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RESEARCH ARTICLE

Research on Dialect Protection: Interaction Design of Chinese Dialects Based on BLSTM-CRF and FBM Theories

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ABSTRACT This study aims to augment the impact of dialect-related cultural elements among adolescents, thereby facilitating a more effective inheritance and progression of Chinese dialect culture within the contemporary socio-cultural milieu.Firstly, based on the LSTM architecture, the bidirectional long short-term memory-conditional random field (BLSTM-CRF) model framework for dialect recognition was optimized and established. Subsequently, employing the BLSTM-CRF model for dialect recognition and the acquisition of dialectal voice samples, the natural language sequence input underwent conversion into word vectors or character vectors. The word vectors or character vectors were input into the BLSTM layer to obtain the hidden state vector corresponding to each position, representing the context information of that position. The hidden state vector was input into a fully connected layer, and the CRF layer was adopted to calculate and find the highest scoring label sequence as the final prediction result. Secondly, the FBM theoretical model was utilized to analyze the target user needs through user research methods. Finally, a design framework oriented by dialect recognition and user needs was constructed, and interactive product design was carried out. On the basis of BLSTM-CRF, the product design framework is improved to complete the interactive application design. Integrating user needs and Long Short-Term Memory (LSTM) algorithms into the design of dialect products, we explore ways to preserve and disseminate dialect culture among the younger generation. This provides new insights for the digital inheritance and development of dialects, and also serves as a reference for the design process of related cultural apps.

INDEX TERMS Dialect protection, FBM theory, long and short-term neural network algorithm, user needs, design.

I. INTRODUCTION

Dialects, serving as a significant medium of traditional culture, boast a substantial foundation in China and have historically played an active role in cultural exchanges. Dialects are cultural artifacts left from the historical evolution of our country. In contemporary society, dialects, as a unique cultural symbol, have become a distinctive mode of communication. With the progression of time and the swift popularization of Mandarin, the understanding and usage of dialects among the youth have seen a varying degree of decline [1].

In the realm of dialectology, scholars such as Schwartz et al. [2] have achieved digital preservation of dialects through methods like the construction of speech corpora, providing an effective pathway for the inheritance of dialect culture. The digitization of dialects is beneficial for the protection and inheritance of dialect culture. Dialects are an integral part of Chinese culture and serve as a medium and manifestation of local culture. With economic globalization

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and societal transitions, dialects are facing the crisis of contraction and extinction. Digitization is an efficacious regenerative protection method [3], which can slow down the decline of dialects, preserve the original state of dialects, promote the dissemination and exchange of dialects, and uphold the diversity and richness of culture. The digitization of dialects can provide a large amount of reliable, retrievable, and analyzable dialect data for the theories and methods of dialectology, promoting the development and innovation of dialectology. The digitization of dialects can also foster the intersection and integration of dialectology with other disciplines, such as experimental dialectology [4], corpus dialectology [5], etc., expanding the research horizon and field of dialectology.

In the field of communication, scholars like Agosti et al. [6] have enriched the non-mainstream language forms of online communication by establishing a digital resource library of dialects. The digitization of dialects can enhance the communicative power and influence of dialects, breaking the constraints of region and time, allowing dialect culture to extend beyond its local roots to the national and even global stage, promoting the exchange and mutual learning of different language cultures, and enriching the diversity of human civilization. The digitization of dialects can utilize modern information technology and media platforms to create dialect culture products in various forms and mediums, meeting the needs and preferences of different audiences and stimulating the communicative vitality and innovative potential of dialects. The digitization of dialects can also establish a standardization and normalization system for dialects, strengthening the management and supervision of dialects, preventing the misuse and abuse of dialects, maintaining the purity and authority of dialects, and protecting the communicative rights and social responsibilities of dialects [7].

In conclusion, the digitization of dialects assumes a pivotal role in the protection and dissemination of dialect culture. Based on the analysis and summary of the importance of dialect digitization, this paper proposes to construct the design framework of dialect digitization products from the two perspectives of dialect voice recognition and user needs, aiming to achieve the goal of innovative dialect inheritance.

This study employs an approach that combines the BLSTM-CRF model and the Fog Theory. The BLSTM-CRF model serves as an advanced computational tool for language analysis and understanding. Through efficient learning, it can capture complex patterns within language and predict their variations. On the other hand, the Fog Theory provides a framework to comprehend patterns in people's language usage behaviors. By integrating these two components, our method not only accurately identifies and preserves unique features of different languages but also contributes to understanding and promoting the use and dissemination of these languages. This integrated approach is particularly suitable for researching and safeguarding endangered languages, as it focuses not only on the languages themselves but also on how people employ them.

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II. INTRODUCTION TO DIALECTAL CULTURE AND ANALYSIS OF CURRENT STATUS

A. DIALECTAL CULTURE IN CHINA

Dialects are the natural carriers of culture, bearing the essence of local culture. They are carriers with more attitude, containing the thinking patterns, customs, humanistic concepts, and historical feelings of a region. However, due to the convenience of transportation and frequent exchanges between regions, the limitations of regional dialects have led to a decline in the scope and frequency of dialect use due to the popularization of Mandarin. This is not only in cities, but also in rural areas where the dialect atmosphere is strong, the dialect environment is quietly changing. In competition with Mandarin, dialects are gradually in a relatively weak position [8].

As the natural carrier of culture, dialects carry the core connotations of local culture and become a more profound way of cultural expression. It not only contains the unique thinking patterns, customs, humanistic concepts, and historical emotions of a specific region, but also forms a unique cultural symbol. However, in modern society, with the convenience of transportation and frequent exchanges between regions, regional dialects are facing severe challenges. The popularization of Mandarin has gradually reduced the scope and frequency of dialect use. This trend is not only significant in cities, but even in rural areas where the dialect atmosphere is strong, the dialect environment is quietly changing. The alternation of dialects and Mandarin has led to a series of difficulties in the inheritance of dialects, gradually losing some unique language features [9].

Despite this, dialects still have irreplaceable value. First, dialects are a precious heritage of local culture, carrying rich historical and cultural traditions. Its unique phonetics, vocabulary, and grammatical structure reflect the unique identity of a specific community, which helps to protect and inherit the diversity of local culture [9]. Dialects help to promote social communication and communication. In specific communities or groups, dialects are an important tool for members to communicate with each other, helping to establish closer social connections. In addition, dialects play a unique expressive role in some literary works, music, and artistic expressions, providing rich materials for the cultural and creative industries.

