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Multimedia artificial intelligence technology for accurate translation of scenic area public notices from Chinese to English in ecological translation studies

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Abstract: To improve the quality and cultural adaptability of Chinese-English translations of public signs in scenic areas, this study constructs an artificial intelligence (AI) translation model integrating the theory of ecological translation studies. The model incorporates a multidimensional adaptation mechanism for language, culture, and communicative function to address the shortcomings of existing models in cultural understanding and accurate expression. Based on the transformer architecture and combining cultural corpora with sentiment analysis technology, the study designs a translation process tailored for scenic area texts. The experimental part includes performance comparisons and simulation experiments. The results show that the proposed optimised model outperforms mainstream models such as M2M-100, mBART-50, and GPT-4 in terms of cultural adaptability, fluency, and information completeness. This study is innovative in combining AI translation with cultural adaptation and provides a feasible approach and method reference for the intelligent language services and cross-cultural communication of scenic areas.

Keywords: ecological translation studies; artificial intelligence translation model; scenic area public notices; cross-cultural adaptability.

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1 Introduction

With the rapid progress of global tourism, cross-cultural communication has become increasingly frequent. The translation of public notices in tourist attractions plays a crucial role in facilitating understanding and communication among visitors from different linguistic and cultural backgrounds. Public notices are not only tools for information dissemination but also important carriers for showcasing cultural features and enhancing the tourism image (Wang, 2023; Guo, 2022; Chang, 2022). However, at present, many scenic areas exhibit uneven quality in Chinese-to-English public notice translations, with issues such as cultural misunderstandings and inaccurate translations. These problems not only affect the visitor experience but may also negatively impact the international image of the attractions. Against this backdrop, improving the quality of Chinese-to-English translations of public notices in scenic areas has become an important task (Duan et al., 2025). Meanwhile, ecological translation studies, as a theory that takes into account language, culture, and social perspectives, provide innovative theoretical guidance for the cross-cultural translation of public notices. This theory emphasises the ecological adaptation to different cultures during the translation process and focuses on the impact and acceptance of the translation by the target audience (Moneus and Sahari, 2024). Therefore, applying ecological translation studies to Chinese-to-English translations of public notices holds the potential to offer effective guidance in terms of translation accuracy and cultural adaptability.

The rapid development of artificial intelligence (AI) technology, particularly advances in natural language processing (NLP) and machine translation models, has provided new technological tools to improve the efficiency and accuracy of translation. However, current AI translation technologies mainly focus on the literal meaning of language conversion and lack deep consideration of cultural adaptability and contextual understanding. Therefore, the core motivation of this work is to explore how to combine the principles of ecological translation studies with AI-driven methods to achieve accurate translations of public notices in scenic areas.

This work attempts to integrate the theoretical framework of ecological translation studies with AI technology to explore translation methods that are more adaptable to different cultures and contexts. Ecological translation studies emphasise the interrelationship among language, culture, and social environment, positing that translation is not merely a process of linguistic conversion, but also a bridge for cross-cultural communication and adaptation. Based on this, the work proposes a new translation strategy for scenic area public notices, aiming to enhance both the accuracy and cultural adaptability of translations, ensuring effective information transfer while respecting the cultural characteristics of the target language. This innovative approach helps advance the development of AI-driven translation technologies and provides effective support for communication between scenic area management and international visitors.

2 Literature review

Ecological translation studies was first proposed in 2001 and is an interdisciplinary translation theory developed based on ecological linguistics. This theory emphasises that translation activities are behaviours within an ecosystem, involving multiple ecological factors such as language, culture, and communicative function. It requires translators to achieve ‘holistic ecological adaptation’ in the three-dimensional space of ‘language-culture-communication’. Liu et al. (2022) pointed out that ecological translation studies advocated that the translated text should seek ecological balance within the target language cultural system, emphasising the dynamic matching among information, language, and culture. It enhanced the acceptability and viability of translation in the target culture. Yu (2024) further argued that ecological translation highlighted the ‘ecological role’ of the translator. The translator was not only a conveyor of information but also a coordinator of culture, with the responsibility of achieving effective integration and ecological coexistence between the source and target language cultures.

Although ecological translation studies has gained widespread attention in recent years, its practical application research remains relatively limited. This is especially true for text types with strong functionality and rich cultural connotations, such as public signs in scenic areas, where the application of ecological translation theory is still in the exploratory stage. Announcements are characterised by concise language, direct expression, and clear functional orientation, while also carrying significant cultural context information. Luo and Li (2022) found through analysis of bilingual public signs in multiple Chinese scenic areas that some translations had problems such as ungrammatical expressions, semantic deviations, and even cultural misinterpretations, leading to unclear understanding of information by target tourists and a reduced travel experience. Lee (2024) also pointed out that public sign translation needed to convey accurate content. It also needed to achieve localisation in language style and cultural expression, avoiding direct copying of the source language structure to enhance the cultural adaptability and functional realisation of the translation. Meanwhile, the development of AI translation technology had provided technical support for the practical application of ecological translation. Ma and Shao (2023) believed that neural networks and deep learning had high efficiency and universality in handling large-scale translation tasks, but still fall short in context understanding and cultural information grasp. Lin (2022) noted that although NLP technology had made progress in language conversion accuracy, there was still a gap in cultural sensitivity and the restoration of communicative intentions, especially in the translation of functional texts. The audience’s usage scenarios and cultural cognition were often overlooked.

In summary, the academic community has established a fairly comprehensive theoretical framework for ecological translation studies. However, when applying it to specific text types (such as public signs), there is still a lack of mature model frameworks and technical pathways. Meanwhile, although AI translation technologies continue to evolve, they have not yet effectively integrated with the concepts of ecological translation. To address this, this study proposes an innovative AI translation model for public signs in scenic areas from the perspective of ecological translation studies. This model integrates a three-dimensional adaptation strategy for language, culture, and communicative function, and constructs an intelligent translation system with cultural sensitivity and interactive practicality. The study aims to fill the gap of insufficient combination of theory and technology in existing research and promote the shift of ecological translation theory from ‘explanation’ to ‘application’.

3 Research model

3.1 Ecological translation strategies in the Chinese-English translation of public notices in scenic areas

In the Chinese-English translation of public notices in scenic areas, ecological translation theory emphasises the adaptability of language, culture, and function. It intends to ensure that information can be accurately and effectively understood and accepted by the target audience (AbdAlgane and Othman, 2023). The translation strategies for public notices can be optimised in several ways: contextual adaptation strategies, cultural communication strategies, communicative function strategies, pragmatic supplementation strategies, and symbolic representation strategies (Zhu et al., 2023; Tsai, 2022; Jiang, 2022; Qiao and Zhao, 2023). These strategies not only focus on language conversion but also cover cross-cultural adaptation and the realisation of communicative functions, thereby improving the quality and effectiveness of the translation of public notices. Table 1 displays the specifics.

