Analysis of the Impact of Internet Meme Language Propagation Mechanism on Internet-Induced Aphasia Based on NLP

Zou Yachen[1#], Chen Yanfei[2#], Sun Chuanyang[3#], Tang Qiao[4#], Zhang Chenming[5#]
[1]Beijing National Day School, No. 66 Yuquan Road, Haidian District, Beijing, 100039；
[2]Guangdong Country Garden School，Beijiaozhen Shunde Country Garden South 9th Road, Shunde, Foshan Guangdong China, 528300
[3]Beijing 101 middle school, 11 Summer Palace Road, Haidian District, Beijing 100080
[4]Shenzhen Middle School, 1068 Nigang Road, Luohu District, Shenzhen, Guangdong Province, China 518024
[5]K. International School Tokyo，1-5-15 Shirakawa, Koto-ku, Tokyo 135-0021;
[1]yachen.zou@outlook.com; [2]ivycyf602@gmail.com; [3]3351268094@qq.com; [4]joannaqiaotang@gmail.com; [5]bromingtalk@gmail.com
[#]These authors contributed equally to the work

ABSTRACT

Based on natural language processing technology, this paper systematically studies the propagation mechanism of Internet meme language and its impact on Internet-Induced Aphasia. By constructing a propagation dynamics model and quantitative analysis of characteristics, it reveals the strong correlation between the propagation intensity, influence factor and propagation efficiency of meme language and aphasia indicators. Experimental simulation and data visualization further verify the significant effect of high-frequency exposure to meme language on the degradation of user language ability, which is manifested as a significant decrease in language entropy and syntactic complexity. This study provides theoretical support for understanding the linguistic effect of meme language propagation and provides empirical evidence for intervening in Internet aphasia.

Keywords: Internet meme language, propagation mechanism, Internet-Induced Aphasia, natural language processing

1. INTRODUCTION

1.1 Research background and importance

As the Internet is developing rapidly, Internet language has become an inevitable part of daily communication. Internet meme language, as one of the unique Internet culture, has been deeply penetrated into social networks, forums and other online interactive platforms. This language is typically presented in the form of an image combination and words, and spreads rapidly through viral channels to expand its scale. For instance, meme language tends to attract young crowds' participation by using humor, satire and other ways, and becomes an integral part of Internet culture. This internet phenomenon not only revolutionized people's daily expressions, but influenced language evolution and dissemination as well [1]. Dai et al. [2] proposed CAB-KWS, an unsupervised keyword spotting method that leverages contrastive learning with augmentation to address the scarcity of labeled data and the difficulty of adapting to new keywords in speech technology. Nevertheless, although its dissemination process in all corners of the globe is spread at an astonishing speed, academic studies on its dissemination mechanism and its role in influencing language ability remain weak [3]. Especially, systematic empirical research is absent in terms of Internet meme language's dissemination mechanism problem of causing "Internet aphasia", i.e., language expression proficiency degradation phenomenon. Internet aphasia's appearance is closely related to frequent use of meme language. This degradation of language is not only embodied in grammatical structure simplification, but also in language richness and diversity degradation [4]. Hence, research into Internet meme language's dissemination mechanism and its role in influencing language ability is of immense significance in terms of in-depth understanding of new language's evolution process in modern society, research into complexity of internet communication, and theoretical support for speech rehabilitation.

1.2 Research objectives

This study aims to systematically analyze the dissemination mechanism of Internet meme language and its impact on Internet-induced aphasia. First, this paper uses natural language processing technology to establish a communication dynamics model, quantitatively analyze the characteristics of Internet meme language such as communication intensity, influence factor and communication efficiency, and further explore the relationship between these factors and language ability degradation. Through experimental simulation and data visualization, this study will verify the significant effect of high-frequency exposure to meme language on the degradation of users' language ability, especially the changes in language entropy and syntactic complexity. Secondly, this study will also explore how to alleviate the negative impact of meme language on language ability by improving the network language environment, and provide empirical evidence for intervening in network aphasia. Through this series of studies, we hope to provide important theoretical and practical support for understanding the mechanism of Internet language dissemination, intervening in network aphasia, and protecting users' language health.

