Advances in Research on Information Distortion in Transmission and Translation Processes

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Abstract. Background: With the increasing complexity of internet information dissemination, transediting, as a dynamic negotiation process across linguistic sign systems, faces significant challenges. The problem of distortion in the translation of memes and texts has become a critical problem requiring urgent resolution. This study reviews literature related to transediting and investigates methods for distinguishing authenticity in the translation of memes and texts. Subsequently, commonalities and differences between the two are compared. Conclusion: The investigation reveals that the commonality in distortion stems from the inherent difficulties in cross-semiotic transfer. Technological advancements have evolved from simple correspondences to intelligent models, yet they remain constrained by culturally implicit knowledge. The distinct characteristics depend on semiotic attributes: memes primarily exhibit emotional distortion and are easier to identify, whereas texts are prone to semantic distortion and are more challenging to discern. Existing technologies, such as the Transformer framework, inadequately address cultural contextualization. Although the ImBD system enables rapid style evaluation, its current application remains limited, primarily in academic papers and social media text detection.

Keywords: Information dissemination, translation, distortion, emojis, text.

1. Introduction

In the information era where the Internet has deeply permeated, the transmission of cross-language and cross-cultural meanings relies on translation. This is not merely a language translation but a dynamic coordination process involving context and culture. This translation requires the integration of context, cultural customs, and the particularity of symbols. However, the phenomenon of translation distortion is increasingly prominent. This research compares specific forms, such as emojis and texts. Emojis, as a composite symbol of "image + text", often lead to emotional translation deviations due to the ambiguity of images and cultural interpretation differences (for example, in East Asian culture, the "smile" emoji implies detachment, conflicting with the "friendly" interpretation in the European-American context) (Zhou, De Souza, Markham, Kwakpovwe, & Zhao, 2024). Cultural differences can greatly exacerbate emotional translation bias since different people interpret emojis differently (Sun, Lasser, & Lee, 2022). AI generated texts distort factual details through grammatical reorganization and semantic confusion, making it difficult to distinguish truth from falsehood, posing a serious challenge to information security. These distortions not only interfere with information transmission but also amplify emotional conflicts (such as the "emotional arousal ability" of emojis being stronger than pure text) and cognitive misguidance (such as forged texts eroding the credibility of information) in social media.

Reviewing the existing studies, the decoding of emojis goes through three stages: in the early stage, a "emoji dictionary" was used to statically map images to text keywords, but it was unable to handle polysemy; in the middle stage, the Transformer framework was introduced, integrating text, audio, and visual data to build a multimodal model, but it still relied on the implicit cultural knowledge in the pre-trained data (insufficient cross-cultural adaptation); this article focuses on the new emoji translation methods in 2025 (ChatGPT replacing human annotators to explain emojis). ChatGPT demonstrates ease of use in daily emoji explanations, but it has not been debugged for special languages and different cultural scenarios, and its accuracy is limited. In the research on text translation distortion, there are mainly two research methods: one is based on evidence, the other is

based on patterns. This paper mainly reviews the pattern-based methods. In the early stage, false texts were detected through dual emotion detection, and by comparing the publisher and social emotions, false texts were identified; in the middle stage, the authenticity of the text was confirmed through a multi-angle and multi-domain joint modeling approach; now, the "imitation first and then detection" ImBD style perception system captures the stylistic features of machine texts (vocabulary, syntax, paragraph-level style deviation) to achieve efficient reasoning at a speed of 1000 words per 0.72 seconds, but it has not fully combined semantic consistency verification, and there is still room for improvement in the identification ability of "taking parts out of context" and other logical tampering.

2. Background of the problem

With the rapid development of the Internet, the scale and diversity of information dissemination have increased, and the responsibility of translation has become greater. Translation is the possibility of reshaping the meaning of the original language through the target language, and its essence is the dynamic negotiation of cross-language symbol systems. Unlike direct translation, it does not have the same meaning as the original language. Translation makes changes in expression based on context, cultural customs, and language characteristics. The multi-dimensionality and context-dependency of translation make it difficult to handle. According to the decoding research of emojis, compared to pure text, their destructive impact on social media is stronger (Qu, Zhou, Song, Ding, Yuan, & Wu, 2024).