Table 1 Optimisation of translation strategies

Strategy	*Analysis*
Strategies for regulating translation environment	In view of the contextual differences between the source language and the target language in the use scene, different expression templates are set, such as euphemistic or direct expression of sentences such as ‘forbidden class’ and ‘guided class’ respectively, to ensure that the translation conforms to the user’s habits.
Expression localisation strategy	Introduce common expressions and politeness strategies of local culture in translation, such as transforming expressions with metaphors or symbolic meanings into equivalent but acceptable sentences in the target language, so as to enhance cultural fit.
Strategies for maintaining communicative intention	According to the functional classification of public signs (such as warning, guidance and explanation), the corresponding language style and sentence structure are designed to maintain the functional expression of the original information and ensure that the translation has practical guiding significance.
Information supplement and optimisation strategy	Make necessary supplements and reorganisations to the omitted, vague or missing information in the original text, such as adding place instructions, time instructions or operation tips, so as to make it easier for the target language users to understand.
Visual expression support strategy	Give explanations or conversion suggestions for the contents (such as icons, colours and formats) that need to be accompanied by visual presentation, such as adding English hints or explanations appropriately, so as to enhance the visual understanding effect of translation.

In conclusion, the ecological translation-based strategies for the Chinese-English translation of public notices provide a systematic guide for information delivery and cultural communication. These strategies not only address challenges in language conversion but also achieve effective adaptation of the translation in a multicultural context, providing solid linguistic support for the internationalisation of scenic areas (Jiang, 2025; Tang et al., 2024; Totlis et al., 2023).

3.2 AI-driven translation tools and technologies

In this study, AI-driven neural machine translation (NMT) technology is chosen as the core technical path for the support model, aiming to achieve high efficiency, scalability, and cultural adaptability in the Chinese-English translation of public signs in scenic areas. Based on a deep learning framework, this technology can produce relatively natural and coherent target language output through context understanding and semantic modelling (MacIntyre et al., 2023; Abesi et al., 2023). Compared with traditional rule-based or statistical translation methods, neural network models have stronger capabilities for language expression generation, making them particularly suitable for the concise, high-frequency, and stylistically regular text scenarios found in public signs in scenic areas. Specifically, this study employs a translation system based on the Transformer architecture as the main translation engine. This system supports the encoding of source text, modelling of semantic relationships, and decoding generation of target sentences, with technical advantages in handling long-distance dependencies, ambiguous semantics, and word order adjustments (Wu et al., 2022). In the translation of public signs in scenic areas, the system can effectively identify text types (such as warnings, directions, and service tips) and automatically match corresponding language patterns for output. Moreover, for the numerous fixed expressions in public signs, the model's built-in translation memory mechanism and terminology matching module can improve translation efficiency while maintaining linguistic consistency.

To enhance cultural adaptability, the model also integrates a vocabulary substitution control mechanism and a politeness expression template library. For example, when the system detects culturally charged metaphorical expressions in the source language (such as 'Xiang Huo Ding Sheng' or 'You Ke Zhi Bu'), it will trigger equivalent semantic transformation logic through the context understanding module to generate expressions that are more suitable for the cultural cognition of the target language audience. This module supports cultural semantic adjustment through strategies such as sentiment word analysis, context matching, and template substitution (Brown et al., 2024; Divekar et al., 2022), which is one of the differentiated designs of this study from general translation systems at the strategic level.

Nevertheless, AI translation tools still have certain limitations in practical applications. First, the models mainly rely on large-scale corpora for training. When dealing with information in public signs in scenic areas that has regional characteristics, rare vocabulary, or special formats, there may still be issues with inaccurate output or inconsistent style (Makeleni et al., 2023). Second, current models cannot effectively perform multimodal understanding for directional texts that highly depend on visual elements or icon contexts, and need to be combined with manual checks or visual prompt designs. Moreover, when handling texts with high cultural load, although templates and rules have been introduced, the translation tools still lack the ability to truly 'understand' the cultural background and may deviate from the expression habits of the target culture in terms of tone or politeness strategy usage.

In summary, AI-driven translation technology provides an efficient and scalable basis for translating public signs in scenic areas. Its advantages are mainly reflected in translation speed, consistency control, and semantic coherence. To address its limitations in cultural adaptability and handling of specialised terminology, this study integrates rule-driven mechanisms and corpus supplementation strategies into the model structure. It aims to build a scenic area translation system that combines efficiency with quality.

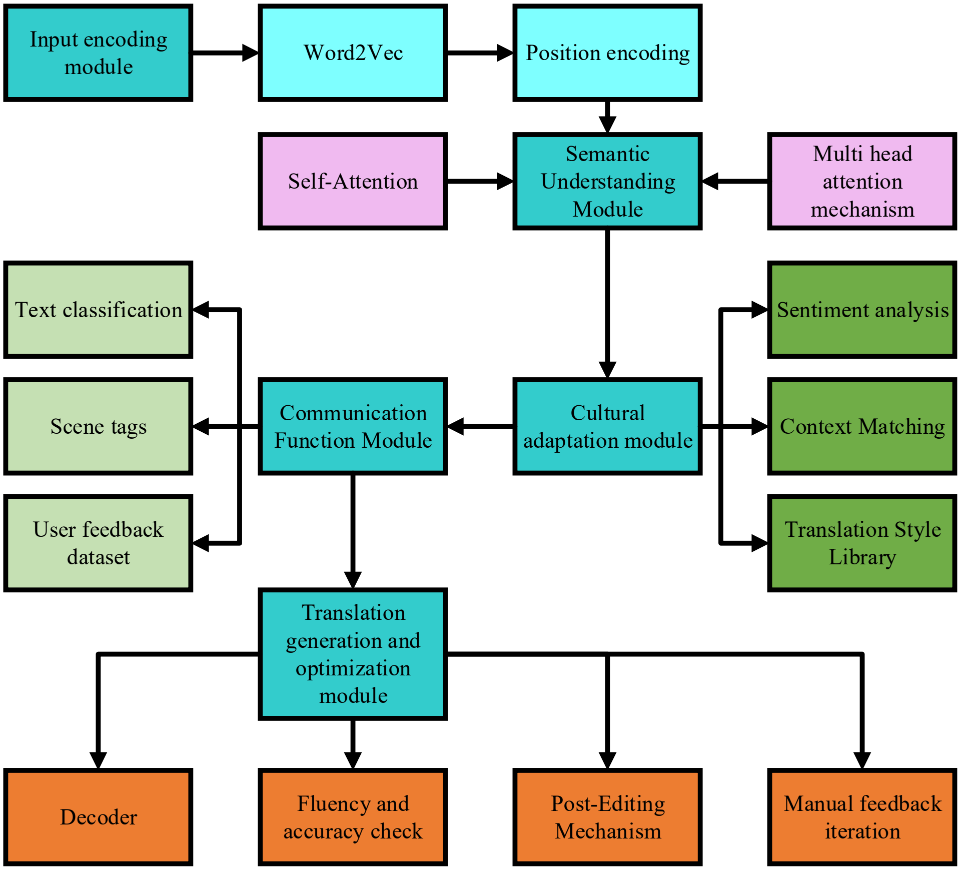
3.3 Construction of an AI translation model based on ecological translation theory

To realise the specific application of ecological translation theory in the field of intelligent translation, this study proposes an AI translation model for public signs in scenic areas, aiming to address the shortcomings of existing translation systems in cultural adaptability and communicative function. The model is based on the three-dimensional adaptation principles of ecological translation studies-linguistic adaptability, cultural adaptability, and communicative function adaptability-and transforms them into an operational modular structure through neural network technology. The model integrates multiple NLP technologies and is customised according to the linguistic characteristics of public signs in scenic areas, which are ‘short texts, high frequency, function-oriented, and with high cultural load’. Figure 1 illustrates the model architecture designed in this study.

