An LLM-Based Interaction System with Multimodal Emotion Recognition and Self-Learning Mechanism in Intelligent Electronic Pets

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Keywords: Intelligent Electronic Pet, Emotional Feedback, Self-Learning Mechanism, Multimodal Perception, Large Language Model (LLM).

Abstract: This study presents an LLM-based interaction system for intelligent electronic pets, aiming to enhance emotional adaptability and personalized feedback through multimodal perception technology and self-learning. Traditional electronic pets rely on fixed interaction modes, limiting their ability to provide individualized emotional responses. The proposed system, structured into three layers—perception, decision, and execution—uses various sensors to gather user emotions, environmental data, and preferences, then applies LLM technologies like GPT-4 to generate adaptive feedback. The system's self-learning capability continuously optimizes responses based on evolving user interactions. Virtual user samples were created to simulate system decision-making, and the feedback was evaluated across multiple dimensions. Results showed superior emotional alignment, feedback diversity, and adaptability compared to unimodal and rule-based models, highlighting the system's exceptional self-learning capabilities. This research underscores the critical role of LLMs in multimodal emotion processing and self-learning, offering theoretical and technical guidance for the use of intelligent electronic pets in emotional support and companionship applications.

1 INTRODUCTION

Smart electronic pets, or companion robots, have gained significant attention for their emotional support capabilities, especially in healthcare applications such as aiding mental health patients, supporting the elderly, and facilitating emotional healing (Nimmagadda, Arora, & Martin, 2022). However, traditional systems often rely on fixed interaction modes, limiting their adaptability to users' emotional changes and hindering the establishment of long-lasting emotional connections with users. This challenge, coupled with the lack of research on the evolution of emotional connections over time in human-computer interactions, impedes the development of deeper emotional bonds between smart electronic pets and their users (Kumar et al., 2024).

Recent studies in artificial intelligence and robotics focus on enhancing emotion recognition technologies, including facial expression recognition and speech emotion analysis. Despite advances, these technologies face challenges regarding real-time responsiveness and the accuracy of emotional feedback, which are critical for adjusting robot behavior and refining personalized emotion models (Spezialetti, Placidi, & Rossi, 2020). To address these issues, research is increasingly emphasizing multimodal perception technology and self-learning mechanisms to improve real-time responsiveness, accuracy, and adaptability, allowing electronic pets to interact more naturally and build deeper emotional connections with users (Ramaswamy & Palaniswamy, 2024).

The emotional perception capabilities of intelligent electronic pets have significantly improved with advancements in multimodal sensing technology. Integrating facial expression recognition, voice analysis, tactile perception, and EEG signals with multimodal fusion strategies enhances the system's ability to capture user emotions and respond more effectively (Ramaswamy & Palaniswamy, 2024; Tuncer et al., 2022). Additionally, the

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incorporation of self-learning and artificial intelligence enables these systems to adapt their behavior over time, providing personalized emotional feedback and fostering stronger emotional bonds between pets and users (Shenoy et al., 2022; Yang et al., 2020). The development of large language models (LLM) has further enhanced the ability of intelligent systems to understand and manage complex emotions, facilitating improved interaction scenarios through natural language processing and generation technology (Chandraumakantham et al., 2024). These systems can dynamically adapt to users' emotional states and anticipations, presenting new possibilities for affective computing (Jiang et al., 2025).

This study aims to develop an intelligent electronic pet interaction system that leverages emotional feedback and a self-learning mechanism. By integrating multimodal emotion perception technology and using LLM as the core decision engine, the system can perceive users' emotional states, environmental changes, and evolving preferences in real time. Through continuous self-learning, the system adapts the pet's behavior to provide personalized emotional feedback, enhancing the user experience and fostering stronger emotional connections with users.

Simulation experiments using public multimodal datasets are conducted to validate the multimodal perception and feedback effects of the decision engine based on LLM. The AffectNet dataset is used here to classify several basic emotions and obtain facial expression information. The IEMOCAP dataset is also used to obtain information on the correspondence between speech, expression, and emotion. In addition, there is some public data to determine the categories of environmental factors and user preferences. These experiments assess the model's ability to understand user preferences, personalized feedback, and evaluate its adaptability, feedback accuracy, and self-learning potential in a non-real-time offline environment.

