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Human-machine Translation Model Evaluation Based on Artificial Intelligence Translation

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Abstract

As artificial intelligence (AI) translation technology advances, big data, cloud computing, and emerging technologies have enhanced the progress of the data industry over the past several decades. Human-machine translation becomes a new interactive mode between humans and machines and plays an essential role in transmitting information. Nevertheless, several translation models have their drawbacks and limitations, such as error rates and inaccuracy, and they are not able to adapt to the various demands of different groups. Taking the AI-based translation model as the research object, this study conducted an analysis of attention mechanisms and relevant technical means, examined the setbacks of conventional translation models, and proposed an AI-based translation model that produced a clear and high quality translation and presented a reference to further perfect AI-based translation models. The values of the manual and automated evaluation have demonstrated that the human-machine translation model improved the mismatchings between texts and contexts and enhanced the accurate and efficient intelligent recognition and expressions. It is set to a score of 1-10 for evaluation comparison with 30 language users as participants, and the achieved 6 points or above is considered effective. The research results suggested that the language fluency score rose from 4.9667 for conventional Statistical Machine Translation to 6.6333 for the AI-based translation model. As a result, the human-machine translation model improved the efficiency, speed, precision, and accuracy of language input to a certain degree, strengthened the correlation between semantic characteristics and intelligent recognition, and pushed the advancement of intelligent recognition. It can provide accurate and high-quality translation for language users and achieve an understanding of natural language input and output and automatic processing.

Keywords: Artificial Intelligence, AI-based translation, attention mechanism, Statistical Machine Translation, translation model

1. INTRODUCTION

Human-machine translation is the combination of Machine Translation (MT) technology with human translation. This kind of translation makes use of the great computing speed and power of computers and the processing capacity of Big Data in order to enhance the efficiency, accuracy, precision, and quality of different language users by helping or supplanting human translation through intelligence and automation. It is extensively applied in English, Spanish, Portuguese, French, Chinese, Japanese, German, Russian, etc. Nevertheless, because the processing technology of personalized texts for various languages is needed, it cannot resolve these problems of semantic understanding in intricate contexts. The debut of AI translation technology has made this possible. Built on machine learning algorithms, machine translation, and deep learning technology, it can create corresponding texts and make proper adjustments and alterations under actual conditions.

Meanwhile, it also possesses the ability of strong self-evolution. Also, it can make analysis, judgment, and prediction of natural language to some degree and enable language users to have a better understanding of the meaning they are eager to express. On the basis of this, this study examines the process of an AI-based model from the perspective of combining humans with machines, which combines the automatic capabilities of AI with the knowledge, competence, recognition, and estimation of translators in order to achieve high-quality translated texts and enhance the cross-cultural verbal communication and exchanges.

It is known that translation plays an important role in transmitting information, knowledge, thoughts, ideas, and opinions. MT can only translate words by words, phrases by phrase, and sentence by sentence directly according to the program set; only manual translation may achieve an understanding of translated texts [1]. The existing translation suggests the potential of massive multilanguage MT by constructing a translation model that runs the translation process in the form of sentence pairs [2]. MT is to make use of computers to render human languages automatically. Of course, its other applications are achieved and occupy a vital position in processing natural language [3-5]. Over the past decades, Neural Machine Translation (NMT) has made breakthroughs by simulating mapping directly between the source language (SL) and target language (TL) with the help of deep neural networks, which have become an important and valuable model of MT [6]. Constructing NMT for multilanguage users can improve multilingual transcultural communication between different foreign language users [7]. Furthermore, a few analysts proposed that Google Translate may transform various texts into English prior to analyzing, building an actual multilingual translation model, and assessing MT's effect on the Bag-of-Words model [8]. AI and MT share similar characteristics, assisting language users in finishing intricate tasks, such as sentence generation, segmentation, and word recognition.

Against the background of globalization, the language barrier is an obstacle to access to ideas and information. At times, it is of impossibility to rely solely on human translation to meet language users' demands [9]. Over the past several decades, though the NMT has made tremendous progress, it confronts the challenges of learning optimal model parameters for lengthy and intricate sentences and making use of different contexts. Employing an attention mechanism to recognize contexts and sentences to be translated can enhance learning parameters and examine the different contexts of translation [10]. As AI advances at a fast pace, MT emerges as the new widespread application form, offering great advantages for its application in foreign language learning and translation [11]. The knowledge of syntax may enhance NMT's performance, efficiency, accuracy, and functions. The syntax-aware encoder can extend the sequences of sentences to dependency; the SL and TL dependency structure can improve translation quality [12]. On the basis of low-level attention, a deep attention model can decide what to translate or suppress in the encoding layer to make representations that adapt to high-level attention and enhance the faithfully translated texts [13]. The advancement and development of AI technology may be conducive to solving language problems and laying the groundwork for successful transcultural communication and exchanges.