3. Specific form

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3.1. The Distortion of the Translation of Emojis

The ambiguity of image symbols often leads to distortion in emotional translation. For instance, the interpretation of the 'smile' expression may vary across different cultures. Emojis convey emotions through a combination of images and text symbols. However, interpretations of the same emoji can differ significantly across different cultural contexts. For example, the "laughing" emoji may represent joy in some cultures but may be regarded as mocking in others (Zhou, Xu, Wang, Lu, Gao, & Ai, 2025). In the decoding research of emoticons, early studies used the construction of emoticon dictionaries to associate static images with text keywords, but they struggled to handle polysemy and contextual differences (Monica & Rao, 2020). In the mid-term, the Transformer framework was incorporated into text, audio, and visual three types of simulated data to expand into a multimodal dialogue scenario, but in terms of cultural context, it still relied on the implicit knowledge in the pre-trained data (Singh, Firdaus, Ekbal, & Bhattacharyya, 2023). In 2025, researchers conducted an emoticon annotation experiment using ChatGPT, with the aim of addressing the following three research questions: the semantics, emotions, and usage intentions of emoticon symbols; whether ChatGPT contains the encoding of emoticon symbols related to different communities; the role of ChatGPT in downstream tasks related to emoticon symbols.

In terms of the semantics of emojis, researchers collected the meanings of emojis from emoji websites and used them to compare with the results provided by ChatGPT. Without any context, the annotations made by humans and the interpretations by ChatGPT were very similar. It is notable that in the explanation of the "purple heart" emoji by ChatGPT, the importance of purple was mentioned, while in the annotations made by humans, the main discussion was about its usage in tweets related

to Korean boy bands. This indicates that the content of ChatGPT's interpretation is complementary to that of human annotations. In the presence of context, ChatGPT still performed well, but it occasionally produced errors when dealing with uncommon objects. In terms of cultural background, researchers retrieved characteristic emojis from the Chinese internet, and ChatGPT could only provide the required explanations after receiving prompts.

In terms of the emotions of emojis, in the experiment, GPT4 was applied to label the positive, neutral, and negative emotional attitudes of 50 selected emojis. The performance of ChatGPT was the same as that of human annotations, with only one exception. This difference indicates that ChatGPT can interpret the emotions contained in emojis, but it differs from humans in certain special cases. For example, for the emoji "rinse face", the human annotation was neutral, while ChatGPT interpreted it as negative. ChatGPT still requires some context reminders.

The interpretation of the usage intentions of emojis by ChatGPT does not have a high degree of overlap with human annotations. The accuracy of GPT4 is only 49.0%. An experiment was conducted on emojis in GitHub posts to study the translation of emoticons expressing emotions and emphasizing the content of the posts by ChatGPT. The researchers found that when ChatGPT translated emojis expressing emotions and emphasizing the content of the posts, it was consistent with human performance. However, for emoticons rarely seen on other social media, ChatGPT's interpretations showed significant discrepancies compared to human annotators. To evaluate ChatGPT's ability to distinguish sarcastic emoticons in different language contexts, the researchers initiated an ICL experiment, which included two databases: one containing sarcastic Arabic text and the other containing English sarcastic tweets with emoticons. In the presence of emojis, ChatGPT's accuracy in judging sarcasm was 81.2%, but it dropped to 77.0% when the emojis were excluded. ChatGPT does not primarily rely on emojis to determine sarcasm; instead, after removing the emojis, the meaning of the text changed, and ChatGPT looked for the irony based on the meaning expressed by the emojis and the text, which indicates that emoticons played a role in conveying sarcasm. To evaluate ChatGPT's understanding of sarcastic emojis in other languages, the researchers selected the recently published Arabic dataset. The accuracy predicted by GPT4 was 60.1%, proving that ChatGPT can distinguish whether an emoji has an ironic meaning.

The usage and intentions of emoticons in different communities can vary greatly. The study aimed to explore whether such encoded information exists in ChatGPT by conducting a confirmation experiment by directly asking about the most common usage patterns of emoticon symbols. The results showed that ChatGPT could reflect the differences in the usage of emoticons in different situations, but it did not cover all of them.

