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Demand Identification and Service Optimization in AI-Powered Banking Customer Service: A Kano Model-Based Approach

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Abstract: To strengthen competitiveness in the digital banking environment, the functional prioritization and optimization of customer service systems enabled by artificial intelligence (AI) must be systematically examined from a user-demand perspective. In this study, user requirements for AI-powered banking customer service were identified, classified, and prioritized through the Kano model combined with a structured questionnaire survey. Four functional dimensions comprising fourteen sub-functions were evaluated to determine their respective impacts on user satisfaction. The results demonstrate that priority should be assigned to rapid transfer to human agents, high response accuracy, risk alerts, service continuity and stability, privacy protection, secure identity verification, rapid response speed, comprehensive business coverage, multi-turn dialogue capability, and accurate user intent understanding. Based on these findings, a set of optimization strategies was proposed. A precise knowledge base should be constructed, and a high-availability system architecture should be deployed. Key algorithmic challenges related to semantic understanding and multi-turn dialogue management should be addressed. Full business-scenario coverage was recommended, while tiered authentication mechanisms and proactive risk-alert strategies should be implemented. Investment in non-core functions may be strategically deferred to achieve optimal resource allocation. By systematically categorizing user demand attributes and clarifying functional priorities, this study provides a robust theoretical foundation and practical decision-making framework for banks seeking to optimize AI-powered customer service systems and maximize user satisfaction in resource-constrained digital environments.

Keywords: AI-powered banking customer service; Kano model; Demand identification; Functional prioritization; Customer satisfaction

1 Introduction

Amid the advancing wave of financial technology and the rapid development of AI, the banking industry has been undergoing a profound digital transformation [1, 2]. As a critical interface for human-computer interaction, AI-powered customer service has progressively evolved from an initial "cost center" into a "strategic center" for enhancing user experience and enabling precision marketing [3]. From simple business inquiries to complex transaction processing, the application scenarios of AI-powered customer service continue to expand. The development of AI-powered banking customer service carries the dual expectations of cost reduction and efficiency enhancement alongside service upgrades within the banking sector [4].

Against this backdrop, systematic and refined research on user requirements for AI-powered banking customer service holds not only theoretical value but also urgent practical necessity. This research introduces the Kano model to reveal the nonlinear relationship between requirements and user satisfaction, providing theoretical guidance for banks to formulate development strategies and optimize resource allocation for AI-powered customer service. Banks have limited resources for research, development, and operations, and blind development yields poor results. By identifying attractive qualities and other qualities through the Kano model, banks can establish priority development strategies, ensuring that resources are deployed where they are most effective [5]. With the rapid development of financial technology, the quality of digital services has become a critical factor for banks to win over customers. An exceptional AI-powered customer service experience in banking helps enhance user satisfaction and loyalty [6, 7].

Therefore, by applying the Kano model, this study systematically identifies and scientifically classifies the user requirements for AI-powered banking customer service, prioritizes them, and subsequently proposes forward-looking and actionable functional optimization strategies. This provides a theoretical reference and practical guidance for the upgrade and optimization of AI-powered banking customer service, ultimately driving the overall improvement of digital service quality in the banking sector.

2 Literature Review

2.1 Development and Research Status of AI-Powered Banking Customer Service

The evolution of AI-powered banking customer service has progressed from simple rule-driven systems to those dominated by complex models. Early systems primarily relied on predefined rules and keyword matching, capable only of handling limited standardized inquiries. Both the scope of services and the level of intelligence were significantly constrained. With advancements in AI technologies such as natural language processing, AI-powered customer service systems have progressively integrated more sophisticated semantic understanding and intent recognition capabilities. Application scenarios have expanded from simple question-answering (Q&A) to more complex interactions, including transaction processing and product recommendations [4]. Three major trends have emerged in the AI-powered customer service domain: widespread technological adoption, exploration of large-model technologies, and close integration with knowledge bases.