Because conventional translation models need a deep understanding of the grammatical and semantic rules and structures for intricate text processing, the deep learning algorithm and AI neural network technology may be used to create different AI-based translation models that conform to corpus features, to some degree, address the various problems caused by the existing methods in resolving complicated texts, and provide accurate, smooth, flexible, readability, acceptable and natural translations[14-15]. By contrast, this new AI-based translation model can convert texts into machine-recognizable ones, present them to language users interactively, and enhance the different language user experience.

2. RELATED WORKS

Language is a tool that makes cultural communication possible. Under globalization, communication with people from different cultural contexts occurs. AI has exerted an influence on many fields, which include translation and its relevant fields and enhanced accurate, faithful, and quality translations. Since its emergence, AI has produced an effect on the reform and development of education, translation teaching, and the translation industry. [16]. Therefore, AI-based translation mode becomes an important tool to enhance intercultural communication through rendering different spoken languages and texts. AI-based translation models enable different groups, organizations, and institutions to communicate successfully.

In recent years, AI technology has developed at a rapid rate; computer vision, pattern recognition, and a large number of machine translations are being widely used in the field of translation. Built on the technologies of deep learning, AI, and neural networks, the AI-based translation model has become a mature model that addresses the translation problems and errors in conventional expressions of English sentences[17]. Nevertheless, because there is a lack of technical support, theoretical guidance, and systematic design, the AI-based model is currently emerging and in its early stages, so it is necessary to conduct an in-depth analysis of AI translation technology.

Based on the achievements of available research, research on machine recognition and translation attaches great importance to voice understanding and natural language processing. As technologies progress continuously, combining various advanced technologies with manual labor focuses on improving efficiency and quality while developing and applying AI translation methods can be promoted. By optimizing AI-based translation models, converting simple text and complex semantic information into the target texts has been achieved, and this model can provide powerful tools and services for language users, translation or language service providers, and foreign language learners. Therefore, it is essential to achieve cross-language communication accurately and efficiently based on the AI-based model.

The AI-based model of translation aims to enable readers to have a better understanding and master the SL texts; regarding various cultural contexts, the translation also displays some other features [18-19]. The conventional model of human translation mainly rests on translators' realization of natural, accurate, and effective meaning transfer between the SL and the TL through multiple methods to convey the meaning and intentions expressed by the SL texts. It makes human translators recognize, master, and understand the features of different texts, conduct an analysis of their content, and incorporate their knowledge of different languages with translation to achieve the desired effects. The conventional translation benchmark models are showcased in Table 1.

Table 1. Limitations of conventional translation models

	Accuracy	**Fluency**	**Naturalness**	**Limitations**
Statistical machine translation model	-	↓	↓	Difficult to handle lengthy texts and specific terminology
Neural network translation model	↑	↑	↑	Difficult to manage long-distance dependencies and rare words
Pre-trained language models	↑	↑	↑	Poor handling of specific languages and particular fields

Note: "-" moderate, “↑" high, and “↓" low.

Statistical machine translation employs the knowledge of vocabulary, syntax, and logical reasoning to create the corpus that enables computers to process texts. The relationships between semantics and characteristics of grammar in sentences in various languages are obtained by analyzing these sentences. Then, it produces corresponding translated texts based on this [20]. Its translation accuracy has reached a middle level among a few sentence pairs. However, the translations' naturalness and fluency in this model are relatively low because they rely on statistics that only involve the extent of interconnection between words and overlook semantic correlations.

Neural network translation and pretrained language models can produce a relatively high-quality, accurate, fluent, and natural translation, better-recognizing contexts, structures, and grammar features. Nevertheless, the conventional translation models are insufficient to meet the intelligent translation demands of rare words and particular languages because of their drawbacks, such as time, speed, quality, readability, and cognition. As a result, as machine learning technology, translation technology, and automation make huge progress, high quality parallel translation texts may be produced with the help of an AI-based translation model, which can significantly improve translation accuracy and efficiency [21].