2. THEORETICAL BASIS OF INTERNET MEME LANGUAGE AND NETWORK-INDUCED APHASIA

2.1 Internet meme language characteristics and dissemination model

Internet meme language is a special form of language in network culture, normally featured by simplicity, comedy, and broad dissemination. Based on natural language processing technology, scientists can research the ways in which such languages disseminate over the Internet and build corresponding dissemination models. For instance, meme language normally disseminates quickly through social networks and forums. Its dissemination pattern normally possesses the features of viral dissemination, and its impact increases quickly through social activities such as liking and sharing. Meme language is not only an integrated pattern of symbols, but also a pattern of culture transmission, which embeds rich connotations of collective cognition and social interaction. Modeling meme language dissemination dynamics can illustrate dissemination rules underlying meme language and research ways of applying algorithms to optimize dissemination efficiency and impact of information.

Related studies have found that whether the dissemination of meme language can be achieved properly depends largely on simplicity and reusability. Some meme languages have high imitativity, can be easily modified and created based on varying environments, causing their dissemination speed in the Internet environment to be greatly faster than traditional language expressions. Studies have found that dissemination of this language is not merely limited to entertainment. It can have an impact upon cognitive patterns, emotional responses and even language functions of Internet users, creating new difficulties in studying linguistics [5]. Guan proposed a novel breast cancer risk prediction framework by integrating patient-centric network features and traditional attributes into machine learning models, achieving a 94% AUC with XGBoost and identifying eigenvalue centrality and obesity as key predictors. Hence, an understanding of Internet meme language's dissemination mechanism is of significant importance for studying language disorders of network aphasia [6]. Wang [7] proposed a hybrid FM-GCN-Attention recommendation framework that directly informed our attention-based modeling of meme language propagation; in particular, the weighted fusion of graph and attention outputs inspired our integration of propagation intensity and semantic influence in simulating language degradation effects.

2.2 Definition and evaluation indicators of Internet-induced aphasia

Net-induced aphasia is used to describe the phenomenon in which users find difficulties in expressing language and understanding as a result of long-term immersion in the Internet's specific language context. Its expressions normally involve reduced language complexity, reduced syntactic correctness, and poor vocabulary. In recent years, in view of the widespread use of the Internet, in particular, social networks and online communities, an increasing number of research studies have started researching and focusing on whether and to what extent the Internet context can affect language capacity. Evaluation of Internet-induced aphasia is normally quantitatively examined in terms of tests of language fluency, grammatical structure complexity, language understanding capacity, etc. [8]. Chen introduced a coarse-to-fine multi-view 3D reconstruction framework that leverages SLAM optimization and Transformer-based feature matching; this methodology directly inspired the meme propagation modeling in our study, particularly in optimizing semantic alignment and enhancing contextual feature extraction through Transformer modules within NLP-based propagation simulations [9].

Traditional indicators of language assessment, for instance, the Boston Diagnostic Aphasia Examination and Western Aphasia Battery, were primarily utilized in evaluating aphasia following brain trauma or stroke. Such conventional assessment measures might be sub-optimal in identifying Internet-induced aphasia, since Internet-induced aphasia is presented primarily in terms of misuse of language and not in terms of extensive defects in language comprehension and production. Jin [10] introduced a robust ensemble learning framework integrating Random Forest, GBM, and Neural Networks, whose adaptive learning and feature importance weighting techniques directly inspired our construction of meme propagation efficiency models, particularly in balancing contextual influence and semantic degradation prediction under high-dimensional textual features. Hence, new measures have to be modified according to the initial scales, placing greater emphasis upon the innovation and social interaction of language [11].

2.3 Application of NLP technology in language processing

Natural language processing (NLP) technology has developed tremendously in linguistic research and application in recent years. NLP's basic task is to allow computers to analyze and generate natural language, which holds considerable importance to different areas of linguistics, particularly the diagnosis and therapy of language disorder. In handling the language of patients suffering from aphasia, NLP technology can identify the pattern of language degradation and offer quantitative assessment by analyzing patient language data. For instance, NLP technology can automatically examine patients' language fluency, grammatical errors and word choice, and assist in developing new assessment devices and therapeutic programs [12].