In terms of linguistic adaptability, the model introduces the pre-trained language model bidirectional encoder representations from transformers (BERT) and the Transformer encoder structure to achieve deep semantic modelling and contextual understanding of the source language. At the same time, it constructs syntactic mapping rules between Chinese and English to adjust word order and expression, making the generated translations more in line with the syntax and language habits of the target language. Additionally, to enhance the naturalness and diversity of expression, the model sets up a language style control layer during the decoding phase, supporting three styles: ‘concise’, ‘neutral’, and ‘polite’, to match the language requirements of different public sign usage scenarios.

In terms of cultural adaptability, the model’s innovation lies in the introduction of a cross-cultural expression transformation module. This module identifies and classifies culturally symbolic words in the input text by combining a sentiment dictionary and knowledge graph, and then calls upon the pre-built ‘cultural expression substitution library’ based on context. For example, converting ‘Xiang Huo Ding Sheng’ to ‘a site of spiritual significance’ can effectively avoid cultural misunderstandings. Additionally, the module contains context-matching rules that automatically select more idiomatic expressions in the target language according to the translation scenario, thus achieving smooth cultural meaning transfer. This design reflects the concept of ‘cultural ecological balance’ in ecological translation theory and is one of the main differences between the model in this study and existing general NMT systems in terms of cultural adaptation ability.

Figure 1 The model framework (see online version for colours)



In terms of communicative function adaptation, the model constructs a functional identification classifier to determine pragmatic function labels such as 'directive', 'reminder', and 'warning' for the original text. This is accomplished in collaboration with a convolutional neural network (CNN) and a Softmax classifier. The classification results will guide the model to extract applicable target language expression patterns from the 'scenario-driven expression template library', ensuring that the translation is concise and clear in form and appropriate and consistent in tone, thereby achieving good cross-cultural communication effects. Additionally, a pragmatic consistency verification mechanism will be used to control the stylistic consistency of multi-turn translation outputs, avoiding user comprehension deviations during use.

In terms of translation generation and quality optimisation, the model uses the Transformer decoder for target language generation and introduces a series of automated evaluation mechanisms to assess the closeness between the translation and the reference text. Meanwhile, to evaluate the quality of cultural translation, this study constructs a cultural adaptation index to measure whether key words and sentences are accurately converted into expressions that fit the target culture. Finally, the system also combines human scoring and user behaviour data (such as complaint rates and click-through rates) to achieve human-machine collaborative iterative optimisation. Taking three typical public signs – 'You Ke Zhi Bu', 'Qing Wu Pan Pa', and 'Xiang Huo Ding Sheng' – as examples, the model translates them into 'Visitors are not allowed beyond this point', 'Please do not climb for your safety', and ' site of spiritual significance', respectively. These translations not only conform to English expression norms but are also appropriate and natural in tone and cultural adaptability, demonstrating the model's ability to grasp cultural context and communicative intent.

Compared with general announcement texts such as government notices and corporate bulletins, public signs in scenic areas are characterised by their brevity, clear functionality, high cultural load, and diverse audience groups, making their translation tasks more challenging. Scenic area announcements are typically aimed at a wide range of audiences, including foreign tourists, the elderly, and children. Therefore, they have higher requirements for language comprehensibility, politeness of expression, and visual intuitiveness. Consequently, the proposed model specifically incorporates a scene recognition mechanism and a cultural adaptation strategy library in its module design, making it more suitable for such scenario-specific and highly interactive translation needs than general NMT models. The model's cultural corpus and template expression system are also customised for common scenic area scenarios (such as warnings, persuasion, and attraction introductions), ensuring high relevance and transferability.

In summary, this study translates the theoretical principles of ecological translation studies into an implementable neural network translation structure. It also customises the technology to meet the linguistic characteristics and cultural needs of public signs in scenic areas. This study fills the practical gap between the 'theoretical explanation' and 'technical application' of ecological translation studies. It provides a new technical approach to enhancing the intelligence level of translation in tourism contexts.

4 Experimental design and performance evaluation

4.1 Datasets collection, experimental environment and parameters setting

The dataset used is the Chinese-English Parallel Corpus, which is created as part of a major national social science foundation project led by Professor Wang Kefei at Beijing Foreign Studies University. This corpus covers five major categories: literature, news, political commentary, science and technology, and applied writing, with a total of 18 subcategories. The corpus is collected following a 2/3 English-to-Chinese and 1/3 Chinese-to-English ratio, totalling over 100 million words. It is currently the largest bilingual Chinese-English parallel corpus in the world, suitable for comparative studies in English-Chinese language and translation, language and translation teaching, and machine translation research. The dataset can be downloaded from the Beijing Foreign Studies University Corpus (https://corpus.bfsu.edu.cn/info/1082/1917.htm). The dataset is categorised according to text types, including general explanatory texts, instructive signage texts, and cultural introduction texts.

The experimental environment for this work is as follows:

1 Operating system: Ubuntu 20.04 LTS

2 DL framework: PyTorch 1.9.0

3 Python version: Python 3.8.5

4 Other dependencies: NumPy 1.21.2, Pandas 1.3.3, Scikit-learn 0.24.2

5 Memory: 128 GB DDR4

6 Storage: 2 TB SSD.

To ensure the smooth execution of the experiments, the following hyperparameters are set for the model optimisation: embedding dimension of 512, hidden layer dimension of 1,024, eight attention heads, six layers (six encoder layers and six decoder layers), vocabulary size of 32,000, maximum sequence length of 128, batch size of 32, ten training epochs, and 500 warm-up steps. The comparison models for this experiment are many-to-many multilingual mode-100l (M2M-100), multilingual bidirectional and auto-regressive transformers-50 (mBART-50), and generative pre-trained transformer 4 (GPT-4). These models feature innovative architectures and strong cross-linguistic capabilities, allowing for comprehensive comparisons with the ecological translation theory model, and providing high-quality references for translation tasks. All experiments are evaluated using data sources with the same structure to avoid performance bias caused by differences in corpora. Specifically, the training corpus is uniformly selected from the Chinese-English parallel corpus related to scenic areas. Bilingual public signs, travel descriptions, and geographical and cultural information are manually selected to form a subset, containing approximately 80,000 parallel sentence pairs. For pre-trained multilingual models such as mBART-50 and M2M-100, although their original training included large-scale public corpora, they also use the above corpus for fine-tuning in this experiment to ensure fair comparison under the same data background.