3. ORIGINALITY

The current trends in translation technology have endowed translators with significant advantages in translation. The human-machine translation model is constructed by comparing other translation technologies, such as machine translation, neural network translation, and conventional translation methods. However, these translation technologies have different setbacks. Human-machine translation can make full use of their advantages and set aside their disadvantages. Real translators play an essential role in this translation model to make up for some advantages that occur in machine translation and other translation models in the field of translation [22]. These methods of automation and human evaluations demonstrate the AI-based model can perfect the matching relations between texts and contexts, strengthen intelligent recognition and semantic expression, improve the accuracy and precision of language input, and offer high-quality translation services.

4. SYSTEM DESIGN

The AI-based translation model is an end-to-end system that contains a few important modules, such as SL input, encoding, processing, decoding, and TL output. These coordinate to make the AI-based translation automatically convert SL texts into TL. It can produce high-quality translation by integrating attention mechanisms, deep learning algorithms, statistical modeling, intelligent recognition, encoder, decoder, computing, etc. The AI-based translation model is shown in Figure 1. The deep learning algorithm is the backtracking algorithm based on information entropy iteration. Its basic idea is to determine a test through two steps. The first step is that the information entropy algorithm is used to establish a temporary diagnosis tree for each candidate test node, and the second is that the optimal diagnosis tree is obtained through heuristic operation, regarded as the optimal test. Moreover, deep learning model is widely used in various fields (e.g., deep learning approaches for automatic drum transcription)[23].

The development of the proposed system is that the test data are preprocessed in the source code, and then each word is part-of-speech tagging. There are several special considerations when pausing in a sentence. Before decoding, the mechanism is used to adjust and optimize the encoding result. Finally, the results of the encoding are input into the corpus. The test steps are as follows:

(1) identify the desired behavior of system functions and the interactions between these functions and other systems;

(2) produce one or more test cases that simulate typical usage of modules, subsystems, or overall systems. Test cases must be based on reference materials, such as documents required and files designed;

(3) Execute test cases, observe responses to systems, and record test results;

(4) Analyze the test results to evaluate that the system meets the predetermined functional requirements;

(5) Create defect reports for failed test cases and track problems until resolved;

(6) Repeat the above procedure until all predetermined system functions are confirmed.

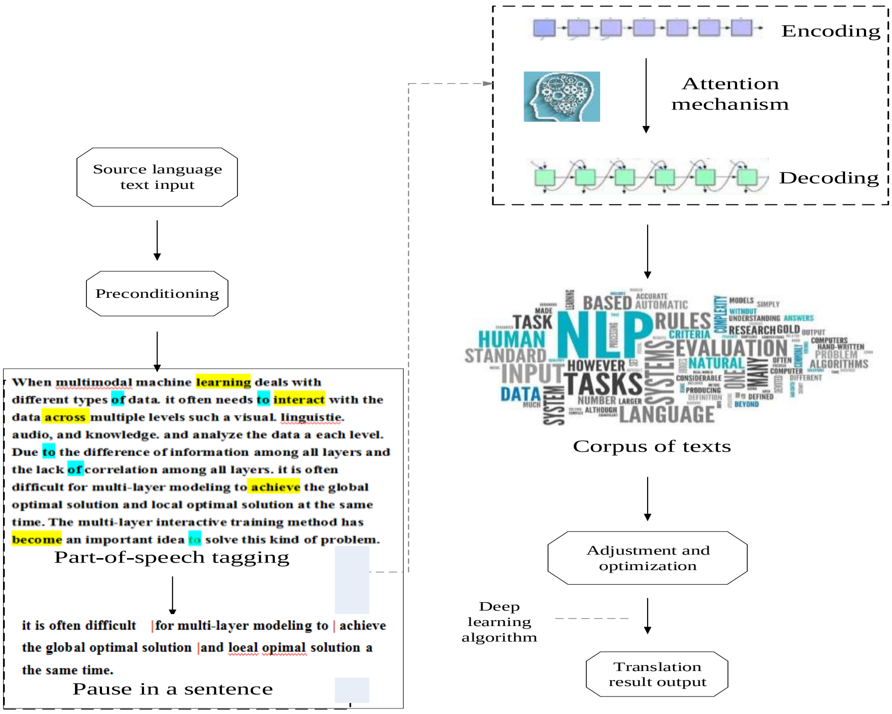

Figure 1. Human-machine translation model evaluation based on AI translation technology

