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The Relationship between Interpreting Anxiety and Learning Motivation Assisted by Long Short-Term Memory Neural Network Algorithms



Abstract: - The Long Short-Term Memory (LSTM) neural network algorithm has achieved significant results in natural language processing and speech recognition. This study explores the application of the LSTM algorithm in the study of the relationship between interpreting anxiety and learning motivation. The article mainly uses questionnaire survey method to obtain research data. The participants include students engaged in translation research and professional translators. After statistical analysis of the research data, it was found that there was a significant correlation between translation anxiety and learning motivation ($r=-0.62$, $p<0.001$). According to calculation results, the average score is 3.42 and the standard deviation is 0.76. The average score of evaluating the learning enthusiasm of participants through corresponding questionnaires is 4.27, with an SD of 0.92. Further regression analysis of the data was conducted, and the results showed that respondents with low translation anxiety had stronger learning motivation ($\beta = -0.43$, $p<0.001$). It can be seen that reducing learners' fear of translation can enhance their learning motivation, thereby stimulating their interest in learning. This indicates that reducing translation anxiety may be helpful to improve the learning motivation level of interpreting learners. The study is of great significance for improving the learning enthusiasm of translation learners and reducing translation anxiety and provides a new perspective and research method for future related research.

Keywords: Long Short-Term Memory Neural Network Algorithm; Translation Anxiety, Learning Motivation, Questionnaire, Natural Language Processing.

INTRODUCTION

In the language learning and application field, interpreting is a highly complex activity requiring immediate information processing. Many challenges often accompany the learning process. Learners often feel different levels of anxiety in interpreting practice or actual work, which is called "interpreting anxiety". Interpreting anxiety may stem from a variety of factors, such as a lack of confidence in one's language ability, excessive worry about the outcome of a task, and fear of public performance. It affects individuals' cognitive resource allocation and information processing efficiency during interpreting and may inhibit learners' enthusiasm, that is, the motivation to perform interpreting tasks. Learning motivation is the internal driving force that drives individuals to learn and persist in learning for a long time. The relevant research results indicate that there is a close correlation between it and the learning behavior, learning persistence, and final learning outcomes of learners. Therefore, revealing the relationship between interpreting anxiety and learning motivation can help teachers grasp the psychological state of interpreting learners, optimize teaching strategies, and accelerate the improvement of students' professional literacy [1-3].

However, analyzing existing literature, it was found that there are relatively few empirical studies on the correlation between anxiety and learning motivation. Most scholars are limited to descriptive surveys or case-based analysis, lacking in-depth data mining and insufficient research depth. With the continuous development of technology, artificial intelligence (AI) technology, especially the concept of long short-term memory (LSTM), has provided strong support for in-depth research in this field. LSTM is a special type of recursive neural network (RNN) that has advantages in temporal data processing compared to other similar algorithms. Therefore, it has been widely used in time series analysis, speech recognition, and natural language processing (NLP) [4,5]. In addition, LSTM can effectively capture and remember the dependency relationships between data points over a long time span, which is of great significance for explaining the emotional fluctuations and behavioral patterns of the respondents. In view of this, this article adopts this algorithm to conduct in-depth analysis of the collected survey dataset, thereby revealing the relationship between anxiety and learning motivation, and exploring the mechanisms of their mutual influence to draw corresponding conclusions. A recent study has found that interpreting anxiety not only has a negative impact on learning motivation, but also reduces learners' learning enthusiasm [6-8]. It can be seen that conducting research in this area is very necessary and has certain practical significance.

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At present, the research on the relationship between interpreting anxiety and learning motivation is relatively limited. Some studies have revealed that students with higher anxiety tend to show lower enthusiasm for learning motivation, which may lead to a decline in learning ability and academic performance. Nevertheless, the existing research is mainly based on the traditional questionnaire and psychometric methods and lacks objective and reliable means of assessment. At the same time, there is no in-depth exploration of how to use advanced DL algorithms to help deal with the problem of interpreting anxiety [9,10]. Hence, this study aims to explore the relationship between interpreting anxiety and learning motivation based on the LSTM algorithm and propose corresponding solutions, thus providing new ideas and methods for interpreting teaching and learning motivation research.

The uniqueness of this study is that it combines the LSTM algorithm and the research on the relationship between interpreting anxiety and learning motivation. This contributes to a deeper understanding of the mechanism of interpreting anxiety's impact on learning motivation. In addition, by collecting and analyzing actual learning data, this study enables an objective and accurate assessment of learners' interpreting anxiety status and its impact on learning motivation. Moreover, an interpreting anxiety assistance solution based on the LSTM algorithm is established to offer learners personalized interpreting learning support and further enhance learning motivation. This study offers a new methodological path for future research in related domains, that is, using advanced technologies such as LSTM for sentiment analysis and behavior prediction, to promote the optimization of teaching and learning effects in a wider range of application fields. Overall, this study has great significance for the education and training of interpretation learners and provides rich inspiration and new research direction for research in the intersection of pedagogy, psychology, and AI.