In order to effectively inherit and protect dialect culture, it is necessary to pay close attention to the evolution of dialects in different social backgrounds and the challenges they face. At the same time, innovative methods, such as digital inheritance of dialects and interactive design of dialects, are expected to stimulate people's interest in dialects to a certain extent [10], and promote dialects to maintain a more active existence in contemporary society. This effort is not only beneficial to maintaining the diversity of local culture, but also provides new possibilities for finding a more suitable development path for dialects in today's multicultural environment.

B. RELEVANT STUDIES AND OPTIMIZATION

In recent years, with the support of relevant policies and a shift in public attitudes, many scholars have initiated research and exploration into the design aspects of dialects. Jiang [11] has undertaken the informatization and graphical visualization of Hakka dialect and characters, presenting not only the symbolic intentions of modern fonts but also retaining the cultural characteristics of ancient Chinese characters. Guan and Wang [12], in their study of the Huai'an dialect, have transformed dialects, functioning as "auditory symbols", into communicable "visual symbols". Zhang and Cai [13] have employed informational graphic and visual design approaches to probe the visualized design of Minnan dialect and characters. Al-Adba transplanted Western fairy tales into Qatari culture to promote and preserve Qatari culture and dialect, and to strengthen children's national identity [14]. Abdulhameed have translated dialects into Modern Standard Arabic (MSA), analyzing the generated MSA text through sentiment analysis algorithms [15]. Chiang has constructed a prosodic model of the Chinese dialect text-to-speech system based on the cross-dialect similarity in syntax and prosodic structure between Mandarin and dialects [16].

To date, most of the research on dialect digitization has been focused on the dialect itself, with a lack of user-related research during the dialect digitization process. Traditionally, Jin et al. have used phonetics and phonology theories to statistically analyze the tone of Chinese dialects, providing a solid foundation for in-depth research on the overall dialect phoneme system [17]. Dodsworth have conducted in-depth research on dialect contact caused by immigration issues against the backdrop of a clear type of dialect convergence [18]. An and Du have researched and discussed the cultural strategic significance of the inheritance of Liaoning dialect culture and related approaches [19].

Currently, in the field of dialect digitization research, de Vriend et al. have use Geographic Information Systems (GIS) to analyze and interpret dialect data, making visualization a tool for dialect research [20]. Aunkaew et al. have proposed a hybrid technique to recognize the southern Thai dialect, constructing a continuous speech recognition corpus for the southern Thai dialect [21]. On the social status level of dialects, Krause and Sappok have analyzed the distribution of Russian dialect and the current status of relevant information differentiation and provided insights and prospects on the use of Russian dialects [22]. Traz et al. analyzed Arabic dialects in social texts and built a annotation tool to support automatic language and dialect recognition [23].

This paper intends to improve the Chinese dialect interaction design product by analyzing user needs based on the BLSTM-CRF speech recognition technology, compared to scholars who only research dialect digitization or the dialect itself. The focus of this method is to further the research on the target group of Chinese dialect dissemination based on dialect digitization, combining BLSTM-CRF and Fogg's theory to construct a new dialect modeling framework. This allows the product to better meet the needs of the target group and promote the dissemination of dialects to a certain extent.

III. RELEVANT THEORIES AND CONSTRUCTION OF DESIGN FRAMEWORK

A. BLSTM-CRF

The BLSTM-CRF model is a commonly used deep learning model for sequence labeling tasks. It combines Bidirectional Long Short-Term Memory networks (BLSTM) with Conditional Random Fields (CRF). This model is particularly well-suited for tasks such as Named Entity Recognition (NER) and Part-of-Speech tagging (POS) because of its effectiveness in handling sequential data and considering dependencies among elements within a sequence.

BLSTM, the abbreviation for bidirectional long short-term memory, is a sequence processing model comprised of two LSTMs: one processes inputs in the forward sequence, and the other processes inputs in the reverse sequence. The ability to learn information simultaneously from both directions (forward and backward) enables BLSTM to capture richer contextual information. This makes BLSTM particularly effective in processing data with sequential characteristics, such as language, where the model can efficiently grasp dependencies and context in both the preceding and succeeding elements of the sequence. In natural language processing tasks, BLSTM excels in capturing bidirectional dependencies within text, making it commonly employed in areas such as language recognition.

BLSTM possesses robust sequence modeling capabilities, enabling it to model and predict temporal sequence features. By integrating information from both preceding and succeeding contexts, it can effectively capture the dynamic changes in relevant dialectal information, facilitating dialect prediction and recognition [24]. Conditional Random Field (CRF) is a statistical modeling method used for structured prediction tasks, such as sequence labeling. It considers dependencies between elements in the input data sequence. In sequence labeling tasks, the conditional probability of a label sequence given an observed sequence can be computed.

The integration of Conditional Random Field (CRF) with Bidirectional Long Short-Term Memory networks (BLSTM) aims to combine BLSTM's powerful capabilities in processing sequential data with CRF's advantages in globally optimizing sequence labeling. While BLSTM extracts deep features by analyzing the context before and after each sequence element, it does not directly consider inter-label dependencies [24].

On the other hand, CRF effectively handles dependencies between labels, optimizing the consistency and accuracy of annotation results. By combining BLSTM and CRF, the model can utilize the deep and complex sequential features extracted by BLSTM and enhance overall performance in sequence labeling tasks through CRF's global optimization. Therefore, incorporating CRF on top of BLSTM enables more accurate and efficient processing and analysis of sequential data. In dialect research, this combination allows for a more precise identification of language features specific to dialects, such as particular vocabulary and grammar rules.

Wang et al. have combined convolutional neural networks with BLSTM to learn local speech features, thereby achieving speech recognition of Mandarin [25]. Alashban and Alotaibi have utilized acoustic signal features to complete the BLSTM architecture, which is used to recognize similar languages in Arabic speech [26]. Younes et al. have based their work on BLSTM-CRF to automatically process the Romanized Tunisian dialect for its recognition and transliteration [27].

It can be seen that the BLSTM structure can complete the recognition of Chinese dialects. However, when applied to the design of Chinese dialect interaction products, there is a lack of subsequent exploration for users. In addition to using the BLSTM algorithm from the perspective of computational linguistics to achieve dialect recognition, this study also uses Fogg's Behavior Model (FBM) from the user research perspective to analyze the behavioral needs of target users, in order to achieve user-centered interaction design. However, what is missing in the current research is a comprehensive understanding of how these models can be adapted and optimized for different dialects and user groups.

