Strategies for Enhancing Intelligent Customer Service Satisfaction: An Analysis of User Interaction Data

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Abstract: To investigate the key issues behind the generally low user satisfaction with current intelligent customer service, this study adopts a mixed-method approach of "exploration and verification". First, content analysis of over 1,000 social media user comments identified that user complaints mainly focus on two dimensions: interaction functionality, which includes issues such as poor communication channels, accounts for over 50% of complaints, representing the primary source of user dissatisfaction; followed by interaction quality issues, notably insufficient comprehension capabilities. Based on these findings, a questionnaire was developed and administered to 206 users. Descriptive statistical results confirm that functionality issues constitute the core weakness, with "inconvenience in transferring to human service" scoring lowest across all experience items. This study concludes that the current user experience dilemma stems from a structural conflict between the "efficiency-first" design philosophy and the users' fundamental need for a "service safety net." Optimization strategies should prioritize ensuring stable and reliable functionality. This finding provides a new perspective for improving intelligent customer service satisfaction, shifting the focus from "technical intelligence" to "functional reliability".

Keywords: Intelligent Customer Service; User Satisfaction; Interaction Functionality; Interaction Quality; Human-machine Collaboration

1. Introduction

With the rapid advancement of artificial intelligence technology, intelligent customer service has become a core tool for enterprises to provide 24/7 service while reducing costs and improving efficiency. However, these technological advancements have not automatically translated into enhanced user experience. Industry reports indicate that despite the increasing adoption rate of intelligent customer service, its overall satisfaction level remains far lower than that of human customer service. Existing literature predominantly centers on technical perspectives such as algorithm optimization and semantic recognition, often overlooking the complexity of users' psychological perceptions in real-world scenarios.

This study posits that intelligent customer service should not be viewed merely as a technological system, but rather as a service interaction system. By mining authentic evaluation data from social media and integrating it with questionnaire-based empirical analysis, this paper aims to clarify the distinct roles and weightings of interaction quality and interaction functionality in shaping user satisfaction. This research not only helps bridge the theoretical gap between the technological development of intelligent customer service and user perception, but also provides actionable guidance for enterprises to optimize human-machine collaboration pathways and enhance service quality and efficiency.

2. Literature Review

2.1 Technological Development and Application Status of Intelligent Customer Service

As a significant application of artificial intelligence technology in the service sector, intelligent customer service systems have exhibited rapid growth globally in recent years. Cheng and Jiang (2022) identify the primary drivers for enterprises deploying intelligent customer service systems as labor cost reduction, service efficiency improvement, and 24/7 service availability [1]. Relevant studies emphasize that the core technologies of intelligent customer service systems encompass natural language processing, machine learning, and knowledge graphs, with the maturity of these technologies directly impacting the system's service quality.

In China, despite high adoption rates, intelligent customer service satisfaction remains significantly lower than human service, indicating a clear technology-user mismatch.

2.2 Research on the Impact of Interaction Quality on User Satisfaction

Interaction quality is a core construct in intelligent customer service research. Based on service-dominant logic theory, interaction quality can be divided into two dimensions: functional interaction quality and social interaction quality. Functional interaction quality includes aspects such as accuracy and efficiency, while social interaction quality encompasses elements like anthropomorphism and emotional resonance. Both dimensions significantly influence user satisfaction.

Research by Ischen et al. in 2020 found that conversational coherence and contextual comprehension capabilities are key factors affecting users' cognitive load and satisfaction [2].Through user interviews, Følstad et al. pointed out in 2018 that the accuracy in understanding user intent was rated as the most critical factor influencing the intelligent customer service experience [3]. These studies collectively emphasize the central importance of "comprehension capability" within interaction quality.

Recent research has begun to focus on the impact of negative interaction experiences. Luo et al. noted in 2019 that when intelligent customer service makes comprehension errors or provides irrelevant answers, users' negative emotions are significantly amplified, and the damage to brand trust far exceeds that caused by human agent errors [4]. Repeated failures in understanding can lead users to develop a sense of helplessness, ultimately causing them to abandon the use of intelligent customer service altogether.