II. RECENT RELATED WORK

A. Application of the LSTM Algorithm in Behavioral Research

LSTM, as an improved RNN, has been widely used in sequence data analysis. Based on the analysis of the relevant information collected, it can be concluded that this algorithm plays a very important role in the field of NLP. Due to its ability to process and remember long-term dependent information, it has advantages over other algorithms in emotional analysis. In the field of educational psychology, LSTM is mainly used to predict emotional states and behavioral patterns, and has achieved significant results. Alkahtani et al. [11] trained the Self Stimulating Behavior Dataset (SSBD) using Visual Geometry Group 16-LSTM (VGG-16-LSTM) and Long Term Recursive Convolutional Network (LRCN) based on previous research results. They found that the accuracy of the latter on the test set was 96%, while the former was 93%. It can be seen that both methods can effectively identify the self stimulating behavior of children with autism, which provides support for clinical intervention in autism. Ala'raj et al. [12] used a bidirectional LSTM model to predict the probability of customers experiencing single or consecutive overdue payments in the future. The experimental results show that compared with traditional methods, LSTM based prediction has higher accuracy and better performance. Jarbou et al. [13] trained a large amount of historical data using LSTM and multi-layer perceptron (MLP) algorithms to predict short-term and long-term absenteeism among students with autism. The experimental results show that both algorithms have high prediction accuracy. Buono et al. [14] proposed an LSTM based model based on previous research experience to predict learners' course participation, which has received widespread attention in the academic community. S ü kei et al. [15] trained big data using a mixed model (MM) and a hidden Markov model (HMM) to predict human emotional states. The research results indicate that these models can effectively process a large amount of observational data. Overall, among existing algorithms, the LSTM model has relatively good performance and can demonstrate significant advantages in many applications in various fields. It is undoubtedly feasible to use this model to process the questionnaires obtained from the questionnaire survey. Zitouni et al. [16] proposed an emotion recognition model based on the LSTM architecture, and experimental results demonstrated the effectiveness of the framework, achieving classification accuracies of over 96% and 93% for individuals and different combinations, respectively. This indicated the high-precision capability of the framework in recognizing activation-value levels. Kansizoglou et al. [17] gradually mapped and learned individual personalities by observing and tracking changes in emotions during the interaction process. Kashyap et al. [18] explored the application of DL technology in predicting human behavior. The study investigated neural networks, including LSTM, convolutional neural networks, and other advanced DL architectures, in capturing complex patterns and dependencies in human behavioral data.

Although existing scholars have made remarkable achievements in using LSTM for predicting emotional states, behavioral patterns, and sentiment analysis, these studies are mainly concentrated in fields such as

medicine, psychology, and consumer credit scoring. Particularly in the field of education, there is still a lack of quantitative analysis on the relationship between learners' internal psychological states, such as interpreting anxiety and learning motivation during the interpreting learning process. Additionally, current research often focuses on performance comparisons of models, with fewer applications of these advanced models in empirical educational data analysis, especially in the specialized field of interpreting learning. Therefore, this study aims to fill this gap by applying the LSTM algorithm to a specific issue in the field of interpreting learning: the study of the relationship between interpreting anxiety and learning motivation. This applied and empirical research orientation validates the feasibility of LSTM in a new domain and affords a scientific basis for translation education practices, aiding educators in developing more effective teaching strategies and intervention measures. Furthermore, the research findings may inspire other related studies in educational psychology, incorporating DL technology into the analysis of learning behavior and psychological states, expanding the existing research paradigm. In summary, the motivation of this study is to address the shortcomings of previous research, particularly in interpreting education. By utilizing LSTM, this study aims to delve into the complex relationship between interpreting anxiety and learning motivation, providing new research perspectives and methods to advance the field's theoretical and practical aspects.

B. The Influencing Factors and Consequences of Interpreting Anxiety

Interpreting anxiety refers to the anxiety, tension, and fear experienced by individuals during the interpreting process. Existing research indicates that anxiety not only diminishes the cognitive processing abilities of interpreters but also negatively influences their learning motivation and performance. When exploring the impact of anxiety on learning outcomes, Namaziandost et al. [19] emphasized the mediating role of interpreters' self-efficacy, suggesting that learners with strong self-efficacy could effectively resist the negative effects of anxiety. Cai et al. [20] assessed the bidirectional relationships between three psychological factors (self-efficacy, motivation, and anxiety) and interpreting students' performance. Correlation analysis and hierarchical regression analysis suggested that, in the first study, both learning motivation and self-efficacy decreased while anxiety remained relatively stable. Interpreting-specific anxiety was negatively correlated with concurrent interpreting performance. Tan et al. [21] integrated traditional research on test anxiety and achievement motivation, examining the relationship between hope for success and test anxiety and incorporating motivational attributes into the concept of test anxiety. Mercader-Rubio et al. [22] analyzed the relationship between anxiety (physical anxiety, self-efficacy, and cognitive anxiety) and basic psychological needs (competence, autonomy, and relatedness). The results showed that autonomous motivation was a more positive form of motivation, as it helped explain the perception of self-efficacy and promoted performance in competition, while controlled motivation had the opposite effect. Miller et al. [23] explored the prodromal factors of anxiety symptoms, covering irrational beliefs and motivation regulation, which may be risk factors for increasing athlete anxiety. Results supported the association between the two factors, indicating a negative correlation between irrational performance beliefs and relative autonomous motivation. Additionally, it was found that irrational performance beliefs were positively correlated with anxiety symptoms, while autonomous motivation was negatively correlated with anxiety symptoms. Barbieri et al. [24] proposed that aesthetic appreciation may link pleasurable feedback with updates of predictive representations. The study suggested that aesthetic appreciation promoted curiosity-driven behavior while being negatively correlated with anxiety. Journault et al. [25] validated whether a rapid intervention could improve adolescents' stress mindset and reduce their sensitivity to perceived stress and anxiety. The results presented that the intervention successfully instilled a mindset that stress can enhance performance compared to the control condition. While Bayesian factor analysis did not show major differences between the two groups in perceived stress or anxiety sensitivity, thematic analysis indicated that the intervention could help participants better cope with their stress. In short, these results denoted that intervention could rapidly change adolescents' stress mindset. Future research needs to determine whether altering a stress mindset is sufficient to change anxiety sensitivity in certain adolescents and environments. Wullenkord et al. [26] verified the validity of the climate anxiety scale in German-speaking samples and studied the relationship between it and psychological factors. The results demonstrated that climate anxiety was related to some psychological factors. Watanabe et al. [27] developed and validated an artificial intelligence anxiety scale and initially applied it to predict learning behavior. The findings indicated that this scale was effective in predicting learning behavior.