B. FBM THEORY

The Fogg behavior model (FBM), a behavior model proposed by BJ Fogg, a psychologist at Stanford University, serves primarily to elucidate the occurrence of a particular behavior [28]. Fogg posits that the realization of a behavior necessitates the presence of three indispensable elements, each of which is integral. These elements include Motivation, denoting the degree of desire to engage in a specific behavior; Ability, signifying the ease or difficulty in executing the behavior; and Prompt, encompassing the stimuli and feedback of triggering the behavior. See Figure 1. The Fogg Behavior Model (FBM) has been successfully applied in various fields such as product design, health industry, and education. Alrige et al. have used the FBM theory to analyze the motivation and ability levels of users to maintain preventive behaviors during the pandemic, thereby improving and formulating relevant preventive measures [29]. Towers has analyzed the obstacles faced by African American women when participating in sports exercises and established relevant sports intervention measures to improve their overall physical health [30]. Based on this, this paper chooses to use the FBM theory to analyze the behavioral needs of the target group and complete the design of the dialect interaction product. By combining the BLSTM speech recognition technology and the FBM user behavior analysis, it not only considers the phonetic features of the dialect but also puts user needs at the core position, which helps to design a more humane and easy-to-use dialect interaction product.

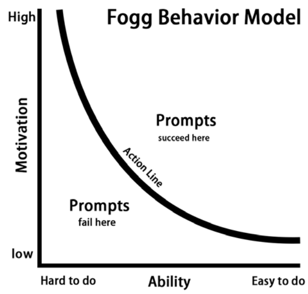

FIGURE 1. FBM theory.

C. THEORETICAL ADVANTAGES OF BLSTM-FBM

With the advancement of mobile internet technology, speech recognition technology is playing an increasingly important role in the process of dialect digitization. The Long Short-Term Memory (LSTM) algorithm based on recursive neural networks, especially its variant bidirectional LSTM (BLSTM) algorithm, can effectively recognize the dialect content in speech signals, which is an important technical basis for realizing dialect digitization. However, speech recognition technology alone is not enough to create a dialect interaction product that truly fits user needs. User experience, as the core of human-computer interaction design, needs to be analyzed using systematic user research methods. The Fogg Behavior Model (FBM) provides theoretical guidance for designing user-centered interaction products by quantitatively evaluating the behavior motivation, ability, and trigger factors of the target user group. Therefore, this research adopts a research framework that combines speech recognition and user experience design, considers the phonetic technical features of dialects, and builds a product design plan oriented towards improving user experience. This multi-disciplinary cross-research paradigm can more comprehensively and systematically guide the design practice of dialect interaction products, realize the effective connection of speech technology and human-computer interaction, and aim at innovation and optimization of user experience. This research provides a model for the combination of speech recognition technology and human-computer interaction design, and also proposes theoretical and methodological references for the design of similar speech interaction products.

D. CONSTRUCTION OF THE DESIGN FRAMEWORK

Firstly, the entire system architecture was constructed by combining C/S (Client/Server) with the blackboard architecture, as illustrated in Figure 2. In the specific product design framework, the foundation of dialect recognition was built based on BLSTM-CRF algorithms. The recognition of dialects is achieved through the following three stages:

Sequence Processing: The input sequence (e.g., words or characters in a sentence) is initially fed into the BLSTM network. BLSTM processes the sequence using both forward and backward LSTM units, generating a feature vector at each time step. Feature Extraction: The feature vectors output by BLSTM at each time step contain contextual information of the current element. These feature vectors are then input into the CRF layer for sequence labeling. Sequence Labeling: The CRF layer receives feature vectors from BLSTM and calculates the probability of possible label sequences. Utilizing a transition probability matrix, the CRF layer identifies the most probable label sequence. This formed the core for developing relevant functionalities in a dialect interaction app. Regarding the app's functionalities, the FBM theory was introduced, utilizing user interviews, questionnaires, and user portraying methods to ascertain user requirements. Eventually, on the basis of these requirements, the relevant design for the dialect interaction app was undertaken, as depicted in the specific process outlined in Figure 3.

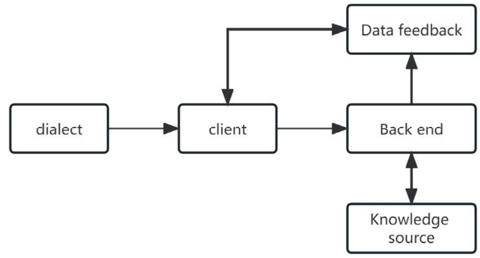

FIGURE 2. System architecture.

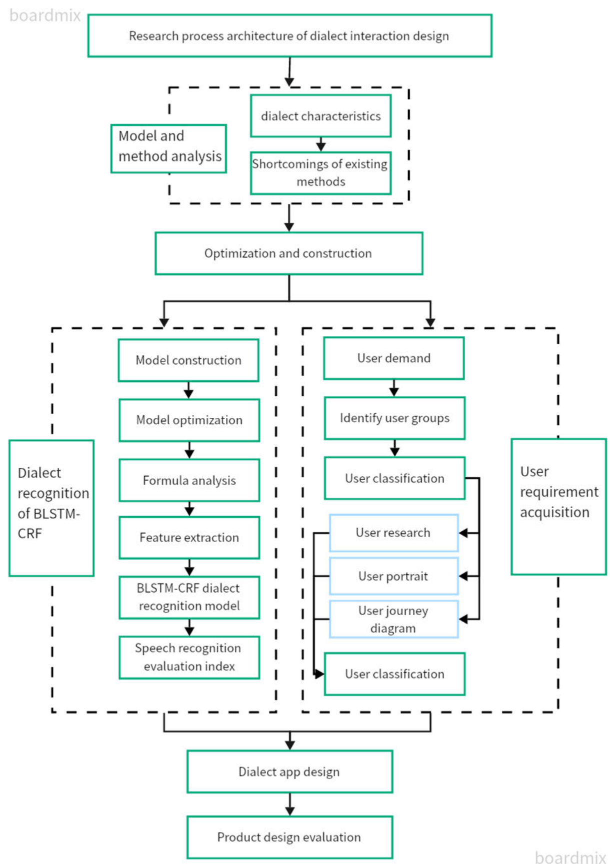

FIGURE 3. Dialect app design process and ideas.

