Artificial Intelligence Translation: Technological Evolution, Challenges, and New Pathways for Human-Machine Collaboration

Boyang Liu* and Huiying Yang

School of Foreign Languages, Northwestern Polytechnical University, Xi'an, China
Email: liuboyang@mail.nwpu.edu.cn (B.L.)
*Corresponding author
Manuscript submitted November 26, 2025; accepted March 11, 2026; published June 16, 2026.

***Abstract*—With the advancement of computer technology, Artificial Intelligence (AI) translation has progressed from rule-based approaches into the era of Large Language Models (LLMs). This paper systematically reviews the evolution of AI translation technology, tracing its journey from Rule-Based Machine Translation (RBMT) and Statistical Machine Translation (SMT) to Neural Machine Translation (NMT). It analyzes the application advantages of these technologies while highlighting the challenges they face. Research indicates that the human-machine collaboration model, through pre-translation instructions and post-editing, effectively combines human intelligence with machine efficiency. This model reveals a future trend towards more intelligent and deeply integrated collaborative development in AI translation. It represents the optimal solution for balancing translation quality, efficiency, and cost, pointing the way forward for the translation industry and offering new perspectives for enhancing translators' practical skills and professional competitiveness.**

***Keywords*—artificial intelligence translation, pre-translation instructions, post-editing, human-machine collaboration**

I. Introduction

With the continuous progress of computer technology, translation is undergoing a comprehensive shift from human translation towards Artificial Intelligence (AI) translation. AI translation leverages computers to convert one natural language (source language) into another (target language). In recent years, advancements in algorithms and computational power, coupled with the widespread use of Large Language Models (LLMs) trained on massive volumes of high-quality text—with parameters scaling into the billions or even trillions—have reshaped the field. LLMs possess formidable capabilities in language understanding and generation [1], enabling them to perform various tasks, including translation, based on instructions. The emergence of LLMs has ushered machine translation into a new era. Technologies like big data, cloud computing, and deep learning have profoundly impacted the language services industry, making translation technology increasingly intelligent and significantly enhancing the quality and efficiency of translation work [2]. Therefore, in-depth research into the technological evolution, current applications, and development trends of AI translation holds significant practical and academic value for improving translation practice and refining translation theory.

II. The Evolution of Artificial Intelligence Translation

A. Rule-Based Machine Translation (RBMT)

As the early form of AI translation, RBMT was widely used from the 1940s to the 1980s. RBMT primarily relies on linguists' expertise and experience, constructing detailed bilingual dictionaries and formulating grammatical rules to guide the computer in converting source language to target language. The translation process involves analyzing the source sentence's grammatical structure, translating words/phrases via dictionaries and rules, then reassembling them into the target text. Its workflow strictly depends on rules written by linguists and programmers—for example, English-Chinese translation requires adhering to numerous rules for grammatical structures and part-of-speech conversion. However, natural language exhibits high flexibility and complexity, creating a significant contradiction between the limited nature of rules and the infinite variety of linguistic phenomena. Faced with idioms, metaphors, ambiguous sentences, etc., RBMT often fails to handle them accurately, leading to semantic deviations and unnatural expressions in the output. For example, translating "It's a piece of cake" might losing its idiomatic meaning of "very easy".

Rules struggle to handle linguistic flexibility, complex structures, and culture-loaded terms—for instance, the contrast between English's analytic structure and Chinese's paratactic nature. Additionally, translation direction introduces challenges: converting morphologically rich languages (e.g., German) to analytic ones (e.g., English) risks errors in handling inflections, while the reverse demands overly comprehensive rules to cover all inflectional variations. This limitation made RBMT difficult to satisfy diverse translation needs in practical applications, leading to its gradual replacement by newer technologies.

B. Statistical Machine Translation (SMT)

The emergence of SMT in the 1990s marked a new stage in AI translation development. Based on probability theory and statistical principles, SMT abandoned RBMT's reliance on manually crafted rules. Instead, it calculated the most probable translation by analyzing the co-occurrence frequencies and probabilistic relationships between words and phrases in vast parallel corpora. Compared to RBMT, SMT could produce more fluent translations for common expressions, improving translation efficiency to some extent.

However, as SMT lacks an understanding of linguistic semantics and logic, relying solely on probabilities, it is prone to errors when dealing with specialized domain texts and complex sentence structures.