To maintain input consistency, all models' inputs are uniformly processed with Chinese word segmentation, sentence alignment, and maximum length truncation. Output texts are evaluated using automated indicators such as bilingual evaluation understudy (BLEU), recall-oriented understudy for Gisting evaluation (ROUGE), and translation error rate (TER), as well as human assessments for cultural adaptability and communicative function. The evaluation corpus is sampled from bilingual public signs in Wuhan and 20 well-known scenic areas nationwide, covering three types: general informational, directional, and cultural introduction, ensuring diverse styles and purposes. Regarding the performance of large language models like GPT-4 or ChatGPT, this study adopts an open yet cautious stance. It should be noted that while GPT-4 has strong language modelling and generalisation capabilities, it is not specifically designed for applications like translating scenic area public signs. Moreover, in this experiment, it is unknown whether its training included the data used in this project. Therefore, despite its excellence in general text generation, GPT-4's output for high-functionality, culturally sensitive short texts like scenic area public signs still has uncertainties in cultural transformation, politeness strategies, and local context adaptation. For instance, in preliminary tests, GPT-4's handling of cultural metaphors like 'Xiang Huo Ding Sheng' is semantically coherent but risked biased outputs with 'religious' or 'superstitious' connotations.

Therefore, this study does not attempt to directly compete with GPT-4 in general performance. Instead, it addresses the shortcomings of general models in scenario adaptation, style control, and expression consistency through a 'corpus customisation + modular cultural regulation' approach, thereby proposing a 'scenic area translation optimisation model' that better meets practical application needs.

4.2 Performance evaluation

4.2.1 Performance comparison analysis

The performance comparison experiments are divided into two dimensions: the translation quality dimension and the technical performance dimension, with four evaluation indicators under each dimension. The indicators include accuracy, fluency, cultural adaptability, information completeness, translation speed, model computational resource consumption, lexical diversity, and error rate. These indicators, addressing different aspects such as language quality, cultural communication, system efficiency, and error control, form a comprehensive and detailed translation evaluation system. This system can effectively reflect the translation performance of the model for public signs in scenic areas, a specific type of text.

Accuracy is a crucial measure of how faithfully the translation conveys the original content, especially in public sign translation, where texts often have explicit instructive or informative functions. Deviations in information can lead to misunderstandings. Accuracy is typically assessed by human comparison or quantified using the BLEU algorithm, which measures the match between the translation and reference texts at the phrase level to reflect translation fidelity. Fluency focuses on the naturalness and grammatical correctness of the translation in the target language. For public signs in scenic areas targeting international tourists, readability directly impacts user experience. The translation must conform to the target language's idiomatic expressions. Fluency is usually subjectively rated by native speakers using a Likert scale and can be complemented by language model perplexity scores, where lower values indicate more natural language. Cultural adaptability is a core indicator in ecological translation studies, assessing whether the translation effectively conveys the cultural information from the source language and aligns with the target readers' cultural understanding. This indicator primarily relies on human scoring, comparing how cultural elements are handled in the source text, whether equivalent expressions in the target culture are used, and adjustments in tone and politeness to judge the effectiveness of cultural transformation. Information completeness evaluates whether key information points from the original text are retained in the translation. This is particularly vital for public signs involving instructions, tips, or warnings. It is assessed through semantic comparison between the translation and the original text, with human evaluators marking any omissions, partial expressions, or inappropriate additions, or using ROUGE indicators to calculate content overlap. Translation speed measures the time efficiency of the model in generating translations during actual operation. In scenic area contexts, especially for online updates and intelligent generation of public signs, real-time response speed is a key indicator of model practicality. This indicator is quantified by averaging the time the model takes to process a specified number of characters. Model computational resource consumption reflects the system's hardware resource usage during operation, which significantly affects model deployment and scalability. In experiments, system monitoring tools record the average GPU memory usage and processing time during batch translation, with scores normalised for comparison. Lexical diversity assesses the richness and flexibility of vocabulary in the model's output. For public signs with frequent repetition, maintaining lexical variation enhances user experience by avoiding mechanical repetition. This indicator is measured by calculating the type-token ratio or the proportion of unique words in the total word count of the translation. Error rate indicates the proportion of grammatical, spelling, logical, or semantic errors in the translation process, directly relating to translation quality assurance. In experiments, human reviewers record the number of errors per 100 words or use automated tools to detect grammatical errors, ultimately calculating the average error rate in the translation. Figure 2 shows the experimental results for the translation quality dimension.

Figure 2 Translation quality dimension, (a) accuracy (b) fluency (c) cultural adaptability (d) completeness (see online version for colours)