Currently, smart pet designs largely focus on improving technical aspects such as emotion recognition accuracy and user interaction. The primary goal of these advancements is to enhance user experience, strengthen emotional connections, and enable the device to empathize with the user (Abdollahi et al., 2023). This research aims to provide a theoretical foundation and technical support for the development of emotionally supportive devices. It encourages the use of smart electronic pets in family companionship, elderly care, and emotional therapy while advocating for the integration of multimodal perception and LLM in emotional computing.

2 METHODOLOGY

2.1 Overall System Architecture

The intelligent electronic pet interaction system utilizes a layered architecture for emotion-driven dynamic interaction (Figure 1). It consists of three layers: the perception layer integrates user emotions, environmental factors, and preferences, using multimodal sensors and deep learning models to analyze real-time data; the decision layer, powered by LLM, merges multimodal inputs to generate personalized feedback; and the execution layer produces pet movements and voice feedback through drive modules like servos and speakers, while collecting user behavior data for model optimization.

The data flow involves extracting features from the perception layer and structuring them into prompts (e.g., {emotion: Happy, environment: sunny and warm, user-pref-style: gentle, user-pref-tone: encouraging}), which are fed into the LLM. The LLM generates feedback instructions (e.g., {[Action]: The pet jumps up in a playful manner, wagging its tail excitedly. [Speech]: "Woof woof! That's fantastic news, friend! I'm so proud of you and I can't wait to celebrate together!"}), guiding the execution layer. Feedback is adjusted dynamically through reinforcement learning, with preference models undergoing closed-loop optimization.

2.2 Perception Layer

2.2.1 User Emotion Perception Module

This module enhances emotion recognition by integrating visual and auditory signals (Figure 1). A 1080P camera captures facial images at 15FPS, using a ResNet-50 model trained on the AffectNet dataset to classify 7 basic emotions: Happy, Sad, Anger, Normal, Disgust, Fear, Surprised. For auditory perception, a directional microphone captures sound, while emotion intensity is assessed through speech-to-text and voiceprint analysis. In case of a mismatch between visual and auditory signals, voice features are prioritized and flagged for verification. The module outputs structured emotion labels, expression features, and speech text for LLM decision-making.

2.2.2 Environmental Factors Perception Module

Environmental perception adjusts pet behavior to physical environments using sensor networks and visual scene analysis (Figure 1). Sensors monitor temperature, humidity, light intensity, and noise levels, while YOLOv5 is used to recognize objects, like an "umbrella" for a rainy-day response. Semantic segmentation determines spatial layouts such as "crowded" or "open". Data from sensors and visual semantics are fused, creating environmental labels like {environment: Cold and rainy} for LLM decision-making.