In recent years, rapid technological advancements have propelled AI-powered banking customer service into a new developmental phase. Large-model-based AI-powered customer service demonstrates enhanced contextual comprehension, multi-turn dialogue management capabilities, and personalized service levels [8]. Regarding application efficacy, existing research has primarily evaluated performance across three dimensions: efficiency gains, service quality, and user satisfaction. In terms of efficiency, AI-powered customer service has achieved significant cost optimization and response speed improvements [9]. Regarding service quality, the accuracy of intent recognition and problem-solving capabilities of AI-powered customer service continues to improve. User satisfaction studies reveal more complex outcomes. On one hand, features such as 24/7 availability, instant responses, and convenient access are well-received by users [10]; on the other hand, satisfaction levels decline markedly when users encounter impersonal interactions, repetitive responses, or unresolved queries [11–13].

Banking customers demand particularly stringent accuracy and security from AI-powered customer service, exhibiting relatively low tolerance for errors. This drives banks to allocate greater resources towards enhancing the service quality of their AI-powered customer service systems [14, 15]. There remains room for improvement, with certain types of requirements yet to be clearly defined. The sector is transitioning from "technological availability" towards "users' one-dimensional quality attributes". Precisely identifying and fulfilling users' quality attribute demands for diverse functionalities has become a critical challenge in optimizing AI-powered customer service systems. This cognitive gap provides both theoretical justification and research scope for this study's application of the Kano model to analyze the quality attributes of AI-powered banking customer service.

However, a review of the literature reveals a critical gap in current research regarding the specific pathways to achieving this "adaptability". Firstly, most studies focus on macro-level assessments of AI-powered customer service capabilities or overall user satisfaction [16–18], lacking a systematic classification of specific functional requirements. This often confines research conclusions to statements such as "accuracy requires improvement" or "satisfaction is complex" [19, 20], failing to address the core issue of prioritization decisions. Secondly, in terms of methodology, existing analyses predominantly employ linear correlation assumptions [21], which struggle to capture and explain the asymmetry in users' responses to the presence versus absence of features.

Therefore, this study aims to address this gap. By introducing the Kano model, the research aims to: (a) classify the demand attributes of specific functions within AI-powered banking customer service at a micro level; (b) reveal the asymmetric influence mechanisms between different functions and user satisfaction; (c) ultimately produce a clearly structured hierarchy of demand priorities, thereby providing precise and actionable strategic guidance for banks to transition from "technological availability" to "experience adaptation".

2.2 Kano Model Theory

Within the field of service quality management and user experience research, the Service Quality (SERVQUAL) model and the Importance-Performance Analysis (IPA) model represent two classic and widely adopted theoretical frameworks. The SERVQUAL model assesses service quality by measuring the gap between user perceptions and expectations, implicitly assuming a linear correlation between service quality and user satisfaction [22]. However, this linear framework struggles to explain asymmetric responses in AI-powered customer service scenarios—such as where the absence of basic functions provokes strong dissatisfaction, yet their flawless implementation is merely taken for granted. The IPA model offers an intuitive view for managerial decisions through its importance-performance matrix [23]. Yet its conclusions heavily rely on users' self-reported importance ratings, which may underestimate the significance of certain foundational needs [24].

Compared to SERVQUAL, the Kano model effectively reveals the nonlinear relationship between demand fulfillment and user satisfaction [25, 26]. By posing dual-sided questions, i.e., "if this feature is provided" and "if this feature is not provided", it directly captures the nonlinear, asymmetric relationship between demand fulfillment and user satisfaction. This enables the objective classification of features into categories such as must-be, one-dimensional, and attractive qualities. Compared to IPA, the Kano model provides a scientific and clear basis for prioritizing demands [26]: must-be quality must be reliably delivered to prevent dissatisfaction; one-dimensional quality should be continuously optimized to linearly enhance satisfaction; while attractive quality can serve as innovation priorities to gain competitive advantage. The Kano model is a significant theoretical framework proposed by a Japanese quality management expert Norimasa Kano in 1984, designed to elucidate and identify the quality attributes of research objectives. Customer satisfaction with specific qualities of a product or service may vary according to their preferences for these attributes [27].