In conclusion, ChatGPT performed well in interpreting daily emoticons in the paper experiments and was convenient to use, which could reduce the cost for daily emoticon users. However, ChatGPT is not the most advanced model at present and has not been debugged for special languages or scenarios. It lacks awareness of the changes in emoticon symbol usage in different regions and countries (Zhou, Xu, Wang, Lu, Gao, & Ai, 2025).

3.2. The Distortion of the Translation of the Text

After the AI-generated text undergoes grammatical restructuring and semantic confusion, the factual details are altered (such as taking isolated sentences out of context and fabricating information), blurring the boundary between truth and falsehood, increasing the difficulty of identification. The AI can generate highly realistic forged texts, while traditional algorithms have difficulty distinguishing between true and false, thereby potentially seriously threatening information security. The methods for detecting the authenticity of text can be roughly divided into two categories: one is based on evidence; the other is based on patterns. This article mainly explores the progress of the latter (Wu, Xu, Liu, Wu, & Wang, 2024).

The pattern-based method only focuses on the patterns of the text and detects them through text features and emotional patterns. In the early stage, researchers used dual emotional detection to detect fake texts. The two forms of expression, emotional resonance (the publisher's emotion is the same or

similar to the social emotion) and emotional imbalance (the publisher's emotion is different from the social emotion), have statistically significant differences in true and false texts. For example, in emotional resonance, the number of fake texts with both "anger" emotions is greater than that of true texts (Zhang, Cao, Li, Sheng, Zhong, & Shu, 2021). After that, researchers adopted a multi-angle and multi-domain approach to jointly model the text information of multiple related fields and proposed a new memory-guided multi-angle and multi-domain fake news detection framework (M^3FEND), which is effective in detecting false information (Zhu et al., 2023).

In 2025, researchers adopted the "immediate imitation followed by detection" ImBD framework. Through style preference optimization (SPO), they captured the subtle stylistic features of machine revisions, thereby improving the accuracy of detecting forged texts. AI differs significantly from humans in terms of vocabulary selection, syntax, paragraph structure, and logical coherence. AI emphasizes emotions, complex grammatical structures, and consistent logic, while humans prioritize lexical diversity, concise writing, and natural leaps in thinking. The ImBD framework introduced style preference optimization (SPO), aligning the scoring LLM model with the style preferences of machine-generated texts. Subsequently, through model calculation of style-conditioned curves (Style-CPC), the deviation of the text from the machine style was quantified, which is particularly suitable for real-time content review. Its reasoning speed reaches 0.72 seconds for 1000 words, making it suitable for real-time review scenarios such as social media and academic papers. Researchers conducted numerous comparative experiments in various scenarios and found that compared with the current state-of-the-art methods (based on two trained models and the logit model), the ImBD framework has improved performance in detecting AI-generated or modified texts (by approximately 10%-20%). Unlike previous methods that focused on the overall features of the text, this article proposes to use "separate style features" as the basis for detection, with a lower training cost. Only 1000 samples and 5 minutes of SPO training are required to surpass the commercial training GPT-Zero (Chen et al., 2025). It is worth noting that LLM alternates rapidly and frequently, with a high degree of variability, and there is a risk of rendering the features ineffective. The ImBD framework can be combined with the latest LLM models and adjusted accordingly. Both deep learning technology and adversarial training can effectively address this limitation.

4. Future Outlook

Future translation research can be deepened and expanded from multiple dimensions. At the technical level, future research should strengthen multimodal integration and the construction of cultural knowledge graphs to improve the decoding accuracy in cross-cultural contexts. By making cultural context variables explicit in the model training, researcher can overcome the limitations of the implicit cultural knowledge in existing pre-trained data and enhance the accuracy of emotion translation of emojis in cross-cultural scenarios. For text translation distortion, the algorithm logic of the ImBD style perception system should be optimized, combined with semantic consistency verification technology, to enhance the ability to identify logical tampering of forged texts, and simultaneously improve the real-time review efficiency to adapt to a wider range of social media scenarios. In terms of research scope, future research can expand to short videos and vocal symbols, explore the translation distortion mechanism of their cross-cultural communication, and establish a cross-symbol translation distortion assessment system. In addition, it is necessary to combine technology application with practical norms. It is necessary to formulate a warning mechanism and industry standards for translation distortion to ensure the credibility of information in academic exchanges and international communication, promote the responsible application of translation technology in academic exchanges, cross-cultural communication, etc., and ultimately achieve a comprehensive improvement in the accuracy, cultural adaptability, and credibility of information translation.