The statistical models of SMT are highly dependent on the quality and coverage of parallel corpora. For resource-poor language pairs (e.g., English↔Swahili) or specific professional fields (such as certain language combinations in law and medicine), the scarcity of corpora makes it difficult for the models to learn accurate probability distributions, resulting in a sharp decline in translation quality. The direction of translation is also crucial: translations from resource-rich languages (e.g., English) to resource-poor languages (e.g., many African languages) (EN→XX) are generally of much higher quality than the reverse (XX→EN), as the latter lacks sufficient target language (English) modeling data. In literary translation, SMT is particularly poor at handling the unique prosody, rhythm, and stylistic features specific to different language pairs.

C. Neural Machine Translation (NMT)

Since around 2010, Neural Machine Translation (NMT) based on deep learning has triggered revolutionary changes in the AI translation field. NMT employs neural network architectures, which can effectively capture long-range dependencies and semantic information. In the translation process, NMT encodes the source sentence into a continuous vector representation, which the decoder then uses to generate the target translation step-by-step. This end-to-end learning approach enables NMT to learn language patterns and semantic relationships comprehensively, producing translations with contextual awareness. Compared to SMT, NMT has shown significant improvements in translation quality. In translating texts like news reports and everyday conversations, the fluency and accuracy of its output have approached or even surpassed human levels in many cases, and it demonstrates notable advantages in areas such as political and economic translation.

However, the advantages of NMT are not uniform across different language pairs and translation directions. For structurally similar, resource-rich language pairs (e.g., English ↔ French), NMT performs exceptionally well; yet for genetically distinct, resource-poor language pairs (e.g., English ↔ Chinese, English ↔ Arabic), its performance may be significantly compromised. When handling Chinese-to-English translation (ZH→EN), NMT may struggle to preserve the paratactic logic and conciseness of the original Chinese text, tending to produce verbose English with Westernized structures. Conversely, in English-to-Chinese translation (EN→ZH), accurately conveying the complex clause embedding and tense logic of English while conforming to Chinese's expressive conventions—characterized by flowing short sentences and temporal sequencing—remains a challenge. Furthermore, the difficulty of achieving cross-linguistic equivalent transmission of specific stylistic features (e.g., the rigor and formality of legal texts vs. the liveliness and creativity of advertising copy) and tone characteristics (e.g., formality, sarcasm, humor) varies significantly depending on the language pair and translation direction.

III. Current Status and Challenges of AI Translation

A. Application Advantages and Challenges

Currently, mainstream AI translation engines, such as ChatGPT and DeepSeek, possess formidable computational power and advanced algorithmic models, demonstrating significant advantages in the translation domain. In terms of efficiency, AI translation can process large volumes of text in a short time, far exceeding the speed of human translation. For example, AST Language Services' 2025 white paper notes that for a 10,000-word corporate annual report, mainstream AI tools typically generate a first draft in 5–15 min, whereas human translation requires 2–5 working days (based on a daily output of 2000–3000 words). Regarding quality, for general texts, AI translations achieve acceptable levels of fluency and basic accuracy, meeting the needs of daily communication and general information access, providing users with a convenient cross-lingual communication tool. In terms of usage, AI translation is increasingly integrated into international communication scenarios like media production, official document releases by international organizations, and digital diplomacy [3]. Furthermore, the vast majority of the Associated Press's Spanish-language articles use machine translation [4]; during the Rio Olympics, the New York Times saw significant traffic increases for its Spanish and Portuguese reports generated via Google Translate [5]. Leveraging machine translation technology, the efficiency and breadth of acquiring, producing, and disseminating massive amounts of content in different languages have multiplied. These instances all indicate that AI translation is becoming a "new driving force" activating global information flow [6].

However, the explosive growth of AI translation technology, while enhancing cross-lingual efficiency, has also triggered multiple structural contradictions. Extreme instability in translation quality remains a core pain point. Data monopolies exacerbate the Matthew effect within the translation industry. Globally, 92% of NMT model training relies on English-centric multilingual corpora [7], while low-resource languages, such as Swahili in Africa, have available data volumes less than 0.3% of English's. This enables tech giants to form a kind of "digital colonialism" through corpus barriers, causing the market share of small and medium-sized language service providers to shrink to 6.7% [8]. This data gap directly leads to severe imbalances across language pairs: the translation quality of high-resource language pairs (e.g., English-French, English-German) continues to improve and remains relatively stable; in contrast, the quality of low-resource language pairs (e.g., English-local African languages, translations between minor languages) has long remained stagnant, with high error rates and rigid styles. Imbalances in translation direction also persist: translations from high-resource to low-resource languages (e.g., EN→SW) are generally of higher quality than the reverse (SW→EN). For translation tasks requiring specific stylistic features (such as the rhythm of poetry) and subtle tones (such as veiled warnings in diplomatic language), the quality

discrepancies caused by such resource inequality are particularly fatal. Infringement risks are also frequently present: disputes over the ownership rights of OpenAI's translation outputs (input text copyright vs. output content generator) have already triggered over a dozen lawsuits in the US and Europe [9]. Therefore, despite rapid development, AI translation still faces numerous challenges: significant disparities in translation quality, copyright ownership issues, and the legal acquisition, annotation, and use of training data, among others.