Once the SL sentences are put into the AI-based translation model, such operations of preprocessing as word and sentence segmentation and part-of-speech tagging are required first to enable the AI-based translation to have a better understanding of the structures and syntactic relations of the input [24]. The attention mechanism is able to encode the context of the input words, sentences, sequences, and semantic information to change the preprocessed SL sentences into a continued vector representation. In addition, the decoder produces translated texts by assessing the conditional probability distribution of the words in the SL. The corpus is the essential element of the AI-based translation model, including many relevant words and phrases from the SL and TL to meet language users' personalized needs for specific vocabulary, phrases, and sentences. Moreover, it is also crucial to adjust the AI-based translation model parameters and optimize training strategies, especially for a few intricate and difficult words, phrases, and sentences. Therefore, it is essential to select proper matching methods and means under the actual situation in connection with the performance and accuracy of machine learning algorithms and produce an effect on the final translation quality. The attention mechanism in the AI-based translation model mentioned above is widely applied in the two encoder and decoder modules. It is assumed that in an SL dataset Q, in which *a* and *b* belong to any one of the set of datasets, Q is expressed as follows:

$$\mathrm{Q} = \left\{\left(\mathrm{a}^{(\mathrm{i})}, \mathrm{b}^{(\mathrm{i})}\right)\right\}_{\mathrm{i}=1}^{\mathrm{I}} \tag{1}$$

The formula consists of the following components: Q represents the SL translation data set; *a* is the sentences from the SL in the dataset; *b* is the sentences from TL in the dataset.

Using $(\mathrm{A}_{<J}, \mathrm{B}_{<J})$ as the indication of J=1 sentence pairs from texts, the probability of translation is expressed as below:

$$\mathrm{P}\left(\mathrm{b}^{(1)}, \ldots, \mathrm{b}^{(\mathrm{J})} \middle| \mathrm{a}^{(1)}, \ldots, \mathrm{a}^{(\mathrm{J})};\ \rho\right) = \prod_{\mathrm{J}=1}^{\mathrm{J}} \mathrm{P}\left(\mathrm{b}^{(\mathrm{J})} \middle| \mathrm{A}_{<j}, \mathrm{B}_{<j}, \mathrm{a}^{(\mathrm{j})};\ \rho\right) \tag{2}$$

$\mathrm{A}_{<j}$ represents the sequence of the source of the first $\mathrm{j}-1$ sentences from SL texts and $\mathrm{B}_{<j}$ indicates the sentence output with the expression:

$$\mathrm{A}_{<j} = \left(\mathrm{a}^{(1)}, \ldots, \mathrm{a}^{(\mathrm{j}-1)}\right) \tag{3}$$

$$\mathrm{B}_{<j} = \left(\mathrm{a}^{(1)}, \ldots, \mathrm{a}^{(\mathrm{j}-1)}\right) \tag{4}$$

$\mathrm{a}^{(\mathrm{J})}$ indicates a phrase or sentence in the SL texts and $\mathrm{a}^{(\mathrm{J})} = \left(\mathrm{a}_1^{\mathrm{J}}, \ldots, \mathrm{a}_{\mathrm{m}}^{\mathrm{J}}\right)$ is in the form of vector expressed as:

$$\mathrm{W_a} = \left[\mathrm{W}\left(\mathrm{a}_1^\mathrm{J};\ \ldots;\mathrm{a}_\mathrm{m}^\mathrm{J}\right)\right] \tag{5}$$

In this formula, *m* indicates the length of sentences. In the module of the encoder, the 3 matrices, which include R, S, and T, are endowed weights with the translations so that the feature vectors are obtained from them. The function of the attention mechanism is considered mapping relation, which is represented as:

$$\mathrm{Attention}(\mathrm{R}, \mathrm{S}, \mathrm{T}) = \mathrm{softmax}\left(\frac{\mathrm{RS}^\mathrm{K}}{\sqrt{\mathrm{d_S}}}\right)\mathrm{T} \tag{6}$$

R, S, and T represent the three matrices used to calculate the attention in the encoder module, and their meanings are as follows: R represents the query vector, which is used to query the "importance" of each position at the encoder end. The attention is obtained by dot product operation with the feature vector at each position at the encoder end. S represents the feature vector at each position of the encoder end and is the result of the encoder output. T represents the feature vector representing each position of the target end, which is the result of the decoder output.