Over time, this model has expanded beyond its initial quality management context into diverse fields, including product design, service development, and healthcare, becoming a vital tool for understanding user needs, optimizing resource allocation, and enhancing satisfaction [28–30]. By analyzing the relationship between product characteristics and customer satisfaction, Professor Kano discovered the differential impact of various demand attributes on satisfaction. Product quality elements were initially categorized into five types: must-be quality, one-dimensional quality, attractive quality, indifferent quality, and reverse quality [27]. Must-be quality (M) represents fundamental product requirements. Failure to meet these causes significant dissatisfaction, yet their fulfillment is merely perceived as "expected". One-dimensional quality (O) exhibits a linear relationship with user satisfaction; the degree of fulfillment of these requirements positively correlates with satisfaction levels. Attractive quality (A) represents features that delight users. Their absence does not cause dissatisfaction, but their presence significantly enhances satisfaction. Indifferent quality (I) has no significant impact on user satisfaction regardless of fulfillment. Reverse quality (R) denotes features whose presence actually causes user dissatisfaction.

Traditional Kano model research has primarily been conducted through questionnaire surveys and data analysis. The Kano questionnaire design includes two opposing questions for each quality element: "How would you feel if this feature were present?" and "How would you feel if this feature were absent?" Each question typically employs a five-point Likert scale for respondents to select from options, including "like", "expect", "indifferent", "dislike", and "strongly dislike". During data analysis, researchers often cross-reference responses to positive and negative questions against the Kano evaluation matrix to classify each quality attribute. For further quantitative assessment, the better coefficient (satisfaction influence coefficient) and worse coefficient (dissatisfaction influence coefficient) are commonly calculated:

$$\text{Better} = \frac{\mathrm{A}+\mathrm{O}}{\mathrm{A}+\mathrm{O}+\mathrm{M}+\mathrm{I}} \tag{1}$$

$$\text{Worse} = -1 \times \frac{\mathrm{O}+\mathrm{M}}{\mathrm{A}+\mathrm{O}+\mathrm{M}+\mathrm{I}} \tag{2}$$

A higher better coefficient indicates a more significant effect of that element on satisfaction enhancement; a larger absolute value of the worse coefficient indicates greater dissatisfaction caused by the absence of that element. Using these two metrics, a quartile diagram can be plotted to visually demonstrate the priority of each quality element. The KANO model distinguishes itself by classifying product attributes and extracting their underlying characteristics through the integration of user sentiments towards the product. This model finds extensive application in requirement analysis and categorization [31].

3 Research Process

A questionnaire-based methodology was employed in this study to quantitatively assess users' one-dimensional quality attributes and perceived performance regarding the functional features of AI-powered banking customer service systems, thereby providing empirical support for system design optimization and service experience enhancement. The research methodology consists of two primary phases. First, through literature review and empirical research, core functionalities of bank intelligent Q&A services are identified and synthesized to establish a structured functional framework, forming the foundation for subsequent analytical procedures. Subsequently, the Kano model is implemented in survey design to identify critical user requirements. The findings enable systematic prioritization of existing functionalities, thus providing a strategic direction for system development and iterative functional improvements.

3.1 Establishing a Requirement Framework for AI-Powered Banking Customer Service

Through a systematic literature review and industry report analysis, over 20 potential functionalities were initially identified. Subsequently, an expert consultation approach was employed, involving two seasoned fintech product specialists who evaluated and discussed these features across three dimensions: user perceptibility, business criticality, and technological maturity. This process distilled the core functionalities of AI-powered banking customer service into 14 key features organized across four dimensions, as presented in Table 1.

