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Use Generative AI and Natural Language Processing to Improve User Interaction Design

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Abstract: Modern artificial intelligence technologies continue to mature, and the applications of generative AI and natural language processing (NLP) have become increasingly widespread across various intelligent systems. This study systematically examines the fundamental principles, technical characteristics, and internal connections between generative AI models and NLP mechanisms, forming the theoretical foundation for constructing a next-generation intelligent interaction system. On this basis, the paper designs and develops an integrated system architecture featuring semantic parsing, instant content generation, cross-modal adaptation, continuous self-adjustment, and closed-loop feedback. Through the combined application of intent recognition, generative reasoning, and multimodal information fusion strategies, the system enhances its capability to understand user needs, improves interaction fluency, and significantly strengthens the naturalness and stability of human-machine communication. The experimental component of this work focuses on three representative application scenarios: intelligent customer service agents, voice-based interactive terminals, and text generation and writing assistants. Leveraging extensive comparative experimental data, the study evaluates the performance of the proposed system in terms of response accuracy, generation quality, latency, user comfort, and interaction smoothness. The results demonstrate that the incorporation of generative AI and self-evolving NLP techniques can effectively enhance response speed, improve user experience, and elevate the overall effectiveness of interactive processes. Overall, the findings indicate that human-machine interaction systems built on generative AI and integrated NLP possess high degrees of intelligence, adaptability, and perceptive capability. These systems provide promising prospects for practical deployment and broader promotion across multiple industry sectors, offering valuable guidance for the development of future intelligent interactive applications.

Keywords: generative AI; natural language processing; user interaction; semantic recognition; multi modal fusion

1. Introduction

The wave of intelligence, represented by digital technologies and centered around artificial intelligence, is reshaping user expectations for human-computer interaction. As interactive devices become more deeply integrated into daily life and work scenarios, users increasingly demand natural, intelligent, and immediate responses from interactive systems. Traditional interaction modes-characterized by mechanical command execution, rigid dialogue structures, and task-oriented workflows-are no longer sufficient to address the expanding complexity of user intentions and contextual environments. To overcome these limitations, more advanced AI technologies capable of autonomous understanding, adaptive reasoning, and context-sensitive response generation are urgently required.

Generative AI provides powerful support for this transformation due to its exceptional content production abilities, contextual reasoning capacity, and dynamic situational awareness. It can generate coherent text, images, and multimodal content, enabling systems to respond with creativity and flexibility. Meanwhile, natural language processing (NLP) plays an irreplaceable role in ensuring precise semantic interpretation, intention recognition, dialogue state tracking, and goal-oriented reasoning. The combination of generative AI and NLP therefore forms a complementary technological foundation for constructing next-generation intelligent interaction models that are more human-like and adaptable.

This study focuses on the integrated design of human-computer interaction systems built upon generative AI and NLP technologies. From three dimensions-technical architecture and framework construction, model modeling and simulation, and scenario-based practical testing-the paper investigates how multimodal parsing, generative reasoning, and closed-loop feedback mechanisms can be organically combined to enhance interaction intelligence. The goal is to explore effective pathways for improving system adaptability, personalization, and conversation quality, ultimately promoting the development of human-computer interaction systems that provide richer user experiences and more efficient interactive outcomes.

2. Overview of Generative AI and Natural Language Processing Technologies

2.1. Principles of Generative AI and Natural Language Processing Technology

Generative AI is trained based on deep learning models, which learn language norms and generate logically sound and fluent language outputs with a large amount of corpus input. Among them, the generative models based on Transformer (GPT series) derive the next word through autoregression and have high-level writing ability. NLP (Natural Language Processing) includes various language processing units such as vocabulary, grammar, semantic parsing, etc. It often uses language models (BERT, T5) as pre training and fine-tuning to enhance language's pragmatic background knowledge and intent recognition ability [1]. The key technologies of both include embedding representation, attention mechanism, and sequence modeling, which can translate language input into structured formats to extract semantic features. After combining the two, not only can a cognitive model of language cognition to language creation be formed, but it will also serve as an important support for realizing intelligent and humanized human-machine system models.