In this study, the attention mechanism is introduced to enable models to handle complicated and long sentences and structures in AI translation, examine the input and output correspondence, and enhance the whole performance of the AI-based translation model [25-26]. Regarding the intelligence of the AI-based translation model, it is measured by the accuracy and efficiency of intelligent recognition, accuracy rate, error probability, and natural language output with the help of human translators and experts, and then based on the defects or insufficiency of natural language processing output, these problems will be improved and solved through using technical support and intervention of translators. By repeating these procedures in different stages, the model's performance will be improved to produce accurate and efficient natural language output, and the error rates and inaccuracy will be reduced to a large extent in the operation of the AI-based translation model so that the better intelligence of the AI-based translation model is achieved.

5. EXPERIMENT AND ANALYSIS

5.1 Experimental Design

For the purpose of obtaining enough scale and typicality of the dataset, the study chooses sentence pairs that include SL texts and TL ones from the dataset, which refers to Workshop on Machine Translation and, at the same time, runs the AI-based translation model and the conventional SMT ones respectively to render the SL sentences into TL ones. In addition, it describes the AI-based translation model as Model 1 and takes the conventional SMT model as Model 2. The translated texts are compared and contrasted through manual and automatic assessment to prove the strengths brought by the human-machine model based on AI translation technology.

5.2 Data Analysis

5.2.1 Automatic Evaluation

The selected 5 sets of sentence pairs as samples are used to examine the translations from both Model 1 and Model 2 in the following indicators as Bilingual Evaluation Understudy (BLEU), Metric for Evaluation of Translation with Explicit Ordering (METEOR) as well as Translation Error Rate (TER). The automated evaluation values of all indicators are often between 0 and 1. In these indicators, if the automated evaluation values of BLEU and METR are closer to 1, the automated evaluation values of TER are closer to 0, which indicates that the translated text quality is better and acceptable. The automated evaluation values of the three indicators are presented in Figure 2.

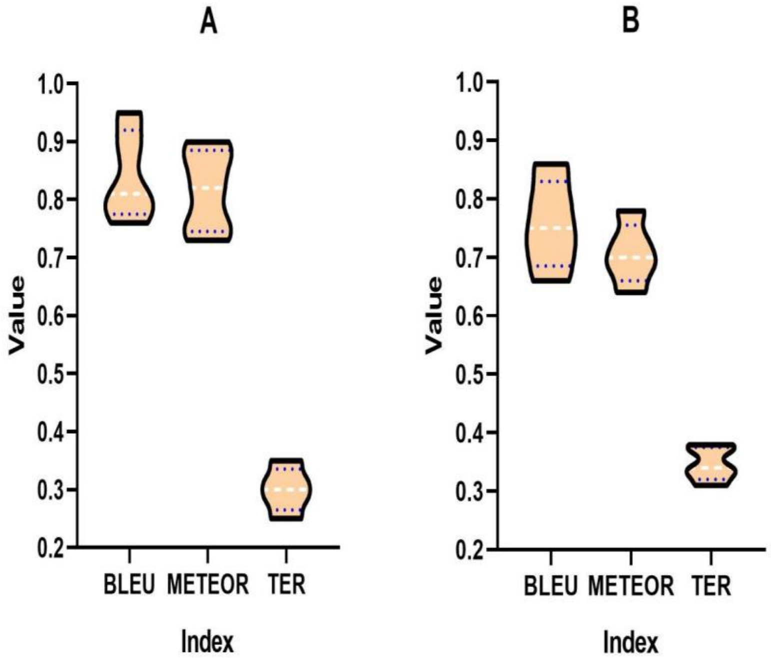

Figure 2. Contrast and comparison of automated evaluation values between the two translation models
Figure 2A: Model 1 Automation Evaluation Values
Figure 2B: Model 2 Automation Evaluation Values

BLEU uses an n-gram match to assess how similar a machine translation result is to a reference translation:

$$BLEU = BP * \exp(\mathrm{sum}(wi * \log(pi))) \quad (7)$$

BP algorithm is designed to process short text and ensure that the length of the translations is close to that of the text reference. In this formula, *pi* represents the geometric average of the n-gram matching degree, and *wi* is the weight corresponding to the matching n-gram.

METEOR assesses translation quality by word match, word order accuracy, and semantic similarities in both the MT results and the translation reference:

$$\text{METEOR} = (1-\alpha) * \text{precision} + \alpha * \text{recall} * (1-\text{similarity}) \quad (8)$$

In the formula, *precision* measures the lexical compatibility between MT and the reference text, *recall* measures the accuracy of the MT and the reference translation in word order, *similarity* measures the semantic similarity between the TL text and the text reference, and α is a weighted value that measures accuracy and recall.