IV. CONSTRUCTION OF AN OPTIMIZED FRAMEWORK FOR DIALECT RECOGNITION BASED ON BLSTM

A. MODEL ESTABLISHMENT

In the model construction phase, the LSTM network was harnessed for dialect recognition. Traditional LSTM algorithms are limited to recognizing past information. Consequently, this paper opts for BLSTM for dialect recognition, as it simultaneously considers both future and past contextual information, resulting in higher recognition accuracy compared to LSTM.

Nevertheless, the BLSTM model is unable to learn the transition dependencies between the output annotations and the constraints of sequence labeling. Thus, CRF was introduced to learn the constraints of sequence labeling, analyzing the sequentiality between the output labels through transition features to ensure the effectiveness of dialect recognition outcomes. The specific model is illustrated in Figure 4:

BLSTM receives the embedding of each character and forecasts the probability of each character for five annotated labels. Consequently, the computation of the values for the forget gates and output gates in the LSTM was carried out. The specific formulas are as follows:

$$f_t = \sigma(W_f \times [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_t \times [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\hat{C} = \tanh(W_C \times [h_{t-1}, x_t] + b_i) \tag{3}$$

$$C_t = f_t \times C_{t-1} + i_t \times \underset{t}{\hat{C}} \tag{4}$$

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \times \tanh(C_t) \tag{6}$$

Equation (1) represents the forget gate taking ht-1 and xt. Through this equation, a value between 0 and 1, denoted as ft, is output, which influences the prior state Ct-1. A value of 1 signifies complete information preservation, while 0 denotes complete information forgetting. Equation (2) signifies the input gate takes ht-1 and xt, outputting a value between 0 and 1 that determines the amount of information to be retained in the current candidate state $\hat{C}$. Equation (3) represents that a new candidate value vector is established based on the tanh level. Equation (4) involves updating the cell status as per the prior state Ct-1, the new state C_t, and the input value it. Equation (5) means a value between 0 and 1 is output, while Equation (6) determines the final amount of information to be output [31].

B. FEATURE EXTRACTION

In BLSTM-CRF, the feature extraction process of cc for input embeddings is shown in Figure 5.

BLSTM receives the embedding of each character and predicts the probability of each character for five annotated

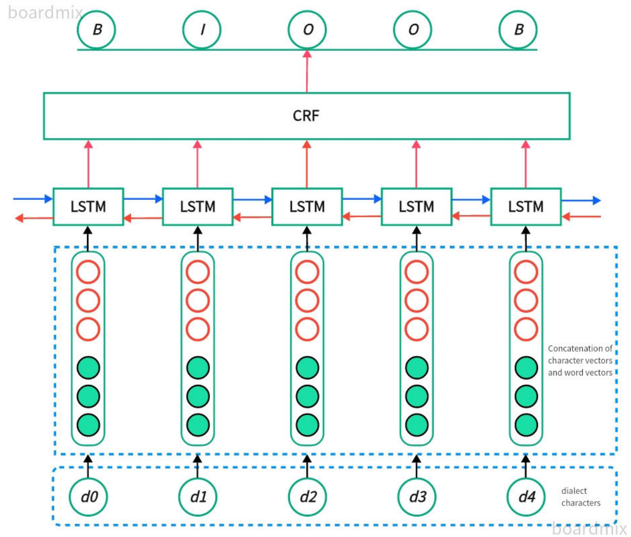

FIGURE 4. **BLSTM-CRF model.**

labels [32]. Nonetheless, the diagram suggests that the dimension of the concatenated vector is [num_directions, hidden_size]. To obtain the scores corresponding to the input character categories, a fully connected layer was added after the BLSTM layer. The softmax functions were then applied to map the vector into a probability distribution containing five values.

By employing the softmax functions to calculate the distribution probability, it becomes possible to discern the label category corresponding to each word. While LSTM can observe dependencies between sequences, the outputs of the softmax layer are mutually independent, lacking the ability to learn the transition dependencies between output annotations and the constraints of sequence labeling. To address this limitation, a CRF layer was introduced to learn the constraints of sequence labeling. Through transition features, the CRF layer took into account the sequentiality between output labels, ensuring the effectiveness of the predicted outcomes. The relevant functions are as follows:

$$P(\mathrm{y}|\,\mathrm{x}) = \frac{1}{Z\,(x)}\exp(\sum_{i,k}\lambda_k t_k(y_{i-1}, y_i, x, i) + \sum_{i,l}\mu_l s_l(y_i, x, i)) \tag{7}$$

$$Z(x) = \sum_{y}\exp(\sum_{i,k}\lambda_k t_k(y_{i-1}, y_i, x, i) + \sum_{i,l}\mu_l s_l(y_i, x, i)) \tag{8}$$

Here, Z(x) represents all possible path combinations. There are 5 input sequences and 5 label types, resulting in a total of 55 different paths as depicted in the diagram. The score for each path was calculated using exp(∗), and the scores of all paths were summed to obtain Z(x). The variable tk represents the feature function on the edges, indicating transition features dependent on the current position and the preceding position. Similarly, sl denotes the feature function on the nodes, signifying state features dependent on the current position. The feature state values obtained through BLSTM are detailed in Figure 6:

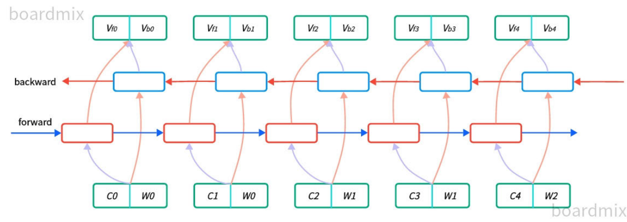

FIGURE 5. **Feature extraction process.**

In Figure 6, the true path:

$$\bar{y} = (B, I, O, O, B) \tag{9}$$

$$score(x, \bar{y}) = \sum EmissionScores + \sum TransitionScores \tag{10}$$

Among them:

$$\sum EmissionScores = P_{0,START} + P_{1,B} + P_{2,I} + P_{3,O} + P_{4,O} + P_{5,B} + P_{6,END} \tag{11}$$

$$\sum TransitionScores = A_{START,B} + A_{B,I} + A_{I,O} + A_{O,O} + A_{O,B} + A_{B,END} \tag{12}$$

Emission Scores originated from the output of the BLSTM layer, while P0, START, and P6, END are set to 0. Transition Scores were derived from the CRF layer. Adding the scores of the two types from the true path yielded the score for the true path, represented by the red route in the diagram.