5. Conclusions

This investigation reveals that the essence of translation distortion stems from the inherent dilemma of cross-symbol transmission. Whether it is emojis or text, they all achieve transmission by reshaping the original meaning into the target symbol system, inevitably resulting in negotiation costs and causing distortion. Emojis, as visual symbols, are more inclined towards the emotional dimension, while text, as language symbols, is more oriented towards semantic logic. The latest method for emojis is to apply advanced AI to conduct a series of comparative experiments with humans. ChatGPT performs well in annotating daily scenarios, but it has not undergone relevant special debugging and does not represent the most advanced AI system. In the future, the most advanced AI system can be adopted to conduct debugging for the decoding of emojis based on this; for the authenticity identification of text, currently ImBD optimizes based on style preferences, and subtle stylistic features are used to distinguish the authenticity of the text. However, as LLM evolves, some features may become ineffective. Therefore, a combination of adversarial training and dynamic evaluation is needed to address this. By combining the latest deep learning technology and adversarial training methods, it is conducive to the in-depth study of this issue

References

[1] Chen, J., Zhu, X., Liu, T., Chen, Y., Xinhui, C., Yuan, Y., Leong, C. T., Li, Z., Tang, L., Zhang, L., Yan, C., Mei, G., Zhang, J., & Zhang, L. (2025). Imitate before detect: Aligning machine stylistic preference for machine-revised text detection. *Proceedings of the AAAI Conference on Artificial Intelligence*, 39(22), 23559–23567. Washington DC: Association for the Advancement of Artificial Intelligence

[2] Monica, K., & Rao, D. R. (2020). Text to image translation using Cycle GAN. International Journal of Engineering and Advanced Technology, 9(4), 1294–1297.

[3] Qu, Z., Zhou, F., Song, X., Ding, R., Yuan, L., & Wu, Q. (2024). Temporal enhanced multimodal graph neural networks for fake news detection. IEEE Transactions on Computational Social Systems, 11 (6), 7286–7298.

[4] Singh, G. V., Firdaus, M., Ekbal, A., & Bhattacharyya, P. (2023). EmoInt-Trans: A multimodal transformer for identifying emotions and intents in social conversations. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 31, 290–300.

[5] Sun, J., Lasser, S., & Lee, S. K. (2022). Understanding emojis: Cultural influences in interpretation and choice of emojis. Journal of International and Intercultural Communication.

[6] Wu, J., Xu, W., Liu, Q., Wu, S., & Wang, L. (2024). Adversarial contrastive learning for evidence-aware fake news detection with graph neural networks. IEEE Transactions on Knowledge and Data Engineering, 36 (11), 5591–5604.

[7] Zhang, X., Cao, J., Li, X., Sheng, Q., Zhong, L., & Shu, K. (2021). Mining dual emotion for fake news detection. *Proceedings of the Web Conference 2021 (WWW '21)* (pp. 3465–3476). New York: Association for Computing Machinery.

[8] Zhou, G., De Souza, S., Markham, E., Kwakpovwe, O., & Zhao, S. (2024, November). Semantics and sentiment: Cross-lingual variations in emoji use. *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing* (pp. 18698–18712). Miami, FL: Association for Computational Linguistics

[9] Zhou, Y., Xu, P., Wang, X., Lu, X., Gao, G., & Ai, W. (2025). Emojis decoded: Leveraging ChatGPT for enhanced understanding in social media communications. Proceedings of the International AAAI Conference on Web and Social Media, 19 (1), 2302–2316. Palo Alto, CA: AAAI Press

[10] Zhu, Y., Wang, H., Zhang, T., Liu, J., Li, F., & Zhou, C. (2023). Memory-guided multi-view multi-domain fake news detection. IEEE Transactions on Knowledge and Data Engineering, 35 (7), 7178–7191.