Table 1. Functional framework of AI-powered banking customer service

Demand Dimension	Requirement	Description	Literature References
Functional completeness	1. Accurate user intent understanding	User intent recognition accuracy (the probability that the system correctly identifies the core business intent of a user query) should exceed 95%, effectively handling colloquial, abbreviated, and misspelled expressions.	[32, 33]
	2. Multi-turn dialogue capability	This means the ability to maintain contextual coherence and accomplish complex tasks during continuous interaction. Within ten consecutive dialogue turns, it should accurately reference previously confirmed key information (e.g., amounts, dates, and product names) with 100% accuracy.	[34, 35]
	3. Comprehensive business coverage	Must cover over 90% of common banking scenarios, including account inquiries, transfers, wealth management, loans, and credit card services.	[36]
Interaction experience	4. Rapid response speed	It refers to the delay in the AI-powered customer service system providing its initial reply to a user's query. 95% of text queries should receive an initial response within five seconds; and complex queries require "processing" feedback within ten seconds.	[37, 38]
	5. High answer accuracy	For standard business queries, the AI-powered customer service must achieve over 98% accuracy in responses, eliminating misleading information.	[39]
	6. Personalized service	This means to proactively address customers by surname (e.g., "Mr Wang") and provide tailored product recommendations based on historical transaction records.	[40, 41]
	7. Emotional interaction	When detecting negative sentiment in user tone, reassuring statements are automatically triggered and human service options are prioritized.	[42, 43]
Service efficiency	8. Rapid transfer to agents	The process from user issuing "transfer to agent" to successful human agent connection must be completed within three clicks or 15 seconds.	[44, 45]
	9. Service continuity/stability	System availability (SLA), the proportion of time during which the system is accessible and operational within a specified period, reaches 99.9%, delivering uninterrupted 24/7 service with no significant performance degradation during peak periods.	[40, 46]
	10. Predictive recommendations	This means to proactively push relevant tools and information (e.g., mortgage calculator or latest interest rates) based on user behavior (such as frequent mortgage rate checks).	[47, 48]
	11. Multi-channel consistency	When users inquire about the same issue across different channels (e.g., app, WeChat, and online banking), the core answers and solutions provided must be entirely consistent.	[49]
Security safeguards	12. Secure identity verification	Prior to sensitive operations like account queries or transactions, identity must be verified through multi-factor authentication (e.g., password, fingerprint, and facial recognition).	[50]
	13. Privacy protection	Users must be explicitly informed of the scope of data collection. Conversation data shall be stored with end-to-end encryption and may not be used for other purposes without explicit user authorization.	[50]
	14. Risk alerts	The system shall monitor and intercept suspicious links or fraudulent language in real time, triggering full-screen warning pop-ups for users.	[36, 51]

3.2 Kano Model Questionnaire for AI-Powered Banking Customer Service

Before formal distribution, the questionnaire was pre-tested. Thirty respondents with prior experience using AI-powered bank customer service were invited to participate, with the primary focus on verifying the logical rigor and clarity of expression within the Kano positive-negative question pairs. Based on the feedback, targeted refinements were made to the questionnaire: certain technical functional descriptions were replaced with more accessible, everyday language. Additionally, concise examples and guidance on "how to understand and respond to positive and negative questions" were incorporated at the outset of the questionnaire.

The questionnaire comprises three sections. The first section is an introductory segment at the outset explaining the Kano model, supplemented by an example of the function "the customer service can understand colloquial questions" to assist respondents in better comprehending the survey questions and completing their responses. The second section is an assessment of the importance of system functions. Based on the Kano model and 14 categorized functional attributes of AI-powered banking customer service, 14 corresponding questions were designed. Respondents were required to evaluate the importance of each functional attribute under two scenarios, “availability” and “unavailability”, using five response options: “I dislike it”, “I can barely accept it”, “I am indifferent”, “It ought to be this way”, and “I greatly appreciate it”. Table 2 shows an example of the functional/dysfunctional question pair. The third section involves the demographic information, including each respondent’s gender, age, occupation, and basic usage patterns of AI-powered banking customer service.

The questionnaire was distributed via the Wenjuanxing platform, with samples drawn from government staff, corporate employees, teachers, medical practitioners, and students. A total of 200 formal questionnaires were disseminated. After excluding 28 invalid questionnaires (defined as those featuring identical responses to all questions), 172 valid questionnaires were obtained, yielding an effective response rate of 86%. The demographic profile of respondents is presented in Table 3. Regarding frequency of usage, approximately half of the respondents reported using AI-powered banking customer service either frequently or occasionally.

