International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 1-14

https://doi.org/10.70917/ijcisim-2025-0283

Exploration of Strategies and Technological Paths to Improve the Quality of English Literature Translation Empowered by Artificial Intelligence

Li Wu[1*]
1. School of Foreign Languages, Chongqing College of Humanities, Science & Technology, Chongqing, 401524, China
T1225109@cqrk.edu.cn

Abstract: Under the environment of artificial intelligence, the construction of an intelligent English translation work system that meets the needs of society is an effective way to improve the efficiency of English translation work. The study discusses the strategy to improve the quality of English literary translation, and gives the technical path to improve the quality of English literary translation through the construction of the corpus of literary field and the English machine translation model based on RNN migration learning. The model combines RNN neural network with Word2vec, transfer learning technology and attention mechanism, which can effectively improve the translation quality of English literature machine translation. The experimental analysis verifies the effectiveness of the corpus in the literature domain and reveals the improvement effect of this paper's model on the performance of the English literature translation model and the translation quality, with its BLEU average value improved by 31.22%~44.18% compared with the comparison method, and it performs the best in the English literature long-sentence translation test. The model in this paper significantly improves the translation quality and can be used for actual English literature machine translation.
Keywords: parallel corpus; RNN; Word2vec; attention mechanism; English literature translation

1. Introduction

Literary translation, as a special language conversion activity, is not just a simple conversion between two languages, it also involves the communication of different cultural backgrounds, values, emotional expressions and so on [1-2]. Therefore, literary translation requires translators to deeply understand the cultural vein behind the original text and accurately grasp the emotional tone of the work while considering the target language readers [3-5]. English literature carries unique culture and diversified ideas, and the quality of its translation is directly related to the effectiveness of cultural dissemination and communication [6-7]. With the development of the times and the progress of society, the demand for cross-linguistic communication of English literature is increasing, and the traditional mode of manual translation is gradually showing its limitations in terms of efficiency and cost, while the introduction of artificial intelligence technology has made the ways of literary translation more diversified [8-11].

The development of artificial intelligence technology has improved the efficiency and quality of literary translation. First, artificial intelligence optimizes the translation process, shortens the translation cycle, and improves the accuracy and fluency of the translation results through the deep application of machine learning, natural language processing and other technologies [12-14]. The machine translation model quickly processes large text through neural networks, coupled with the introduction of pre-trained language models, to achieve precision in machine understanding of semantic relationships [15-16]. Secondly, the application of AI technology in translation memory and terminology management provides powerful support for literary translation [17-18]. Translation memory reduces repetitive work and ensures consistency of literary style by storing and reusing previous translation segments [19-20]. Meanwhile, terminology management tools can automatically identify and manage specialized terminology, avoiding translation errors caused by terminology inconsistencies, which is especially important for literary translation scenarios involving complex cultural backgrounds and specialized terminology [21-23]. In addition, the development of artificial intelligence technology, especially the progress of natural language processing technology, makes personalized translation possible [24-25]. Machine learning algorithms are able to mine the linguistic specialties of specific writers or works from massive data, and through deep learning of a large number of texts, the system can capture the original author's unique expression habits, vocabulary selection preferences, and sentence structure features [26-29].

The development and application of artificial intelligence technology has completely subverted all fields of human society, and in the translation of language and literature, as a new method to improve the quality of translation, it overcomes the limitations of traditional translation, and realizes more accurate cross-cultural communication. Literature [30] examined the future prospects of human translators in the era of AI translation technology, and through interviews strengthened the important role of AI in improving the quality of literary translation, but it needs to be combined with human translation in order to improve cultural relevance. Literature [31] explored the output effect of ChatGPT to translate English literature into Arabic, and compared its output effect with other tools such as Google Translate, aiming to explore the accuracy of artificial intelligence tools is in literary translation. Literature [32] analyzes the potential of Google Translate in providing higher quality translations of literary texts and illustrates the achievements of AI in literary translation based on translated passages. Literature [33] reports the results of two experiments in an ongoing project aimed at developing a machine translation system for literature, concluding that machine translation is able to understand themes and concepts in translated literature and categorize stories. Literature [34] compares the use of different AI translation tools in literary translation and affirms the advantages of ChatGPT's translation tool in improving translation quality, among other things, by evaluating accuracy, fluency and cultural understanding. Literature [35] assessed the effectiveness of a multilingual AI translation system, emphasizing that the system's translation accuracy in constructing appropriate tone, intonation, and emotional coloring in literary translation exceeded 80%. Literature [36] examined the possibility of applying AI in the field of literary translation, noting that AI-generated translations achieved acceptable accuracy and lacked in richness and emotional subtlety. Literature [37] emphasized the impact of AI on translation practice, including the translation of literary works rich in cultural connotations and stylistic features, and verified the accuracy of AI translations in generating structure and semantics through translation practice. Literature [38] describes the remarkable development in the field of machine translation, especially the emergence of neural machine translation, which further improves the accuracy and fluency of translation, and the interactivity possessed by AI makes it possible to modify the translation according to the translator's needs. Literature [39] proposed an AI-based fuzzy semantic translation method for English language based on semantic analysis, which was verified to be able to avoid the ambiguity of semantic understanding and improve the accuracy of English language translation.

However, although AI has shown significant advantages in the field of language and literature translation, its application still faces multiple challenges, especially in dealing with the complexity, culture, humanistic connotations, and ethics of literary works. Literature [40] describes the complexity and challenges faced by AI in translating Arabic literature, affirms the efficiency of AI translation, and points out its limitations in terms of cultural and emotional resonance in literature. Literature [41] describes the widespread use of AI in translation tools, indicating the positive as well as the negative effects that cause artificial translators to rely too much on technology. Literature [42] emphasized that AI translation tools such as machines and computers have facilitated the development of literary translation, but they have also led to emerging ethical issues in literary translation, especially with regard to the professional identity and copyright of literary translators. Literature [43] assessed the benefits and challenges of AI in translation research, and through a literature review, it was noted that AI tools play an important role in improving translation efficiency and quality, reducing costs, and high accuracy, but there are shortcomings and technological problems originating from natural language processing. Literature [44] emphasizes the synergy between human and AI translation, which not only improves the quality of translation but also ensures cultural fit, but also brings ethical considerations. Literature [45] describes resistance literature and the application of AI in translating such literature, emphasizing the bias of AI in translating resistance literature, as well as the fact that it can compromise the essence of the literature due to a lack of nuanced understanding. Literature [46] analyzes the application of AI in Arabic-English literature translation and concludes that AI can play an important role in translation, but human supervision is needed in the translation of literary texts in order to ensure cultural authenticity, stylistic integrity, and ethical presentation. Literature [47] examined the differences between machine translation and human translation in Arabic literary poetry into English, showing that machine translation cannot be a good tool for translating poetry into English after failing to capture the cultural context of the work.