2.3 Research on the Relationship between Functional Design and User Experience

The functional design of intelligent customer service directly impacts users' task completion efficiency and overall experience. The Information Systems Success Model proposed by DeLone and McLean in 2003 provides an important theoretical foundation for research in this field. This model emphasizes that system quality, including reliability, response speed, and ease of use, is a key antecedent variable affecting user satisfaction [5].

In their latest 2023 study, Kumar et al. pointed out that users' core expectations of intelligent customer service have shifted from quick responses to effective problem resolution. This shift requires enterprises to re-examine the functional positioning of intelligent customer service [6]. Ashfaq et al. (2020) identified convenient human-agent transfer as a decisive continuance factor, revealing intelligent customer service as a supplement rather than replacement for human service [7].

From a linguistic strategy perspective, Huang and Rust argued in 2023 that the application of AI in services should focus on the fluency of human-machine collaboration, rather than merely the degree of automation [8].

2.4 Research on the Formation Mechanism of User Expectations and Satisfaction

The formation of user satisfaction is a complex psychological process. The Expectation Confirmation Theory proposed by Bhattacherjee in 2001 provides a classic framework for understanding user satisfaction, positing that satisfaction depends on the gap between actual experience and expectations [9]. The application of this theory in the context of intelligent customer service reveals that when users’ actual experiences fall short of their expectations, the intensity of negative emotions significantly outweighs that of positive emotions. This "negativity bias" effect is particularly pronounced in scenarios of service failure.

Users hold a "dual standard" toward intelligent customer service: they expect it to understand complex needs like a human, yet are unwilling to tolerate mistakes that humans might make. Through longitudinal research, Cheng and Jiang discovered in 2022 that user satisfaction with intelligent customer service exhibits dynamic characteristics. The novelty of initial usage diminishes with increased frequency of use, and satisfaction significantly declines as system shortcomings gradually become apparent·

2.5 Research Commentary

A synthesis of the above literature reveals that while existing research has yielded substantial insights in the field of intelligent customer service satisfaction, the following three gaps remain:

First, methods lean heavily toward confirmatory studies using preset frameworks, lacking exploration of authentic user feedback and risking oversight of core pain points (Wang et al., 2024) [10]. Flavián et al. called in 2023 for future research to adopt more mixed-methods approaches, integrating qualitative exploration with quantitative verification [11].

Second, research perspectives tend to focus on singular dimensions, overlooking the synergistic effects between interaction quality and functional design. While existing studies have explored the impact of interaction quality and functional design on satisfaction separately, few have systematically examined the interaction effects and synergistic optimization pathways of the two. Li and Park emphasized in 2023 that the user experience of intelligent customer service is a multidimensional, multi-layered integrated system, and optimization within a single dimension often fails to bring about significant improvements in overall satisfaction [12].

Third, research settings predominantly favor laboratory environments, lacking in-depth insights into real-world usage scenarios. Most studies are conducted under laboratory conditions or through simulated tasks, which may fail to capture users' actual experiences and pain points in authentic, complex situations.

To address these gaps, this study adopts a mixed-method "exploration-verification" design, using web crawling to identify core complaints from authentic user feedback. Subsequently, based on these findings, a structured questionnaire is designed for confirmatory research. This combined research paradigm can more accurately capture users' genuine needs and bridge the gap between theoretical exploration and practical application.

Second, it focuses on a dual-dimensional synergistic analysis of interaction quality and interaction functionality. Unlike the singular perspectives of previous studies, this research simultaneously examines the impact of both interaction quality and interaction functionality on user satisfaction, and explores the potential for their synergistic optimization, thereby providing enterprises with more systematic and actionable improvement solutions.

Third, it enhances the ecological validity of the study by utilizing authentic user data. The data in this research are derived from spontaneous user comments in real-world usage scenarios, offering higher ecological validity and practical value compared to laboratory-based studies. Consequently, the findings can more directly guide enterprises in optimizing their intelligent customer service systems.

3. Research Process

3.1 Data Collection

The data collection for this study was conducted in two stages.

The first stage involved exploratory qualitative data collection. To ensure that the subsequent questionnaire design accurately reflects users' genuine pain points, this study employed content analysis, collecting a total of 1,315 relevant user comments from the Douyin e-commerce platform during the period from July 2024 to November 2025.