Table 2. Example of a Kano question pair

Options	**I greatly appreciate it.**	**It ought to be this way.**	**I am indifferent.**	**I can barely accept it.**	**I dislike it.**
If this feature is available.	_	_	_	_	_
If this feature is unavailable.	_	_	_	_	_

Note: Accurate user intent understanding (can accurately interpret colloquial phrasing such as “I’d like to send some money to Lao Wang” without requiring specific keywords like “transfer”.

Table 3. Demographic characteristics of the survey sample

Variable	**Category**	**No.**	**Percentage**
Gender	Male	42	24.42%
	Female	130	75.58%
Age	Under 25	88	51.16%
	26–30	12	6.98%
	31–40	33	19.19%
	41–50	24	13.95%
	51–60	15	8.72%
Occupation	Government/public institution staff	12	6.98%
	Corporate employee	9	5.23%
	Student	82	47.67%
	Teacher	27	15.7%
	Medical practitioner	19	11.05%
	Other	23	13.37%
Frequency of using AI-powered banking customer service	Frequently	16	9.3%
	Occasionally	79	45.93%
	Rarely	77	44.77%

3.3 Analysis of AI-Powered Banking Customer Service Requirements

The survey options were categorized into five levels, with each respondent’s attitude towards a specific feature classified according to Table 4. The Kano model classification method aggregates the proportion of responses sharing the same attribute. The attribute dimension with the highest total sum represents the Kano attribute for that feature. To determine development priorities, the better-worse coefficient method was employed in this survey. Satisfaction and dissatisfaction levels for each feature attribute were calculated using the formula, yielding the research results presented in Table 5.

Based on the absolute values of the better and worse coefficients for each function, a scatter plot was generated (Figure 1). The quadrants are delineated according to the overall functional means. Specifically, Quadrant I denotes the one-dimensional quality, Quadrant II is the attractive quality, Quadrant III is the indifferent quality, and Quadrant IV is the must-be quality.

Table 4. Kano evaluation matrix

Requirement Metric		Not Available				
		I greatly appreciate it.	It ought to be this way.	I am indifferent.	I can barely accept it.	I dislike it.
Available	I greatly appreciate it.	Q	A	A	A	O
	It ought to be this way.	R	I	I	I	M
	I am indifferent.	R	I	I	I	M
	I can barely accept it.	R	I	I	I	M
	I dislike it.	R	R	R	R	Q

Table 5. Results of requirements based on the Kano model

Dimension	**Requirement**	**No.**	**M**	**O**	**A**	**I**	**R**	**Q**	**Kano Model**	**Better (Satisfaction)**	**Worse (Dissatisfaction)**
Functional completeness	Accurate user intent understanding	1	6.98%	9.88%	38.37%	33.14%	3.49%	8.14%	A	54.61%	-19.08%
	Multi-turn dialogue capability	2	9.88%	28.49%	29.07%	26.16%	0%	6.4%	A	61.49%	-40.99%
	Comprehensive business coverage	3	9.88%	23.84%	33.14%	22.09%	0.58%	10.47%	A	64.05%	-37.91%
Interaction experience	Rapid response speed	4	6.4%	25.58%	36.05%	21.51%	1.16%	9.3%	A	68.83%	-35.71%
	High answer accuracy	5	10.47%	40.12%	23.26%	15.7%	0%	10.47%	O	70.78%	-56.49%
	Personalized service	6	1.74%	10.47%	26.74%	47.09%	3.49%	10.47%	I	43.24%	-14.19%
	Emotional interaction	7	2.91%	14.53%	35.47%	37.21%	0.58%	9.3%	I	55.48%	-19.35%
Service efficiency	Rapid transfer to human agents	8	7.56%	35.47%	30.81%	15.12%	0%	11.05%	O	74.51%	-48.37%
	Service continuity and stability	9	8.14%	33.14%	25%	22.67%	0%	11.05%	O	65.36%	-46.41%
	Predictive recommendations	10	1.74%	9.3%	36.63%	41.28%	2.33%	8.72%	I	51.63%	-12.42%
	Multi-channel consistency	11	5.23%	25%	25.58%	33.72%	0.58%	9.88%	I	56.49%	-33.77%
Security safeguards	Secure identity verification	12	11.05%	36.63%	16.28%	26.16%	0.58%	9.3%	O	58.71%	-52.9%
	Privacy protection	13	16.28%	48.26%	10.47%	15.7%	0%	9.3%	O	64.74%	-71.15%
	Risk alerts	14	9.88%	40.12%	20.35%	19.77%	0%	9.88%	O	67.1%	-55.48%