Learning initiative is defined as the inner driving force of learners to commit themselves to learning and persevere. According to self-determination theory, learning motivation can be further divided into intrinsic and extrinsic motivations. Based on the above literature review, it can be found that existing studies in related fields

revealed the relationship among learning performance, motivation, and anxiety. Mobile AR technology positively impacted learning motivation and performance, while reducing math anxiety. Students' motivation and cognitive level can influence their preferences for various learning styles. In an online learning environment, achievement emotion was essential as a mediating factor between learner characteristics and learning outcomes. Competitive games with balanced cognitive complexity can positively affect English learners' learning performance, anxiety, and behavior. Additionally, cognitive bias correction interventions were effective in the treatment of anxiety and depression disorders. By referring to the research results of relevant literature, the relationship between anxiety and learning motivation assisted by the LSTM algorithm can be more deeply understood. Future studies could combine the LSTM algorithm to take more contextual factors and individual characteristics into account when exploring the relationship between them, to furnish more effective support and guidance for improving interpreting learners' learning experience and outcomes.

III. ESTABLISHMENT OF THE EVALUATION MODEL OF THE RELATIONSHIP BETWEEN INTERPRETING ANXIETY AND LEARNING MOTIVATION BY THE LSTM

A. *Selection of Experimental Participants and Determination of Sample Size*

This study evaluated the relationship between anxiety and learning motivation, and an evaluation model was implemented based on LSTM [28]. This article obtains a large amount of information through a questionnaire survey, and then summarizes and organizes these materials, using algorithms to calculate the data. During this process, the respondents will be limited to students and professional interpreters. They have different levels of practical experience and learning motivation. The ultimate goal of incorporating these two groups into the study is to reveal the correlation between anxiety and learning motivation. In terms of sample size setting, this article refers to previous research results and considers various factors, selecting an appropriate sample size [29]. In the questionnaire survey, a total of 200 students studying interpretation and 50 professional interpreters were invited to participate in this survey. Fill out the questionnaire anonymously.

B. *Data Collection Methods and Processes*

This article uses a questionnaire survey method to collect the necessary data for research, and then trains the data through algorithms to clarify the relationship between interpretation anxiety and learning motivation. The distribution, collection, statistics, analysis, and other aspects of the questionnaire follow strict procedures to ensure the reliability of the data.

The survey questionnaire designed in this article includes items related to interpreting anxiety and learning motivation. The selected indicators are all representative [30]. Subsequently, the research group contacted several schools and interpretation organizations, and invited students from the schools and professional interpreters from the organizations to participate in this questionnaire survey.

Firstly, send a link to the respondents and explain the purpose, content, and methods of this study to ensure that they fill out the questionnaire correctly.

The respondents need to complete the questionnaire survey within the specified time. During this process, the research group strictly kept their personal information confidential.

After collecting data, invalid questionnaires that do not meet the requirements will be removed. Calculate the effective rate of questionnaire collection [31]. Afterwards, the data will be processed, correlation analysis will be conducted, and descriptive statistics will be conducted.

Based on the statistical results of the data, create corresponding graphs and tables to intuitively reflect the relationship between anxiety and learning motivation. The specific process structure of data collection and model establishment in the study is displayed in Figure 1:

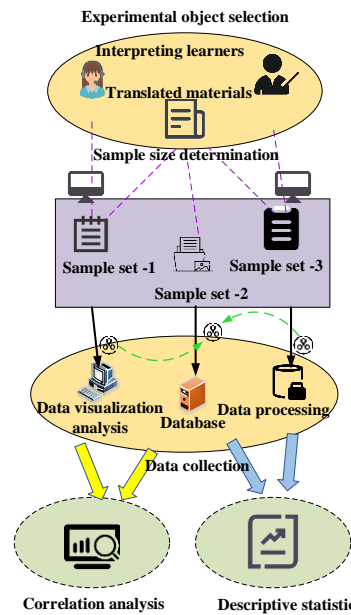


Figure 1: Process of Data Collection and Model Building

C. Establishment of Structural Equation Model (SEM) and Analysis of the Variable Relationship

In this section, we mainly use scanning electron microscopy to study the relationship between anxiety and learning motivation. SEM is a multivariate analysis method by which theoretical models can be validated, and causal relationships between different latent variables can be studied.