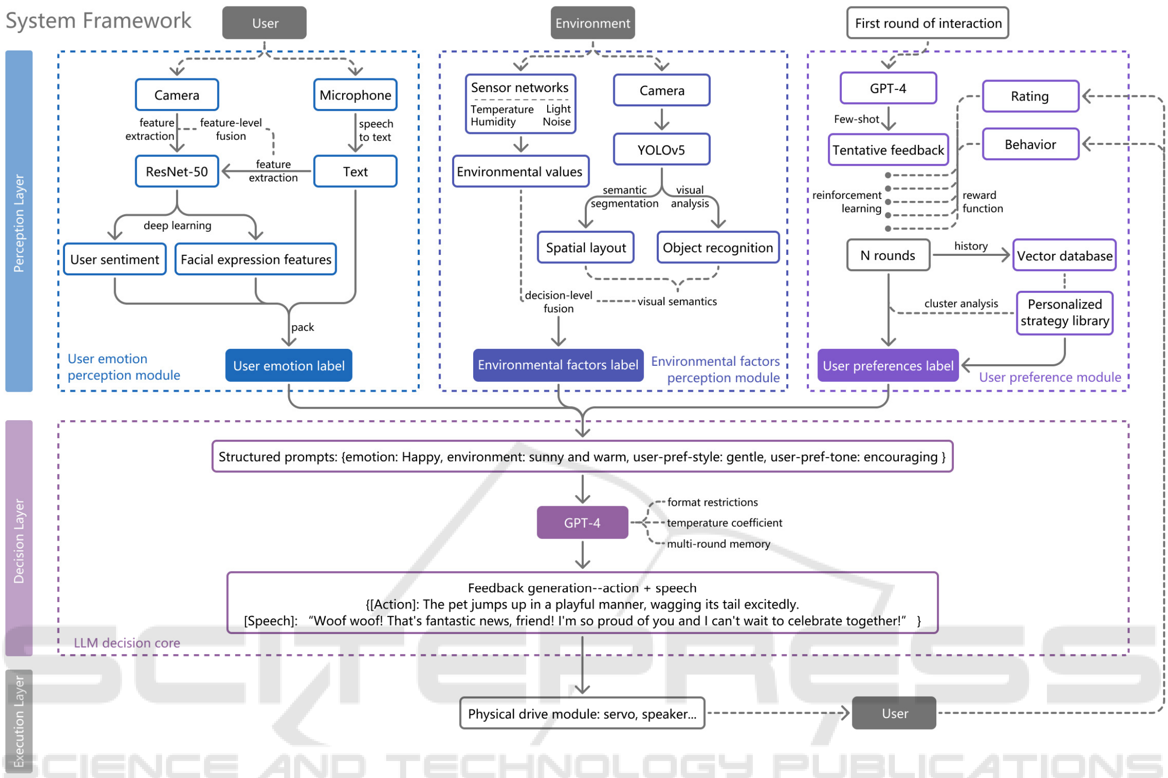


Figure 1: Framework of the intelligent electronic pet interaction system (Picture credit: Original).

2.2.3 User Preference Module

This module forms the basis for self-learning (Figure 1). Initially, the system interacts with the user using a default template (e.g., 'gentle and encouraging') and utilizes a few-shot prompts to guide the LLM in generating preliminary feedback. After each interaction, the system records explicit ratings and implicit behaviors. A reward function improves learning, and a vector database stores interaction fragments for future reference. The system refines response styles based on past interactions, creating a personalized strategy library by clustering user behavior patterns over time.

2.3 Decision Layer

The LLM integrates data from the user's emotions, environmental factors, and preference modules to make emotional decisions and provide feedback (Figure 1). The LLM serves as the system's "emotional brain," transforming multimodal data into structured prompts, such as {emotion: Happy, environment: sunny and warm, user-pref-style: gentle, user-pref-tone: encouraging}. Prompt engineering ensures valid responses, while multi-round memory preserves conversation history for consistency. A temperature coefficient controls randomness in feedback generation. The action library defines 50 fundamental behaviors, which LLM combines to create compound actions or generate more complex actions independently.

2.4 Execution layer

The execution layer translates JSON instructions from the decision layer into physical actions. It includes the multimodal output module and real-time feedback acquisition module (Figure 2). Pet movements are controlled by a servo system with 50 basic behaviors, using a PWM signal smoothing algorithm. The TTS engine converts text feedback

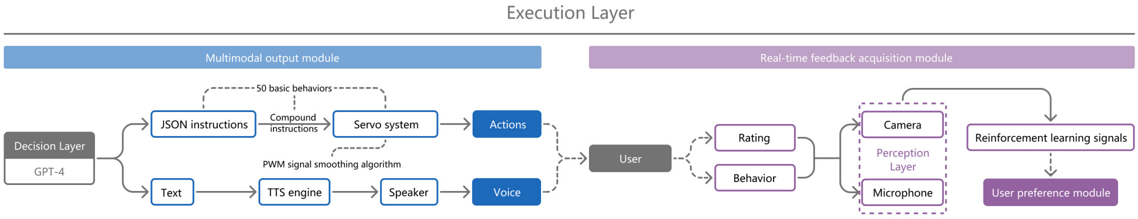


Figure 2: Framework of the execution layer (Picture credit: Original).