In analysing the results, we discovered discrepancies between the conclusions drawn from the Kano model classification method and those obtained via the Better-Worse coefficient quadrant approach. Specifically: under the Kano model classification method, no functions were categorised as must-be qualities; whereas in the coefficient diagram, a function fell within the must-be quality quadrant. Classification outcomes for some functions also diverged.

The Kano model classification method determines each functions's single quality category based on the highest frequency of direct user selections in the Kano questionnaire. Its core advantage lies in the clarity of its qualitative classification. The absence of must-be qualities in this study precisely reveals that the subjects' fundamental services are tacitly regarded by users as "expected to exist"by default. Users' explicit focus has shifted from "presence or absence" to "quality or deficiency", thus functions are more likely to be perceived as one-dimensional or attractive qualities.

The Better-Worse coefficient chart serves as a continuous, relative diagnostic tool for influence. A function falling into Quadrant IV merely indicates that its "average potential risk of triggering overall dissatisfaction when poorly performed" is relatively highest among all features. This does not equate to users universally categorizing it as a must-be quality in their cognition.

This study adopts the conclusions of the Kano model classification method, with the coefficient diagram serving as supplementary illustration.

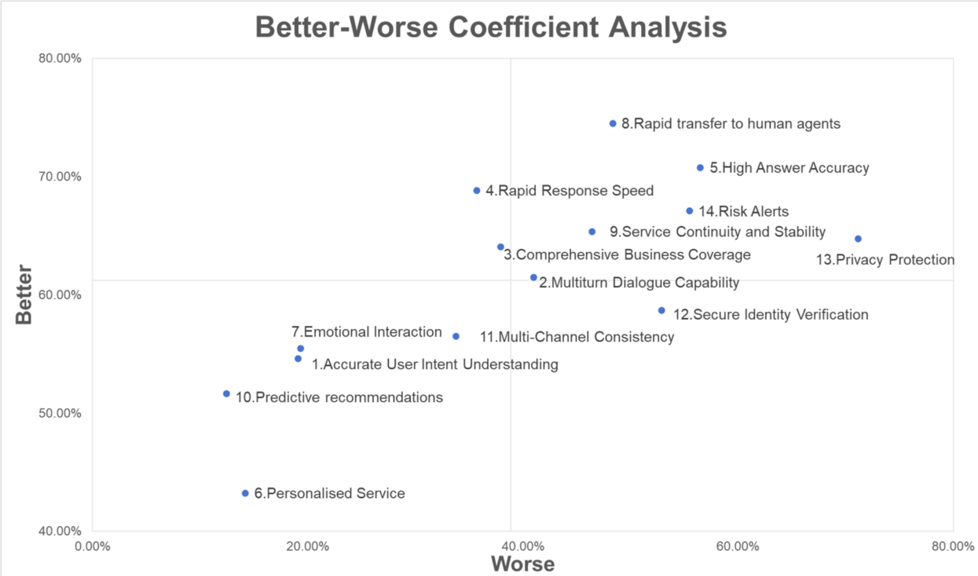

Figure 1. Kano better-worse coefficient matrix

For AI-powered banking customer service, the following classifications apply:

- One-dimensional quality: rapid transfer to human agents, high answer accuracy, risk alerts, service continuity and stability, privacy protection, and secure identity verification;
- Attractive quality: rapid response speed, comprehensive business coverage, multi-turn dialogue capability, and accurate user-intent understanding;
- Indifferent quality: multi-channel consistency, emotional interaction, predictive recommendations, and personalized service.