This paper applies the science of artificial intelligence to the work of English translation to explore the strategy of improving the quality of English literary translation under the empowerment of artificial intelligence. Out of the demand for optimization of English translation model, a corpus of literature field is constructed, and based on RNN neural network, English word vectors are processed by Word2vec model, so as to extract linguistic features, and then machine translation model is constructed by using improved Encoder-Decoder model, and machine translation method of English literature by integrating linguistic features + migration learning is proposed. Subsequently, multi-dimensional indicators are constructed to evaluate the effectiveness of the corpus in the field of literature, and the constructed corpus is used as an experimental dataset to explore the translation performance of this paper's translation model for English literature through the comparative analysis of the model. The research in this paper applies artificial intelligence technology to English literature translation, which can provide technical paths for

English literature translation application scenarios and promote the development of English literature machine translation.

2. Strategies for Improving the Quality of English Literature Translation Empowered by AI

With the technical support of artificial intelligence, the staff of the translation industry can utilize the artificial intelligence technology to carry out targeted training according to their own work arrangements, and improve the accuracy and work efficiency of translation. In the era of artificial intelligence, the improvement of English literature translation work needs to take practical work as the entry point, take artificial intelligence as the technical support for the innovation of translation work, search the auxiliary role of intelligent technology on English literature translation in multiple dimensions, and really improve the overall quality and efficiency of English literature translation work.

2.1. Incorporating literary thinking

To improve the quality of English literature translation, the first thing is to incorporate literary thinking into the translation and highlight the artistic features of the literary work as much as possible. English literature has a lot of expressive techniques, including irony, metaphor, lyricism, anthropomorphism, rendering, argument, description, exaggeration, comparison, pun and so on. When translating, the translator should establish a literary mindset, and no matter which expressive technique he translates, he needs to fully understand the content of the original text, and when dealing with the text, he doesn't need to confine himself to the text, but he should take the whole text as the basis of his secondary creation. From a certain point of view, English literary translation is also a kind of art, with its own unique artistic characteristics, the English language is different from the Chinese language, many English vocabulary is a word with multiple meanings, in the creation of literary works, writers will often use puns on the expression, in the translation into Chinese, we should pay attention to the application of the expression, and not the more the better the use of the expression, should be in the original on the basis of respect for the use of appropriate means of expression, so that it is the only way to translate into Chinese, and the original is the most important. It is not better to use more and more expressive techniques, but to use appropriate expressive techniques on the basis of respecting the original work, so as to truly reflect the literary thinking of English literature translation, otherwise, the use of non-selective will only make the work obscure and difficult to understand, and the audience will naturally not be willing to read it. As a translator, you need to master the use of various expressive techniques in your own country's literature, and you also need to master the expressive techniques and expressions of English literature, understand the differences between English and Chinese, and emphasize the artistic value of the literary works. When translating, first of all, you need to understand the aesthetic habits and aesthetic needs of the audience in your country, and use literary thinking to accurately convey the image, and secondly, when translating, you can't isolate any word, but combine it with the specific context, and choose the way of translation in connection with the context, to make sure that the translated work is both literary and the closest to the text of the original.

2.2. Integration of Intelligent and Human Translation

At present, intelligent translation technology is still in the stage of development, and if intelligent translation technology is reasonably utilized, it can make human translation and intelligent translation promote each other and develop together. For one thing, the current intelligent translation technology has made certain achievements, which has brought new changes to English literature translation and even the whole translation field, saving a lot of energy and time for translation staff. For some text translations which are less difficult to translate and do not require too much human understanding and feelings, intelligent translation tools can be used directly to complete the work quickly, saving translation costs and improving work efficiency. Secondly, although intelligent translation technology has made great breakthroughs and can accomplish some simple work, the translation level of literary works and so on has yet to be improved, and it is not comparable to works translated by human beings. Therefore, people engaged in translation work need to deeply understand the advantages and functions of intelligent translation tools, use it as a tool to improve their own translation level, update their work and study concepts, keep abreast of the times, and improve their competitiveness in the field of translation. In conclusion, the translation of English literature is human-centered, and will be affected by context, emotion, history and culture, etc. Artificial translation is irreplaceable, but intelligent translation also has its unique advantages, and the two must be deeply integrated in order to achieve long-term development in the fierce competition in the industry.

2.3. Innovative Intelligent Translation Tools

Although the emergence of intelligent translation tools has brought a greater impact on the English translation industry, even making some practitioners face unemployment, in order to adapt to the rapidly developing society, translation practitioners must correctly understand and treat intelligent translation tools, reasonably utilize intelligent translation tools, and promote the development of the English industry. Under the background of artificial intelligence, in the process of development and reform of the English literature translation industry, relevant researchers and high-level English translation practitioners must cooperate to explore the auxiliary role of artificial intelligence technology on translation work, use intelligent technology to design specialized English literature translation tasks for the majority of English translation workers, help them learn specialized vocabulary and hot topics with large omissions in a relatively short period of time, and develop intelligent tools that can assist the Staff to complete the translation task of the intelligent tool, the tool can assist the translators to complete the work at the same time, guide the workers to clarify the translation of the text of the idea, so that the staff quickly produce a systematic cognition of the target translation text, significantly improve their work efficiency. For example, senior translators and AI researchers can cooperate to design an intelligent translation assistance model to help translators carry out translation training and assist them in their daily work. The staff will import the target translation text into the model, get the first draft of the translation with the assistance of intelligent tools, and then incorporate their own subjective thoughts to improve the accuracy and translation efficiency of the translated content of English literature.

3. Technical paths for improving the quality of English literature translation

Based on the demand for quality improvement of English literature translation with innovative intelligent translation tools, this paper constructs a corpus in the field of literature and, based on recurrent neural networks, proposes an English machine translation method that integrates linguistic features and neural networks.

3.1. Parallel corpus construction

3.1.1. Corpus construction process

Machine translation can be trained to produce a high-quality machine translation model by using a large number of parallel texts in the source and target languages in a parallel corpus. The process of corpus construction and evaluation is shown in Figure 1. In order to build a standardized parallel corpus of multilingual literature domain, firstly, the English monolingual data on the website of literature domain are collected on the Internet, and a large number of literary texts in English are obtained. Then the preliminary chapter data are cleaned, chapter cut, and filtered by literary domain to get the English monolingual corpus. Then the monolingual corpus is translated from English into five languages, Chinese, German, French, Japanese, and Spanish, using the Baidu translation model to form a parallel corpus of these six languages. Finally, the corpus is automatically evaluated, and the evaluation results are used as the standard to filter the final multilingual parallel corpus in the field of literature.