2.2. Characteristics of Generative AI and Natural Language Processing Technologies

Generative AI has strong contextual modeling and language generation capabilities, capable of generating coherent, clear, and meaningful text based on user provided information. It has the characteristics of regulating language style, controlling content, and regulating emotional tone, and is suitable for complex interactive environments such as open-ended questioning dialogues and content generation. Natural language processing (NLP), on the other hand, focuses on processing the formal aspects of language and understanding its meaning, demonstrating high accuracy in parts of speech tagging, entity recognition, syntactic analysis, and other aspects, which can help improve intent recognition and multi turn dialogue control capabilities. The technical architecture formed by the combination of these two technologies not only achieves further improvement in semantic understanding, but also enhances the response accuracy of natural language expression in the interaction process. This architecture demonstrates good scalability through modular structure construction and pre trained knowledge transfer, which can meet the application needs of various languages and fields, and can be continuously optimized and improved [2].

2.3. Advantages of Generative AI and Natural Language Processing Technologies

At the level of dialogue design, the technological advantages of generative AI and NLP are very obvious. In the decoding stage, NLP can accurately process requirements through deep semantic construction, analyze and solve fuzzy and ambiguous problems, and improve the system's natural language understanding level. In the coding stage, generative AI can assist in content generation, making interactive content more organized and differentiated, and enhancing user language resonance experience [3]. From the perspective of interactive effects, the method based on pre training data and adjustment of real-time data enables the system to meet user needs more quickly and in real time, reducing the dependence on rule tuning. Based on the fluency of language, this generative AI+NLP interaction has great advantages such as high intelligence, strong processing depth, and strong scalability in content generation and emotion management [4].

3. Generative AI and Natural Language Processing Technologies Enhance User Interaction Design Architecture

3.1. Semantic Recognition and Intent Modeling

Semantic recognition and intent modeling are the main components of natural language processing in interactive systems, and are also the main tasks of language understanding. They parse and extract explicit interaction intentions from natural language information provided by users [5]. Generative AI and natural language processing technologies achieve precise semantic parsing and intent recognition here. Generally, the method based on conditional probability is used for intent recognition, namely:

$$I^* = \arg \max_{i \in I} P(i \mid U, C) \tag{1}$$

Among them, is the most likely user intent type, I is the intent set, U is user input, and C is contextual information.

In the semantic recognition layer, sequence labeling methods are used for entity recognition, slot extraction, and other operations. Common models include BiLSTM CRF, and the loss function is defined as:

$$\mathcal{L}_{CRF} = -\log P(Y \mid X) = -\left(s(X, Y) - \log \sum_{Y'} e^{s(X, Y')}\right) \tag{2}$$

Among them, s (X, Y) represents the weighted score function of the input sequence X and the label sequence Y, with the aim of making the labeling of the global optimal path consistent. We also need to choose modeling methods that are suitable for multi round dialogue systems, such as memory networks or RNN based state memory models:

$$s_t = f(s_{t-1}, u_t) \tag{3}$$

Among them, s_t represents the current session state, u_t is the input of the current round, and function f represents the semantic state update function to achieve context consistency. By using Transformer's word embedding, classifier modeling, sequence annotation, and state tracking methods, it is possible to accurately extract and parse user semantics and identify dynamic requirements, providing a stable foundation for subsequent response generation and interaction improvement.

3.2. Controllable Text Generation Engine

The controllable text generation engine is the part of user communication in AI intelligent assistants. It selectively modifies language attitude, style, text length and other characteristics based on user parameters. Its "controllability" is also an important factor affecting the quality of text expression and the accuracy and experience of human-computer interaction.

This engine is designed based on transformer and adopts autoregressive modeling approach. Its generation process is described as follows:

$$P(y \mid x, c) = \prod_{t=1}^{T} P(y_t \mid y_{<t}, x, c) \tag{4}$$

Among them, x is the user input corpus, c is the control factor, and y_t is the generated t-th word element. The design forms of control factor c include Style Tag, Topic

Vector, Tone Label, etc. Add it to the input and adjust the generation process by controlling these regulatory parameters.

In order to achieve more output and better practicality, predictive models often choose to use a combination of temperature control and top-k/top-p sampling methods. The temperature control formula is as follows:

$$P'(y_t) = \frac{P(y_t)^{1/\tau}}{\sum_i P(y_i)^{1/\tau}} \quad (5)$$

Among them, the randomness of generating new vocabulary is determined by the temperature parameter τ. When τ is less than 1, it tends to select words with higher probability values for output, while when τ is greater than 1, it increases the diversity of the vocabulary. For the Top-k sampling method, the first k high probability words are sampled, while Top-p is limited by the total probability of all words appearing, which can achieve better flexibility and control in language generation.

