

# **Design of Intelligent Customer Service Dialogue Systems Integrating Affective Computing and Strategies for Improving User Experience**

Xiexiaorong Renmin Xujiangnan

Mongolian National University, Ulaanbaatar, Bayangol, 16060;

Abstract: With the deep penetration of artificial intelligence technology in the service sector, intelligent customer service dialogue systems have become core tools for enterprises to optimize service processes and reduce operational costs. However, traditional systems mostly focus on functional implementation, lacking the ability to perceive and respond to users' emotional needs, leading to homogenized service experiences and low user satisfaction. Based on affective computing theory and incorporating technologies such as natural language processing and speech signal analysis, this paper proposes a design framework for intelligent customer service dialogue systems that integrates affective computing. The core architecture is constructed from the affective recognition layer, affective decision-making layer, and affective response layer. Furthermore, strategies for improving user experience are discussed around three dimensions: emotional interaction design, personalized service adaptation, and service scenario extension, providing theoretical reference and practical pathways for the emotional upgrade of intelligent customer service systems.

Keywords: Affective Computing; Intelligent Customer Service; Natural Language Processing

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#### Introduction

In digital services, intelligent customer service has become the primary touchpoint for communication between enterprises and users, thanks to advantages such as 24/7 response and multi-channel coverage. Its penetration rate exceeds 60% in fields like finance and e-commerce. However, most systems can only perform "problem identification answer matching" and cannot perceive user emotions such as anxiety or dissatisfaction. Consequently, when users encounter complex problems or negative emotions, they struggle to receive emotional support, often switching to human agents or abandoning inquiries, which increases enterprise costs and damages brand perception.

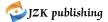
Affective computing, proposed by MIT's Professor Picard in 1997, aims to use technology to recognize, analyze, and simulate human emotions to achieve "human-computer emotional interaction." Integrating it into intelligent customer service can compensate for the lack of emotional perception in traditional systems and reconstruct the service logic to be "user-centered." Therefore, researching related system design and user experience improvement paths is of great significance.

## 1 Design Framework for Intelligent Customer Service Dialogue Systems Integrating Affective Computing

An intelligent customer service dialogue system integrating affective computing needs to add emotional perception and response modules on the basis of traditional dialogue systems, forming a closed-loop logic of "Affective Recognition -Affective Decision - Affective Response." The overall system architecture is divided into five layers, each with independent yet collaborative functions, ensuring efficient flow and processing of emotional information. [3]

#### 1.1 Data Collection Layer

As the foundation of affective computing, the data collection layer is responsible for collecting multimodal data from



user interactions. Its core tasks are "multi-channel data integration" and "data preprocessing." Multi-channel data integration covers three types of data: text (text input, speech-to-text), speech (speech rate, tone, volume), and behavior (input intervals, click frequency, dialogue interruption count), providing raw material for affective recognition. Data preprocessing involves cleaning and standardizing raw data, including text denoising, speech signal noise reduction, and behavior data normalization, to prevent noise from affecting recognition accuracy.

#### 1.2 Affective Recognition Layer

The affective recognition layer is the "emotional perception center," using algorithms based on multimodal data to determine the user's emotional state and intensity, adopting a "multimodal fusion recognition" strategy. Text sentiment analysis relies on NLP technology, combining deep learning models and sentiment lexicons to determine text sentiment polarity and output intensity scores. Speech emotion recognition focuses on speech features, converting them into emotion labels and scores through signal processing algorithms. Behavioral emotion inference indirectly infers emotions from interaction behaviors, combining mapping rules and machine learning models to output results. Finally, the results from the three modalities are weighted and fused (e.g., Text 0.5, Speech 0.3, Behavior 0.2, adjustable dynamically), and the emotional state and intensity are transmitted to the affective decision-making layer.

#### 1.3 Dialogue Understanding Layer

The dialogue understanding layer parses the user's consultation intent, providing the "demand context" for affective decision-making. It adds "emotion-intent correlation analysis" on top of traditional intent recognition. Intent recognition uses classification models to match user input to predefined intent categories, clarifying functional needs. Emotion-intent correlation analysis constructs a correlation matrix to analyze the relationship between emotions and intents, such as "complaints/suggestions" often accompanying "anger," and "business handling" often accompanying "confusion," aiding in accurately understanding the user's emotional motivation.