Before implementing the SEM, a theoretical model was formulated to describe the hypothetical relationship between interpreting anxiety and learning motivation. Based on literature reviews and previous studies, interpreting anxiety, learning motivation, and possible mediating variables were taken to construct a potential variable model [32].

Through SEM, it is possible to quantitatively evaluate the influence, and direct and indirect effects of different paths. The explanatory power of each variable to the model can be tested, as well as the significance of the individual path coefficients. Meanwhile, possible mediating effects can be explored, and the relationship between interpreting anxiety and learning motivation can be further understood.

D. Construction and Training Methods of the LSTM Model

The LSTM model is utilized to construct and train a predictive model for interpreting anxiety and learning motivation. Massive sample data on interpreting anxiety and learning motivation are used for model training. The sample data is divided into training and validation sets, and the model parameters are iteratively updated by backpropagation algorithms and gradient descent optimizers (such as Adam) to minimize prediction errors. To prevent overfitting, some regularization techniques, such as dropout layer and L2 regularization, are employed to reduce the model's complexity and improve the generalization ability [33]. Besides, using the early stopping strategy to avoid over-fitting and select the best model parameters, the overall structure of the established LSTM-based neural network model is presented in Figure 2:

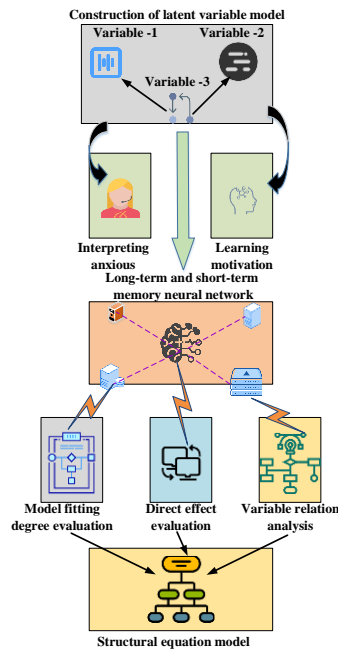


Figure 2: The Structure of the Established LSTM-Based Neural Network Model

In addition, to compare the performance of the proposed evaluation model based on LSTM, the performance of LSTM is compared with traditional evaluation models based on SVM multilayer perceptron (MP). Performance is compared from the standard deviation (SD) and average score of anxiety level, the average score and SD of learning motivation level, emotional analysis score, the difference score, regression coefficient, and correlation between anxiety level and learning motivation, and other aspects. Through the performance comparison of all aspects above, the purpose is to comprehensively evaluate the unique advantages and innovations of the LSTM-based evaluation model in alleviating interpreting anxiety and promoting learning motivation, thus offering useful reference and practical guidance for interpreting education.

IV. RESULTS AND DISCUSSION

A. Comparison of Average Score and SD of Interpreting Anxiety Levels Assessed by Different Algorithms

Figure 3 reveals evaluation models for diverse algorithms that assess average scores for anxiety levels. Figure 4 depicts the assessment of SD of anxiety levels by evaluation models of various algorithms.

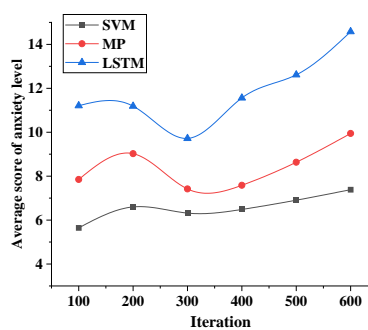


Figure 3: Evaluation Data of the Average Score of Anxiety Level for Evaluation Models of Different Algorithms

Figure 3 denotes that the evaluation score of the LSTM model is relatively high. The results reveal that the LSTM model performs better in predicting anxiety levels. As the number of iterations rises, its scores gradually improve. This may indicate that the LSTM model has strong learning abilities and better captures characteristics related to anxiety levels. In comparison, the evaluation scores of the SVM and MP models are relatively lower, showing fluctuating trends with an increase in the number of iterations. With fewer iterations, the evaluation scores of all three algorithms increase. Still, the performance improvement of SVM and MP models in subsequent iterations is limited, while the LSTM model seems to continuously improve with more training rounds. Future research will need to delve into the strengths and weaknesses of each model and explore the potential for their improvement.

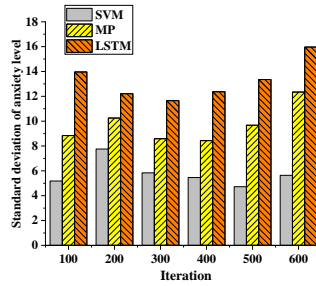


Figure 4: Evaluation Data of the SD of Anxiety Level for Evaluation Models of Various Algorithms

Figure 4 signifies that in the initial stage, the SD of the three algorithms rises, but with the increase in the number of iterations, the SD gradually becomes stable. This may be because the initial prediction of anxiety level varies greatly, but as training progresses, the model gradually learns to capture relevant features better, thereby reducing sample-to-sample variability. With the addition of the number of iterations, the consistency of the evaluation results of the three algorithm models on anxiety levels gradually improved. In the training process, the consistency of the SVM model is the highest, followed by the MP model, while the LSTM model’s consistency is relatively low. These results guide selecting the appropriate model and the number of iterations.

B. Comparison between the Average Score of Learning Motivation Levels Evaluated by Different Algorithms and SD

Figure 5 plots the evaluation results of the average score of learning motivation level, and compares the performance of evaluation models with diverse algorithms. It can be used to understand the average score of each algorithm in predicting the level of learning motivation. The evaluation results of SD at the learning motivation level are illustrated in Figure 6, which compares the performance of evaluation models under various algorithms.