The second stage involved confirmatory quantitative data collection. This study employed the online questionnaire survey method, utilizing the professional platform "Questionnaire Star" to collect data from Chinese users who had experience with intelligent customer service within the past six months. To ensure data quality, the questionnaire included screening questions and set a minimum completion time, effectively filtering out invalid responses. Ultimately, a total of 206 valid questionnaires were collected. The sample encompassed user groups with varying frequencies of use, and proved representative.

Figure 1 presents the frequency analysis of coded issues from the first-stage exploratory research. Within the interaction quality dimension, user complaints are most concentrated on "comprehension ability."

Figure 2 illustrates the interaction functionality dimension, where "poor channel accessibility" and "difficulty in transferring to human service" are the two most frequently complained-about issues.

Figure 3 reveals a stark imbalance: interaction functionality complaints substantially outnumber quality-related ones, confirming functionality deficits as the primary dissatisfaction driver.

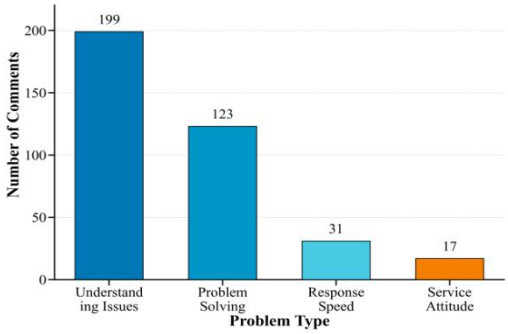

Figure 1. Frequency Distribution of Issues in the Interaction Quality Dimension

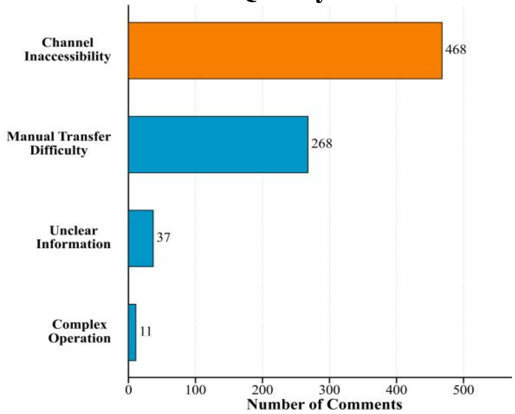

Figure 2. Frequency Distribution of Issues in the Interaction Functionality Dimension

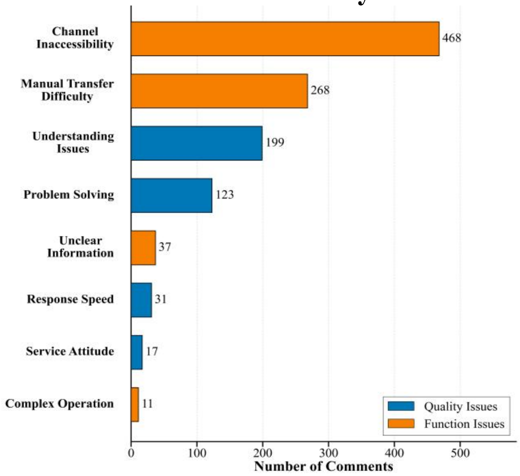

Figure 3. Overview of Complaint Types and Their Frequencies

3.2 Data Analysis

3.2.1 Questionnaire design and variable measurement

The questionnaire design of this study strictly adheres to academic standards. The questionnaire primarily consists of two parts: the first part collects respondents' basic demographic information; the second part contains measurement scales for the core variables, with all items measured using a seven-point Likert scale (1 indicating "strongly disagree" and 7 indicating "strongly agree"). The measurement of this study's core constructs—Interaction Quality (IQ), Interaction Functionality (IF), and Overall Satisfaction (SAT)—was developed by adapting well-established scales from authoritative domestic and international literature, tailored to the practical application context of intelligent customer service to ensure good content validity. The specific items for each construct are presented in Table 1.