The cumulative score of all paths was computed through a method of score accumulation. This involves initially calculating the total score for all paths leading to C0. Subsequently, the scores for all paths from C0 to C1 were computed, and this process was repeated iteratively, culminating in the calculation of scores for all paths from C0 to C1…to Cn, and the final outcome was obtained.

The final dialect recognition model, based on BLSTM-CRF, is depicted in Figure 7:

During the application phase of the dialect app, the trained model was employed for users' speech commands in the process of using the dialect app. Users input speech signals to be recognized, which, after feature extraction, were fed into the trained model. Following model recognition, the relevant dialect commands were executed.

C. CHINESE DIALECT SPEECH RECOGNITION EVALUATION INDEX

Combining the dialect-specific accuracy rate and this error rate, an evaluation system for evaluating Chinese dialect speech recognition was constructed, as follows (13) and (14), shown at the bottom of page 8.

Dialect-specific accuracy (DSA) and word error rate (WER) are related formulas as follows:

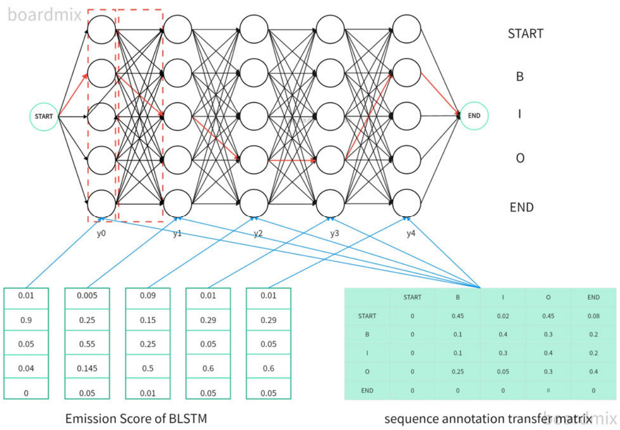

FIGURE 6. Extraction of state feature values.

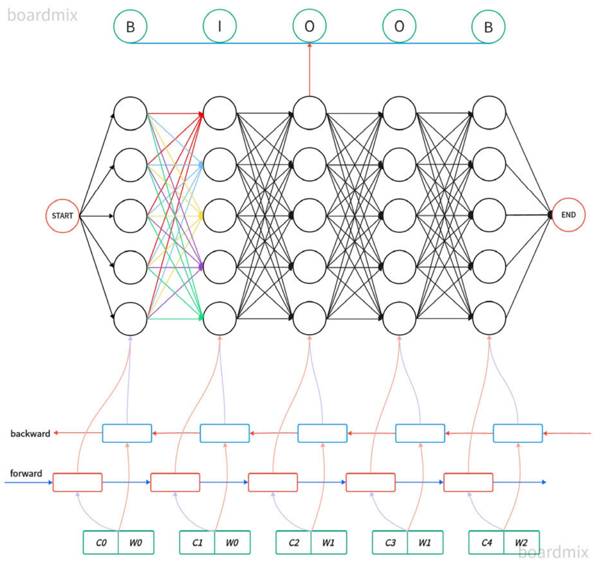

FIGURE 7. BLSTM-CRF dialect recognition model.

Based on the above formula, a comprehensive evaluation index S is created:

$$S = \alpha \times (1 - \mathrm{WER}) + (1 + \alpha) \times DAS \tag{15}$$

In this context, $\propto$ is a weight parameter that balances the Word Error Rate (WER) and Dialect Accuracy Score (DAS), which can be adjusted according to different task requirements. Then, based on the confusion matrix and error analysis, a deep understanding of the error patterns and confusion situations in each dialect category is obtained. The confusion matrix is a tool used to understand the system's performance in each dialect category in the task of dialect speech recognition in detail. Error analysis is used to deeply understand the error patterns and confusion situations in different dialects. In the confusion matrix, the rows represent the actual dialect categories, and the columns represent the predicted dialect categories of the system. Let V be the total number of samples, C be the number of dialect categories, and M be the confusion matrix. The element Mij of the confusion matrix represents the number of samples that are actually the ith dialect and predicted by the model as the jth dialect.

$$M_{\mathrm{ij}} = \sum\nolimits_{\mathrm{k}=1}^{N} \delta(\mathrm{i}, \mathrm{yk}) \times \delta(j, \hat{y}k) \tag{16}$$

In this context, δ(a,b) represents the Kronecker Delta function, which equals 1 if a = b, and 0 otherwise. yk represents the actual dialect category of the kth sample, and $\hat{y}k$ represents the predicted dialect category of the kth sample by the model.

When performing error analysis on the confusion matrix, metrics such as Precision, Recall, and F1 score can be calculated for each dialect category. The formulas for these metrics are as follows:

$$\mathrm{Pr}\,ecision_i = \frac{M_{ii}}{\sum_{j=1}^{C} M_{ij}} \tag{17}$$

$$Recall_i = \frac{M_{ii}}{\sum_{j=1}^{C} M_{ji}} \tag{18}$$

$$F1_i = \frac{2 \times \mathrm{Pr}\,ecision_i \times Recall_i}{\mathrm{Pr}\,ecision_i + Recall_i} \tag{19}$$

In this context, Precisioni represents the precision of the ith dialect category, Recalli represents the recall of the ith dialect category, and F1 represents the F1 score of the ith dialect category.

These metrics provide detailed information about the system's performance on each dialect category, helping to identify which dialect categories perform better or worse, thereby guiding the improvement of the dialect speech recognition system.

V. QUALITATIVE ANALYSIS OF FBM

A. BACKGROUND ANALYSIS OF USER DEMANDS

Dialectal culture in China boasts a profound history, with diverse regional linguistic and cultural variations owing to distinct geographical environments and customs. However, as societal development progresses, the proportion of young individuals proficient in dialects and possessing a comprehensive understanding of dialects is diminishing, exacerbating the severity of dialectal attrition. Therefore, safeguarding and redesigning dialectal culture have become pivotal measures for the preservation of traditional cultural heritage. Dialect learning has rapidly evolved with advancements in new media, internet technologies, and related tools, transitioning from traditional oral transmission to contemporary dissemination facilitated by digital technologies.