The priority hierarchy of requirements is as follows: must-be quality > one-dimensional quality > attractive quality > indifferent quality. Within each quality category, a larger better coefficient indicates a higher development priority for the corresponding function. Consequently, the development-priority sequence for the functions of the AI-powered banking customer service system was obtained (Table 6).

Table 6. Priority order for functional development of AI-powered banking customer service systems

AI-powered Banking Customer Service Function	Priority Order
Rapid transfer to human agents	1
High answer accuracy	2
Risk alerts	3
Service continuity and stability	4
Privacy protection	5
Secure identity verification	6
Rapid response speed	7
Comprehensive business coverage	8
Multi-turn dialogue capability	9
Accurate user intent understanding	10

It can be recognized that the Kano model's categorization of continuous user perceptions into discrete demand categories may introduce classification ambiguities due to individual cognitive differences. By cleansing invalid data and focusing analysis on the "dominant demand categories" where each function's vote share significantly predominates, the validity of the research findings is ensured.

4 Suggestions

The results of the Kano model research indicate that a distinct, tiered functional optimization strategy is essential for improving user satisfaction and AI-powered banking customer service's competitiveness in the market. In light of this, the following recommendations were proposed:

4.1 Top Priority: Reinforce One-Dimensional Qualities and Build a Foundation of User Trust and Satisfaction

4.1.1 Building core service capabilities of "precision, security, and stability"

A closed-loop management programme for the "financial precision knowledge base" should be implemented. To guarantee answer accuracy, it is essential to establish a rigorous knowledge base and update procedure. "Seamless integration" in human–computer collaboration should be established. To ensure rapid transfer to human agents and consistent service stability, it is necessary to facilitate smooth transitions between AI-powered and human-operated services at the system design level. On one hand, an effective one-click access to human support should be embedded within the interaction interface; on the other hand, an intelligent scenario recognition system should be developed. When issues such as user frustration, repeated queries, or complex complaint procedures are detected, the system should proactively prompt for human agents' assistance and simultaneously transfer dialogue records and contextual information to human agents, thereby achieving a seamless transition from AI-powered to human-led support.

4.1.2 Constructing a "proactive and trustworthy" security and risk defence

A layered and graded intelligent security authentication strategy should be implemented. For low-risk transactions, basic authentication methods—including SMS verification codes—may be deemed sufficient. In contrast, for high-value or sensitive operations—the use of enhanced authentication mechanisms, including digital certificates, fingerprint recognition, or facial biometrics, must be mandatory. This approach ensures that the rigor of authentication is dynamically aligned with the associated level of operational risk.

Furthermore, an end-to-end data protection framework, integrated with a proactive early warning system, must be established. To safeguard privacy, all sensitive customer data should be subject to encryption and desensitization throughout its lifecycle—during storage, transmission, and display. Concurrently, behavioral analytics should be leveraged to define individualized transaction baselines for each user. This enables the real-time monitoring of anomalous activities—such as atypical login behavior or substantial transfer requests—and the generation of timely risk alerts.

4.2 Strategic Breakthrough Points: Focusing on Attractive Qualities to Forge Differentiated Competitive Advantages

4.2.1 Developing a core "cognitive intelligence" engine

Optimized large language models, fine-tuned for the financial domain, should be leveraged to enhance system capabilities. To advance semantic comprehension and ensure coherence in multi-turn dialogues, dedicated resources should be allocated for domain adaptation training. This process utilizes advanced natural language understanding architectures and extensive banking dialogue corpora, enabling the AI-powered banking customer service to master domain-specific terminology and operational scenarios. In addition, dedicated modules should be developed for dialogue state tracking and contextual management. To achieve genuine multi-turn conversational ability, backend systems must be engineered to track and retain real-time dialogue context.