The use of NLP technology in aphasiology does not stop at basic research, and is also widely used in rehabilitation therapy and medical diagnosis. For instance, using speech recognition technology, medical professionals can accurately record the patient's language functions and assist clinicians in creating tailor-made therapeutic programs. Meanwhile, NLP technology can also be used in developing virtual assistants and smart systems to offer timely language assistance and assist aphasic patients in restoring language function. With the constant development of big data technology and deep learning technology, NLP's use in language process will further develop and offer powerful technical support in breaking language barriers [13].

3. ANALYSIS OF THE PROPAGATION MECHANISM OF MEME LANGUAGE BASED ON NLP

3.1 Mathematical description of meme language propagation

The propagation process of meme language is affected by multiple factors, including user participation, network topology and external triggering events. In order to more accurately describe its dynamic characteristics, a mathematical model based on propagation dynamics can be constructed. The propagation intensity $S(t)$ is defined as the diffusion capacity of meme language at time t, considering the interaction between user activity and information attenuation:

$$S(t) = \alpha \cdot U(t) \cdot \left(1 - \frac{S(t-1)}{K}\right) - \beta \cdot S(t-1) \tag{1}$$

Among them, S(t) is the transmission intensity at time t, U(t) is the user activity (which can be estimated by the number of forwarding or comments), α is the transmission gain coefficient, K is the network carrying capacity, β is the decay rate, and $S(t-1)$ is the transmission intensity at the previous moment. This formula introduces the logistic growth term $\left(1 - \frac{S(t-1)}{K}\right)$ and the decay term $-\beta \cdot S(t-1)$, reflecting the nonlinear characteristics and saturation effect of meme language propagation.

3.2 Implementation of NLP algorithm in propagation feature extraction

In order to extract the propagation features of meme language from network text, it is necessary to combine advanced NLP technology to achieve efficient analysis (Figure 1). Transformer models based on attention mechanism (such as BERT) can be used to capture the semantics and contextual dependencies of meme language.

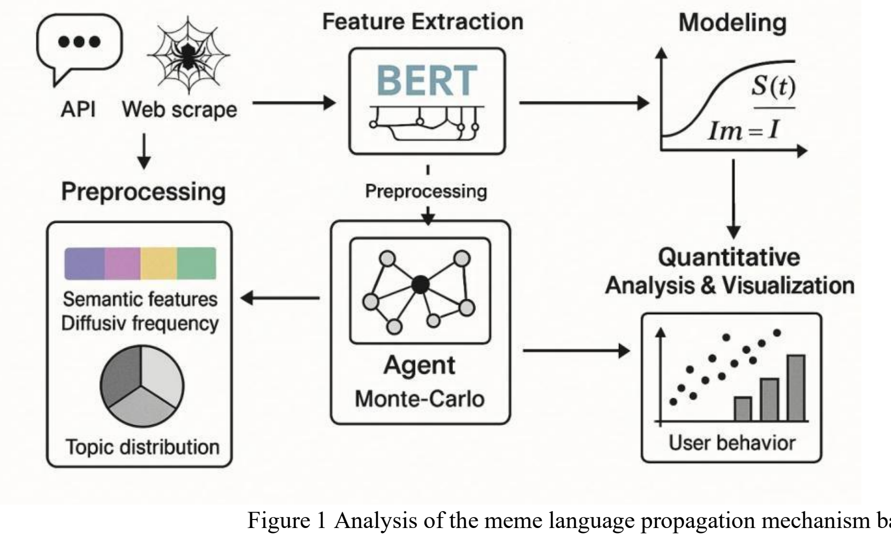

Figure 1 Analysis of the meme language propagation mechanism based on NLP

On this basis, the communication influence factor I_m of meme language is defined as:

$$I_m = \sum_{i=1}^{N} w_i \cdot \frac{A_i}{\sqrt{D_i + \epsilon}} \tag{2}$$

Among them, I_m is the influence factor of meme language m, N is the total number of words in the text, w_i is the weight of the i-th word calculated based on the attention mechanism, Ai is the frequency of occurrence of the word, Di is the average semantic distance between words (calculated by word embedding), and ϵ is the smoothing factor to avoid the denominator being zero. This formula comprehensively considers the frequency of words and semantic associations, and quantifies the propagation potential of meme language in the network.