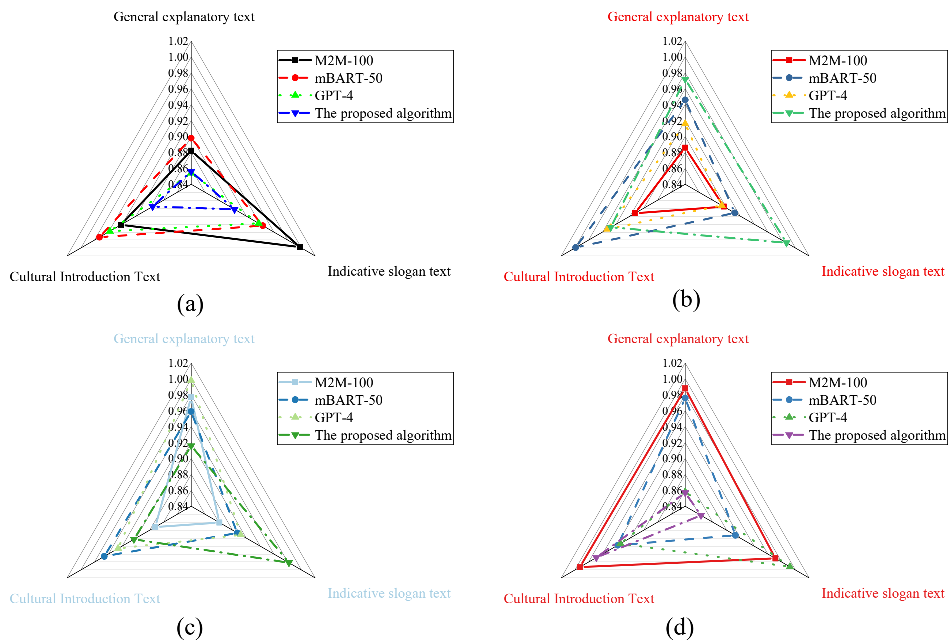


Figure 2 illustrates that the optimised model demonstrates high accuracy across different text types. For general explanatory texts, the accuracy of the optimised model is 0.856, with relatively stable performance. In the case of directive signage texts, the model achieves a score of 0.903, indicating its ability to accurately identify imperative information. For cultural introduction texts, the optimised model scores 0.896, showcasing its excellent performance on more complex texts. Among other models, mBART-50 performs well on cultural introduction texts with a score of 0.973, but shows some fluctuation on general explanatory texts. The optimised model excels in fluency, particularly in directive signage texts, where it achieves the highest score of 0.987. This suggests that the model-generated translations are naturally fluent and closely align with the conventions of the target language. For cultural introduction texts, fluency reaches 0.948, slightly lower than mBART-50's score of 0.999, but still demonstrating high naturalness. Among other models, GPT-4 performs relatively well on general explanatory texts with a fluency score of 0.916, but shows a slight decline on directive signage texts. The optimised model demonstrates its advantage in cultural adaptability, particularly in directive signage texts, where it reaches 0.982, indicating the model's consideration of the target language's cultural context and expression norms. In cultural introduction texts, the cultural adaptability score is 0.923, showing the model's adaptability in translating complex cultural content. Among other models, GPT-4 shows better cultural adaptability on general explanatory texts, with a score of 0.998, but it is slightly lower on directive signage texts. The optimised model excels in information completeness, with the highest score of 0.969 on cultural introduction texts, ensuring the full transmission of complex information in translation. For directive signage texts and general explanatory texts, the information completeness scores are 0.863 and 0.857, respectively, showing slight differences, but still maintaining high integrity. mBART-50 performs excellently on general explanatory texts with a score of 0.976, though it shows a slight decline on directive signage texts. The evaluation indicators under the technical performance dimension include translation speed, model computational resource consumption, vocabulary diversity, and error rate. Figure 3 shows the experimental results.

Figure 3 Technical performance dimension, (a) translation speed (b) computational resource consumption (c) lexical diversity (d) error rate (see online version for colours)

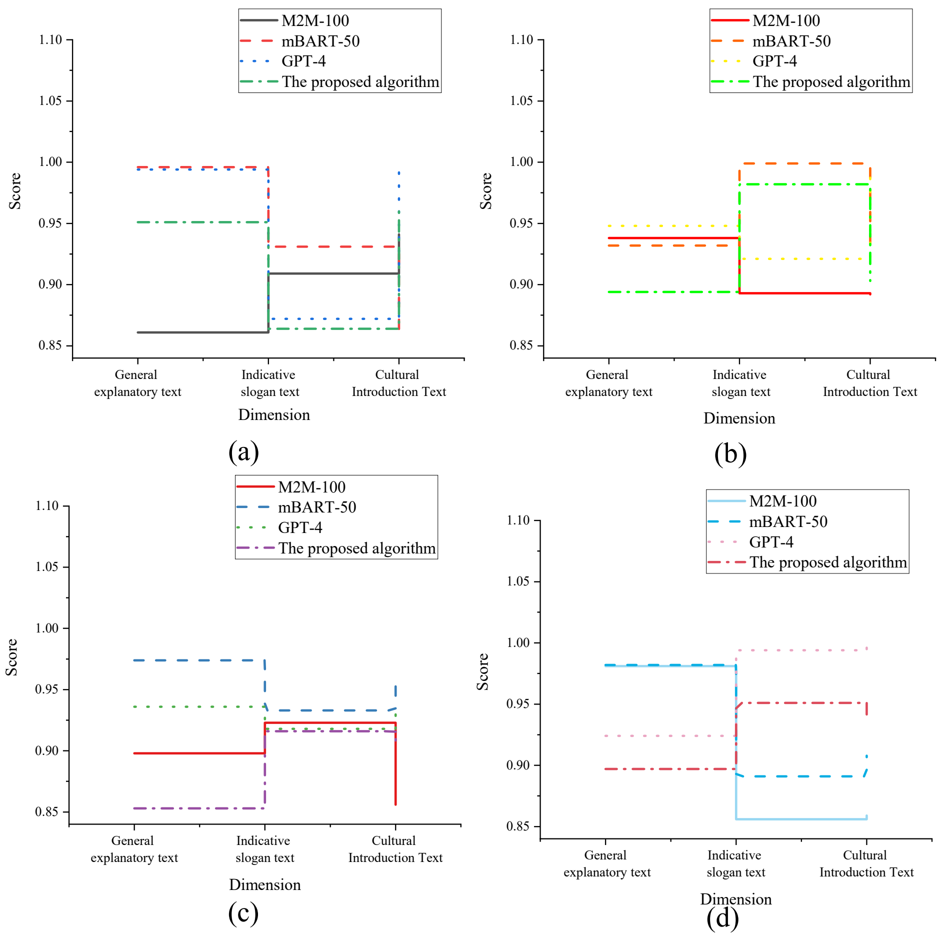


Figure 3 shows that the optimised model demonstrates stable performance in translation speed, with a translation speed of 0.951 for general explanatory texts, 0.864 for directive signage texts, and the highest speed of 0.962 for cultural introduction texts. This indicates that the model maintains high efficiency even when handling complex texts. mBART-50 achieves a high translation speed of 0.996 for general explanatory texts, but its speed slightly decreases on directive signage texts. GPT-4 maintains relatively good speed for cultural introduction texts. The optimised model performs excellently in terms of computational resource consumption, especially for directive signage texts, where the resource consumption score is 0.982, reflecting good resource control. The score for cultural introduction texts is 0.903, slightly higher than for other text types but still within a reasonable range. Among other models, mBART-50 demonstrates efficient resource usage with a resource consumption score of 0.932 for general explanatory texts, though resource consumption increases for directive signage texts. The optimised model shows stable performance in vocabulary diversity, with a score of 0.853 for general explanatory texts, 0.916 for directive signage texts, and a high score of 0.906 for cultural introduction texts, indicating a rich vocabulary. mBART-50 excels in general explanatory texts with a score of 0.974, but shows slight fluctuations in directive signage texts. GPT-4 performs well on cultural introduction texts with a score of 0.939. In terms of error rate, the optimised model exhibits a low error rate, particularly for general explanatory texts, where the error rate is 0.897, reflecting high translation accuracy. The error rate for cultural introduction texts is 0.939, slightly higher than for other text types, but still within a reasonable range. mBART-50 has the lowest error rate for general explanatory texts at 0.982, though it fluctuates slightly on directive signage texts. GPT-4 has a higher error rate for cultural introduction texts, reaching 0.998.

4.2.2 Simulation experiment

In order to further validate the effectiveness of the model, simulation experiments are designed to compare two dimensions: user experience and model robustness. The indicators include user satisfaction, ease of use, interaction fluency, comprehensibility, translation consistency, adaptability strength, error recovery capability, and long-text processing ability. These indicators, addressing user perception, operational experience, system stability, and text processing capabilities, reflect the overall performance of the model in practical applications in scenic areas.