4.2.2 Expanding service boundaries and optimizing interaction performance

Functional capabilities should be expanded to achieve comprehensive coverage across all key business scenarios. The scope of the AI-powered banking customer service should be systematically expanded beyond conventional, standardized queries—such as account inquiries, fund transfers, and bill payments—to incorporate more complex, advice-oriented scenarios. These include wealth management consultations, comparative loan product analyses, and detailed insurance product interpretations. In addition, underlying technical infrastructure should be optimized to achieve near-instantaneous system responsiveness. Rapid response latency is a critical factor shaping user perception of service convenience. Through technical interventions such as model lightweighting, deployment of high-performance computing resources, and intelligent caching strategies, system performance must be continuously refined.

4.3 Cost Control: Conducting Prudent Evaluation of Indifferent Qualities to Achieve Efficient Resource Allocation

4.3.1 Maintaining basic experiences and suspending the development of advanced functions

Basic consistency should be guaranteed and excessive investment should be avoided. For multi-channel consistency, it is essential to ensure that the core business information and processes remain consistent across various channels, such as mobile banking, WeChat mini-programs, and official websites. The development of core functions, including the system's core semantic understanding and business processing capabilities, should be focused on, while suspending the development of "embellishing" functions. The development of advanced functions like emotional interaction and predictive recommendations incurs high costs; moreover, as the related technologies are still immature, such functions are prone to producing counterproductive effects due to "inaccurate empathy" or "inadequate prediction". For personalized services, a minimum viable solution can be adopted—for instance, providing personalized greetings or service entitlement reminders based on users' basic identities (e.g., premium customers)—rather than building complex user portraits and recommendation systems at the initial stage.

It should be emphasized that the findings and conclusions of this study are primarily based on China's specific financial and digital services environment. China's banking sector is profoundly influenced by a unique regulatory framework, the high prevalence of digital payments, and the distinct technological acceptance and interaction preferences of its domestic users. Consequently, the research outcomes and optimization strategies presented herein are principally applicable to the Chinese banking industry.

5 Conclusions and Future Work

5.1 Conclusions

Based on a thorough assessment of existing literature and questionnaire surveys, a user demand indicator system was developed in this study for AI-powered banking customer service. Using the Kano model, demand attributes were categorized systematically, and quantitative analysis was conducted via better-worse coefficients to establish the priority of specific functions. The findings show that core user demands for AI-powered banking customer service can be divided into three attribute types, with functional optimization priorities ranked as follows: rapid transfer to human agents, high response accuracy, risk alerts, service continuity and stability, privacy protection, secure identity verification, rapid response speed, comprehensive business coverage, multi-turn dialogue capability, and accurate user intent understanding.

At the theoretical level, it dismantles the linear mindset within AI-powered banking customer service that equates "more features and higher performance with better experience", revealing the complex mechanism whereby satisfaction is driven nonlinearly by diverse attribute requirements. At the practical level, it establishes a prioritization framework for requirements, systematically translating user needs into actionable resource allocation strategies. This propels AI-powered banking customer service away from pursuing "feature completeness" towards designing "exceptional experiences".

5.2 Limitations and Future Research

This study acknowledges certain limitations, primarily concerning the composition of the sample. Among the 172 valid questionnaires, 82 (approximately 47.67%) were collected from the student population. While students, with their higher receptivity and sensitivity to technological innovation, represent a potential and existing user group for AI-powered bank customer service, this proportion may result in a sample that does not fully and evenly represent the overall characteristics of the bank's entire customer base in terms of age, income, professional background, and the complexity of financial needs. For instance, the demand for more complex services related to investment, wealth management, or loans is likely stronger among working professionals, a dimension not sufficiently captured in the current sample.

To address this limitation, future research should aim to enhance the diversity and representativeness of the sample by incorporating a broader spectrum of users. Efforts should be made to construct a sample that is more balanced in its distribution across age, occupation, income, geographical location, and financial asset scale. Particular attention should be paid to increasing the proportion of key user groups, such as working professionals and mid-to-high-net-worth individuals, thereby improving the generalizability of the findings.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflict of interest.

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