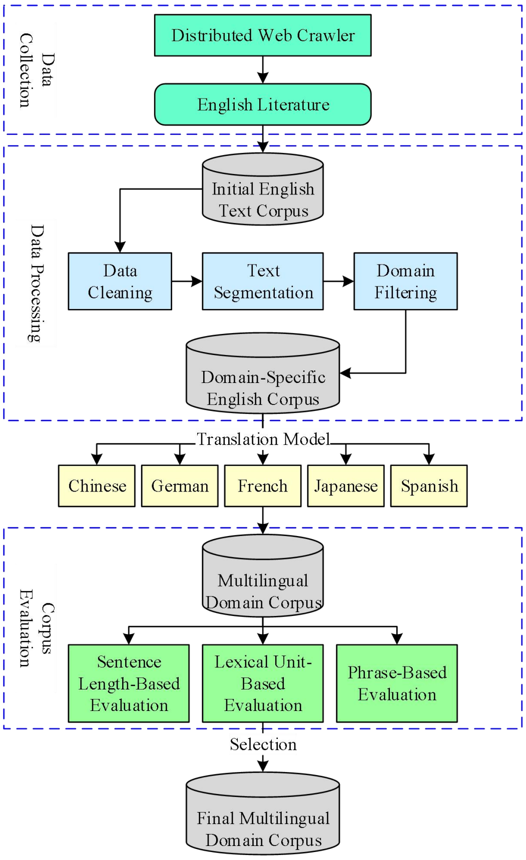

Figure 1. The building and evaluation process of corpus.

3.1.2. Data acquisition

In this paper, a distributed web crawler design based on Scrapy crawler framework, Redis database, and MongoDB database is carried out to obtain the English text of literary works websites.

3.1.3. Data processing

Since the initial collected information contains a lot of noise and does not conform to the text structure of the corpus, it is necessary to carry out data cleaning, chapter cutting, domain filtering, text translation and other processes on the initial English chapter text collected.

Data Cleaning: Using regular matching, the redundant text tags and web page tags are cleaned to obtain the standardized chapter text.

Chapter cutting: Since the standard format of the corpus is based on a single sentence, chapter text information needs to be cut. The text cutting script is utilized to cut the chapter information into individual statements using the separators (period, question mark, exclamation mark) as the specific segmentation criteria to form the initial English monolingual corpus.

Domain filtering: Since the initial English monolingual corpus contains textual information in multiple domains, it is necessary to perform domain adaptation on a large amount of textual information to filter out the corpus in the field of English literature.

Text Translation: The generic domain translation model of Baidu Translate is invoked to translate the English text data into Chinese, Japanese, German, French and Spanish sentence by sentence, respectively. A preliminary multilingual literature domain corpus is formed.

3.2. English Literature Translation Model

3.2.1. Translation models

As a kind of basic recurrent neural network, the biggest advantage of RNN over ordinary neural networks is that the computation result of the current hidden layer of RNN is related to the current input information and the output result of the previous hidden layer. In this way, the computation result of the current unit of RNN has the characteristic of "memorizing" the previous results. Therefore, RNN has a big advantage in dealing with video, speech and text problems. The reason why RNN is good at solving sequential problems is that it can memorize the data information of each moment, and the data information of the hidden layer of each moment is not only determined by the input layer of the moment, but also by the data information of the hidden layer of the previous moment.

3.2.2. Transfer learning

Transfer learning can be categorized into four types based on the learning approach, which are sample, mapping, network and adversarial based transfer learning methods. Network based migration is selected based on the content, network migration i.e. construction of parameter sharing model. This method is commonly used in neural networks to migrate the network structure.

In migration learning, the network is first trained on the initial region, and after the training is completed, the data that meets the criteria is migrated to the target region, and finally the information in the network is continuously adjusted and corrected according to the standard requirements, so as to improve the network recognition effect.

Migration learning is commonly used to solve data classification problems in different domains, and its main role is to employ a large amount of data in the source domain to learn an effective migration model to improve the recognition effect in the target domain.

3.2.3. Word Vector Model

In order to better train the machine translation model, firstly, we propose to use Word2vec model to preprocess the English language, and after Word2Vec mapping, we get one-dimensional consecutive vectors, and then the trained word vectors are used in the training of English literature machine translation model.

The Word2vec model converts words into vectors with small dimensions, and can represent the connection between words according to the similarity between vectors. Word2vec has two training models: continuous bag-of-words model (CBOW) and skip-gram model (Skip-Gram).

(1) Continuous bag of words model

CBOW model includes input layer, implicit layer and output layer, the model predicts the center word based on the context words and learns new word vectors in the prediction.

The output content and prediction result of the model are not important, what we want is the word vector formed by the input weight matrix during the model training process. Each row of the word vector matrix represents the word vector of the corresponding word in the vocabulary, and the number of rows is the size of the vocabulary.

(2) Skip-gram model

The Skip-gram model reverses the causality of the CBOW model, which predicts context words based on the center word. The input layer is the one-hot form of the center word w_t, the product of the input layer and the input weight matrix W gets the hidden layer vector h, and the hidden layer vector h dot-multiplied by the output weight matrix W' gets the output value, i.e., the predicted context word.

During Word2vec model training, if the provided corpus vocabulary list is too large, the weight matrix from the input layer to the implicit layer and the weight matrix from the implicit layer to the output layer are of a huge order of magnitude. Gradient descent in such a large neural network is extremely slow and will cause extremely high time complexity for training during weight optimization, and also requires weight adjustment on a large amount of training data to avoid data fitting phenomenon. Therefore, the negative sampling method is used to optimize the model training process.

(3) Negative Sampling Based Modeling

In the field of natural language processing, if two words are context words and target words are called positive samples. On the contrary, if the relationship between a context word and a random word in the vocabulary is called negative sample, the process of random sampling is negative sampling. The idea of negative sampling is to update the weight parameters of a few training samples to reduce the amount of computation during gradient descent.

Suppose there is a corpus C. Words appear differently in the vocabulary, if they appear more often, then the chance of being selected is high and the probability of being a negative sample is high, and vice versa, which is also known as weighted sampling. This is like taking all the words to form a unit line segment of length "1", if a point is randomly thrown onto the line segment, the probability of being hit is higher for a larger proportion of the length, which also forms a mapping relationship.

3.2.5. English Machine Translation Model Construction

The small sample data often makes the translation effect of the machine translation model poor. In order to achieve better results, after processing the word vectors by Word2vec, a small neural translation model is first trained, and then the neural machine translation model is trained on a large scale by using the migration learning technique. The specific process of English-Chinese machine translation model construction based on RNN migration learning is shown in Figure 2.