An examination of existing dialectal apps has revealed certain challenges in the dialect app landscape, outlined as follows:

1. Currently, the majority of dialectal cultural apps tend to exhibit homogeneity in their product models [33]. These apps primarily aggregate various regional dialects and incorporate dialect recognition functionalities. In terms of dialect learning, the prevalent approach involves listening and repeating, resulting in a lack of distinctiveness among most dialectal cultural apps. Consequently, in a landscape marked by a

plethora of similar dialect apps, individual apps risk being overlooked by users.

2. Regarding interactive interfaces and methods, many dialect apps suffer from shortcomings such as a lack of aesthetic appeal, simplistic visual effects, and excessive white space. The deficiency in visual allure, coupled with rudimentary interfaces, complicated operations, and relatively basic interactive approaches, attenuates user experience. Additionally, an abundance of dialectal textual explanations impacts usability, and the popularization content related to dialects appears rigid.

3. In contrast to the broad audience base for gaming and leisure apps, dialectal apps cater to a relatively smaller audience, designed to meet specific user demands. This niche audience comprises individuals with a fondness for dialectal culture and a strong emotional connection to their hometowns, particularly among the youth demographic. Thus, a thorough analysis and survey of the target audience are imperative to understand their specific requirements for dialect apps, facilitating the enhancement of relevant features.

B. USER RESEARCH

1) USER INTERVIEWS AND QUESTIONNAIRES

The target demographic was identified as the youth population, categorized into three groups based on their familiarity with dialects: those with little understanding, moderate understanding, and deep understanding. In-depth interviews were conducted using relevant interview questions listed in the table. The interview content was tailored to different dimensions based on the distinct characteristics of each cohort, as illustrated in Table 1.

User portraits were constructed based on the segmentation of the three groups. Those with little understanding may have never encountered dialects or may only occasionally hear some dialectal words or phrases. Their motivation and ability to learn dialects are relatively low, necessitating simple and foundational learning content and methods. Those with moderate understanding frequently encounter or use dialects, possibly having learned some rules or usages. Their motivation and ability to learn dialects are higher, requiring rich and engaging learning content and formats, along with challenging learning tasks and assessments. Those with deep understanding have long-term experience or study in dialects, possibly mastering the characteristics and differences of multiple dialects. Their motivation to learn dialects may be strong, requiring challenging or innovative content to satisfy their curiosity or expressive desires. They need in-depth and professional learning content and methods, as well as learning communities and platforms for sharing and interaction.

TABLE 1. Dialect spp user interview content.

User group	Interview content
Do not understand the dialect	1. The dialect of knowledge through what channels to understand.
	2. Will you search online?
	3. What software will you use to learn about dialects?
	4. How did you become interested in dialects?
Have some knowledge of dialects	1. What do you care about when using dialect-related software?
	2. Is knowledge easy to understand? Which way do you think is better?
	3. Are you willing to share your dialect knowledge on the app?
Have a deep understanding of dialects	1. Any suggestions for dialect apps?
	2. Are you willing to share your dialect knowledge on the app?
	3. Do you have any ideas or suggestions for those who are willing to learn about dialects?
	4. Are you willing to help users who love dialects? Which way do you prefer?

Due to the qualitative nature of the interview sample size, which was relatively small, a quantitative analysis was harnessed through the use of surveys to gather information from the target demographic regarding dialectal culture, as well as related app design and usage. It aimed to explore the demands of the "Z Generation" for dialectal interactive apps, considering the influence of Mandarin language propagation policies and multicultural factors. On July 26, 2023, 56 questionnaires were distributed to relevant target groups (college undergraduates and postgraduates) for investigation. After removing the six invalid questionnaires, the obtained survey data were processed using the KJ method [34] and integrated with information acquired from user interviews.

Considering that the above-mentioned three user groups might transition over the app's usage lifecycle, those with a moderate and deep understanding of dialects were allowed to share experiences and insights, offering advice and guidance to those with little understanding. This formed a positive user development cycle [35]. Ultimately, based on user value, this study designated those with little understanding and moderate understanding as the primary users of the dialect app.

2) QUALITATIVE ANALYSIS OF DEMAND

User experience journey maps provide a more accurate understanding of how users interact with a product. By delineating

$$DSA = \frac{(TP + TN)}{(TP + FN + FP + TN)} \tag{13}$$

$$WER = \frac{\text{Number of insert, delete, and replace operations within dialect categories}}{\text{The total number of words within a dialect category}} \times 100\% \tag{14}$$

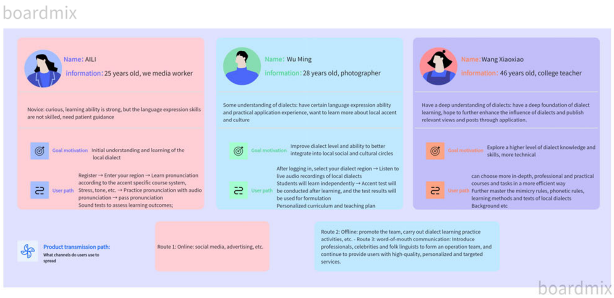

FIGURE 8. User portrait.

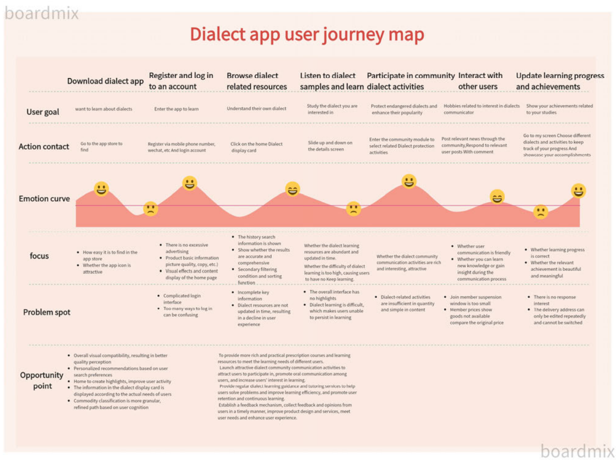

FIGURE 9. User journey diagram.

key steps or touchpoints in users' journeys from encountering the product to achieving goals, these maps capture users' emotions, pain points, and opportunities for needs arising during product usage. As shown in Figure 9, an analysis of user behaviors using dialect apps was conducted from different dimensions.

Drawing on the FBM theory, the identified user pain points were summarized and organized, yielding outcomes as presented in Table 2. The objective was to classify demands in accordance with FBM's behavioral motivation elements, behavioral ability elements, and trigger elements. This served as the foundation for generating functional points aligned with FBM elements.