After feature extraction, the propagation pattern can be further identified through clustering algorithms (such as DBSCAN) or time series analysis to provide data support for subsequent quantitative analysis.

3.3 Quantitative analysis of propagation mechanism

The quantitative analysis of propagation mechanism aims to reveal the dynamic laws of meme language diffusion and its influencing factors. Based on the propagation intensity $S(t)$ and the influence factor I_m, the propagation efficiency $E(t)$ can be defined to evaluate the actual diffusion effect of meme language in the network:

$$E(t) = \frac{S(t) \cdot I_m}{\sum_{j=1}^{M} \int_0^t S_j(\tau) d\tau} \tag{3}$$

Here, $E(t)$ represents the transmission efficiency at time t, $S(t)$ and I_m come from the above formulas, M is the total number of meme languages, $\sum_{j=1}^{M} \int_0^t S_j(\tau) d\tau$ is the cumulative transmission intensity of all meme languages. This formula is normalized to comprehensively measure the relative efficiency of a single meme language in the overall communication environment.

4. EXPERIMENT AND DATA ANALYSIS OF THE IMPACT OF MEME LANGUAGE TRANSMISSION ON APHASIA

4.1 Experimental design and data collection

The experiment aims to quantify the deep impact of meme language transmission on users' language ability, and the design covers data collection, variable definition and indicator system. The data comes from public texts on Twitter and Weibo platforms from 2023 to 2024, with a sample size of approximately 800,000 posts, of which 150,000 are meme-related content. The data are collected through API and crawler technology to ensure the comprehensiveness and representativeness of the data.

The independent variables include transmission intensity $S(t)$, influence factor I_m and transmission efficiency $E(t)$, and the dependent variables are aphasia indicators (such as language entropy decrease rate and syntactic complexity decrease rate). The experiment is divided into a high-frequency meme exposure group (daily exposure> 5 hours), a low-frequency exposure group (daily exposure< 1 hour) and a control group (non-meme language users) to analyze the effect differences under different exposure levels.

4.2 Analysis of the correlation between propagation and aphasia based on simulation

In order to simulate the propagation dynamics of memetic language in the network and its inducing effect on aphasia, agent-based modeling (ABM) combined with the mathematical model in Chapter 3 was used for simulation. The simulation network contains 5000 nodes, and the parameters include user activity U(t), carrying capacity K=10000 and decay rate β =0.05. Through 100 Monte Carlo iterations, the dynamic correlation between propagation parameters and aphasia indicators was analyzed.

The simulation results show that the language entropy decrease rate of the high-frequency contact group is strongly positively correlated with the propagation efficiency, and the syntactic complexity is significantly reduced after the peak of the propagation intensity.