3.2.2 Reliability and validity tests

To examine the reliability and validity of the questionnaire scales, this study employed SPSS 26.0 and AMOS 24.0 software for data analysis. The results are presented in Table 2. First, in terms of reliability, the Cronbach's α coefficients for the three constructs—Interaction Quality, Interaction Functionality, and Overall Satisfaction—were 0.869, 0.850, and 0.861, respectively, while the composite reliability (CR) values were 0.869, 0.850, and 0.862. All of these values exceed the commonly accepted threshold of 0.7 in academia, indicating good internal consistency and reliability of the scales used in this study. Second, regarding convergent validity, the average variance extracted (AVE) values for the constructs were 0.690, 0.654, and 0.675, respectively—all above the standard of 0.5—and all factor loadings of the items exceeded 0.7, suggesting satisfactory convergent validity of the scales. Finally, in terms of discriminant validity, as shown in Table 2, the square roots of the AVE values for all three constructs were greater than their correlation coefficients with other constructs, demonstrating good discriminant validity among the constructs. In summary, the measurement tools used in this study exhibit both good reliability and validity, making them suitable for subsequent data analysis.

3.2.3 Descriptive statistical analysis and regression analysis

Descriptive statistical analysis of the core variables (see Table 3) shows that the mean scores for Interaction Quality ($M = 4.74$), Interaction Functionality ($M = 4.76$), and Overall Satisfaction ($M = 4.77$) are all around 4.7. On a seven-point scale, these scores are slightly above the midpoint of 4 but still far from reaching a "satisfactory" level. This preliminarily indicates that users' overall evaluation of intelligent customer service currently falls into a "neutral to slightly negative" range, and the experience remains far from the ideal level.

Table 1. Measurement Scales for Core Variables

Construct	Item Code	Item
Interaction Quality (IQ)	IQ1	I believe the intelligent customer service can accurately understand my intentions and questions.
	IQ2	The interaction process with the intelligent customer service is smooth and coherent.
	IQ3	I find the responses provided by the intelligent customer service to be of high quality and helpful.
Interaction Functionality (IF)	IF1	I find the intelligent customer service to be reliable and capable of successfully helping me complete tasks.
	IF2	I believe I can conveniently locate and initiate the intelligent customer service when I need assistance.
	IF3	When the intelligent customer service cannot resolve an issue, the option to transfer to human service is clear and easy to operate.
Overall Satisfaction (SAT)	SAT1	Overall, I am satisfied with my interaction experience using the intelligent customer service.
	SAT2	I consider using the intelligent customer service to handle my issues a wise decision.
	SAT3	If I encounter similar problems in the future, I am still willing to use the intelligent customer service first.

Table 2. Reliability Analysis Results

Construct	α	CR	AVE	IQ	IF	SAT
Interaction Quality	0.869	0.869	0.690	(0.831)		
Interaction Functionality	0.850	0.850	0.654	0.839***	(0.80)	
Overall Satisfaction	0.861	0.862	0.675	0.843***	0.852***	(0.822)

Table 3. Descriptive Statistics of Core Variables

Construct		Mean	Standard Deviation
Interaction Quality		4.740	1.728
	IQ1	4.70	1.972
	IQ2	4.80	1.924
	IQ3	4.72	1.925
Interaction Functionality		4.759	1.685
	IF1	4.82	1.928
	IF2	4.79	1.911
	IF3	4.67	1.922
Overall Satisfaction		4.770	1.695
	SAT1	4.76	1.863
	SAT2	4.81	1.91
	SAT3	4.74	1.973

To investigate the relative influence of interaction quality and interaction functionality on overall satisfaction, this study conducted a multiple regression analysis (see Table 4). The results indicate that interaction functionality ($\beta = 0.490$, $p < 0.001$) has a greater impact on overall satisfaction than interaction quality ($\beta = 0.432$, $p < 0.001$).

Table 4. Regression Model Coefficients

Model	Standardized Coefficient (Beta)	t	Sig.
Interaction Quality	0.432	7.164	<.001
Interaction Functionality	0.490	8.124	<.001

3.3 Problem Analysis

The regression analysis reveals an unbalanced structure underlying user satisfaction. Although both Interaction Quality (IQ) and Interaction Functionality (IF) significantly predict satisfaction, IF (β = 0.490) exerts a stronger influence than IQ (β = 0.432). This indicates that the core user experience tension has shifted from "whether the bot is smart enough" to "whether the system is reliable at critical moments." Functional reliability, rather than perceived intelligence, now forms the cornerstone of satisfaction.