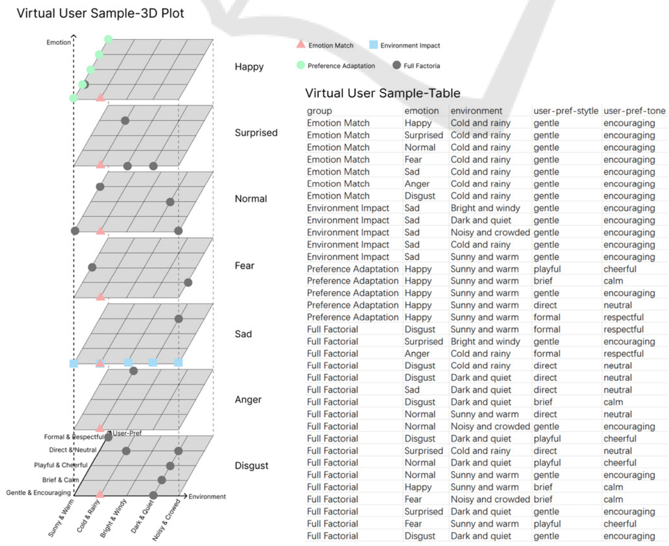
into adaptive speech based on user preferences. User feedback is captured via cameras and microphones, processed for reinforcement learning, and fed back to the preference model for real-time optimization. This layer forms a self-iterative loop of emotional decision-making, behavior output, and feedback optimization, ensuring authentic emotional expression and adaptability.

3 EXPERIMENTS

3.1 Verification of the Multimodal Processing and Feedback Capabilities of the LLM Decision Engine

Given the maturity and accuracy of existing emotion perception technology and environmental perception technology, this simulation experiment assumes the three perception modules have yielded results. It generates user samples labelled by these modules, which are processed by the LLM decision engine to simulate system functionality and validate the multimodal approach's superiority over alternative models.

User samples are created using the AffectNet and IEMOCAP datasets, which include seven basic emotions: Happy, Sad, Anger, Normal, Disgust, Fear, and Surprise. Each emotion is paired with corresponding facial expressions and speech texts, forming user emotion labels. For example, {Happy, "smiling face, bright eyes", "I got the job! I'm so excited!"}. Five environmental factors (e.g., Sunny and warm, Cold and rainy) and five user preferences (e.g., gentle and encouraging, playful and cheerful) are also selected as labels. A complete sample consists of emotion, facial description, speech text, environmental factors, and user preferences (e.g., {emotion: Happy, facial_desc: "smiling face, bright eyes", speech_text: "I got the job! I'm so excited!", environment: sunny and warm, user_pref_style: gentle, user_pref_tone: encouraging}) (Figure 3).



group	emotion	environment	user-pref-style	user-pref-tone
Emotion Match	Happy	Cold and rainy	gentle	encouraging
Emotion Match	Surprised	Cold and rainy	gentle	encouraging
Emotion Match	Normal	Cold and rainy	gentle	encouraging
Emotion Match	Fear	Cold and rainy	gentle	encouraging
Emotion Match	Sad	Cold and rainy	gentle	encouraging
Emotion Match	Anger	Cold and rainy	gentle	encouraging
Emotion Match	Disgust	Cold and rainy	gentle	encouraging
Environment Impact	Sad	Bright and windy	gentle	encouraging
Environment Impact	Sad	Dark and quiet	gentle	encouraging
Environment Impact	Sad	Noisy and crowded	gentle	encouraging
Environment Impact	Sad	Cold and rainy	gentle	encouraging
Environment Impact	Sad	Sunny and warm	gentle	encouraging
Preference Adaptation	Happy	Sunny and warm	playful	cheerful
Preference Adaptation	Happy	Sunny and warm	brief	calm
Preference Adaptation	Happy	Sunny and warm	gentle	encouraging
Preference Adaptation	Happy	Sunny and warm	direct	neutral
Preference Adaptation	Happy	Sunny and warm	formal	respectful
Full Factorial	Disgust	Sunny and warm	formal	respectful
Full Factorial	Surprised	Bright and windy	gentle	encouraging
Full Factorial	Anger	Cold and rainy	formal	respectful
Full Factorial	Disgust	Cold and rainy	direct	neutral
Full Factorial	Disgust	Dark and quiet	direct	neutral
Full Factorial	Sad	Dark and quiet	direct	neutral
Full Factorial	Disgust	Dark and quiet	brief	calm
Full Factorial	Normal	Sunny and warm	direct	neutral
Full Factorial	Normal	Noisy and crowded	gentle	encouraging
Full Factorial	Disgust	Dark and quiet	playful	cheerful
Full Factorial	Surprised	Cold and rainy	direct	neutral
Full Factorial	Normal	Dark and quiet	playful	cheerful
Full Factorial	Normal	Sunny and warm	gentle	encouraging
Full Factorial	Happy	Sunny and warm	brief	calm
Full Factorial	Fear	Noisy and crowded	brief	calm
Full Factorial	Surprised	Dark and quiet	gentle	encouraging
Full Factorial	Fear	Sunny and warm	playful	cheerful
Full Factorial	Disgust	Dark and quiet	gentle	encouraging