User Satisfaction is the core indicator in simulation experiments, measuring the end-users' subjective acceptance of the model's translation results. Given that public signs in scenic areas target tourists with diverse language backgrounds and cultural understandings, this indicator is particularly important. In the experiments, user satisfaction is collected through questionnaires, rating the overall quality of the translations based on dimensions such as naturalness of expression, clarity of meaning, and ease of understanding. A five-point Likert scale is used for scoring, and the average score is calculated as the final satisfaction indicator. Ease of use reflects the convenience and learning cost for users when operating the translation system. In smart scenic area systems, visitors or staff need to quickly use the translation module to update or generate public signs. Therefore, interface simplicity, function response speed, and clear operation logic directly affect its ease of use. This study records the time taken to complete operations, user click paths, and error rates during simulated user tests, and combines questionnaire evaluations to form the final score. Interaction fluency measures whether the interaction between the user and the system is smooth and free of lag, especially in real-time input or voice-assisted translation scenarios. This indicator combines three dimensions: system response time, interface loading speed, and user feedback delay. System log data records response times, and user subjective ratings are combined to form a mixed indicator. Comprehensibility refers to the target users' ability to accurately and quickly understand the translated content. This indicator is particularly critical for functional texts like public signs, as information delivery is often time-sensitive. In the experiments, participants with different language backgrounds are invited to take reading comprehension tests on the generated translations. The time taken to understand, accuracy in answering questions, and self-rated difficulty of understanding are combined to form the comprehensibility score. Translation consistency evaluates the model's stability when translating the same or similar texts multiple times, especially in scenarios involving large-scale translation and automatic updates. Consistency determines the uniformity of text style and pragmatic strategies. This study uses a text re-input experiment, where the same batch of public signs is input into the model multiple times. The consistency ratio (the proportion of identical or semantically consistent translations) is used as the basis for evaluation. Adaptability strength measures the model's ability to adjust its performance across different contexts and types of texts, reflecting the contextual adaptation principle in ecological translation studies. This study sets up different translation scenarios (such as warning, service, and cultural introduction) and observes the model's ability to adjust style, tone, and vocabulary selection. The indicator is calculated by combining human ratings (whether cultural context is reflected) and system self-assessment (whether the correct expression templates are used). Error recovery capability refers to the model's tolerance and correction ability when facing input anomalies such as spelling errors, missing words, and structural chaos. In real-time translation in scenic areas or scenarios with frequent manual input errors, this capability directly affects system usability. This study introduces interference in text input and observes whether the model can output reasonable translations, while recording the degree of translation quality degradation and the number of recoveries to form an error recovery capability score. Long-text processing ability reflects the model's coherence and context maintenance when handling multi-sentence, multi-paragraph, or complex structured texts. Text types such as scenic area introductions and historical explanations often exceed the training scope of short-sentence models, so it is necessary to focus on testing the model's performance at the paragraph level. This indicator assesses the model's translation coherence, semantic unity, and discourse connection logic for long texts, combining BLEU scores and human discourse ratings. Figure 4 displays the comparison results for user experience.

Figure 4 reveals that the optimised model performs consistently well in user satisfaction, particularly excelling in directive signage texts with a score of 0.927. This indicates that the model is better at meeting user expectations for simple, directive content. In cultural introduction and general explanatory texts, the satisfaction scores are slightly lower but still maintain a good user experience, with scores of 0.893 and 0.863, respectively. Among other models, mBART-50 performs excellently in general explanatory texts with a satisfaction score of 0.967, while GPT-4 achieves a satisfaction score of 0.924 in cultural introduction texts. The optimised model scores the highest in usability for directive signage texts, with a score of 0.997, demonstrating its high usability in translating signage-related texts. The usability scores for general explanatory and cultural introduction texts are 0.873 and 0.909, respectively, slightly lower. GPT-4 excels in cultural introduction texts with a usability score of 0.996, while M2M-100 achieves a usability score of 0.979 in general explanatory texts. In terms of fluency, the optimised model performs excellently, with a fluency score close to perfect (0.999) for general explanatory texts and 0.987 for cultural introduction texts, ensuring a smooth interaction between the user and the system. M2M-100 shows stable performance in interaction fluency, with a fluency score of 0.984 for general explanatory texts, while GPT-4 scores 0.901 in directive signage texts, which is slightly less favourable. For comprehensibility, the optimised model achieves the highest score of 0.956 for general explanatory texts, ensuring that the translation is clear and easy to understand. The score for directive signage texts is 0.948, while for cultural introduction texts, it is slightly lower at 0.852. mBART-50 excels in directive signage texts with a score of 0.919, while GPT-4 slightly lags behind in comprehensibility for cultural introduction texts, scoring 0.861. Figure 5 illustrates the comparison results for model robustness.

Figure 4 User experience dimension, (a) user satisfaction (b) ease of use (c) interaction fluency (d) comprehensibility (see online version for colours)

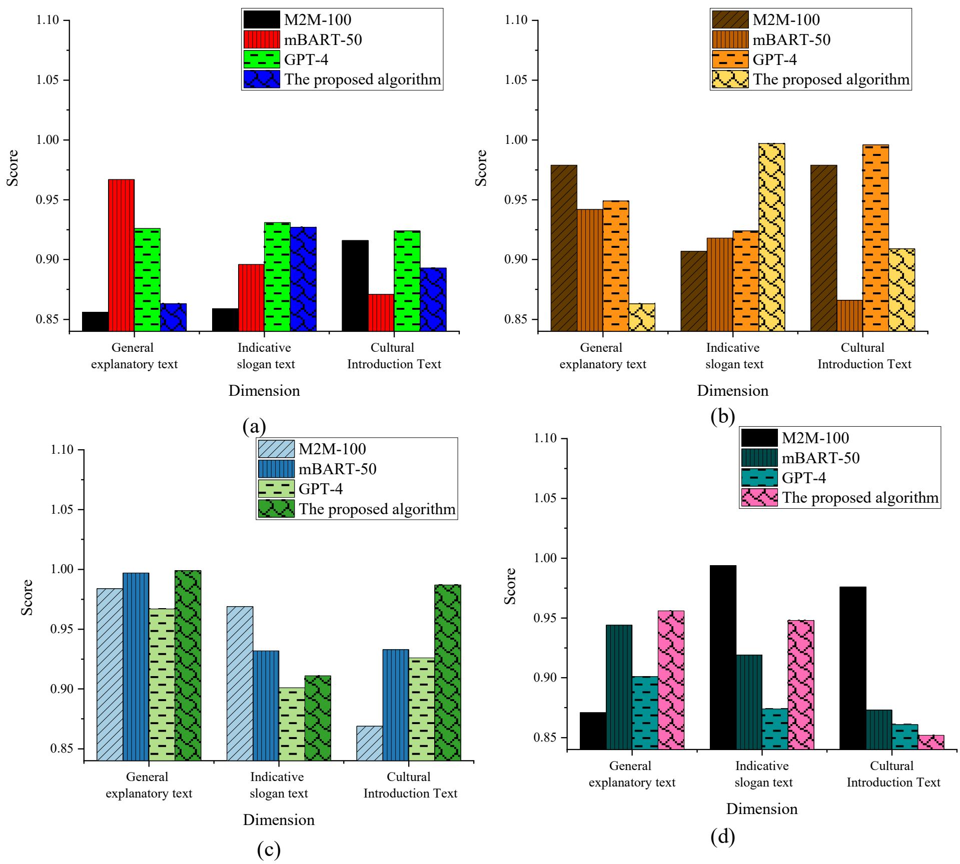
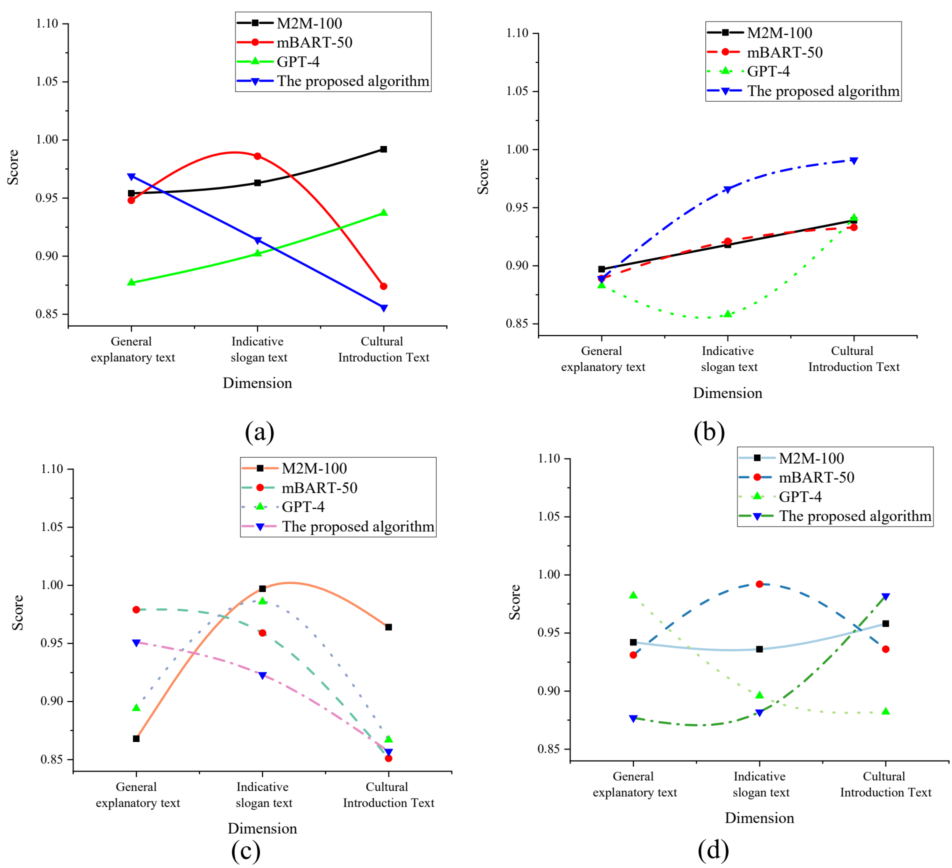