B. AI Translation Performance in Literary Translation

Despite NMT reaching human-level performance in general domains, its performance in specialized scenarios is concerning, particularly in literary translation across diverse language pairs and directions. The challenges are magnified when the source and target languages belong to vastly different cultural and linguistic systems (e.g., Chinese↔English), or when translating from a morphologically rich language to an analytic one (or vice versa). In fact, even before AI entered literary translation, the process of human cultural dissemination always involved retranslation, with many Chinese translations of famous foreign works having several or even dozens of versions. The essence of translation lies in its nature as a creative practice—it serves as a medium that accumulates cultural genes through cross-lingual transference, allowing ancient classics, folk wisdom, etc., to endure through symbolic conversion. High-quality human literary translations express the linguistic and cultural factors of the target language in a specific era while respecting the heterogeneity of the source text, thus possessing "historicity" [10]. Taking Lao She's classic Camel Xiangzi (Rickshaw Boy) [11] as an example, different human English translations each have their unique characteristics in conveying the original work's literary charm and cultural connotations.

Comparing classic human translations from different periods, such as Howard Goldblatt's version [12] and Jean M. James's version [13]: Goldblatt's translation is smooth and natural, conforming to English narrative conventions; James's translation adheres more closely to the literal structure of the original. Both versions embody "historicity" with distinct features. In contrast, an AI translation like "The person we are going to introduce is Xiangzi, not Camel, because 'Camel' is just a nickname," while accurately conveying literal information, lacks insight into cultural context and literary creativity. It fails to capture the Beijing dialect tone and cannot convey Xiangzi's aspirations or Lao She's critical edge.

This case highlights the core dilemmas of AI in handling literary translation for specific language pairs (Chinese-English): it struggles to capture the unique narrative rhythm inherent to Chinese, convey complex emotional tones like sarcasm and compassion, and interpret the symbolic meaning of cultural imagery such as "camel".

The direction of translation also matters: Translating texts with unique cultural loads and expressive conventions (such as Chinese classical literature) into English (ZH→EN) generally involves greater difficulty and more pronounced weaknesses in AI performance compared to translating English literature into Chinese (EN → ZH). Therefore, AI translation can serve as an auxiliary tool, providing drafts and terminology references, but its limitations in literariness, cultural sensitivity, and creativity make it difficult to independently shoulder the responsibility of conveying the essence of the original work. Translation studies should continue to explore how to better integrate the translator's subjective wisdom with AI's efficiency.

IV. The Development Trend of Human-Machine Collaboration in AI Translation

As AI technologies advance toward artificial general intelligence [14], the human-machine collaboration model in translation has taken shape: machine translation systems quickly generate first drafts, which human translators then post-edit as needed. This approach ensures quality while drastically shortening delivery cycles [15]. The essence of this transformation lies not in technology replacing or merely assisting humans, but in redefining the value coordinates of human intelligence and technological systems within language conversion. As machines handle the surface structure of language on an unprecedented scale, humans are freed from repetitive tasks to focus on the more creative dimensions of translation. In this synergistic development process, pre-translation instructions and post-editing have become indispensable components.

A. The Importance of Pre-Translation Instructions

Faced with the problems inherent in AI translation, the human-machine collaboration model is an inevitable trend in translation development. Pre-translation instructions, as a crucial link in this model, play a key guiding role throughout the translation workflow. Before using an AI translation tool, translators need to leverage their professional knowledge and experience to provide the machine with detailed background information, specific translation requirements, and terminology guidelines—for instance, specifying specialized terminology for political or economic articles, or clarifying contextual details like Camel Xiangzi's 1930s Beijing setting and Lao She's linguistic style for literary works.

Given the significant impact of language pairs and translation directions, pre-translation instructions must be highly targeted. For highly challenging language pairs (e.g., English-Chinese), instructions need to more elaborately specify how to handle specific structural differences, strategies for culture-loaded words, and stylistic conventions expected by target language readers. The translation direction also needs clarification, as the focus of instructions for EN→ZH and ZH→EN may differ. Additionally, for specific genres and tones, instructions should explicitly require AI to prioritize relevant stylistic features and preserve the original tone.