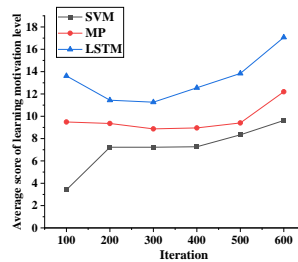


Figure 5: Evaluation Trend of the Average Score of Learning Motivation Level for Evaluation Models with Diverse Algorithms

Figure 5 implies that, first, the average score of the LSTM model is still comparatively high. This manifests that the LSTM model still performs well in predicting the learning motivation level, and its score also rises gradually with the iterations increase. This may be due to the LSTM model’s stronger learning ability to capture the relevant features of the learning motivation level. Different from previous anxiety level analyses, the SVM and MP models have relatively low scores in the assessment of learning motivation levels. Their scores are significantly lower, especially when the iterations are lower than the LSTM model's. It can be seen that when using SVM and MP models to analyze learning motivation, their ability to capture information features is limited, especially in the initial stage, which has significant limitations. Moreover, it is found that as the number of iterations grows, the MP and SVM models’ scores tend to be stable overall, while the LSTM model’s scores continue to rise. That is to say, increasing the number of iterations does not improve the prediction accuracy of SVM and MP models, and their performance is inferior to LSTM models. However, the additional number of iterations fails to cause a significant jump in performance. The LSTM model can continuously benefit from more training times and improve its predictive performance.

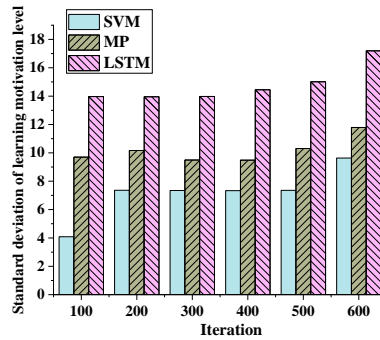


Figure 6: Evaluation Trend of SD of Learning Motivation Level for Evaluation Models with Different Algorithms

In Figure 6, firstly, the LSTM model’s SD is relatively high. This means the LSTM model has greater differences in predicting learning motivation levels, possibly because it can better capture changes and uncertainties among samples. Unlike the previous analysis, in evaluating learning motivation level, the SD of the LSTM model exceeds that of the MP and SVM models, indicating that it has high flexibility and sensitivity in this task.

Secondly, it is observed that with the increase in iteration times, the three algorithms’ SD presents a stable trend on the whole. This may illustrate that as the models are trained and iterated, they become more consistent and stable in predicting learning motivation levels. In particular, SD tends to be stable under high iterations, demonstrating that the model has been able to predict the learning motivation level relatively accurately, and there is little difference in the prediction results under different iterations.

C. Comparison of Correlation and Regression Coefficient between Anxiety Level and Learning Motivation

Figure 7 shows the changing trend of the correlation data between different algorithms' evaluation of the anxiety level and learning motivation. In Figure 7, it is possible to understand the results of different algorithms' evaluation of the correlation between anxiety levels and learning motivation. The variation trend of the regression coefficient of different algorithms evaluating anxiety level on learning motivation is drawn in Figure 8. It can be used to compare the performance of different algorithms in predicting the influence of the anxiety level on learning motivation.

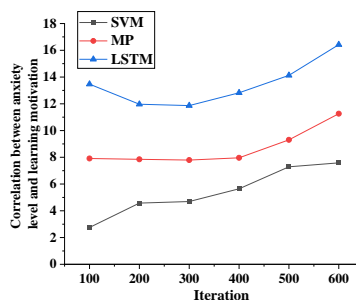


Figure 7: The Changing Trend of Correlation between Anxiety Level and Learning Motivation of Evaluation Models under Different Algorithm Models

In Figure 7, with the increase of iterations, the correlation between anxiety level and learning motivation of the three algorithm models presents different changing trends. First, the correlation score of the SVM model is 2.75, which gradually increases with the number of iterations and reaches 7.58 after 600 iterations. This illustrates that through training and optimization, the correlation ability of the SVM model between anxiety level and learning motivation is gradually enhanced. At the initial stage, the correlation score of the MP model is 7.91. As the number of iterations rises, the relevance score decreases slightly, reaching 11.26 after 600 iterations. It can be seen that the MP model has a certain stability in the correlation between anxiety level and learning motivation, but on the whole, it shows a slight upward trend. At the initial stage, the LSTM model’s correlation score is 13.47, the highest. However, as the number of iterations increases, the relevance score gradually declines and achieves 16.42 after 600 iterations. This indicates that, in the training process, the correlation between the two in the LSTM model fluctuates to a certain extent, showing a downward trend. It can be observed that the correlation scores of the SVM and MP models are gradually improved, while the LSTM model’s correlation scores are slightly

fluctuating. These results provide some references for further research on the relationship between the anxiety level and learning motivation.