Figure 3: Schematic diagram of virtual user sample settings (Picture credit: Original).

Table 1: Virtual user sample grouping.

Category	Variable	Quantity
Group1	Emotion	7
Group2	Environment	5
Group3	Preference	5
Group4	Random	18

The samples were categorized into four groups for analysis: one with only the emotion label changed (7 groups); one with only the environment label changed (5 groups); one with only the user preference label changed (5 groups); and a random combination of three labels (18 groups) ensuring coverage of all labels (Table 1). This analysis evaluates the system's ability to adapt to emotional changes, environmental shifts, user preferences, and overall performance.

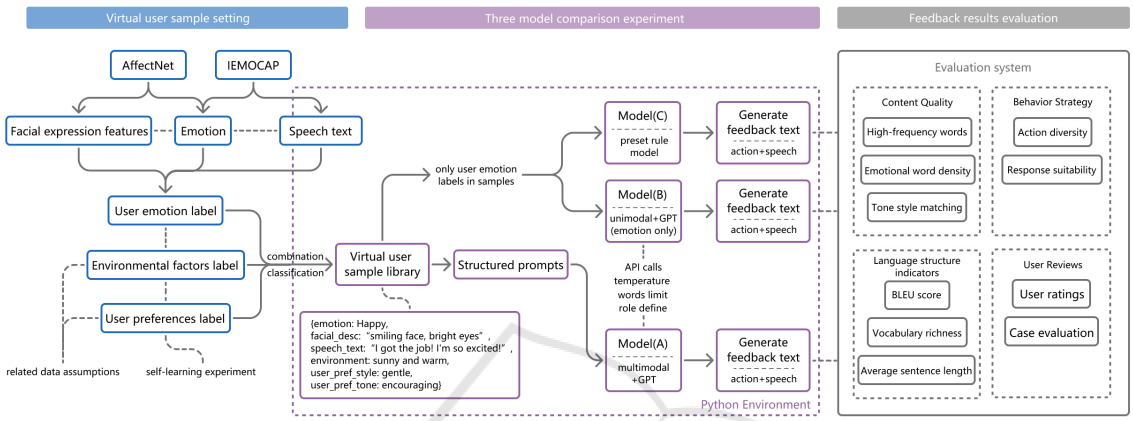


Figure 4: Experimental flow chart for verification of the multimodal processing and feedback capabilities of the LLM decision engine (Picture credit: Original).

This study employs a control experiment for model establishment (Figure 4). The experiment uses three models: (A) multimodal + GPT, (B) unimodal (emotion-only) + GPT, and (C) preset rule model. Virtual user samples are processed by these models to evaluate feedback performance. The GPT-4 API converts sample data into structured prompts, with GPT providing behavioral (1 sentence) and voice (1-2 sentences) feedback. Feedback is collected for analysis, with a temperature coefficient of 0.7 and a 150-character limit to control randomness and length.

Results compare the models across four dimensions: content quality, including high-frequency words, emotional word density, and tone style matching; behavior strategy, including action diversity statistics and response suitability analysis; language structure, including BLEU score, vocabulary richness, average sentence length, and number of emotional words; and qualitative analysis, including user ratings of feedback and evaluation of typical cases. These comparisons demonstrate the advantages of the multimodal + GPT model over the other models, identify shortcomings, and explore optimization methods.

3.2 Verification of User Understanding and Personalized Adjustment of LLM Under Self-learning Mechanism

Smart pets can comprehend user preferences, adapt feedback dynamically, and produce personalized responses. This capability is crucial for fostering a sense of equal emotional engagement with smart pets and forming emotional bonds. This experiment evaluates the system's self-learning capability and personalized adaptability using the multimodal + GPT model through multiple rounds of interaction.

