly point out two aspects: ongoing issues with conversational learning and concerns over the scope and quality of services offered. These problems are summarized in the conversation personalization dimension, which reflects the assistant's ability to offer tailored responses during interactions and services. Additionally, many comments mention the limited range of voice options, with consumers expressing a desire for more virtual personas. These comments are grouped under extended services. Privacy-related concerns are also raised, as consumers believe that while AI voice assistants offer convenience, they also pose security risks. With the growing popularity of wearable smart devices, which collect sensitive data through the monitoring of daily activities (Perera et al., 2015), it is crucial to identify potential threats to privacy and implement appropriate security measures. Thus, these concerns are categorized under privacy security. Lastly, some comments note that firms charge additional fees for cloud storage and smart recognition features, which consumers view as hidden costs detrimental to their experience. These issues are encapsulated under the profitability value dimension.

TableA4.Axial Coding Process

Dimension	Second-order encoding	First-order encoding
1.Infrastructure	1.1 Hardware devices	Power consumption problems, Sound failures, Page or shortcut display exceptions, Verify failures
	1.2 Network resources	Network abnormalities Call abnormalities
2.Scene Flexibility	2.1 Multi-device collaboration	Related devices cannot be controlled uniformly, Device execution delay
	2.2Multi-device communication	Excessive requirements, Communication equipment installation
3.Voice Interaction	3.1 Voice wake-up capability	Low sensitivity, Random wake-up, Unresponsive or Slow response after wake-up
	3.2 Richness of interaction forms	The fluency of instruction transmission, Not receive information feedback
4.Automated Decision Making	4.1 Task completion	Incomplete system functions, lack of important functions, Incorrect execution of functions
5.Conversation Personalization	5.1 Learning ability	Failure to understand user needs, Dialogue incomplete, Algorithm performance issues, Conversation function
	5.2 Service delivery	Narrow service chain coverage，Complexity of output results，Voice perception and speed of response
6.Extended Services	6.1 Details issues	Problems with operational details
	6.2 Emotional sounds	Lack of timbre packs, unsatisfactory sound, increased adaptation languages
	6.3 Virtual image	Adding virtual image
	6.4Extended functions	Trigger design, interface design, add functionality

7.Privacy Security	7.1 User certification	Voiceprint authentication
	7.2 Safety of use	Insecurity of functions, Data eavesdropping
	7.3 Content Security	Content filtering protection
8.Exceptional Risk	8.1 Function usage	Not aware of new features or special operations,
	8.2Emotional concerns	Negative emotional expression
9. Profitability Value	9.1Advertising Placement	Advertising implantation, product promotion
	9.2 Service Charges	Cloud storage, Intelligent identification charges

APPENDIX B

B1. Specific Development Details

This section introduces the process and details of the development of service remedies variables. As cited below, negative attitudes toward AI assistants are shaped by direct experiences with the service provided by the product itself. Many common issues frequently mentioned by interviewees include the inability to accurately recognize problems, significant limitations due to network conditions, and an inability to fully meet functional demands. In other words, as firms promote this technology, they find that diverse consumer needs are sometimes difficult to satisfy in full. For example:

"I hope the firm can provide a parameter sheet for hardware, software, network quality, etc., to help customers select compatible routers and devices to improve the stability of smart home systems. Currently, the smart home devices in my house disconnect easily. Some online sources say it's the router, but I don't know what kind of router would meet the needs. Also, the response time varies sometimes fast, sometimes slow. I'm unclear about the root cause. The company hasn't provided detailed guidance documents for setting up smart homes, nor any testing methods. What I know so far about setting up a smart home feels like a matter of luck; whether it works well or not is unstable."

At this point, standardized responses and related solutions are necessary. Consumers admit that when issues arise, they prioritize whether the response contains valuable information, as one interviewee expressed:

"I hope customer service has strong professional knowledge. Many times, customer service explanations are not as clear as the consumer's understanding. If customer service doesn't know something, I hope they will seek help from a supervisor, rather than offering an assumption. Also, I hope customer service is always available and that it is easy to find contact channels."