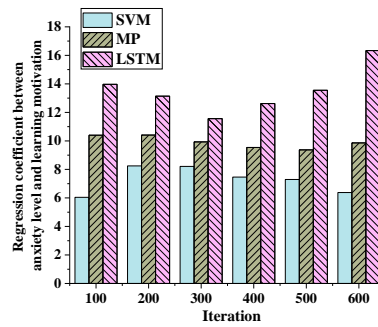


Figure 8: Variation Trend of Regression Coefficient of Anxiety Level on Learning Motivation of Evaluation Models under Various Algorithm Models

Figure 8 expresses that the regression coefficient of the SVM model gradually improves with the number of iterations, but the growth rate is comparatively slow. The regression coefficient of the MP model gradually tends to be stable after the previous iteration, and the variation range is small. The regression coefficient of the LSTM model also tends to be stable after the previous iteration, but the growth rate is faster. Moreover, it can be noted that for all models, with the rise of iterations in the initial stage, the increase of the regression coefficient is large. Still, the growth rate gradually slows down with the continuous increase of iterations. This phenomenon suggests that, in the initial stages of the model, the impact of anxiety levels on learning motivation may exhibit remarkable fluctuations. However, as the number of iterations adds, the model tends to stabilize, and the effect on learning motivation almost remains unchanged. Further observation of the differences between the models reveals that the SVM model has lower regression coefficients, while the MP and LSTM models have relatively higher regression coefficients, implying that the latter two may be more effective in assessing how anxiety levels influence learning motivation. In contrast, the applicability of the SVM model may be weaker for this task.

D. A Comparison of Interpreters' Sentiment Analysis Scores and Different Models' Difference Scores

The changing trend of interpreters' sentiment analysis scores evaluated by different algorithm models is portrayed in Figure 9. The variation trend of the difference scores between anxiety levels and learning motivation assessed by different algorithm models is suggested in Figure 10.

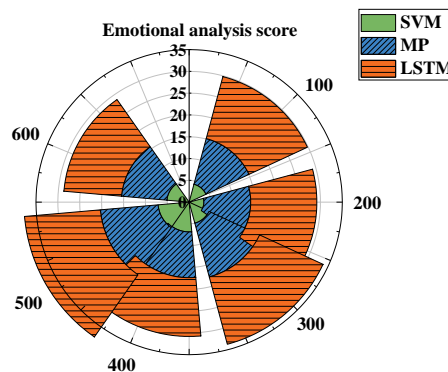


Figure 9: Changing Trend of Interpreters' Sentiment Analysis Score for Various Algorithm Models

Figure 9 presents that the sentiment analysis score of the SVM model gradually increases as the number of iterations grows, but the growth rate is relatively slow. The sentiment analysis score of the MP model gradually stabilizes after the previous iteration, and the change range is small. The sentiment analysis score of the LSTM model also tends to be stable after the previous iteration, but the growth rate is faster. Besides, it is worth noting that for all models, an increase in the number of iterations in the initial stage results in a significant increase in sentiment analysis scores, but as the iterations continue to add, the growth rate gradually slows down. This may be because the influence of the model on the interpreter's sentiment analysis changes greatly in the initial stage, but as the number of iterations increases, the model gradually stabilizes, and the impact on sentiment analysis does not change much.

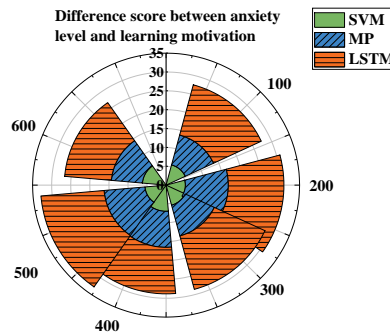


Figure 10: Variation Trend of the Difference Score between Anxiety Level and Learning Motivation for Diverse Algorithm Models

In Figure 10, with the rise of iterations, the difference scores between the anxiety level and learning motivation of the SVM model are comparatively stable, while the MP and LSTM models' scores show a certain change trend. For the SVM model, the difference score between anxiety level and learning motivation remains at about 5, with no obvious change trend. This indicates that the relationship between the two is relatively stable in this model.

To sum up, according to the given data, it can be preliminarily concluded that there are differences in the variation trends of various models in evaluating the scores between anxiety level and learning motivation. The SVM model's score is relatively stable, the MP model's score gradually decreases, and the LSTM model's score shows an apparent increasing trend. These analysis results have specific academic and scientific research and can give a reference basis for further research on the relationship between anxiety level and learning motivation.

V. CONCLUSION

This study takes the relationship between anxiety and learning motivation assisted by the LSTM algorithm as the background and uses a questionnaire and LSTM algorithm to interpret the relationship. In terms of research methods, this study implements an evaluation model for interpreting anxiety and learning motivation, uses the LSTM algorithm to train the model, and compares it with SVM and MP algorithms. At the same time, SEM is used to analyze the relationship between the variables. This research framework, which combines the LSTM algorithm with traditional methods, provides a new perspective for psychological research in interpreting. The results manifest that the LSTM algorithm can better capture the characteristics of interpreting anxiety and learning motivation. As the training times increase, the LSTM algorithm performs better than SVM and MP algorithms in evaluating various indexes. In the continuous improvement of sentiment analysis performance regarding anxiety levels, LSTM demonstrates its unique superiority. This highlights the special value of LSTM in handling time-series data related to interpreting learning.