The trained machine translation model is used as the initial model for migration learning. Migration learning is added to retrain the deep parameters of English utterances to extract their English features and improve the learning ability of the machine translation model.

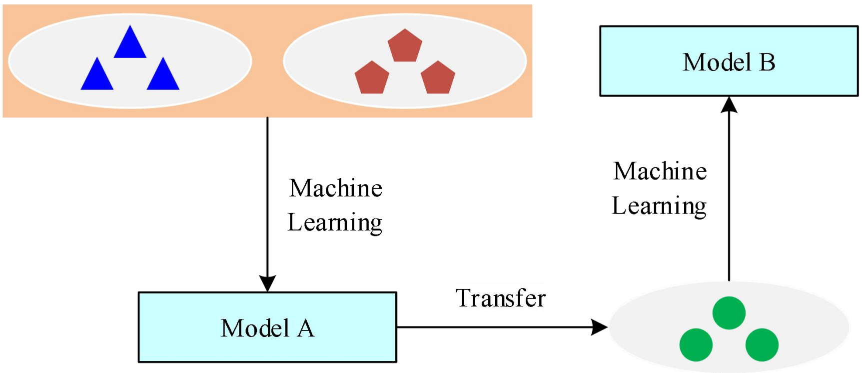

Figure 2. The machine translation model based on RNN migration learning.

4. Experiments and analysis of results

4.1. Experimental analysis of corpus evaluation

4.1.1. Evaluation index

In order to assess the quality of the preliminary multilingual literature domain corpus constructed in this paper, this paper will use a multidimensional assessment method to assess the quality of each corpus, and finally screen out the high-quality corpus to form a multilingual literature domain corpus. This paper evaluates each corpus from the dimensions of the length of the corpus, the translation quality of real words, and the translation quality of phrases.

(1) Quality assessment based on sentence length

Sentence length-based utterance quality evaluation feature mainly determines whether the ratio of the number of words between the source language and the target language translation is reasonable or not.

(2) Real-word based quality assessment

The evaluation features based on real words need to use bilingual dictionaries, and in this project, we use the authoritative dictionaries published by Yudao Dictionary, which only examine the degree of word intertranslation of real word lexical properties according to the lexical properties of the words in the sentence.

(3) Phrase-based quality assessment

The phrase-based assessment method needs to perform phrase partitioning of sentences, still using the NLTK tool to divide English sentences, and determine whether the translation of these phrases exists in the phrase table, in order to examine the translation quality of phrases. Using the phrase translation table for English-Chinese, Japanese, French-German, and Spanish published by the authority of Yodo Translator.

4.1.2. Analysis of assessment results

A parallel corpus of 10,000 items from processed English to Chinese, German, Japanese, French, and Spanish is used for training, where the size of the training set is 8,000 items, and 1% of the data (1,000 items) is randomly selected from the corpus as the validation set and 1% of the data (1,000 items) as the test set.

In order to verify the functionality of the above corpus evaluation indexes, each evaluation index for each language pair respectively is calculated on the preliminary corpus, and the utterances are sorted from high to low according to the score of the evaluation indexes, and the neural machine translation model training is carried out on the former 25% and the latter 25% of the data respectively, and the performance of the model is tested. The results of the validity analysis of the corpus composition evaluation are shown in Fig. 3, where E-C, E-G, E-J, E-F and E-S denote English → Chinese, English → German, English → Japanese, English → French and English → Spanish, respectively.

The BLEU values of all languages in the translation models trained with the evaluation scores in the first 25% of the corpus are significantly higher than those in the second 25%, and the BLEU values of the training in the first 25% of the corpus and the second 25% of the corpus are 39.21-43.63 and 38.39-42.48, respectively, which proves that the evaluation method in this paper is effective. And in English→Chinese, English→German, and English→Spanish translations, the evaluation indexes based on real words have the greatest influence on the BLEU values compared with the other two indexes, and the BLEU values of the evaluation indexes based on real words are 39.34, 43.16, and 41.83, respectively. whereas the evaluation indexes for the length of the sentence have less influence on the BLEU values, which proves that the data processing method of this paper is efficient that filters out most of the sentences with different lengths. The evaluation metrics based on phrases also demonstrate an increase in BLEU values, validating the previous paper's processing of the corpus in the field of English literature.

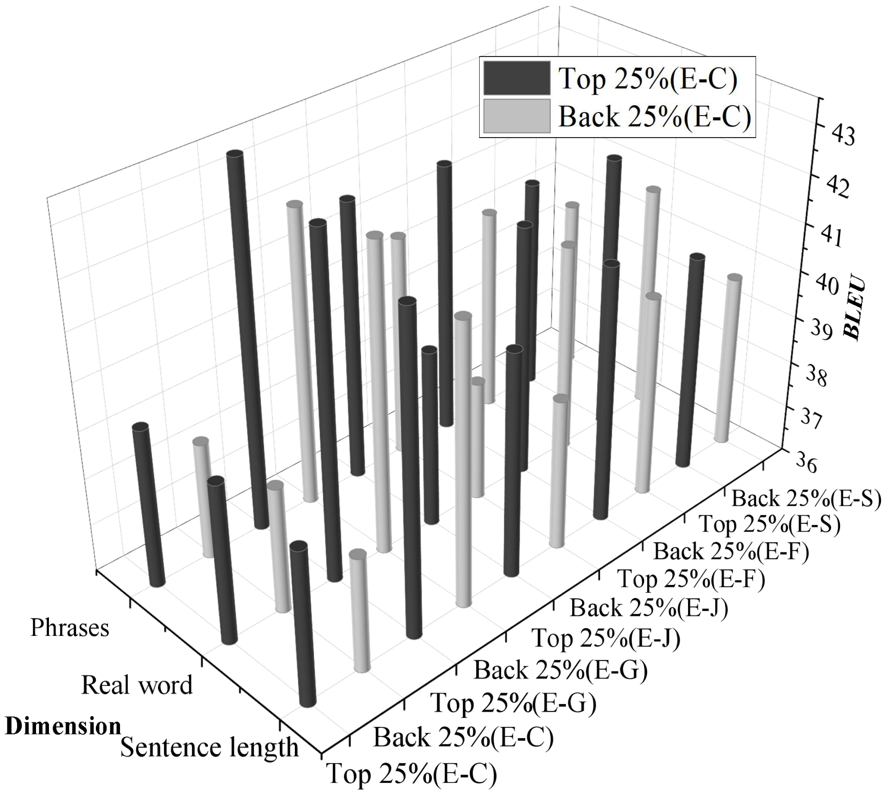

Figure 3. Analysis of the effectiveness of corpus evaluation.