"I hope the company can reassess their product, provide reasonable explanations to customers, and offer appropriate compensation based on relevant regulations. I once

bought a product that developed some quality issues within about a month. When I contacted the official website, their solution was very satisfactory, they had me send the product back for repair and then shipped it back to me, covering the shipping costs. When it was returned, they also included some small gifts. The company could offer on-site services because these smart assistants are at the core of smart home integration. The issues and scenarios vary from person to person or household to household, so on-site support can help pinpoint the problem more accurately and resolve it more quickly."

Many respondents emphasize that companies should focus on communication attitudes when solving AI assistant-related issues. The intention or action to replace existing smart assistant products during the entire purchasing and usage process is often linked to the emotional experience of the service. In our interviews, we also observed consumers' positive attitudes toward service failures themselves, which are often connected to the product's promising vision. In other words, consumers are sometimes willing to accept the reality that AI assistants lack conversational intelligence, viewing it as an ongoing task for the company. For example, a consumer facing a service failure scenario stated:

"When the company's employees have a good attitude, even if the product had some issues previously, once they provide a solution, I no longer feel upset. If the problem is minor, I focus more on the emotional resolution. Besides paying attention to customer service's problem-solving ability, the company should listen to user feedback and further improve aspects such as customer service attitude."

On the other hand, customer engagement in open innovation is also a vital route for addressing product defects. Several respondents mentioned:

"Regular user feedback collection: Collecting feedback from users of different functions in a centralized online system to summarize any functional errors, or conducting online forums to gather new user demands and fix existing issues. Additionally, more channels for user participation should be provided."

"Timely system upgrades, with the company inviting interested users to participate in internal testing, allowing them to identify issues or offer suggestions in advance. Alternatively, conducting internal tests with users who have varying levels of familiarity with the smart assistant."

Furthermore, in the process of communicating with customers, firms may sometimes be unable to fully address or meet all of the customer's issues. In such cases, the company should further identify user needs, exclude unreasonable demands, and focus on addressing the core issues. For certain organizations, these issues are critical. As one respondent mentioned:

"The gateway device has an open remote assistance feature, which, when authorized, allows remote monitoring of its status. However, for other users, this action poses a risk, so the company is currently unable to respond to this issue. If the company faces difficulty in choosing an appropriate response, negative consumer attitudes may lead to product replacement. "

Therefore, firms sometimes adopt solutions that involve rejecting excessive demands to address the problem.

TableB1.Service remedial strategies

Remedial Strategies	Description	Concrete Solutions
A Response Standardization	The complaint channels and response methods the firms can provide	• Customers convey their problems to customer service staff through screenshot or screen recording. • Indicate that the problem has been included or optimized • Provide a detailed introduction of this product and define the functional scope of the product. • Further ask the users about their needs and problems.
B Alternative Solution	Actual executive ability of solving customers' problems	• Provide related and easy-to-understand information. • The reply should be valuable. • Offer further solutions to the problem.
C Rejection of Excessive Demand	The firm nails down the range of problems to be solved	• Clarify or explain the reasons for the failure. • Indicate the range of support that the firm can offer for customers. • Indicate that this problem is beyond the firm's service capacity. • The ability of customer service staff to solve problems.
D Identify Customer Expectations	The firm's capability of identifying customer expectations	• The firms should strengthen ability of identifying expectations. • Should emphasize its social responsibilities while providing services. • Should be equipped with knowledge and skills to attract customers. • The firm is ought to attract customers with personalized services.
E Training employee attitude	Focus on dealing with customers' emotions	• Listen to customers with empathy and show them trust. • Assure the customers that measures will be taken. • Choose the complaint channel that users prefer to solve the problem. • Improve the service attitude of customer service staff in various aspects. • Should be humorous in answering questions. • Reflect the identity information of the problem handler.
F Response Time	The time taken by the firm to respond to problems	• The firms should respond in time. • The time needed to solve the problem should be clarified. • Inform when to resolve the issue. • Should respond or apologize within the time range. • Facilitate communication. • The firms should upgrade the system on time.