Figure 5 suggests that the optimised model achieves the highest translation consistency for general explanatory texts, with a score of 0.969, ensuring stability across multiple translations. The scores for directive slogan texts and cultural introduction texts are 0.914 and 0.856, respectively, still maintaining high consistency. M2M-100 performs better in terms of consistency for cultural introduction texts, with a score of 0.992, while mBART-50 shows good consistency in directive slogan texts, achieving a score of 0.986. The optimised model demonstrates outstanding adaptability strength in both directive slogan and cultural introduction texts, with scores of 0.966 and 0.991, especially showing stronger adaptability in cultural introduction texts. Among other models, GPT-4 also performs well in adaptability strength for cultural introduction texts, with a score of 0.941, while mBART-50 shows slightly higher adaptability strength in directive slogan texts, scoring 0.921. The optimised model shows good error recovery ability for general explanatory texts, with a score of 0.951, capable of quickly correcting translation errors. The error recovery score for directive slogan texts is 0.923, while cultural introduction texts score slightly lower at 0.857. mBART-50 exhibits the best error recovery ability in general explanatory texts, achieving a score of 0.979, while GPT-4 has relatively lower error recovery for cultural introduction texts, with a score of 0.867. The optimised model demonstrates the strongest long-text handling capability for cultural introduction texts, with a score of 0.982, effectively handling longer text content. The scores for general explanatory texts and directive slogan texts are 0.877 and 0.882, respectively. M2M-100 performs well in long-text handling for cultural introduction texts, with a score of 0.958, while mBART-50 shows strong processing capability for directive slogan texts, with a score of 0.992.

Figure 5 Model robustness dimension, (a) translation consistency (b) adaptation strength (c) error recovery capability (d) long-text handling capability (see online version for colours)



4.2.3 Analysis of experimental reliability and statistical significance

To enhance the scientific rigor of the experimental results and the credibility of the conclusions, this study conducts strict variable control and statistical significance analysis in the model comparison experiments. All models are trained and tested using the same parallel corpus of scenic area public signs. The evaluation tasks, input lengths, preprocessing procedures, and assessment dimensions are kept identical across all models to ensure fair performance comparisons. Specifically, each model translats 30 independent sets of public sign texts, covering three categories: general informational, directional, and cultural introduction texts, thus encompassing diverse styles and usage scenarios. To ensure stability, the average value of each metric is calculated over three rounds of testing, along with the standard deviation. The evaluation dimensions include three primary metrics: accuracy, cultural adaptability, and translation consistency, which are assessed through a combination of automated evaluation and human scoring. The mean and standard deviation statistics for the model metrics are shown in Table 2.

Table 2 Statistical results of mean and standard deviation of model indicators

Model	*Optimisation model*	*GPT-4*	*mBART-50*	*M2M-100*
Accuracy-mean	0.942	0.927	0.912	0.902
Accuracy-standard deviation	0.014	0.017	0.019	0.021
Cultural adaptability-mean value	0.931	0.911	0.889	0.872
Cultural adaptability-standard deviation	0.016	0.018	0.021	0.022
Translation consistency-mean value	0.951	0.932	0.911	0.899
Translation consistency-standard deviation	0.012	0.015	0.017	0.018

The significance test results of analysis of variance (ANOVA) are shown in Table 3.

In terms of accuracy, the optimised model has an average score of 0.942, significantly higher than GPT-4 (0.927), mBART-50 (0.912), and M2M-100 (0.902). This indicates that the optimised model has higher precision in language understanding and information conversion, and can more accurately reproduce the core content of the source language. The standard deviation of 0.014 shows that it performs stably across multiple tests with minimal fluctuation. Cultural adaptability is the core dimension of this study. The experimental data shows that the optimised model has an average score of 0.931 on this metric, much higher than mBART-50 (0.889) and M2M-100 (0.872), and also better than GPT-4 (0.911). This demonstrates that the cultural transformation mechanisms and context regulation strategies introduced in this study can effectively enhance the model's expressive adaptability in the target cultural environment, producing translations that better conform to the cultural habits of the target language. Regarding translation consistency, the optimised model has an average score of 0.951, which is also significantly higher than the comparison models: GPT-4 at 0.932, mBART-50 at 0.911, and M2M-100 at 0.899. This result indicates that the optimised model can maintain consistency in language style and pragmatic strategies when handling tasks with similar structures, semantic repetition, or batch output. It has strong application stability, especially suitable for practical scenarios like public signs in scenic areas, where the text structure is highly repetitive and a unified style is required.