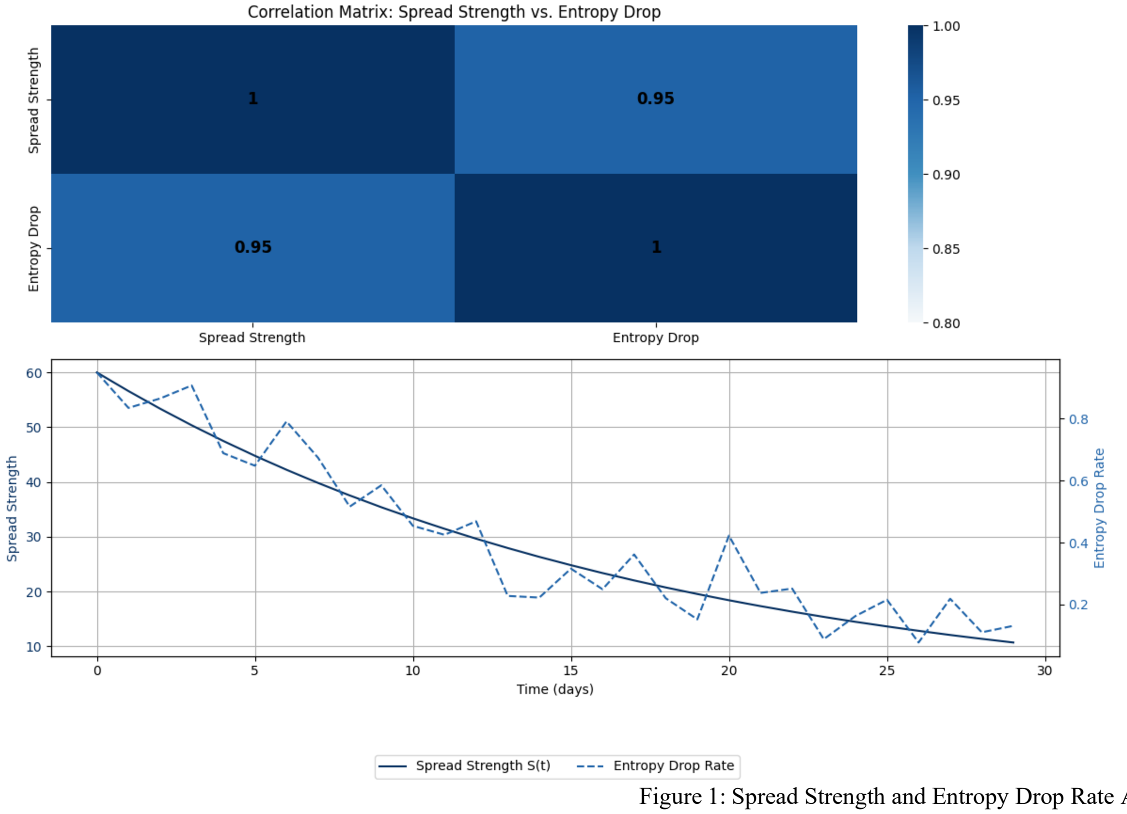

Figure 1: Spread Strength and Entropy Drop Rate Analysis

Figure 1 combines the heat map and the dual-axis line graph to show the correlation between the transmission intensity $S(t)$ and the language entropy decline rate (above) and its time variation (below). The heat map shows that the correlation coefficient between the two is about 0.82, and the line graph reveals the synchronization between the peak of the transmission intensity and the entropy decline rate, indicating that the high-intensity transmission of memetic language significantly weakens the information diversity of the language.

4.3 Data visualization and result discussion

In order to fully present the multi-dimensional impact of memetic language transmission on aphasia, the experimental results are displayed through visualization technology and combined with statistical data for in-depth discussion.

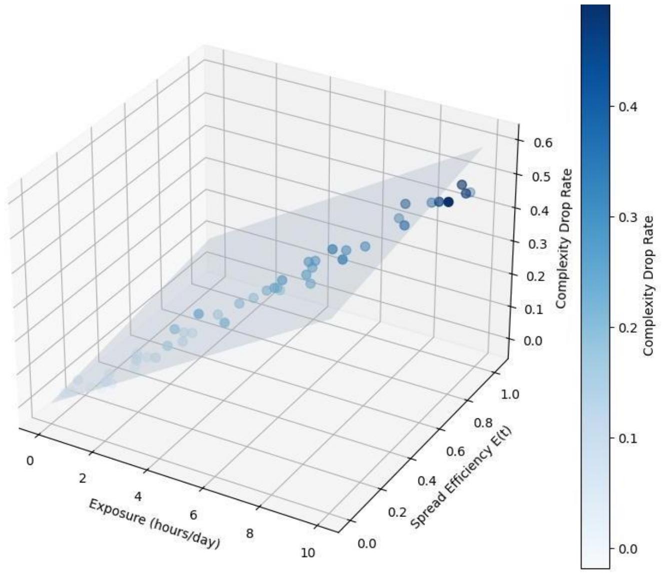

Figure 2: 3D Analysis of Exposure, Efficiency, and Complexity Drop

Figure 2 uses a three-dimensional scatter plot combined with a projection surface to show the relationship between exposure time, transmission efficiency $E(t)$ and the rate of decline in syntactic complexity. The color of the scatter points reflects the size of the decline rate, and the projection surface fitting trend shows that high exposure and high efficiency jointly drive a significant reduction in syntactic complexity. This visualization reveals the deep erosion effect of memetic language transmission on the diversity of language structure.