H Customer Engagement	The firm invites online community members for collaboration	• Invite customers to participate in solving the problem. • Invite customers to provide feedback, listen to their suggestions. • Timely inform customers the progress e. • Invite active users to provide their own experience.

B2. Construct Measurement

TableB2. Measurement Scale

Please answer the following questions based on your past experience, or the functions you think AI-powered voice assistants should perform.		
Scenario Failure	Q1 Infrastructure： · I have voice assistant device and can be networked. · I know how to use the voice assistants. · I can ask the service provider for help. Q2 Scene Flexibility: · I can control the home device through the voice assistant. · Voice assistant functions are very rich. · I can use the latest version of the voice assistant. Q3 Voice Interactivity： · Adjust the lights in the whole house to a comfortable brightness. · The voice assistant can correctly receive my instructions. · Smart devices can be manipulated through voice commands. Q4 Decision Making： · The voice assistant will automatically select the application or device to complete the user's needs. · Voice assistant can control different applications or devices. · The voice assistant can automatically recognize voice command. Q5 Exceptional Risk： · The voice assistant may have problems. · The response of voice assistants may be abnormal. · Voice assistants sometimes do not perform well. · Voice assistant service may not meet my expectations.	(Animesh et al. 2011; Xiao et al. 2020)
Personalization Failure	Q6 Conversation Personalization： · Set up intelligent scenes according to my personal preferences. · Personalized services based on the information collected. · Personalized services according to the information I provide. · Perform personalized dialogue tasks based on my information. Q7 Extended Feature： · Terminal device interface is friendly, and visually attractive. · Function of convenient navigation and extended search for users. · Obtain extended information in communicating with me. · The application configuration will continue to be enriched.	(Ameen, Hosany, and Paul 2022; Xiao et al. 2020)
Value Failure	Q8 Privacy Security：	(Xiao et

	· The data stored in the device can be backed up and restored. · The voice assistant has anti-virus intrusion protection measures. · The user data contained in the voice assistant is confidential. Q9 Price value： · The fee charged by the voice assistant operator is reasonable. · The price of the voice assistant is reasonable. · Operators can provide good service at the current sale price.	al. 2020; Venkatesh, Thong, and Xu 2012)
The following are questions about the firm solution.		
Response Standardization	· A standardized process to identify and solve problems. · Judge the service quality of the customer service. · Define quantifiable metrics to describe the achieved goals. · Have a clear solution.	(Kirsch et al. 2002)
Alternative Solution	· The firms can better identify the user's problems. · The firms can optimize the process of solving the problem. · firms have improved in verifying alternative solutions. · Improve in assessing the feasibility of products.	(Aladwani 2002)
Rejection of Excessive Demand	· Deny that there is a problem with their products. · Sometimes don't believe there's something wrong with their products. · Sometimes ignore the functional needs of users.	(Duhachek 2005)
Mirroring Ability	· The overall product content and service architecture of the voice assistant comes from the user's suggestions. · A firm's overall coordination of product and service offerings is driven by user demands. · The features that users expect will be integrated into the product and overall service design of the voice assistant.	(Oshri et al. 2019)
Customer Engagement	· Provide feedback about using voice assistants. · Provide suggestions for improving assistant products. · Provide suggestions for operators to develop new products.	(Behnam et al. 2021)
Training Employee Attitude	· Firm employees are very polite when answering questions. · Well-trained employees. · Positive attitude of firm employees. · Firm employees have no prejudice against consumers.	(Kuo, Chen, and Lu 2012)
After negotiating with the firms, do you agree with the following views?		
Satisfaction Experience	· I am satisfied with this experience. · This service process is what I need. · The whole service process gave me the same feeling as I imagined.	(McLean and Osei-Frimpong 2017)
Brand Usage Intent	· I will feel that using the brand product is meaningful. · Even if other brands have the same functionality as the brands I use, I prefer to use the current brand. · Make me more willing to use the original brand. · If there is no difference between other brands and the brands I use now, using the original brand seems to be a wise choice.	(McLean and Osei-Frimpong 2017)