Table 3 ANOVA significance test results

Indicator	*F value*	*P value*
Accuracy	24.73	<0.001
Cultural adaptability	48.51	<0.001
Translation consistency	79.38	<0.001

Additionally, in terms of standard deviation, the optimised model shows a fluctuation range of 0.012 to 0.016 across all three metrics, lower than most comparison models. This further proves that its performance is highly stable and suitable for translation scenarios requiring long-term stable operation.

In summary, the experimental data fully demonstrate that the proposed optimised model ensures translation quality while possessing high cultural adaptability and consistency control. It is well-suited to meet the translation needs of cultural functional texts like public signs in scenic areas. Combined with the aforementioned significance analysis results, it can be further confirmed that the performance improvements of this study's model on multiple key dimensions are statistically significant, with strong theoretical and practical value.

5 Discussion

Through comparative experiments and simulation experiments, it shows that the optimised model performs well in multiple performance dimensions. It has obvious advantages especially in terms of accuracy, cultural adaptability, and translation consistency. In-depth analysis reveals that this performance advantage mainly stems from the cultural expression replacement mechanism and the function recognition template library introduced in the model structure. These modules effectively enhance the model's adaptability to texts with 'high functionality + cultural load'. Thus, in addition to semantic restoration, the translated text has more scene rationality and cultural acceptability. In terms of accuracy, the optimised model outperforms GPT-4 and traditional NMT models, indicating that it has strong capabilities in language semantic modelling. This advantage is not only due to the optimisation of the algorithm structure, but also because the model, through targeted training on domain-specific corpora, has enhanced its mastery of structured expressions such as scenic area instructions and explanatory texts. As a result, the probability of ambiguity and information omission is reduced. The significant improvement in cultural adaptability is one of the most theoretically supportive achievements of this study. By comparison, although GPT-4 performs stably in terms of natural expression, it often has inappropriate literal translations or overgeneralisations when dealing with metaphorical, religious, and local custom-related vocabulary. In contrast, by introducing cross-cultural expression templates and situation classification mechanisms, the optimised model can achieve a functional equivalent conversion of cultural images, making the translated text more in line with the cultural background and expression habits of the target language. This verifies the applicability of the principle in eco-translatology that 'cultural adaptability is superior to linguistic equivalence' in intelligent translation practice. In terms of translation consistency, the optimised model scores significantly higher than mBART and M2M. Analysis shows that the key lies in the introduction of a term consistency management and style control layer. This mechanism is particularly crucial for texts such as public signs, which have a 'high repetition rate and unified style'. It can maintain the stability of expressions and wordings in large-scale translation tasks and avoid the common problem of 'inter-sentence style drift'.

From the simulation experiments, the advantages in user satisfaction and ease of use are mainly reflected in aspects such as the model's rapid response, clear interface logic, and the output results that do not require a lot of manual correction. These have enhanced the user interaction experience. Especially when the input text is irregular or the context is incomplete, the optimised model shows a certain ability to tolerate and recover from errors. This is particularly crucial for mobile and instant interactive translation. However, it is worth noting that the optimised model still has limitations in the ability to process long texts. Although it generally maintains good coherence, compared with GPT-4, its paragraph-level context reasoning ability is slightly insufficient. This is mainly because the proposed model is designed with a greater focus on the optimisation of short sentences and high-frequency functional texts. In addition, when dealing with extremely local or rare place names and expressions of customs, due to the limited coverage of the corpus, the model may still have problems such as translation omissions or semantic ambiguities. Furthermore, compared with existing studies, the main contribution of this study lies in the technical implementation of eco-translatology. Most previous studies only stayed at the theoretical discussion of 'cultural adaptability', and there were few technical implementations and system integrations at the model level. In this study, by introducing mechanisms such as rule replacement, scene matching, and template invocation in the Transformer architecture, the three-dimensional adaptation goal of 'language-culture-communication' can be technically realised. This attempt provides a feasible path for the engineering application of eco-translatology and also offers ideas for intelligent translation systems oriented to specific text scenarios.

In summary, the optimised model demonstrates good translation ability and user experience in practical applications. It is especially suitable for text types such as public signs in scenic areas, which are highly culturally sensitive and have clear functional orientations. However, there is still room for improvement in the model's ability to handle long texts, complex discourse structures, and obscure cultural elements. Future research can further explore aspects such as multimodal understanding, multilingual expansion, and closed-loop optimisation of user feedback. This will promote the practical application of the concept of eco-translation in a wider range of fields.

6 Conclusions

This study takes public signs in scenic areas, a type of culturally functional text, as the entry point and proposes an AI translation model that integrates the concept of eco-translatology. It aims to achieve the dual optimisation of language conversion and cultural adaptation. The core contribution of the study does not lie in the iteration of translation technology itself, but in the technical implementation path of eco-translation theory. That is, through modular design, principles such as cultural adaptation, context regulation, and function recognition are embedded in the neural translation system, enabling the model to have the ability to make cross-cultural expressions in specific contexts (such as tourist scenarios). The proposal of this mechanism expands the applicable boundaries of eco-translatology in the field of intelligent translation and also provides a methodological reference for the research on the automated translation of functional texts. From a practical perspective, the proposed model not only meets the high-frequency, standardised, and multilingual requirements of public signs in scenic areas, but also shows obvious advantages in terms of the consistency of cultural expressions and the friendliness of user interaction. It has strong system deployability and scene replicability. Compared with general translation systems, this study emphasises the model construction ideas of 'customisability' and 'pragmatic function-driven', which are especially suitable for application scenarios with strong sensitivity to cultural differences and clear semantic functions. This research achievement has positive significance for promoting the intelligence of tourism language services and driving the international communication of the public language system.

Nevertheless, there are still some limitations in this study. Currently, the model is mainly designed in a targeted manner based on a single language pair. There has been no expansion to multiple languages or robustness testing for cross-cultural migration. The coverage of the corpus is also concentrated on domestic scenic areas, failing to fully incorporate the expression diversity in a multilingual cultural context. At the same time, the ability to understand deep cultural connotations, historical allusions, or ethnic language variations still relies on rules and templates, lacking semantic reasoning and knowledge tracing capabilities. Future research can be expanded in the following three directions. Firstly, further enrich the sources of the corpus, covering various types of scenic areas and multicultural regions, and construct large-scale parallel corpora to enhance the model's migration and generalisation abilities. Secondly, deepen the intelligence level of the cultural adaptation module. For example, introduce knowledge graphs, situation modelling, and causal reasoning mechanisms to achieve a deeper level of pragmatic understanding and cultural interpretation. Thirdly, explore the possible cross-domain applications of this model in other public language systems, such as urban wayfinding, cultural relics interpretation, educational notifications, etc. to widely expand the concept of eco-translation in the scenarios of social multilingual services.

In conclusion, this study not only provides a feasible model for intelligent translation in specific contexts, but also conducts a beneficial exploration of the engineering path of eco-translatology from three dimensions: theoretical implementation, system construction, and application practice. It has positive enlightenment significance for promoting the deep integration of AI technology in translation research.

Declarations

Data will be made available on request.

All authors declare that they have no conflicts of interest.

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