In conclusion, this study validates the effectiveness of LSTM in exploring the relationship between interpreting anxiety and learning motivation, especially in the application of modeling time-sensitive data. Although this study has made significant progress in data analysis using the advanced LSTM algorithm, some limitations remain. Firstly, the research data mainly came from questionnaire surveys, which self-reporting biases of participants may influence. For example, social desirability effects might lead participants to provide "ideal" answers. Secondly, the generalizability of the research results may be challenged due to limitations in the scope and quantity of sample collection. Additionally, in the implementation of the LSTM model, technical details such as parameter selection, network structure, and training processes may prominently impact the results, and these factors are not thoroughly discussed here. Finally, although this study reveals the correlation between interpreting anxiety and learning motivation, further exploration of the specific causal relationship between the two is needed. Looking ahead, several possible directions for future research are anticipated. First, future research can employ more diverse data collection methods, such as laboratory tests or observations of actual interpreting tasks, to obtain more objective and multidimensional data. Second, enhancing the generalizability of the study by increasing the sample size and diversifying the sample composition is recommended. For instance, including participants with diverse cultural backgrounds and educational levels or exploring the relationship between other forms of translation (such as written translation) and learning motivation. Moreover, refining and optimizing the LSTM model and experimenting with different configurations are worthwhile pursuits. Comparing or combining LSTM with other types of neural network models to improve the accuracy and reliability of sentiment analysis is also worth considering. Lastly, based on the findings of this study, subsequent studies can design targeted interventions to empirically test effective strategies for reducing interpreting anxiety and enhancing learning

motivation. Further exploration of the dynamic interactions and underlying mechanisms between the two is possible through interdisciplinary approaches, providing richer theoretical support and applied tools for educational practices in the future.

REFERENCES

- [1] Wang Y Y, Wang Y S. Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments*, 2022, 30(4): 619-634. Doi: <https://doi.org/10.1080/10494820.2019.1674887>
- [2] Bárkányi Z. Motivation, self-efficacy beliefs, and speaking anxiety in language MOOCs. *ReCALL*, 2021, 33(2): 143-160. Doi: <https://doi.org/10.1017/S0958344021000033>
- [3] Chen M R A, Hwang G J. Effects of experiencing authentic contexts on English speaking performances, anxiety and motivation of EFL students with different cognitive styles. *Interactive Learning Environments*, 2022, 30(9): 1619-1639. Doi: <https://doi.org/10.1080/10494820.2020.1734626>
- [4] Zhang Q, Gao T, Liu X, et al. Public environment emotion prediction model using LSTM network. *Sustainability*, 2020, 12(4): 1665. Doi: <https://doi.org/10.3390/su12041665>
- [5] Fan L, Li J, Zhang X P. Load prediction methods using machine learning for home energy management systems based on human behavior patterns recognition. *CSEE Journal of Power and Energy Systems*, 2020, 6(3): 563-571. Doi: <https://doi.org/10.17775/CSEEJPES.2018.01130>
- [6] Pan C, Zhang X. A longitudinal study of foreign language anxiety and enjoyment. *Language Teaching Research*, 2023, 27(6): 1552-1575. Doi: <https://doi.org/10.1177/1362168821993341>
- [7] Li C, Bao Z, Li L, et al. Exploring temporal representations by leveraging attention-based bidirectional LSTM-RNNs for multi-modal emotion recognition. *Information Processing & Management*, 2020, 57(3): 102185. Doi: <https://doi.org/10.1016/j.ipm.2019.102185>
- [8] Kosan M A, Karacan H, Urgen B A. Predicting personality traits with semantic structures and LSTM-based neural networks. *Alexandria Engineering Journal*, 2022, 61(10): 8007-8025. Doi: <https://doi.org/10.1016/j.aej.2022.01.050>
- [9] Kour H, Gupta M K. An hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM. *Multimedia Tools and Applications*, 2022, 81(17): 23649-23685. Doi: <https://doi.org/10.1007/s11042-022-12648-y>
- [10] Du X, Ma C, Zhang G, et al. An efficient LSTM network for emotion recognition from multichannel EEG signals. *IEEE Transactions on Affective Computing*, 2020, 13(3): 1528-1540. Doi: <https://doi.org/10.1109/TAFFC.2020.3013711>
- [11] Alkahtani H, Ahmed Z A T, Aldhyani T H H, et al. Deep Learning Algorithms for Behavioral Analysis in Diagnosing Neurodevelopmental Disorders. *Mathematics*, 2023, 11(19): 4208. Doi: <https://doi.org/10.3390/math11194208>
- [12] Ala'raj M, Abbod M F, Majdalawieh M. Modelling customers credit card behaviour using bidirectional LSTM neural networks. *Journal of Big Data*, 2021, 8(1): 1-27. Doi: <https://doi.org/10.1186/s40537-021-00461-7>
- [13] Jarbou M, Won D, Gillis-Mattson J, et al. Deep learning-based school attendance prediction for autistic students. *Scientific Reports*, 2022, 12(1): 1431. Doi: <https://doi.org/10.1038/s41598-022-05258-z>
- [14] Buono P, De Carolis B, D'Errico F, et al. Assessing student engagement from facial behavior in on-line learning. *Multimedia Tools and Applications*, 2023, 82(9): 12859-12877. Doi: <https://doi.org/10.1007/s11042-022-14048-8>
- [15] Sükei E, Norbury A, Perez-Rodriguez M M, et al. Predicting emotional states using behavioral markers derived from passively sensed data: data-driven machine learning approach. *JMIR mHealth and uHealth*, 2021, 9(3): e24465. Doi: <https://doi.org/10.2196/24465>
- [16] Zitouni M S, Park C Y, Lee U, et al. LSTM-Modeling of Emotion Recognition Using Peripheral Physiological Signals in Naturalistic Conversations. *IEEE Journal of Biomedical and Health Informatics*, 2022, 27(2): 912-923. Doi: <https://doi.org/10.1109/JBHI.2022.3225330>
- [17] Kansizoglou I, Misirlis E, Tsintotas K, et al. Continuous emotion recognition for long-term behavior modeling through recurrent neural networks. *Technologies*, 2022, 10(3): 59. Doi: <https://doi.org/10.3390/technologies10030059>
- [18] Kashyap B, Sachdeva V, Shirahatti A, et al. A Novel Approach for Human Behaviour Prediction Using Deep Learning Algorithms. *International Journal of Intelligent Systems and Applications in Engineering*, 2024, 12(1): 793-801. Doi: <https://www.ijisae.org/index.php/IJISAE/article/view/4192>