VI. DIALECT APP DESIGN

A. DESIGN POSITIONING AND APP ARCHITECTURE

Based on the identified user requirements outlined earlier, it is evident that the key focus of the dialectal app design is to cultivate user interest in dialects. Additionally, the app is supposed to maintain user adhesiveness through community-associated features and the implementation of a reward system. With these considerations, the design positioning for the product was established.

After the relevant features and information of dialectal apps were integrated, the product framework diagram was

TABLE 2. User requirements analysis based on FBM theory.

User pain point	User demand	FBM elements	Factor function point
Users lack interest or motivation to learn dialects	Users need some internal or external factors that motivate them to learn dialects	motive	Provides some interesting dialect content
			Provides some common dialect words and phrases
			Provide valuable dialect information
			Provide challenging dialect learning tasks
			Provide an online community for users to communicate and interact
			Provide functions such as dialect dubbing, so that users can express their emotions and creativity in dialects
Users find it too costly or difficult to learn dialects	Users need measures to reduce the cost or difficulty of	Ability	Provide some flexible and convenient learning methods
			Provide preferential or incentive mechanisms,
User pain point	User demand	FBM elements	Factor function point
	learning dialects		users can get more services or content.
			Provide a relaxed and comfortable learning environment and interface
			Provide intelligent and personalized study recommendation and review functions
			Provide rich and interesting learning content and forms that make users curious and excited
			Provide smooth and progressive learning difficulty and pace, so that users feel comfortable and safe

TABLE 2. ***(Continued.)*** **User requirements analysis based on FBM theory.**

Users do not have the right time or situation to use dialect apps	The user needs some suitable time or scene to use the dialect app	trigger	Provide smooth and progressive learning difficulty and pace, so that users feel comfortable and safe
			Provide measures to reduce difficulty or increase convenience to assist users in using dialect apps
			Provide clear and timely information to remind users to use the dialect app

derived, as depicted in the following figure. The overall architecture of the product was established based on the logic framework of dialect recognition using LSTM as discussed earlier and the target user requirements derived from the FBM theory. The functional requirements were then translated into the core functions of the dialectal app, considering specific aspects such as user behavior, user motivation, product processes, and interface operations [36]. Different user demands were merged, and functional cluster modules were formed. Each functional module was further subdivided to develop the information architecture of the entire dialectal app, as delineated in Figure 10.

B. PROTOTYPE DESIGN

The prototype of the dialectal app involves the exploration of operational task flows based on the app's information architecture. It considers how the product can align with user requirements, enhance user experience, and generate interest among the target audience. The prototype intends to address user issues during app usage and attract users through logical interactive operations.

C. PRODUCT DESIGN BASED ON THE FBM THEORY

The primary target users of the product have limited knowledge of dialects but possess high motivational capacity with slight deficiencies in ability. For users characterized by high motivation and low ability, catalyzing their behavior requires catalysts to assist them in gradual improvement. Catalysts, in the context of high motivation and low ability, serve as solutions to help users enhance their capabilities. There are primarily two approaches: one involves training users to continuously improve themselves until they can achieve the target behavior, and the other focuses on reducing the difficulty of behavior—simplifying user paths and the user experience journey. Predicated on this, the product solution design was structured around the FBM elements, addressing motivation, ability, and triggers as obtained in the preceding sections. As shown in Table 3.

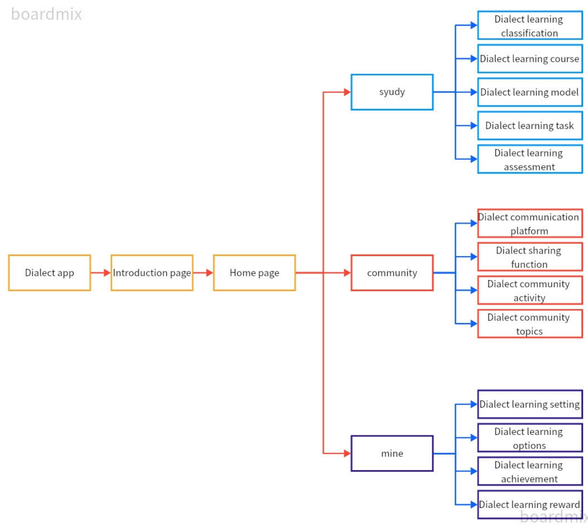

FIGURE 10. **App information architecture.**

We plan to design a user-friendly interface for our dialect app, with special consideration for the needs of non-technical users, ensuring that all user groups, especially those unfamiliar with complex technical operations, can easily understand and use it. This approach aims to facilitate wider adoption of the app among a broad range of users, thereby generating significant social impact.

We began by conducting an in-depth analysis of our target user groups, focusing particularly on the usage habits, skill levels, and potential challenges faced by non-technical users. This analysis aided us in designing an intuitive, simple, and easy-to-navigate interface, ensuring that users can effortlessly access and utilize various features of the app, such as dialect search and learning modules. Additionally, to ensure the app's accessibility and adaptability, we considered users of different ages and ability levels, ensuring that the app's interface and functions are friendly and easily accessible to everyone. For instance, the app offers clear iconography, a straightforward menu structure, and easily understandable interactive prompts.

The interface we have designed not only promotes technological innovation but more importantly, reflects a deep understanding and respect for user needs. This ensures that the app can be adopted by a larger audience and create a positive social impact. The specific design is displayed in Figure 11:

D. DESIGN EVALUATION

In the post-design phase of the product, an evaluation was done to assess whether the proposed solution has advantages compared to other relevant dialect apps in the market. A sample of 50 participants who underwent user interviews and questionnaire surveys rated the app on a ten-point scale. A paired samples t-test was performed to examine the significance of the differences in the means of the harvested data before and after the design, aiming to infer the feasibility of the app.

TABLE 3. Product scheme design.