#### 1.4 Affective Decision-Making Layer

As the "emotional strategy center," the affective decision-making layer formulates "emotional response strategies" and "dialogue progression strategies" based on the emotion and intent results, following the principle of "emotion priority, function adaptation." Emotional response strategies determine the response direction according to the emotional state and intensity. For example, "Anger (8 points)" adopts "Apology + Pacification," while "Confusion (6 points)" adopts "Explanation + Breakdown." Dialogue progression strategies adjust the pace and content depth based on emotions. For example, "Satisfaction (7 points)" might allow for a faster pace and recommendation of value-added services, while "Anxiety (9 points)" requires slowing down the pace and focusing on problem resolution.

#### 1.5 Affective Response Layer

The affective response layer is the interactive "output end," translating strategies into dialogue content and interaction forms. Response content generation relies on an emotional response template library and NLG technology to generate personalized text, avoiding negative vocabulary. Interaction form adaptation adjusts the response form based on emotion and channel. For example, adding 安抚 emojis for "dissatisfaction" in text channels, or using a gentle tone for "sadness" in voice channels.

## 2 Strategies for Improving User Experience in Intelligent Customer Service Based on Affective Computing

The ultimate goal of integrating affective computing into intelligent customer service dialogue systems is to enhance user experience - enabling users to have their functional needs met while also gaining emotional recognition and comfort. Based on the system design framework, user experience improvement strategies can be formulated from three dimensions: emotional interaction design, personalized service adaptation, and service scenario extension.<sup>[1]</sup>

### 2.1 Emotional Interaction Design: Building an "Empathic" Dialogue Relationship

The interaction mode of traditional intelligent customer service is mostly the one-way logic of "command-feedback," lacking emotional resonance. The core of emotional interaction design is to build an "empathic" dialogue relationship, allowing users to feel the system's "understanding" and "care," which can be achieved through the following two methods:

Instant Emotional Feedback: Upon recognizing a change in user emotion, the system needs to provide an emotional response within 1-2 dialogue turns, avoiding emotional delay that could exacerbate user dissatisfaction. For example, if a user says, "I've been waiting for half a month without a resolution, so disappointed," the system must immediately capture the "disappointment" emotion and prioritize responding to the emotional need in its reply (e.g., "I fully understand your disappointment after waiting for half a month. This is indeed a service oversight on our part. I will escalate the processing priority for you to ensure a solution is provided within today.") before proceeding with the problem-solving process. Instant emotional feedback makes users feel valued and reduces emotional opposition.

Anthropomorphic Dialogue Tone: Break away from the "robotic" tone style of traditional systems by adopting a more human-like, anthropomorphic tone to enhance the naturalness and warmth of the interaction. For example, after a successful user inquiry, the system could use a tone like, "Congratulations on successfully completing your business! If you have other needs later, feel free to come find me again~" instead of the rigid "Business processing completed. Thank you for using." When a user encounters operational difficulties, the system could use an encouraging tone like, "No problem, many users encounter this issue when starting out. Let's take it step by step," instead of the instructional tone, "Please try again according to the operation guide." The anthropomorphic tone should adhere to the "principle of moderation," avoiding excessive informality that might reduce professionalism.

# 2.2 Personalized Service Adaptation: Achieving a "Thousand People, Thousand Faces" Service Experience

Users' emotional needs exhibit significant individual differences: the same problem may evoke different emotional reactions in different users (e.g., young people might show "dissatisfaction" towards "service delay," while older adults might show "anxiety"); the same emotion might require different response methods from different users (e.g., some users want "quick problem resolution," others want to "fully express their emotions"). Therefore, personalized service adaptation is key to improving user experience. It requires achieving "thousand people, thousand faces" service adjustments based on user profiles and historical emotional data:

User Emotional Profile Construction: The system constructs a user emotional profile by recording historical interaction data (emotional states, response preferences, consultation scenarios), containing three dimensions: "Emotional Sensitivities," "Response Preferences," and "Scenario-specific Emotional Characteristics." For example, a user's history shows frequent "anxiety" due to "long waiting times" (Emotional Sensitivity), greater satisfaction with "step-by-step breakdown" responses (Response Preference), and a tendency towards "confusion" in "bill inquiry" scenarios (Scenario-specific Emotional Characteristic). User emotional profiles need real-time updates to ensure alignment with the user's current emotional needs. [2]