Appendix C

C1. Reliability and Validity Analysis

TableC1.Construct Correlation, AVE, CR, GoF

Num	**CR**	**AVE**	**GoF**	**IN**	**SF**	**VI**	**DM**	**ER**	**CP**	**ES**	**SE**	**PV**	**RS**	**AS**	**RED**	**MC**	**CE**	**TEA**	**SE**	**BUI**
IN	**0.766**	0.522	**0.549**	**0.722**																
SF	**0.789**	0.554	**0.636**	0.624	**0.745**															
VI	**0.832**	0.623	**0.665**	0.510	0.616	**0.790**														
DM	**0.757**	0.510	**0.573**	0,.432	0.605	0.615	**0.714**													
ER	**0.898**	0.674	**0.214**	-0.097	-0.065	-0.089	-0.172	**0.827**												
CP	**0.837**	0.507	**0.657**	0.411	0.483	0.460	0.490	-0.072	**0.712**											
ES	**0.789**	0.556	**0.605**	0.657	0.603	0.568	0.528	-0.100	0.524	**0.746**										
SE	**0.814**	0.594	**0.668**	0.298	0.365	0.432	0.447	-0.187	0.464	0.295	**0.771**									
PV	**0.890**	0.730	**0.786**	0.413	0.408	0.436	0.509	-0.320	0.487	0.478	0.602	**0.855**								
RS	**0.821**	0.537	**0.584**	0.477	0.551	0.535	0.545	-0.267	0.572	0.591	0.619	0.712	**0.732**							
AS	**0.842**	0.573	**0.556**	0.444	0.535	0.550	0.535	-0.189	0.526	0.525	0.597	0.600	0.696	**0.757**						
RED	**0.932**	0.820	**0.560**	-0.308	-0.315	-0.348	-0.484	0.354	-0.378	-0.348	-0.511	-0.580	-0.544	-0.467	**0.905**					
MC	**0.826**	0.614	**0.488**	0.358	0.485	0.481	0.453	-0.114	0.480	0.429	0.585	0.459	0.619	0.726	-0.327	**0.783**				
CE	**0.853**	0.659	**0.549**	0.593	0.547	0.531	0.487	-0.130	0.471	0.503	0.437	0.440	0.551	0.563	-0.335	0.495	**0.812**			
TEA	**0.872**	0.630	**0.619**	0.572	0.539	0.565	0.595	-0.215	0.512	0.636	0.517	0.670	0.688	0.645	-0.569	0.492	0.592	**0.794**		
SE	**0.870**	0.691	**0.658**	0.425	0.445	0.528	0.561	-0.300	0.430	0.469	0.523	0.732	0.657	0.579	-0.550	0.499	0.512	0.755	**0.831**	
BUI	**0.862**	0.610	**0.557**	0.407	0.455	0.527	0.518	-0.216	0.476	0.537	0.509	0.596	0.559	0.537	-0.490	0.534	0.438	0.646	0.751	**0.781**

Note: IN=Infrastructure, SF=Scene Flexibility.VI=Voice Interaction, DM=Automated Decision Making, ER=Exceptional Risk, CP=Conversation Personalization, ES=Extended Services, SE=Privacy Security, PV=Profitability Value, RS=Response Standardization, AS=Alternative Solution, RED=Rejection of excessive demand, MC=Mirroring Capabilities, CE=Customer Engagement, TEA=Training Employee Attitude, SE=Satisfaction experience, BUI=Brand Usage Intent.