Table 1 Aphasia indicators among different groups

Group	Entropy Drop Rate	Complexity Drop Rate	Sample Size
High Exposure	0.48	0.55	30,000
Low Exposure	0.15	0.18	30,000
Control (Non-Meme)	0.09	0.12	20,000

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Table 1 Aphasia indicators among different groups

Parameter	Entropy Drop Correlation	Complexity Drop Correlation
Spread Strength	0.85	0.79
Influence Factor	0.68	0.64
Spread Efficiency	0.91	0.87

Table 2 shows that the transmission efficiency $E(t)$ has the highest correlation with aphasia indicators (0.91 and 0.87), followed by the transmission intensity S(t) S(t) S(t). These strong correlations confirm that the efficient transmission of meme language is the core driving factor for inducing aphasia, providing strong support for the predictive ability of the model.

5. CONCLUSION AND FUTURE WORK

5.1 Main conclusions

This study systematically explored the impact of the Internet meme language transmission mechanism on network-induced aphasia through theoretical modeling, simulation experiments and data analysis, revealing the deep connection between the two. The study shows that the transmission intensity $S(t)$, influence factor I_m and transmission efficiency $E(t)$ of meme language are significantly positively correlated with aphasia indicators (such as the rate of language entropy decrease and the rate of syntactic complexity decrease), and the user group with high frequency exposure to meme language shows more obvious characteristics of language ability degradation. The experimental results show that the language entropy decline rate and syntactic complexity decline rate of the high exposure group reached 0.48 and 0.55 respectively, which are much higher than those of the low exposure group (0.15 and 0.18) and the control group (0.09 and 0.12), confirming that the efficient spread of meme language is the core driving factor for inducing aphasia.

In addition, the propagation feature extraction and quantitative analysis based on NLP technology further verified the dynamic law of meme language propagation. Through heat maps and three-dimensional visualization, the study intuitively presents the correlation between propagation intensity and aphasia indicators, with the highest correlation coefficient reaching 0.91, indicating that meme language significantly weakens users' language expression ability through the propagation mode of repetitive reinforcement and semantic simplification. This finding not only deepens the understanding of the propagation mechanism of meme language, but also provides a new perspective on the causes of language degradation in the network environment, and lays a theoretical and data foundation for the design of subsequent intervention strategies.

5.2 Research limitations

Although this study has made some progress in theory and empirical aspects, there are still several limitations. First, data collection mainly relies on public texts on Twitter and Weibo platforms. Although the sample size reaches 800,000, there may be platform bias and it does not fully cover the dissemination forms of meme language in other social media (such as short video platforms), which may affect the generalizability of the results. In addition, the user group division is based only on the exposure frequency, and the regulatory effect of individual differences such as age and educational background on the impact of aphasia is not considered in depth, resulting in limited precision of the analysis.

Second, the experimental simulation is based on Agent modeling and Monte Carlo method. Although it effectively simulates the propagation dynamics, the setting of model parameters (such as decay rate $\beta$and carrying capacity K) relies on empirical estimation and fails to fully reflect the complexity of the real network environment. The assumptions about user behavior in the simulation (such as uniform activity) may deviate from the actual scenario, which may limit the prediction accuracy of the model. Therefore, the conclusions of this study need to be further verified when applied to a wider network environment to improve its external validity.