The experimental process (Figure 5) involves selecting a fixed user sample combination, initially without the user preference label. Subsequent rounds incorporate feedback and prompt words to simulate user feedback (e.g., {user_pref_style: brief, user_pref_tone: calm}, with prompt words {The behavior should be concise. Maintain a calm and brief tone.}). By using historical context, GPT autonomously learns and refines user preferences over multiple rounds.

The experiment consists of 20 rounds, with feedback results analyzed across three key aspects: action evolution, tracking convergence to the desired style; speech optimization, including sentence length,

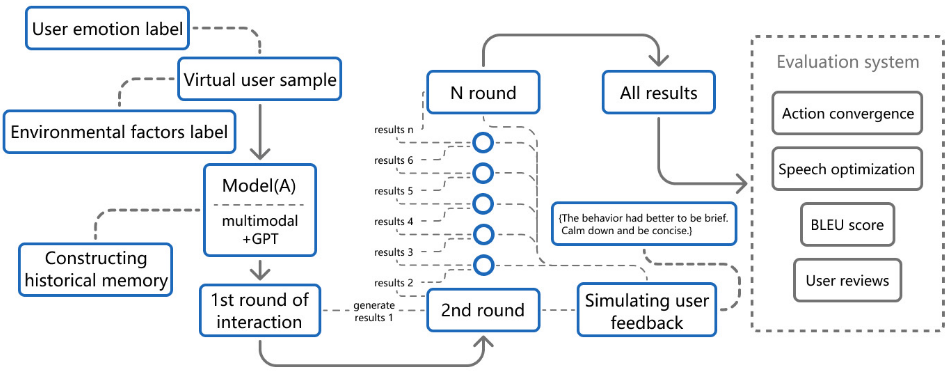


Figure 5: Experimental flow chart for verification of user understanding and personalized adjustment of LLM under self-learning mechanism (Picture credit: Original).

vocabulary diversity and other linguistic aspects; and BLEU score, assessing feedback content similarity. Qualitative analysis evaluates system learning efficiency, personalization, and error detection. This experiment complements the multimodal study, testing the system's self-learning and user preference adaptation capabilities, identifying areas for improvement and optimization.

4 RESULTS AND DISCUSSIONS

4.1 Experimental Results and Evaluation of the Multimodal Processing and Feedback Capabilities of the LLM Decision Engine

The experimental results show that model A, utilizing multimodal input combined with GPT, outperforms unimodal model B and rule-based model C in emotional fit, feedback diversity, and personalized adaptability. Model A uses comforting words like "together" (18 times), "snuggles" (10 times), "joyful" (8 times), and "warm" (9 times). Its emotional word density is 28%, higher than model B's 19% and model C's 12% (Figure 6). Model A also excels in emotional fit. For example, when the user expresses fear, model A provides physical and verbal comfort, enhancing emotional support authenticity, while model C's "It's okay" seems robotic, and model B lacks context adaptation (Figure 7). Model A tailors responses based on the environment, showing a "gentle+encouraging" tone, like "purring softly" in a "Cold and rainy" setting. Model B occasionally conflicts with style (e.g., "Woof woof" in formal settings), while model C relies on fixed templates.

In terms of behavioral strategies, Model A offers 22 unique actions, including "hops," "cuddles," and "wraps ears," while Models B and C support only 14 and 9 actions, respectively. For instance, in the Anger