This macro-level finding is reflected in micro-level user experience data. Among all measured items, the lowest score belongs to IF3: "When the intelligent customer service fails to solve a problem, the option to transfer to human service is clear and easy to operate" (M = 4.67). This pinpointsthe most acute user pain point: after an initial failure due to poor interaction quality, encountering a second failure—difficulty in transferring to human assistance—amplifies frustration and undermines trust.

The core obstacle is thus not merely technical but philosophical: an "efficiency-first" design paradigm that sacrifices the user's right to reliable assistance. To reduce costs, systems often intentionally hinder seamless transfer to human agents, creating a service process without a "safety net." When automated processes fail, users are left without accessible support, leading to profound dissatisfaction. Consequently, improvement strategies must shift from isolated technical optimization toward constructing seamless and reliable human-machine collaboration pathways.

4. Strategic Recommendations

The findings indicate that user dissatisfaction stems more from unreliable interaction functionality than from insufficient interaction quality. Therefore, collaboration among government, enterprises, and consumers is essential to shift intelligent customer service from an "efficiency-first" to an "experience-centered" model.

The three parties should jointly build and safeguard a "service safety net," ensuring seamless human-machine collaboration as the foundation for functional optimization. Regulatory authorities should establish guidelines specifying minimum usability standards for human-agent transfer channels, such as requiring proactive offering of human assistance after three consecutive ineffective interactions. Enterprises must reframe transfer not as a cost leak but as a critical service recovery function, implementing always-visible transfer buttons and intelligent early-warning systems triggered by signals like negative sentiment. Consumers should enhance rights protection awareness and provide explicit feedback on transfer difficulties through complaints or reviews, generating market pressure for functional improvement.

Concurrently, efforts should strengthen AI's core capabilities to improve interaction quality at the source. Governments can incentivize investment in core technologies like natural language processing through special funds or tax benefits. Enterprises should establish data-driven iteration mechanisms, analyzing failed dialogues and integrating effective human solutions into AI knowledge bases. Consumers can contribute by using clearer, more structured queries and utilizing in-system feedback options, providing high-quality data for model optimization.

Furthermore, a differentiated, scenario-specific service ecosystem should be promoted to achieve dynamic optimization between interaction quality and functionality. Regulators and industry associations can explore tiered service standards, permitting different human-machine pathways based on task complexity while defining clear privacy protection red lines. Enterprises can leverage technology to predict user intent, automating low-complexity tasks while lowering intervention thresholds for complex or emotional issues and offering prioritized access to human experts. Consumers can also proactively select appropriate channels (e.g., dedicated portals for complex problems), aiding rational resource allocation and enabling better contextualized service experiences.

5. Conclusion

5.1 Research Findings and Theoretical Contributions

Through empirical analysis, this study found that interaction functionality (β = 0.490) exerts a significantly greater influence on user satisfaction than interaction quality (β = 0.432). This finding reveals that the core tension in the current application of intelligent customer service has shifted from "whether the bot is smart enough" to "whether the system is reliable at critical moments."

In concrete terms, the issue of "inconvenience in transferring to human service" (M=4.67), which falls under interaction functionality, represents the most prominent pain point across all experience dimensions. This observation aligns with the view of Ashfaq et al. (2020) regarding the importance of human-machine collaboration. When users encounter an initial failure due to poor interaction quality, if they are again hindered at the functional stage of transferring to a human agent—constituting a "second failure"—their satisfaction is significantly diminished.

This research contributes by reframing user dissatisfaction from singular technical bottlenecks to the structural conflict between an "efficiency-first" design philosophy and users' need for a "service safety net." These findings demonstrate that optimizing interaction quality without reliable interaction functionality yields diminishing marginal returns.

5.2 Research Limitations and Future Prospects

The limitations of this study provide directions for future research. First, as it employed cross-sectional data, it could not capture the dynamic changes in user satisfaction. Future longitudinal studies could address this gap. Second, the core variables in this study were relatively focused.

Future research could introduce moderating variables such as user personality traits and service contexts to construct more comprehensive contingency models. Additionally, this study did not differentiate between specific industries. Future cross-industry comparative research would help verify the applicability and boundary conditions of our findings in different contexts, thereby offering more targeted practical guidance.

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