TER measures the relative number of editing operations (insert, deletion, replacement) between the MT result and the reference translation:

$$\text{TER} = (S + D + I) / N \quad (9)$$

In the mathematical formula, S represents the number of replacements, D indicates that of deletions, I indicates that of inserts, and N represents all number of words from the translation reference.

In Figures 2A and 2B, the horizontal axis indicates the three indicators, BLEU, METEOR, and TER, while the vertical shows the evaluation value of the indicators. The evaluation values of BLEU and METEOR, which are gained from Model 1, range from 0.7 to 1, and BLEU reaches the highest (above 0.9). In addition, the evaluation values of BLEU and METEOR, which are obtained from Model 2, are between 0.6 and 0.9, and the highest is not more than 0.9. It is relatively lower than the value from Model 1, which may make full use of existing resources and have a better understanding of and utilize contexts. Its translation results are finally more accurate. Moreover, the TER evaluation values of Model 1 range from 0.2 to 0.4, and those of Model 2 are 0.3 and even above. The TER evaluation values of Model 2 are a little higher than those Model 1 produced. Therefore, Model 1 may produce more accurate and fluent translated texts than Model 2 and reduce error probability and vagueness to a large extent.

Table 2. Comparison of different translation systems

Evaluation indicators	**Translation system A**	**Translation system B**	**Translation system C**
BLEU score	0.78	0.81	0.85
METEOR score	0.75	0.82	0.80
TER score	0.20	0.18	0.21
Manual evaluation score (1-10)	7.5	8.2	9.1

BLEU, METEOR, and TER are the scores of the automated evaluation metrics, which are used to measure the quality of machine translation. A higher score indicates a better quality of translation. Suppose that translation system A is based on neural machine translation, translation system B is based on statistical machine translation, and translation system C is a text system. The comparison of different translation systems is shown in Table 2. All the parameters of this translation system are relatively high. The manual evaluation score of this translation system is as high as 9.1.

5.2.2 Manual Evaluation

In order to obtain two versions of translation, the same SL texts were translated by making use of the two different models. The evaluation results of 30 linguistic experts were obtained, which included the four aspects: style, language expression, translation skills, and language fluency. Translation style means the translator's full reproduction of the original style and the emergence of his style, and it is embodied in the words, sentence patterns, rhetorical devices, and writing methods of translated texts; language expression can be defined as the ability to use words, phrases, sentences, and paragraphs in translation; translation skills refer to some translation methods and skills which are mastered to achieve better translation quality and effect in the process of translation, and they help translators better understand the original text, choose appropriate vocabulary and translation methods, and be able to accurately and quickly transfer the meanings of the SL texts; language fluency is one of the basic requirements for language expression in translation, specifically, it means that the language of the translation is fluent and the sentence is smooth. The score is 1-10, with the highest score of ten. The score of six or above is treated as qualified, and Figure 3 demonstrates the detailed score of the manual evaluation of the two translation models.

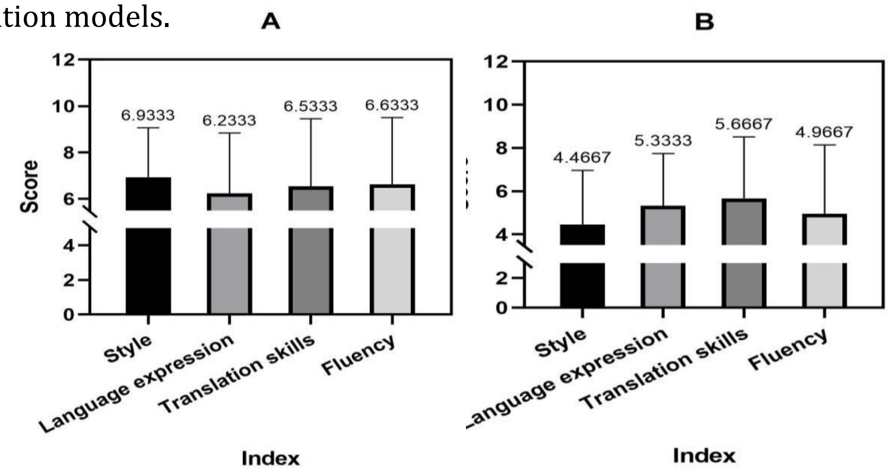

Figure 3. Contrasts of manual evaluation score of translation models
Figure 3A: Model 1 manual evaluation score
Figure 3B: Model 2 manual evaluation score