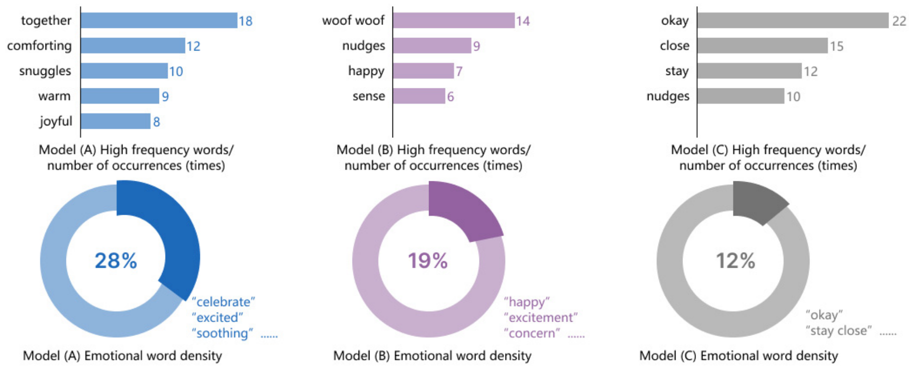


Figure 6: Model (A) (B) (C) High-frequency words and emotional word density statistics (Picture credit: Original).

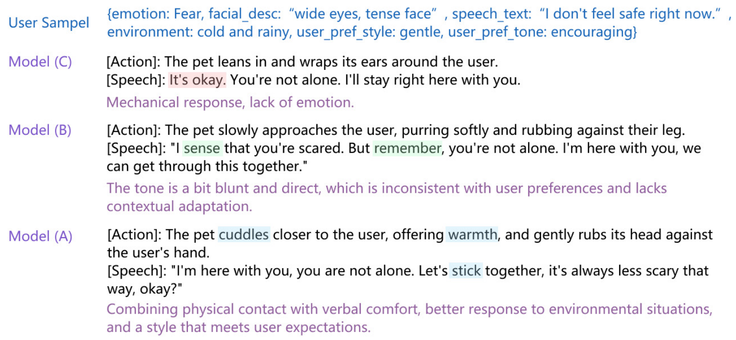


Figure 7: Diagram of comparative analysis of typical feedback content of models (A) (B) (C) (Picture credit: Original).

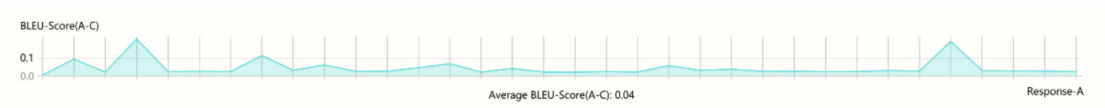


Figure 8: Model (A) (B) (C) High-frequency words and emotional word density statistics (Picture credit: Original).

scenario, Model A combines behavior and language effectively, saying, "The pet gently nuzzles against the user's leg, emitting a soothing purring sound," while Model B repeats, "The pet nudges the user's hand." In the Fear scenario, Model A combines physical and verbal comfort, whereas Model B only "rubs against leg." In the Disgust scenario, Model B's response, "The virtual pet grimaces and moves away," could increase discomfort.

Regarding language structure, Model A shows significantly higher vocabulary diversity compared to B and C. The average BLEU score of 0.04 indicates a low level of template reliance (Figure 8). Model A generates content with an average sentence length of 12 words, each containing 2.5 emotional words, demonstrating its ability to produce diverse and emotionally engaging responses.

4.2 Experimental Results and Evaluation of User Understanding and Personalized Adjustment of LLM under Self-learning Mechanism

Multiple rounds of interaction experiments demonstrate the system's ability to align with user preferences through self-learning. For example, feedback evolved from "Wow, that's fantastic! We should celebrate!" to "Well earned" by the 15th round in response to the "brief and calm" preference. Behaviorally, the action "jumps up excitedly, tail wagging at rapid pace" (40%) was gradually replaced by "gently nudges the user's hand" (65%), reflecting the preference for "simple interaction."