In order to make the evaluation program more perfect, the comprehensive evaluation indexes based on sentence length, real words and phrases are explored. In this paper, the optimal weighting coefficients of the three evaluation indexes are explored. In this paper, the scores of each evaluation method are directly multiplied by the corresponding weighting coefficients and summed up to get the final evaluation scores. The weights of sentence length, real words and phrases are fixed to 0.1 respectively, and then the weights of the other two evaluation methods are changed with 0.1 as the weight gradient, and the evaluation is carried out on the English→Chinese corpus, and according to the evaluated scores, they are ranked, and the results of the experiments of multidimensional weight analysis are shown in Fig. 4. When the weight of the index of sentence length is increased, the BLEU value of the model has decreased, proving that sentence length is not a key factor affecting the quality of the corpus. When the weight of sentence length assessment was set at 0.1 and the weight ratio of real word and phrase assessment was 5:4, the BLEU value of the model was the highest at 40.24, which indicates that both real word and phrase assessment are the key factors in evaluating the quality of the corpus.

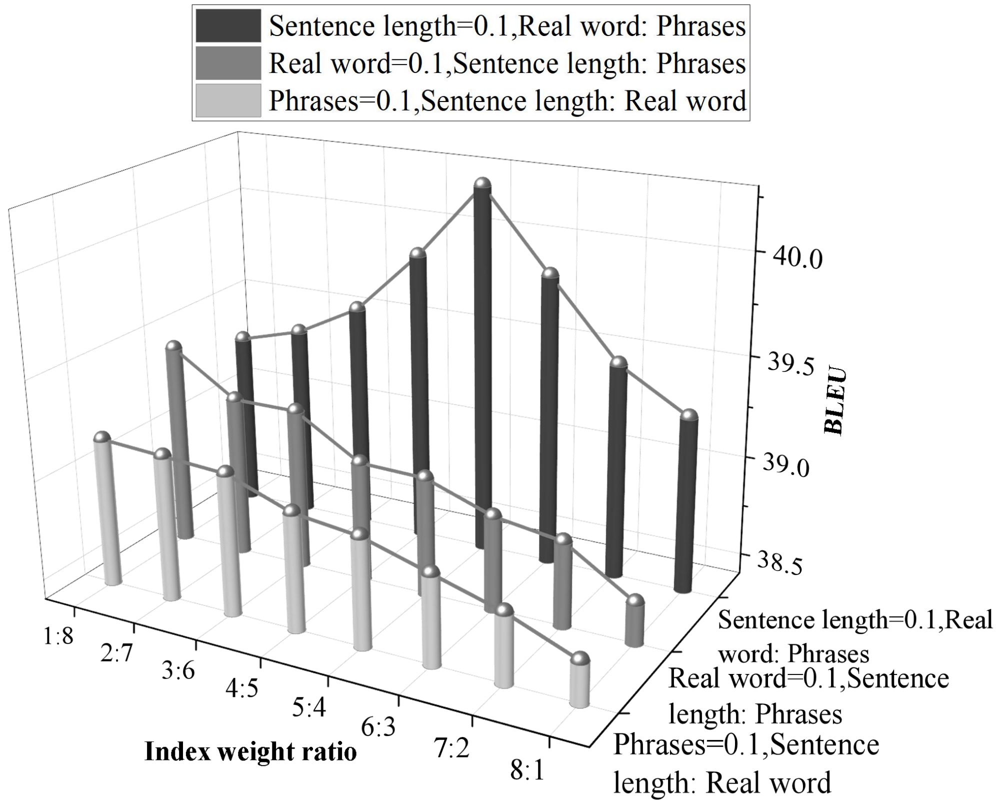

Figure 4. Experimental results of multidimensional weight analysis.

4.2. Experimental Analysis of English Translation

4.2.1. Experimental setup

In order to verify the effectiveness of the proposed English machine translation model based on RNN migration learning in this paper, the study builds an RNN migration learning English machine translation system on TensorFlow framework. The study selects the constructed literature domain corpus as the experimental dataset of this paper, which is divided into one training set, three test sets (sentences, real words and phrases) and one validation set. The study chooses the BLEU value as the index to evaluate the translation quality of the translation model, and the larger its value, the higher the quality of the translation.

4.2.2. Analysis of ablation experiments

This paper takes the RNN model as the Baseline and optimizes the RNN machine translation model in three ways. The first is to process the word vectors through Word2vec. The second is to train the model using transfer learning technology. The third is to add an attention mechanism to the RNN network. They are respectively denoted as "+Word2vec", "+Migration learning" and "+Attention mechanism". This paper's experiment adopts different methods for combination verification. Method One, Method Two and Method Three are integrated into machine translation in different combination ways. They are respectively recorded as "+Word2vec+ Migration learning", "+Word2vec+ Attention mechanism", and "+Migration learning + Attention" "mechanism", "+Word2vec+Migration learning+ Attention mechanism" Different methods were integrated into the RNN model for experimental comparison on the training set and the test set. The analysis results of the ablation experiment are shown in Table 1.

The combination of using the different methods mentioned above into the machine translation model all resulted in the improvement of translation quality in the field of English literature. Among them, the best improvement effect is achieved by Word2vec representation of linguistic features and the simultaneous incorporation of the migration learning technique and the attention mechanism, which improves the BLEU scores of the different data selection models by 3.21, 3.49, 4.43, and 2.75 points, respectively, compared to the Baseline model, which verifies the effectiveness of the RNN-based migration learning method for English machine translation proposed in this paper. Effectiveness.

Table 1. Ablation experiment analysis results.

Models	Training set	Test set 1	Test set 2	Test set 3
Baseline	21.97	22.57	24.52	25.41
+Word2vec	22.53	23.39	25.07	26.32
+Migration learning	22.93	23.18	25.31	26.86
+Attention mechanism	22.50	24.72	25.49	26.48
+Word2vec + Migration learning	23.31	24.63	25.56	27.29
+Word2vec+ Attention mechanism	23.67	24.36	26.27	27.55
+Migration learning + Attention mechanism	24.76	25.03	27.69	27.45
+Word2vec+Migration learning+ Attention mechanism	**25.18**	**26.06**	**28.95**	**28.16**

4.2.3. Comparative analysis of models

In order to verify the translation effect of the proposed English machine translation model based on RNN migration learning, the study uses the traditional LSTM English machine translation model, the RNN English machine translation model, the GRU-Attention English machine translation model and the LSTM-Attention English machine translation model, as well as the proposed English translation model to train on the experimental dataset, respectively, and the different translation models on the experimental dataset and the results of BLEU values are shown in Fig. 5. The BLEU values of the proposed English machine translation model based on RNN migration learning on the training, test and validation sets, respectively, are 22.77, 19.12, 18.36, 20.29 and 18.11, which are higher than those of the English machine translation models based on the traditional LSTM, and RNN, GRU-Attention, and LSTM-Attention BLEU values, and the average value of BLEU is improved by 44.18%, 38.17%, 35.23% and 31.22% than the four English machine translation models, respectively, indicating that compared to the comparison translation models, the proposed translation model improves the performance of the English literary translation model and the quality of the translation by embedding the attention mechanism in the RNN network, and verifies the RNN-based migration learning English machine translation model's effectiveness.