A controllable text generation system that deeply integrates language models and control systems not only improves language quality and coherence of language styles, but also enables users to achieve intelligent and personalized interactive behavior.

3.3. Multi Modal Interaction Adaptation Structure

Developing a multi modal human-computer interaction platform is seen as the key to achieving barrier free communication between humans and machines. Its pursuit is to combine various methods such as text, speech, images, and body language to enhance the system's comprehensive cognitive and response capabilities. Under the architecture of AI generation and natural language processing, multimodal interaction should be integrated at the receiving stage and collaborative expression should be achieved during the generation process. A basic component can be represented by a weighted fusion model:

$$M = \alpha T + \beta V + \Gamma a \quad (6)$$

Among them, m represents the representation of fusion modality, t represents the vector of text, v represents the vector of vision (such as images and interface elements), and A represents the vector of hearing (such as speech tone). Optimize the learning of weight coefficients α, β, and γ using training data.

Generally, BERT or GPT is used for semantic embedding, CNN or Vision Transformer is used for feature extraction of image and sound modalities, and Mel spectrogram and LSTM are used for feature model construction of sound modality; The early combination method was to directly stack various modal information at the input layer, which is suitable for tasks with tight feature fusion; In the later stage, each modality is processed separately and then combined at the decision level to improve its scalability; The fusion between the two adopts a shared attention mechanism, which enables various modalities to understand each other and further improves semantic consistency. Multi modal creation can be achieved through the use of joint attention mechanisms:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (7)$$

The parameters Q, K, and V can have different mapping modes. Based on this, the generated text can freely change its output mode to fit the image or audio input and context. Multi modal interaction not only enhances the coherence of communication, but also extends the machine's ability to grasp complex tasks and perceive human situations, further providing technical support for creating more vivid artificial intelligence devices.

3.4. User Feedback Driven Self-Learning Mechanism

In the collaborative system of intelligent users, user interaction behavior and feedback have a significant impact on improving the model and enhancing services. By using a self-learning mechanism driven by user feedback to keep the system in an open evolutionary state, personalized satisfaction can be achieved. This mechanism relies on generative AI and natural language processing technologies, which extract and analyze the explicit or implicit feedback generated by users in interactions to adjust model parameters and response strategies in a timely manner, thereby enhancing interactive intelligence. Mainly based on reinforcement learning optimization mechanism:

$$\pi^* = arg \max_{\pi} \mathbb{E}_{\tau\sim\pi} \left[\sum_{t=0}^{T} r_t\right] \quad (8)$$

Among them, π represents the current strategy, τ is the interactive behavior, and is the immediate reward at time t. It is usually constructed from user feedback signals such as click through rate, browsing time, and satisfaction. User feedback can be divided into explicit and implicit, with explicit feedback such as user ratings and proactive questioning; Implicit feedback such as reading style, mouse trajectory, and conversation pause time. Various feedbacks are transformed into training data or evaluation metrics through behavioral modeling functions, which have an impact on the generated model. Here, a closed-loop feedback adjustment system can be further constructed:

$$f_{t+1} = f_t + \eta \cdot \nabla_\theta \mathcal{L}(y_t, y^*) \quad (9)$$

Among them, f_t represents the current model state, η is the learning rate, $\mathcal{L}$ is the loss function, and y^* is the ideal output. In multiple rounds of interaction, the model continuously adjusts parameters to gradually approach the user's preferences.

The feedback driven self-learning mechanism not only improves the adaptability of the system and user stickiness, but also makes interactive content approachable, continuous, and sustainable, providing necessary support for building a truly customer-centric interactive platform.

4. Analysis of User Interaction Design Practices Enhanced by Generative AI and Natural Language Processing Technologies

4.1. Interactive Optimization of Intelligent Customer Service System

By applying generative AI and NLP technologies, improve the communication quality between intelligent customer service systems. By interpreting the context and using goal building techniques, we can more accurately understand user questions and reduce the rate of erroneous perception; With the support of a flexible text generator, the content of the answer can be adjusted according to personal preferences, improving the natural expression and emotional color of the system; With the support of my learning ability, I can continuously optimize the dialogue style and knowledge matching based on user feedback information.