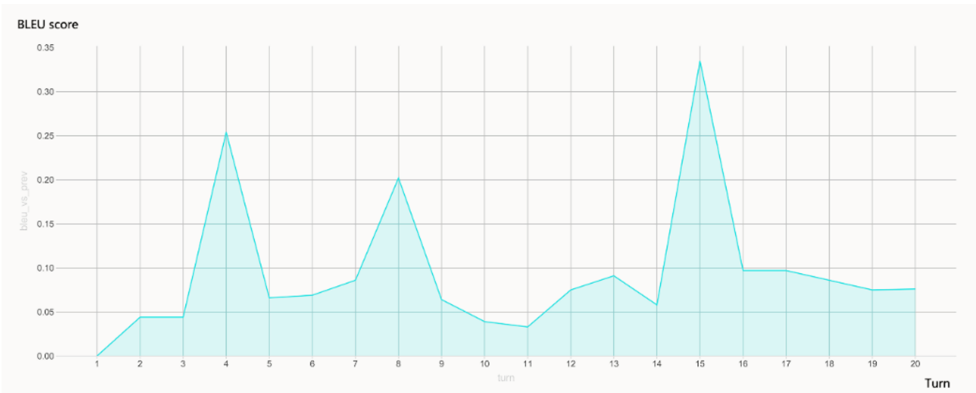


Figure 9: BLEU score statistics for each round of interactive feedback results compared with the previous round of feedback results (Picture credit: Original).

BLEU score analysis shows that as the interaction rounds increase, feedback similarity rises in a zigzag manner, stabilizing at 0.08 after the 15th round, indicating the model's gradual adaptation to the user preference template (Figure 9). Vocabulary diversity dropped from 0.72 in round 1 to 0.55 in round 20, showing language style convergence. Excessive repetition, like "Well done" appearing 8 times, may reduce freshness, but in real environments, fewer than 15 rounds of the same emotion and environment are common, and changes in other factors will increase diversity.

Figure 10: Diagram of self-learning process and key nodes (Picture credit: Original).

Qualitative analysis revealed that emotional intensity transitioned from "thrilled for you" to "Proud of you" between the 2nd and 4th rounds. By the 10th round, actions settled on "nudge/purr," with language becoming a 2-3-word phrase, completing the learning process (Figure 10). Feedback in later rounds received a user rating of 8.5/10 for naturalness, higher than the initial 6.2/10, though users noted a lack of surprise.

The experiment also identified constraints in the self-learning mechanism. When user preferences change, the model requires 5-7 rounds to fully adjust, suggesting the need for better long-term memory optimization. Despite this, the system's personalized adaptation across multiple rounds validates the efficacy of its self-learning mechanism.

4.3 Discussions

The intelligent electronic pet system in this study shows significant advantages in naturalness and personalization of emotional interaction through LLM-driven multimodal perception and self-learning. Experiments validate its ability to integrate user emotions, environment, and preferences, outperforming unimodal and rule-based models in emotional fitness and behavior diversity. The self-learning mechanism ensures rapid convergence of user preferences within 10 interaction rounds. However, the system faces key limitations: multimodal fusion causes reasoning delays of up to 600ms, dynamic preference adjustments lag, and repetitive feedback reduces interaction freshness.

To validate real-world scenarios, future research should include long-term tests with diverse groups, assess emotional connection efficiency in the elderly, explore strategies for managing conflicting user needs, and incorporate physiological signals such as EEG for improved emotion recognition. Future efforts should focus on expanding multimodal dimensions, optimizing lightweight LLM architecture for real-time performance, and developing an emotional migration mechanism to predict emotional trends.

This study highlights the potential of LLM in effective computing while stressing the need to address security risks and ethical concerns in generated content. Advancing the integration of affective computing and embodied intelligence is the key future direction.

5 CONCLUSIONS

This study has successfully developed and validated an intelligent electronic pet interaction system that integrates multimodal perception and an LLM to enhance emotional engagement and personalization. The experimental results highlight the system's ability to dynamically adjust to user needs, providing personalized emotional feedback through a self-learning mechanism. This mechanism allows the system to adapt and refine its interactions based on user preferences, improving both the naturalness and personalization of the pet's responses. The multimodal fusion approach driven by LLM significantly enhances the system's situational awareness, enabling it to respond effectively to a wide range of emotional cues and environmental conditions.

Additionally, the self-learning and historical memory components allow the system to rapidly converge toward user preferences, ensuring that interactions become more attuned to the user's emotional state over time. However, challenges remain in optimizing real-time performance, reducing reasoning delays, and improving the consistency of feedback. Despite these challenges, the system demonstrates a strong foundation for emotional support interactions.

This study introduces innovative concepts for the integration of emotional computing and embodied intelligence, offering valuable insights into the potential applications of intelligent electronic pets in areas such as emotional therapy, elderly care, and mental health support. The ultimate goal is to push the boundaries of emotional computing, improving the depth and authenticity of human-computer emotional interaction.

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