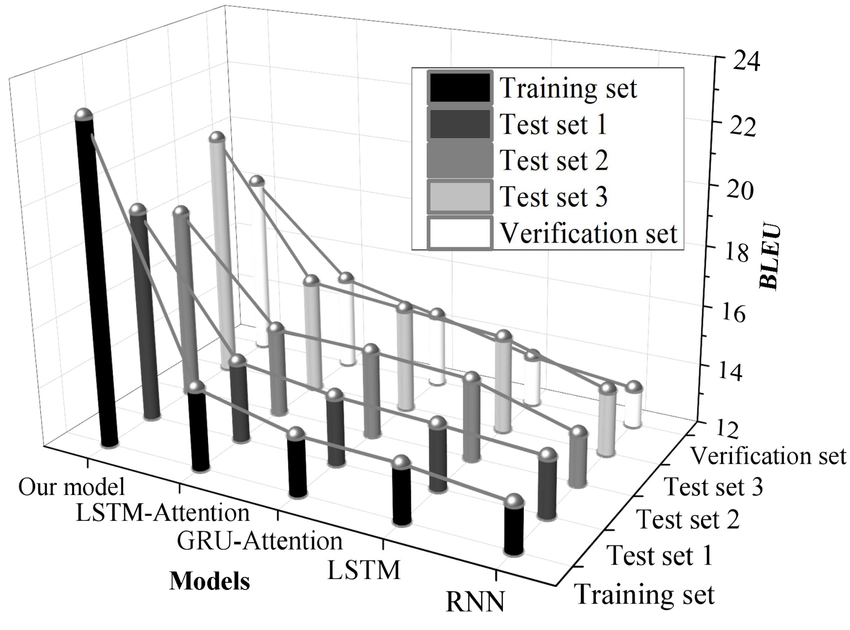

Figure 5. The BLEU value of the different translation models in the experimental data set.

The following is the 2nd comparison experiment, the sentences of the literary corpus are clustered and analyzed according to their length, after which the translation model is tested using sentences of different lengths to verify the translation model's ability to translate long sentences, and the results of the model's long-sentence translation test are shown in Fig. 6. In the case of different sentence lengths, the performance of the algorithm model constructed in this paper is still optimal, when the sentence length is 60, the BLEU values of the traditional LSTM, and RNN, GRU-Attention and LSTM-Attention English machine translation models are 2.88, 4.99, 7.94, 12.14, and at this time, the BLEU value of the model in this paper is 25.40, which is improved by 109.23%~781.94% compared with the comparison translation model, proving that the proposed model in this paper also has strong translation performance in terms of English literature long sentence translation. Moreover, with the increase of sentence length, the decrease of translation performance of the model in this paper is smaller compared with the traditional algorithm, which indicates that the model is less sensitive to the change of sentence length and more accurate.

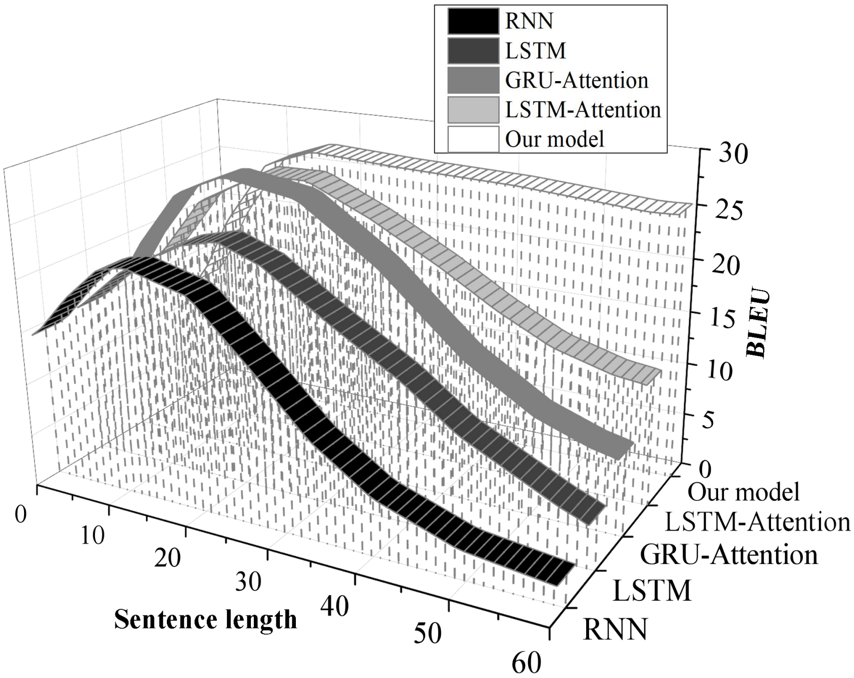

Figure 6. Test results of model long sentence translation.

4.2.4. Impact of the volume of corpus data

In order to verify the effect of the constructed corpus data volume in the field of literature on the translation model, in this paper, 50% of the terms are randomly selected from it and added to the English translation model, or all of them are added to the English translation model, or they are copied twice or twice and then added to the neural machine translation system, and at the same time, they are analyzed in the analysis with the use of different methods, including the traditional LSTM, and RNN, GRU-Attention and LSTM-Attention English machine translation models. Figure 7 lists the experimental results of incorporating the corpus with different amounts of data into the English translation model.

The BLEU values of the machine translation models gradually increase with the increase of the amount of data in the literary domain corpus, and all of them peak at 200% of the amount of data, when the BLEU values of the models are 26.87, 26.52, 27.23, 27.11, and 27.51, which may be due to the fact that the literary domain corpus can bring the model with more accurate domain information, and is more favorable for the model to migrate towards the domain direction, thus improving the translation quality of English literature. However, with the increase of the number of literary corpus, the model will not be able to achieve any significant effect when the information carried in the corpus reaches its peak.