Dynamic Service Strategy Adjustment: Based on the user emotional profile, the system dynamically adjusts service strategies during each interaction. For example, for the aforementioned user, when they consult about "bill inquiry" again, the system can preemptively predict "confusion" and proactively use a "step-by-step breakdown" response, reducing waiting steps (e.g., "You might have encountered operational issues when querying bills before. This time, I'll directly tell you the specific steps: 1. Click 'My' on the homepage; 2. Select 'Bill'; 3. Select the query month. Then you can see the detailed record. Feel free to ask if anything is unclear."). When the user consults about "service delay," the system can prioritize responding to the "anxiety" emotion, clearly informing them of the processing progress (e.g., "Please don't worry. I have checked for you that your service is being expedited. The current progress is 90%, expected to complete within 5 minutes."). Personalized service adaptation should avoid "over-personalization"; core functions (e.g., security verification, information confirmation) must remain standardized to ensure service security and accuracy.

### 2.3 Service Scenario Extension: From "Problem Solving" to "Emotional Prevention"

Traditional intelligent customer service scenarios are limited to "user actively consults - system passively responds,"

meaning the system only handles emotional needs after problems occur. Intelligent customer service integrating affective computing can extend service scenarios to "before problems occur," achieving "emotional prevention" through emotional early warning and proactive intervention, thereby reducing the generation of negative emotions at the source:

Emotional Early Warning Mechanism Establishment: The system identifies "potential emotional risk scenarios" by analyzing user behavior data and business data, and issues emotional early warnings in advance. For example, if the system detects that a user's "bill overdue reminder was not sent" (business data) and their recent login frequency has significantly increased (behavior data), it can predict that the user might develop "anxiety" or "dissatisfaction" due to "forgetting the bill," triggering an emotional warning. If the system detects a user staying on a "service processing page" for over 5 minutes without operation (behavior data), it can predict the user might develop "frustration" due to "operational confusion," triggering an emotional warning.

Proactive Emotional Intervention: In response to emotional warnings, the system proactively initiates interaction to alleviate potential negative emotions in advance. For example, for the "bill overdue reminder not sent" warning, the system can proactively send a message (e.g., "Friendly reminder: Your bill for this month has not been paid yet. The amount is XX. The payment deadline is XX. Please pay on time to avoid affecting your credit. If you have already paid, please ignore this message."). This both addresses the potential problem of user forgetfulness and avoids subsequent negative emotions due to "overdue." For the "operational confusion" warning, the system can proactively ask (e.g., "I noticed you've been on the service processing page for a while. Are you encountering any operational problems? Would you like me to explain the specific steps?"), providing help in advance to prevent user "confusion" from turning into "frustration." Proactive emotional intervention must adhere to the "frequency principle," avoiding excessive disturbance to users (e.g., no more than 2 proactive interventions per day for the same user).

#### 3 Conclusion and Outlook

Based on affective computing theory, this paper proposed a design framework for intelligent customer service dialogue systems integrating affective computing, constructing the system architecture from the data collection layer, affective recognition layer, dialogue understanding layer, affective decision-making layer, and affective response layer, realizing the closed loop of "Affective Recognition - Decision - Response." Furthermore, it proposed user experience improvement strategies centered on emotional interaction design, personalized service adaptation, and service scenario extension, providing ideas for the emotional upgrade of intelligent customer service systems.

From a practical perspective, intelligent customer service dialogue systems integrating affective computing need to address two core challenges: First, the accuracy of affective recognition requires further optimization of multimodal fusion algorithms to enhance emotion judgment capability in complex scenarios (e.g., dialectal speech, ambiguous text). Second, the appropriateness of emotional responses requires balancing emotionalization and professionalism, avoiding excessive emotionalization that leads to decreased service efficiency. Future research could focus on the "Integration of Affective Computing and Large Language Models" — leveraging the semantic understanding and generation capabilities of large language models to enhance the naturalness and personalization of the system's emotional responses. Simultaneously, exploring "Cross-Channel Emotional Consistency" is crucial to ensure users receive a unified emotional service experience across different interaction channels (APP, WeChat, phone), further enhancing user satisfaction and brand loyalty.

Intelligent customer service dialogue systems integrating affective computing represent not only a technological upgrade but also a shift in service philosophy – from "function-centered" to "user emotion-centered." Through the combination of technology and philosophy, intelligent customer service will truly become an "emotional bridge" between enterprises and users, promoting the development of the service industry towards greater warmth and humanization.

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