As shown in Table 1 Key Performance Comparison of a Platform Before and After Introducing AI-NLP Architecture.

Table 1. Key Performance Comparison of a Platform Before and After Introducing AI-NLP Architecture.

Index	Traditional customer service system	AI-NLP Customer Service System	Increase amplitude
User problem recognition accuracy (%)	70.5	91.2	+20.7
Average response time (seconds)	2.8	1.1	-60.7
User satisfaction rating (5-point scale)	3.6	4.5	+25.0
First response resolution rate (%)	62.3	85.4	+23.1

From data statistics, it can be seen that the combination of NLP and generative AI with customer service systems has greatly improved the response rate, recognition rate, user satisfaction, and other aspects of the customer service system, which can help create a scientific, efficient, intelligent, and personalized service system.

4.2. Interface Upgrade of Voice Assistant

In addition to traditional voice command functions, voice assistants can also perform functions such as multi round conversations in all scenarios, voice emotion recognition, and multimodal output. Through semantic and intent recognition and intent construction technology, they can accurately identify user needs in complex scenarios. Combined with control based text creation and speech synthesis models, their responses are smoother. The system interface also incorporates image feedback and voice notifications, improving the convenience of user use.

As shown in Table 2 Performance Comparison of a Voice Assistant System Before and After Upgrade.

Table 2. Performance Comparison of a Voice Assistant System Before and After Upgrade.

index	Traditional voice assistants	Upgraded AI voice assistant	Increase amplitude
Multi round dialogue understanding accuracy (%)	63.4	88.1	+24.7
User task completion rate (%)	68.9	91.5	+22.6
User rating for naturalness of response (on a 5-point scale)	3.7	4.6	+24.3
Average interaction time (seconds)	19.2	11.4	-40.6

The above table indicates that the new generation of voice assistants has made significant improvements in semantic understanding, interaction capabilities, and user experience, creating a technological paradigm for building scene aware human-machine dialogue systems.

4.3. Interactive Content Generation in the Creation Platform

Generative AI and NLP modules have a wide range of applications in generating relevant data for machine writing, which can help users produce dialogue copy, advertising slogans, etc. that meet the requirements. Can analyze the initial input content and writing requirements, and then use a language generation control system to generate a preliminary draft that conforms to its preset style and style; Through semantic recognition and feedback systems, interactive designs such as parameter correction and suggestion feedback based on text communication can also be carried out, greatly reducing the threshold for creation and improving production efficiency.

As shown in Table 3 Key Performance Comparison of a Content Creation Platform Before and After Introducing AI-NLP Technology.

Table 3. Key Performance Comparison of a Content Creation Platform Before and After Introducing AI-NLP Technology.

index	Traditional creative platforms	AI-NLP Creative Platform	Increase amplitude
Average creation time (minutes)	42	14	-66.7
User satisfaction rating (5-point scale)	3.9	4.7	+20.5
Draft adoption rate (%)	58.2	87.6	+29.4
Number of modifications (times)	4.2	1.6	-61.9

The above table demonstrates the effectiveness of generative AI and NLP technologies in improving creative efficiency, optimizing content quality, and enhancing user experience, providing technical support for interactive content platforms.

5. Conclusion

This article combines generative AI technology and NLP (natural language processing) technology to reconstruct the design structure of user interaction systems. Designed an understanding layer with semantic modeling as the core, and added a control layer for text output, incorporating different forms of I/O structures, and designed a self-learning self-looping mode. Effectively enhance the machine's understanding of language depth, accuracy of response content, and personalized communication effectiveness. The change in technological structure can not only greatly enhance the adaptability and processing speed of machines to human needs, but also make the communication forms and relationships between humans and machines more harmonious and smooth. This experiment has been validated in typical scenarios in various production and daily life fields, such as intelligent customer service, voice assistants, article generation platforms, etc., all of which have good answer quality and sustained stability. With the continuous improvement of the expression ability of interaction models and real-time adjustment of feedback methods, there is greater scalability and reliability in language logic structure, automatic matching of language styles, and multi round interaction consistency, forming a complete technical support network of artificial intelligence, high efficiency, high quality, and harmonious coexistence, promoting the development of human-computer interaction experience.

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