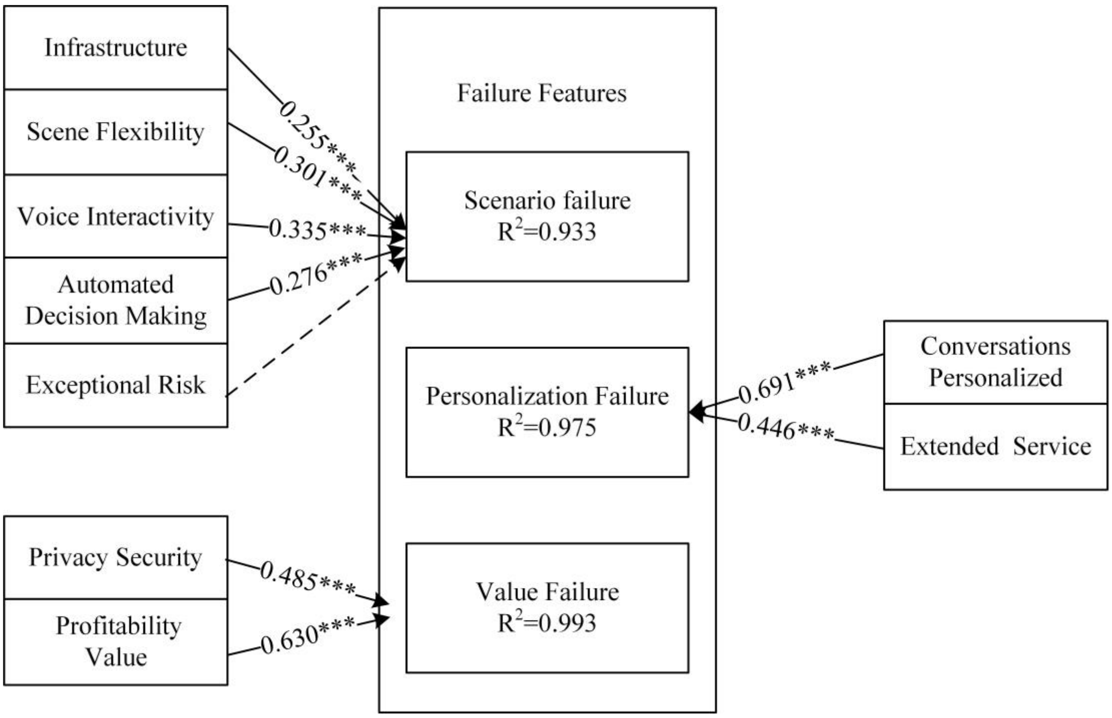
TableC2. PLSpredict and CVPAT results

Latent Variable	Q^2predict	PLS loss	Benchmark loss		Average loss difference	
			IA loss	LM loss	PLS-IA	PLS-LM
RS	0.614	0.519	0.769	0.655	-0.250	-0.136
AS	0.514	0.610	0.857	0.739	-0.247	-0.130
RED	0.372	1.774	2.544	1.904	-0.770	-0.130
MC	0.354	0.676	0.857	0.790	-0.180	-0.113
CE	0.413	0.546	0.745	0.721	-0.199	-0.175
TEA	0.590	0.577	0.935	0.703	-0.358	-0.126
SE	0.520	0.560	0.867	0.689	-0.307	-0.129
BUI	0.442	0.700	0.958	0.962	-0.258	-0.262

Note: RS=Response Standardization, AS=Alternative Solution, RED=Rejection of excessive demand, MC=Mirroring Capabilities, CE=Customer Engagement, TEA=Training Employee Attitude, SE=Satisfaction experience, BUI=Brand Usage Intent.

C2. Assessment of Second-Order Formative Constructs

These coefficients are positive and statistically significant, except for the exceptional risk construct (see FigC1).



FigC1.Assess the validity of the construct