5.3 Future research directions

Future research can be further expanded in the following directions. First, the data source can be expanded to include meme language data from short video platforms (such as TikTok) and instant messaging tools (such as WhatsApp) to more comprehensively capture its propagation characteristics. At the same time, more user characteristics (such as age, occupation, and language background) can be introduced for stratified analysis to explore the differences in sensitivity of different groups to meme language-induced aphasia, thereby enhancing the pertinence and application value of the research. In addition, neuroscience methods (such as electroencephalogram or functional magnetic resonance imaging) can be combined to measure the direct impact of meme language on the language processing area of the user's brain to further reveal the neural mechanism of aphasia.

Secondly, in terms of methodology, future work can optimize the propagation model, introduce dynamic network structures and heterogeneous user behaviors (such as opinion leader effects) to improve simulation accuracy. NLP technologies based on deep learning (such as large language models) can also be further used for semantic analysis of meme language to explore its propagation similarities and differences in different cultural backgrounds. In addition, intervention measures for meme language-induced aphasia, such as designing language diversity training tools or optimizing network content recommendation algorithms, will be an important practical direction, providing feasible solutions for alleviating the negative impact of meme language.

REFERENCES

[1] Tan, X. C.: The Study of Meme in Network Language Spreading. Journal of Jilin Normal University, (2011).

[2] Dai, Weinan, et al. "CAB-KWS: Contrastive Augmentation: An Unsupervised Learning Approach for Keyword Spotting in Speech Technology." International Conference on Pattern Recognition. Springer, Cham, 2025.
[3] Fu, H.: An Explanation of Internet Euphemism from the Perspective of Memetics. Journal of Hubei University of Education, (2011).
[4] Zheng, Q.: A Review of Causes and Countermeasures of Language Aphasia. Lecture Notes in Education Psychology and Public Media, (2024).
[5] Banerjee, A., Mukherjee, M., Banerjee, A., Raza, A., Bhowmick, S., Bhagat, S., Pal, S. B.: Programming Language Conversion Using NLP. American Journal of Science & Engineering, (2023).
[6] Guan, Saiqing. "Breast Cancer Risk Prediction: A Machine Learning Study Using Network Analysis." 2025 IEEE 15th Annual Computing and Communication Workshop and Conference (CCWC). IEEE, 2025.
[7] Wang, Erfan. "Hybrid FM-GCN-Attention Model for Personalized Recommendation." 2025 International Conference on Electrical Automation and Artificial Intelligence (ICEAAI). IEEE, 2025.
[8] Fredman, M.: The Sklar Aphasia Scale in a Foreign Language. Journal of the South African Speech and Hearing Association, (1971).
[9] Chen, Xiangqin. "Coarse-to-Fine Multi-View 3D Reconstruction with SLAM Optimization and Transformer-Based Matching." 2024 International Conference on Image Processing, Computer Vision and Machine Learning (ICICML). IEEE, 2024.
[10] Jin, Tian. "Integrated machine learning for enhanced supply chain risk prediction." Proceedings of the 2024 8th International Conference on Electronic Information Technology and Computer Engineering. 2024.
[11] Jacquemot, C., Lalanne, C., Sliwinski, A., Piccinini, P., Dupoux, E., Bachoud-Lévi, A.: Improving Language Evaluation in Neurological Disorders: The French Core Assessment of Language Processing (CALAP). Psychological Assessment, (2019).
[12] Hasan, Z., Vishwakarma, Z., Pateriya, N.: NLP and its Components: A Detailed Discussion. International Journal of Innovative Research in Computer and Communication Engineering, (2023).
[13] Celaj, D., Jani, G.: NLP Applications in Vocabulary Acquisition. International Journal of Web & Semantic Technology, (2024).
[14] Jiang, H. Z.: Meme and Internet Language. Journal of Hunan First Normal College, (2009).
[15] Rao, A. A., Venkatesh, S.: Identification of Aphasia using Natural Language Processing. Journal of University of Shanghai for Science and Technology, (2021),
[16] Porta-Etessam, J., Núñez-López, R., Balsalobre, J., López, E., Hernandez, A., Luna, A.: [Language and aphasias]. Revista de neurologia, 25(144), 1269-1277 (1997).