Factor	Requirement	Option
Motivational factor	Want motivation: that is, the user's desire, interest, desire, etc.	Provide interesting and attractive dialect cultural content to stimulate users' interest
	Need motivation: that is, the user's internal needs and requirements	A variety of interactive functions are designed to enhance the user's sense of participation in dialects
	Desire motive: that is, the desire to be stimulated by some kind of stimulus.	The use of gamification design to increase the user's enjoyment of learning dialects
Ability factor	Prerequisite Capabilities: Basic capabilities and resource requirements of users	Providing users with free dialect learning content can help them learn dialects better.
	Authority: The information provided when a user seeks a service	Provide personalized learning to build a relaxed and comfortable use environment.
	Prime power: The user's action process, to obtain the necessary energy for the target.	Provide relevant rewards social support and encouragement to increase user engagement
Trigger factor	Natural triggers: Actions occur naturally when the target action is the user's normal daily behavior	Timely update the dialect topics and other content in the community to stimulate the interest of users
	Bait triggers: Encourage the user to take a certain action by offering an attractive reward.	Design personalized push and push-related resources for users according to their browsing habits.
	Signal trigger element: This is a warning signal that prompts the user to take action	Provide smooth transition dialect learning, and increase the convenience of dialect learning.

The null hypothesis (H0) was established as $\mu1= \mu2$, assuming no remarkable disparity between the two sets of ratings, which indicated that the proposed solution is not different from existing market solutions. H1 implies the opposite [37].

A paired sample of the market solution versus the proposed solution with a sample size N<5000 was subjected to the Shapiro-Wilk test (S-W test) with a significance P-value of 0.226, which did not exhibit significance at the chosen level and failed to deny the null hypothesis.

Therefore, the data met normal distribution, as evidenced by a kurtosis value of -0.748 (absolute value less than 10) and skewness of 0.15 (absolute value less than 3). The normality distribution histogram further supported this analysis.

The figure above shows the outcomes of the normality test for the quantitative variable, which represents the difference data between the market scheme and the proposed scheme. If the normality plot essentially displays a bell-shaped curve (higher in the middle, lower at the ends), it unveils that although the data is not perfectly normal, it is generally acceptable as a normal distribution.

FIGURE 11. Dialect app interface.

TABLE 4. Pairwise difference normality test results.

variable	Sample size	Mean value	Standard deviation	skewness	kurtosis	S-W test	K-S test
Market Plan	50	3.9	2.082	0.35	-0.799	-------	-------
The Plan	50	5.92	1.805	0.016	-0.953	-------	-------
The market plan is paired with this plan	50	-2.02	3.014	0.15	-0.748	0.97(0.226)	0.104(0.609)

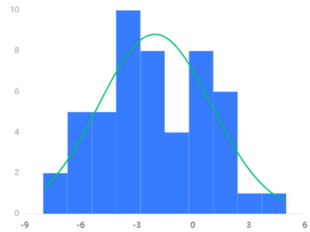

FIGURE 12. Normality test histogram.

TABLE 5. Paired-sample T-test results.

Pairing variable	Mean value±Standard deviation Pair 1	Pair 2	Pairing difference (pairing 1-pairing 2)	t	df	P	Cohen's d
The market solution is paired with this solution	3.9±2.082	5.92±1.805	-2.02±0.277	-4.74	49	0.000	0.67

The results of the paired-sample t-test confirmed a notable difference between the market scheme and the proposed scheme, with a significance P-value of 0.000***, rejecting the null hypothesis. Therefore, there is a conspicuous distinction between the market scheme and the proposed scheme. Cohen's d value of the magnitude of the difference stood at 0.67, signifying a moderate level of distinction [38].

VII. CONCLUSION AND FUTURE PROSPECT

In response to the insufficient influence and propagation of dialect culture among teenagers, a recognition framework for dialect interaction has been optimized and constructed based on LSTM, providing basic support for the design scheme. At the same time, through user interviews and questionnaires, the relevant needs of the target group are analyzed based on the FBM theory, and the design of the dialect app is carried out based on LSTM-CRF. Different functions are provided for users to better understand the related culture of Chinese dialects and to learn.

A. CONCLUSION

Through the research on BLSTM and user needs, the possibility of applying BLSTM and FBM theory to dialect interaction products is explored. The main goals of this research are as follows: (1) The quantitative score of this scheme is higher than that of the market scheme, so the product designed based on BLSTM-CRF and FBM theory is more effective for the related product design of dialects. (2) Because the user's motivation has been explored, the user has a higher learning motivation and interest. (3) Users maintain a positive attitude towards the acceptance of the product and user stickiness.

B. SUGGESTIONS AND FUTURE WORK

The concepts of long short-term neural algorithms and user needs involved in this research are not used in all senses. Applying them to the research of dialect interaction design is an attempt and exploration, providing some ideas for the inheritance and promotion of dialect culture in the current era. In the future, by establishing a related dialect database or cooperating with existing databases, users' dialects can be recognized and retrieved more conveniently and quickly. At the same time, according to the needs of users of different age levels, the product can be designed specifically, such as for children, the product should be designed to be more interesting and add related game functions; for the elderly, dialect voice chat and related dialect opera playback functions can be added. We believe that through these efforts, our work will not only be valuable to the academic community but will also be made more accessible and meaningful to a wider readership.

According to the results of this research, this study reveals the tremendous potential of combining the BLSTM-CRF model with Fogg's Behavior Model in the field of language processing and behavior analysis. This innovative approach is not only applicable to the analysis and processing of Chinese dialects but also has the potential to be extended to languages and dialects in other regions of the world. The BLSTM-CRF model, as an advanced sequence modeling tool, demonstrates exceptional capabilities in identifying and predicting complex language patterns. Meanwhile, Fogg's Behavior Model, as a framework for analyzing user behavior, provides profound insights into understanding how users employ and interact with languages in their daily lives.

The integration of these methods has not only had a significant impact on the study of Chinese dialects but also opened new avenues for global language diversity research and preservation. Especially for endangered minority languages, this combination offers new perspectives and tools for identifying, preserving, and promoting their learning and use. By deeply analyzing the behavioral motives in language use, researchers can better understand how languages evolve and change in different cultural and social contexts.

Furthermore, the wide adaptability of this interdisciplinary approach means that it can support the preservation of language diversity in different regions around the world, thereby making a significant contribution to the protection of global cultural heritage. For instance, by applying this method, endangered languages can be identified and protected more effectively, while also stimulating public awareness and appreciation of language diversity.

In summary, this research not only demonstrates the potential of combining the BLSTM-CRF model with Fogg's Behavior Model but also highlights the importance of interdisciplinary approaches in addressing complex issues at the intersection of linguistics and behavioral science. It offers new perspectives and strategies for the protection, research, and promotion of languages and dialects globally, having a profound impact on the maintenance and promotion of global cultural diversity.

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