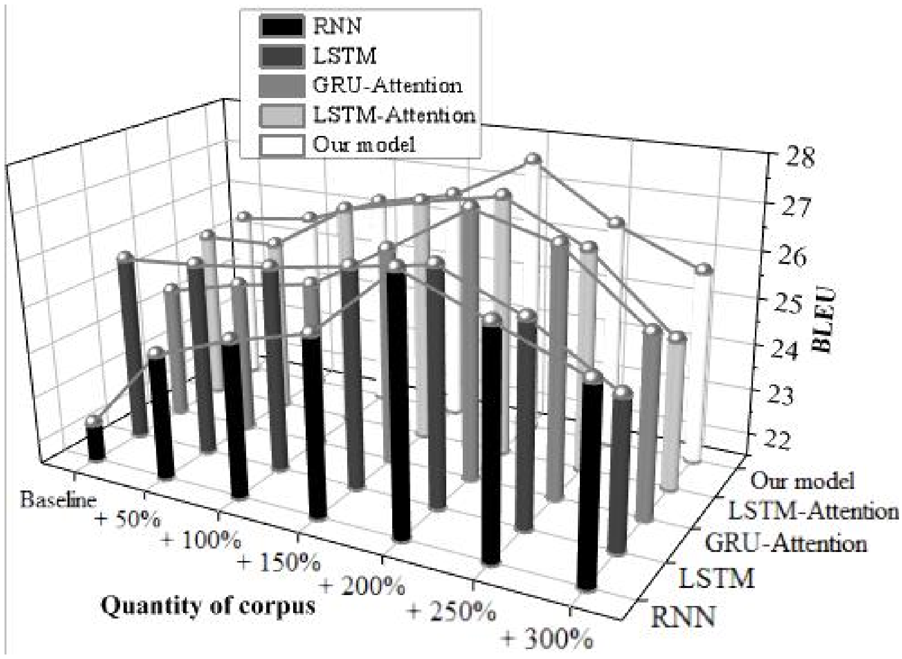

Figure 7. Experimental results of different data quantities.

5. Conclusion

Under the information environment, artificial intelligence provides much convenience for English translation work. This study analyzes the strategies to improve the quality of English literature translation in the context of artificial intelligence, and constructs a corpus in the field of literature and proposes an English machine translation model based on RNN migration learning to improve the translation quality of English literature. The main research results are as follows:

(1) In the evaluation experiments of the constructed corpus, the BLEU values of the experiments in which the first 25% of the corpus is significantly trained are 39.21~43.63, which are significantly higher than those of the second 25% of the corpus, which are 38.39~42.48, indicating that the method of constructing and evaluating the corpus of the literature domain proposed in this paper is effective.

(2) Compared with the four comparison models, the English machine translation model in this paper improves the average value of BLEU on the dataset by 31.22%~44.18%, which shows better English literature translation model performance and translation quality. Meanwhile, the translation quality of the model in the English literature long sentence translation test is also optimal, with higher BLEU values of 109.23%~781.94%, and the more data volume of the constructed corpus, its translation quality gradually increases. The results show that the translation performance of the English machine translation model based on RNN migration learning is significantly better than that of the traditional translation model, and achieves a more ideal English literature translation effect.

The improvement method proposed in this paper makes the performance of the English literature machine translation model significantly improved, but there is still the problem of relying on the corpus. Future research will combine the unsupervised learning approach to alleviate the translation problem in the case of zero resources, and mine and make full use of domain features to improve the quality of translation in the field of English literature.

References

1. Delabastita, D. (2012). Literary translation. In Handbook of Translation Studies: Volume 2 (pp. 69-78). John Benjamins Publishing Company.
2. Koster, C. (2014). Literary translation. In Translation: A multidisciplinary approach (pp. 140-157). London: Palgrave Macmillan UK.
3. Scott, C. (2018). The work of literary translation. Cambridge University Press.
4. Kardiansyah, M. Y., & Salam, A. (2020, December). Literary Translation Agents in the Space of Mediation. In International Joint Conference on Arts and Humanities (IJCAH 2020) (pp. 592-598). Atlantis Press.
5. Katan, D. M. (2015). Translating the 'literary'in literary translation in practice. Lingue e Linguaggi, 14, 7-29.
6. Ghazala, H. S. (2015). Literary translation from a stylistic perspective. Studies in English Language Teaching, 3(2), 124-145.