Figure 3 indicates the contrasts of the manual evaluation score of the two translation models; Figure 3A shows the Model 1 score of manual evaluation in the translation model, and Figure 3B indicates the Model 2 manual evaluation score. The abscissa axis shows the four indicators of evaluation, and the axis of ordinates indicates the average score of the four indicators. By calculating, we can see that regarding the style of translation, the score obtained from Model 1 is 6.9333, while the score gained from Model 2 is 4.4667. It can be seen that some characteristics of the register and the style of translation that are not in line with the TL are shown in Model 1, which produces a lesser effect on the whole rendering. Nevertheless, the style of translation in Model 2 is not distinct, and a few errors may have an impact on the understanding and experience of language users or alter the SL meanings of texts. The gap between them has been reduced to some degree in terms of language expression and translation techniques. Nevertheless, the diction in Model 2 is no more accurate than those in Model 1, and the Model 2 may not resolve the problems in translation. In the case of language fluency, the score of Model 1 is 6.6333, and the score of Model 2 is 4.9667. Therefore, Model 1 has more significant advantages over Model 2 in terms of TL usage habits and can be adjusted in a flexible way to achieve naturalness under actual conditions. On the basis of the evaluation of the indicators mentioned above, it comes to the conclusion that Model 1 reaches a high level in each rating among the indicators, produces a better quality translation through decoding, and enhances the experience of language users.

In short, the AI-based translation model possesses enormous strengths compared with traditional SMT models in terms of such aspects as instant translation, accuracy, efficiency, flexibility, and context understanding. All these strengths enable AI-based translation models to occupy an important position in the field of MT and offer the advancement and application of translation technology a broad space.

6. CONCLUSION

The human-machine translation is an intricate language phenomenon conducive to human beings who can have a better understanding of the differences in languages and cultures in real-language communication. It makes up for the deficiencies and drawbacks of manual translation, although human translation plays an essential role in the translation market. This translation model, which is built on the technology of AI translation, can better indicate the basis features of automation and intelligence in the field of AI translation, conduct a dialogue effectively between human beings and computers, change the way that human beings and machines communicate with each other, and advance the application and development of the information technology. The article elucidated the drawbacks and solutions of conventional translation models by analyzing and expounding the influence and significance of AI translation in this study. By integrating the technology strengths of AI translation, the new AI-based translation model was proposed, which described and verified its functions and efficiency—the translation model aimed to enhance translation efficiency and lower error rate. By combining the strengths of AI and human translation, the AI-based translation model offers essential support in technology to achieve effective and accurate intercultural communication.

Moreover, the research results showed that AI-based human-machines effectively improve the mismatching between texts and contexts and strengthen the efficiency of intelligent recognition and language expressions by evaluating 30 language experts. It also enhances the accuracy of language input and intelligent recognition, offers language users high-quality and efficient language services in intercultural communication, and achieves natural language processing and output. Therefore, with the rapid advance in translation technology, AI-based human-machine translation significantly impacts knowledge and cultural resource management, and in-depth further research is also needed in the future.

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REFERENCES

[1] P. Xiu and L. Xeauyin, **Human translation vs machine translation: The practitioner phenomenology,** *Linguistics and Culture Review*, vol. 2, no. 1, pp.13-23, 2018.

[2] A. Fan, S. Bhosale, H. Schwenk, Z. Ma, A. El-Kishky, et al. **Beyond English-centric multilingual machine translation,** *The Journal of Machine Learning Research*, vol. 22. no. 1, pp. 4839-4886, 2021.

[3] S. Huang, **Design and development of educational robot teaching resources using artificial intelligence technology**, *International Journal of Emerging Technologies in Learning (IJET)*, vol. 16, no. 05, p. 116, 2021.

[4] B. Yi and D. Mandal, **English teaching practice based on AI technology**, *Journal of Intelligent and Fuzzy Systems*, vol. 37, no. 1, pp. 1–11, 2019.

[5] L. Yu and N. Peng, **Research on English teaching reform based on artificial intelligence matching model**, *Journal of Intelligent and Fuzzy Systems*, no. 1, pp. 1–10, 2021.

[6] J. Zhang, and C. Zong, **Neural machine translation: Challenges, progress, and future,** *Science China Technological Sciences*, vol. 63, no. 10, pp. 2028-2050, 2020.

[7] P. Lohar, G. Xie, D. Gallagher, and A. Way, **Building Neural Machine Translation Systems for Multilingual Participatory Spaces,** *Analytics*, vol. 2, no. 2, pp. 393-409, 2023.