- [19] Namaziandost E, Razmi M H, Ahmad Tilwani S, et al. The impact of authentic materials on reading comprehension, motivation, and anxiety among Iranian male EFL learners. *Reading & Writing Quarterly*, 2022, 38(1): 1-18. Doi: <https://doi.org/10.1080/10573569.2021.1892001>
- [20] Cai R, Lin J, Dong Y. Psychological factors and interpreting competence in interpreting students: a developmental study. *The Interpreter and Translator Trainer*, 2023, 17(2): 246-263. Doi: <https://doi.org/10.1080/1750399X.2023.2182590>
- [21] Tan S H, Pang J S. Test Anxiety: An Integration of the Test Anxiety and Achievement Motivation Research Traditions. *Educational Psychology Review*, 2023, 35(1): 13. Doi: <https://doi.org/10.1007/s10648-023-09737-1>
- [22] Mercader-Rubio I, Ángel N G, Silva S, et al. Levels of Somatic Anxiety, Cognitive Anxiety, and Self-Efficacy in University Athletes from a Spanish Public University and Their Relationship with Basic Psychological Needs. *International Journal of Environmental Research and Public Health*, 2023, 20(3): 2415. Doi: <https://doi.org/10.3390/ijerph20032415>
- [23] Miller A, Calder B, Turner M, et al. Exploring the association between irrational beliefs, motivation regulation and anxiety in ultra-marathon runners: a mixed methods approach. *Journal of Rational-Emotive & Cognitive-Behavior Therapy*, 2023, 41(2): 392-410. Doi: <https://doi.org/10.1007/s10942-022-00465-z>
- [24] Barbieri P, Sarasso P, Lodico F, et al. The aesthetic valve: how aesthetic appreciation may switch emotional states from anxiety to curiosity. *Philosophical Transactions of the Royal Society B*, 2024, 379(1895): 20220413. Doi: <https://doi.org/10.1098/rstb.2022.0413>
- [25] Journault A A, Cernik R, Charbonneau S, et al. Learning to embrace one's stress: the selective effects of short videos on youth's stress mindsets. *Anxiety, Stress, & Coping*, 2024, 37(1): 29-44. Doi: <https://doi.org/10.1080/10615806.2023.2234309>
- [26] Wullenkord M C, Tröger J, Hamann K R S, et al. Anxiety and climate change: A validation of the Climate Anxiety Scale in a German-speaking quota sample and an investigation of psychological correlates. *Climatic Change*, 2021, 168(3-4): 20. Doi: <https://doi.org/10.1007/s10584-021-03234-6>.
- [27] Watanabe K, Okusa S, Sato M, et al. mHealth Intervention to Promote Physical Activity Among Employees Using a Deep Learning Model for Passive Monitoring of Depression and Anxiety: Single-Arm Feasibility Trial. *JMIR Formative Research*, 2023, 7(1): e51334. Doi: <https://doi.org/10.2196/51334>.
- [28] Farrag T A, Elattar E E. Optimized deep stacked long short-term memory network for long-term load forecasting. *IEEE Access*, 2021, 9: 68511-68522. Doi: 10.1109/ACCESS.2021.3077275.
- [29] Han S, Qiao Y, Yan J, et al. Mid-to-long term wind and photovoltaic power generation prediction based on copula function and long short term memory network. *Applied energy*, 2019, 239: 181-191. Doi: <https://doi.org/10.1016/j.apenergy.2019.01.193>.
- [30] Sui Y, Zhang B. Determinants of the perceived credibility of rebuttals concerning health misinformation. *International Journal of Environmental Research and Public Health*, 2021, 18(3): 1345. Doi: <https://doi.org/10.3390/ijerph18031345>.
- [31] Akther T, Xu F. An investigation of the credibility of and confidence in audit value: evidence from a developing country. *Accounting Research Journal*, 2021, 34(5): 488-510. Doi: <https://doi.org/10.1108/ARJ-11-2019-0220>.
- [32] Breien F S, Wasson B. Narrative categorization in digital game-based learning: Engagement, motivation & learning. *British Journal of Educational Technology*, 2021, 52(1): 91-111. Doi: <https://doi.org/10.1111/bjet.13004>.
- [33] Forgione M, Piga D. Continuous-time system identification with neural networks: Model structures and fitting criteria. *European Journal of Control*, 2021, 59: 69-81. Doi: <https://doi.org/10.1016/j.ejcon.2021.01.008>.