7. Marin-Lacarta, M. (2017). Indirectness in literary translation: Methodological possibilities. Translation Studies, 10(2), 133-149.
8. Yousef, T. (2012). Literary translation: Old and new challenges. International Journal of Arabic-English Studies, 13(1), 49-64.
9. Carl, M. (2020). Translation, artificial intelligence and cognition. In The Routledge Handbook of Translation and Cognition (pp. 500-516). Routledge.
10. Alkodimi, K. A., Alqahtani, O. A., & Al-Wasy, B. Q. (2024). Human-AI collaboration in translation and back translation of literary texts. Journal of Social Studies, 30(2), 173-192.
11. Jibreel, I. (2024). Translation Quality of Artificial Intelligence and Machine Translation Vs. Human Translation Utilizing MTPE Skills (An Empirical Study on Allusion Translation). Journal of Social Studies, 30(3), 46-72.
12. Mughal, U. A., Seemab, S., Zaigham, M. S., Bhatti, A., & Khan, H. (2024). The intersection of linguistics and artificial intelligence: a corpus-based study of idiom translation. Journal of Applied Linguistics and TESOL (JALT), 7(4), 1453-1460.
13. Visby, M. (2020). The future relationship of literary translation and AI. Counterpoint, 4, 28-30.
14. Das, A. K. (2018). Translation and Artificial Intelligence: Where are we heading. International journal of translation, 30(1), 72-101.
15. Doan, T. T. P. (2025). ASSESSMENT OF HUMAN TRANSLATION VS. AI TRANSLATION IN A LITERARY WORK. VNU Journal of Foreign Studies, 41(3), 126-141.
16. Mukti, M. A. P., Maulana, M. T., Rohmah, K. N., Abqoriyyah, F. H., & Saehu, A. (2024, June). The Effectiveness of Artificial Intelligence Usage as Translation Medium among English Literature Student of UIN Sunan Gunung Djati Bandung. In Journal of English Education Forum (JEEF) (Vol. 4, No. 2, pp. 107-112)
17. Walter, K., & Agnetta, M. (Eds.). (2025). Applying Artificial Intelligence in Translation: Possibilities, Processes and Phenomena. Taylor & Francis.
18. Moulavinafchi, A., Madahiian, M., & Hosseini, S. M. (2025). Generative AI and the Transformation of Literary Translation: A Qualitative Inquiry into the Perspectives of Literature Students. Journal of Foreign Language Research, 15(2), 171-193
19. br Sembiring, S. A., Sipayung, K., & Lestari, F. D. (2024). AN ANALYSIS OF TRANSLATION TECHNIQUES BETWEEN AI AND HUMAN TRANSLATOR IN TRANSLATING CULTURAL WORDS IN THE GADIS KRETEK NOVEL. Dharmas Education Journal (DE_Journal), 4(3), 689-699.
20. Mohsen, M. (2024). Artificial intelligence in academic translation: a comparative study of large language models and google translate. Psycholinguistics, 35(2), 134-156.
21. Manapbayeva, Z., Zaurbekova, G., Ayazbekova, K., Kazezova, A., & Pirmanova, K. (2024). AI in Literary Translation: ChatGPT-4 vs. Professional Human Translation of Abai's Poem ‘Spring’. Procedia Computer Science, 251, 526-531.
22. Pan, Q., Song, Q., & Feng, T. (2024). Comparative Study of English and Chinese Translation Theory: Revealing the Potential of Digital Technologies. Translation Review, 118(1), 28-43.
23. Guo, X. (2022). Optimization of English machine translation by deep neural network under artificial intelligence. Computational intelligence and neuroscience, 2022(1), 2003411.
24. Wang, S., & Wang, X. (2024). Cross-language translation and comparative study of English literature using machine translation algorithms. Journal of Electrical Systems, 20(6s), 2221-2229.
25. Alsalemi, S. S., Alhazmi, M. D., & Al-Humari, M. A. (2025). Poetry is the Last Resort of Translation in the Age of Artificial Intelligence. Arts for Linguistic & Literary Studies, 7(3), 660-691.
26. Aydın, B. C. (2024). A CASE STUDY ON ARTIFICIAL INTELLIGENCE AND THE PROBLEM OF EQUIVALENCE IN LITERARY TRANSLATION: TRANSLATION OF THE NOVEL ‘SINEKLI BAKKAL’BY HALIDE EDIB ADIVAR INTO ENGLISH. Kırıkkale Üniversitesi Sosyal Bilimler Dergisi, 14(3), 81-117.
27. Wang, Y. (2022). Aesthetic characteristics in an English translation of modern art in the context of artificial intelligence. Frontiers in Educational Research, 5(6).
28. Saeed, H. Q. (2025, October). Challenges of Using Literary Translation and Artificial Intelligence for Postgraduate Students: A Case Study of Baghdad University. In Pattern Recognition and Artificial Intelligence: Selected papers from the 6th Mediterranean Conference on Pattern Recognition and Artificial Intelligence (MedPRAI24) (pp. 701-712). Cham: Springer Nature Switzerland.
29. Li, Y. (2025, May). Innovation of Artificial Intelligence Empowering Literary Translation Teaching. In 2025 5th International Conference on Artificial Intelligence and Education (ICAIE) (pp. 231-235). IEEE.
30. Al Mudarra, A. (2025). The Future of Human Translators in the Era of Artificial Intelligence Translation Technologies. Journal of Language Teaching and Research, 16(4), 1213-1224.
31. Malkawi, M. A. K. M., Altalahin, A., Abushunar, M. S. H., & Aldelaa, A. S. (2025). AI-Aided Translation: An Eye on ChatGPT as a Tool of Translating Literary Texts. Technium Soc. Sci. J., 75, 311.
32. Constantine, P. (2019). Google translate gets voltaire: literary translation and the age of artificial intelligence. Contemporary French and Francophone Studies, 23(4), 471-479.
33. Al-Batineh, M., & Rabadi, R. (2019). Will the machine understand literary translation? A Glimpse into the future of literary machine translation through the lenses of artificial intelligence. Studies in Translation, 5(1), 151-169.

34. Abdelhalim, S. M., Alsahil, A. A., & Alsuhaibani, Z. A. (2025). Artificial intelligence tools and literary translation: a comparative investigation of ChatGPT and Google Translate from novice and advanced EFL student translators' perspectives. Cogent Arts & Humanities, 12(1), 2508031.
35. Chen, S. (2025, August). Research on the accuracy and style preservation of a multilingual artificial intelligence translation system based on deep learning in English literary translation. In 2025 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA) (pp. 1-6). IEEE.
36. Iskakbayeva, A., Tussupova, A., Zhalalova, A., & Uzbekova, Z. (2025). Comparative Analysis of Literary Translation Using Artificial Intelligence: An Experiment Based on EA Poe's Short Story "The Tell-Tale Heart". Dibon Journal of Languages, 1(3), 304-313.
37. Siregar, N. A. Z., & Zawawi, M. (2025). Artificial Intelligence in Translating Literary: An Accuracy and Satirical Representation of the Arabic Short Story. International Journal of Arabic Language Teaching, 7(01), 126-144.
38. Yong-shan, L. I. U. (2024). A Comparative Study of Artificial Intelligence and Translation Software in Chinese-English Translation: A Focus on Literary and Technical Texts. Journal of Literature and Art Studies, 14(9), 815-820.
39. Sun, Y. (2023). Artificial Intelligence Method for Accurate Translation of Fuzzy Semantics in English Language and Literature. International Journal on Semantic Web and Information Systems (IJSWIS), 19(1), 1-16.
40. AlSajri, A. (2023). Challenges in translating Arabic literary texts using artificial intelligence techniques. EDRAAK, 2023, 5-10.
41. Wang, L. (2023). The impacts and challenges of artificial intelligence translation tool on translation professionals. In SHS Web of Conferences (Vol. 163, p. 02021). EDP Sciences.
42. Li, B. (2023). Ethical issues for literary translation in the Era of artificial intelligence. Babel, 69(4), 529-545.
43. Charles-Kenechi, S. (2024). Artificial intelligence in translation studies: Benefits and challenges. Cascades, Journal of the Department of French & International Studies, 2(1), 5-15.
44. Soysal, F. (2023). Enhancing translation studies with artificial intelligence (AI): Challenges, opportunities, and proposals. Karamanoğlu Mehmetbey Üniversitesi Uluslararası Filoloji ve Çeviribilim Dergisi, 5(2), 177-191.
45. Obeidat, M. M., & Jaradat, M. A. (2024). Artificial intelligence accuracy in translating resistance literature from Arabic into English: Google Translate and ChatGPT as a model. Research Journal in Advanced Humanities, 5(2), 45-62.
46. Abdulmughni, H. M. A. (2025). Artificial Intelligence in Arabic-English Literary Translation: Technological Innovations, Linguistic Accuracy, and Ethical Implications. International Journal of Language and Literary Studies, 7(3), 107-129.
47. Alowedi, N. A., & Hassan Al Ahdal, A. A. M. (2023). Artificial Intelligence based Arabic-to-English machine versus human translation of poetry: An analytical study of outcomes. Journal of Namibian Studies, 34.