[8] E. De Vries, M. Schoonvelde, and G. Schumacher, **No longer lost in translation: Evidence that Google Translate works for comparative bag-of-words text applications,** *Political Analysis*, vol. 26, no. 4, pp. 417-430, 2018.

[9] I. Rivera-Trigueros, **Machine translation systems and quality assessment: a systematic review,** *Language Resources and Evaluation*, vol. 56, no. 2, pp. 593-619, 2022.

[10] J. Su, J. Zeng, D. Xiong, Y. Liu, M. Wang, and J. Xie. **A hierarchy-to-sequence attentional neural machine translation model,** *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 26, no.3, pp. 623-632, 2018.

[11] B. Klimova, M.Pikhart, A. D. Benites, C. Lehr, and C. Sanchez-Stockhammer, Neural **machine translation in foreign language teaching and learning: a systematic review,** *Education and Information Technologies*, vol. 28, no.1, pp. 663-682, 2023.

[12] S. Wu, D. Zhang, Z. Zhang, N. Yang, M. Li, and M. Zhou. **Dependency-to-dependency neural machine translation,** *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 26, no.11, pp. 2132-2141, 2018.

[13] B. Zhang, De. Xiong, and J. Su, **Neural machine translation with deep attention,** *IEEE Transactions on pattern analysis and machine intelligence*, vol. 42, no.1, pp. 154-163, 2018.

[14] S. Ranathunga, E. A. Lee, M. P. Skenduli, R. Shekhar, M. Alam, R. Kaur, **Neural machine translation for low-resource languages: A survey,** *ACM Computing Surveys*, vol. 55, no.11, pp. 1-37, 2023.

[15] S. Maruf, F. Saleh, and G. Haffari, **A survey on document-level neural machine translation: methods and evaluation,** A*CM Computing Surveys (CSUR)*, vol. 54, no. 2, pp. 1-36, 2021.

[16] B. Yi and D. Mandal, **English teaching practice based on AI technology,** *Journal of Intelligent and Fuzzy Systems*, vol. 37, no. 1, pp. 1–11, 2019.

[17] W. Che, Z. Yu, Z. Yu, Y. Wen, and J. Guo, **Towards integrated classification lexicon for handling unknown words in Chinese-Vietnamese neural machine translation,** *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)*, vo. 19, no. 3, pp. 1-17, 2020.

[18] S. Shi, X. Wu, R. Su, and H. Huang, **Low-Resource Neural Machine Translation: Methods and Trends,** *ACM Transactions on Asian and Low-Resource Language Information Processing*, vol. 21, no. 5, pp. 1-22, 2022.

[19] M. Sepesy and M. J. Brest, **Slavic languages in phrase-based statistical machine translation: a survey,** *Artificial intelligence review*, vol. 51, no.1, pp. 77-117, 2019.

[20] S. K. Mahata and D. Das, S. Bandyopadhyay, **Mtil2017: Machine translation using recurrent neural network on statistical machine**

translation, *Journal of Intelligent Systems*, vol. 28, no. 3, pp. 447-453, 2019.

[21] K. Ralph, **Some Translation Studies informed suggestions for further balancing methodologies for machine translation quality evaluation,** *Translation Spaces*, vol. 11, no. 2, pp. 213-233, 2022.

[22] M. Kolhar and A. Abdalla, **Artificial Intelligence Based Language Translation Platform**, *Intelligent Automation & Soft Computing, vol.* 28, no. 1, pp.1-9, 2021.

[23] Z.A. Cahyaningtyas, D. Purwitasari, C. Fatichah, **Deep Learning Approaches for Automatic Drum Transcription**, EMITTER International Journal of Engineering Technology, vol. 11, no. 1, pp. 21-34, 2023.

[24] V. H. Vu, Q. P. Nguyen, K. H. Nguyen, J. C. Shin, and C. Y. Ock, **Korean-Vietnamese neural machine translation with named entity recognition and part-of-speech tags,** *IEICE TRANSACTIONS on Information and Systems*, vol. 103, no. 4, pp. 866-873, 2020.

[25] M. Zheng, **Research on Intelligent English Translation Methods Based on Improved Attention Mechanism Models,** *Electronic Technology*, vol. 33, no. 11 pp. 84-87, 2020.

[26] J. Li and F. Yang, **Text level Machine translation based on joint attention mechanism,** *Chinese Journal of Information Technology*, vol. 33, no.12, pp. 45-53, 2019.