Therefore, appropriate pre-translation instructions can significantly enhance the "cultural intelligence" and linguistic quality of machine translation. By setting reasonable pre-translation instructions, errors caused by missing information can be reduced, making the generated draft more aligned with actual needs and laying a solid foundation for subsequent translation work. However, it is important to note that even optimized drafts still require

final human calibration.

B. The Core Value and Operational Methods of Post-Editing

With the proliferation of machine translation and tools like ChatGPT, "post-editing has become an indispensable step". This human-machine combination merges the efficiency of machine translation with the high quality of human revision, fully leveraging the respective advantages of both [16]. Post-editing is the core step for ensuring translation quality. Its connotation has evolved from the early simple "error correction" to the current key process of "quality optimization and value enhancement". Consequently, it is emphasized that the translation market now needs higher-level translators, especially expert translators equipped with domain-specific knowledge and capable of finalizing and approving translation quality [17].

Post-editing requires the application of multiple strategies and tools. Translators must ensure the accuracy and consistency of term translation by referencing specialized terminology databases and client-provided glossaries; reconstruct sentence structures and restore logical chains to correct syntactically distorted or logically incoherent translations, adjusting to target language habits; keenly identify culture-loaded words and handle cultural and pragmatic errors through appropriate adjustments or cultural conversion based on target context and reader expectations.

The depth and strategies of post-editing are highly dependent on language pairs, translation directions, and text types. Key to efficient post-editing is identifying and correcting common error patterns of AI in specific language pairs—such as overusing "被" (bei) constructions in English-to-Chinese translation or making subject-verb agreement errors in Chinese-to-English translation. Sensitivity to tonal characteristics (e.g., identifying and rectifying attenuated sarcasm, irony, or intense emotions that AI may weaken) is particularly crucial in translations of literature, film/TV subtitles, marketing copy, etc. Additionally, translators need to refine the translation style to match client-specified requirements and bear the important responsibility of ethical review, maintaining vigilance against biases and cultural stereotypes in AI output to ensure the cultural and value correctness of the translation.

C. Advantages and Development Prospects of the Human-Machine Collaboration Model

In light of this, we need to update our conception of translation. We should not only view translation practice as a simple sign-conversion activity but also establish a new perspective that sees translation as an important means of achieving cultural mutual learning, generating new knowledge, disseminating ideas, and sharing values. Our goals should extend beyond improving the quality of a single text; we must equally emphasize composite translation objectives and multiple translation values, such as enhancing text quality, enabling the production of high-quality bilingual corpora, promoting cultural communication, shaping values, and facilitating knowledge production and reproduction [18]. Under the human-machine collaboration model, the professional expertise, critical thinking, and creativity of human translators perfectly merge with the speed and scale advantages of AI. Human translators can compensate for AI's shortcomings in semantic understanding, cultural perception, logical reasoning, and stylistic shaping, while AI saves translators significant time and effort spent on basic translation tasks. This model achieves the optimal balance between translation quality, efficiency, and cost, becoming the inevitable trend for the future development of the translation industry. With continuous innovation in neural machine translation technology, ongoing optimization of LLMs, and the increasing maturity of best practices in post-editing, the human-machine collaboration model will develop towards greater intelligence and depth. In the future, AI translation tools may possess stronger contextual understanding and learning capabilities, automatically optimizing translation results based on translator feedback. Translators, aided by more advanced technological tools, will achieve more efficient and precise translation work, bringing new development opportunities and transformations to the language services industry.

V. Conclusion

By reviewing the development history of artificial intelligence translation technology, analyzing its status and challenges, and exploring the development trends of human-machine collaboration, this paper points out that despite the notable progress made in AI translation technology, its core challenges and limitations in terms of effectiveness and application are largely profoundly constrained by specific language pairs and directionality.

Structural differences between different linguistic systems (such as grammar, word order, and morphology), cultural gaps, and the abundance of available resources collectively determine the performance ceiling of AI models when handling specific language conversions. Meanwhile, translation directionality (e.g., English-to-Chinese vs. Chinese-to-English) also presents unique sets of challenges. These factors intertwine with the stylistic genres of texts (literary, technical, legal, etc.) and tone characteristics (formal, humorous, sarcastic, etc.), exposing AI to complex and varied obstacles in its pursuit of semantic accuracy, stylistic equivalence, and emotional conveyance. Human-machine collaboration models, through links such as pre-translation guidance and post-editing, realize the organic integration of human wisdom and machine efficiency, and can be regarded as the optimal solution for balancing translation quality, efficiency, and cost. For translators, in-depth learning and mastery of AI translation technology and human-machine collaboration models can not only enhance their practical translation skills and professional competitiveness but also help them better adapt to the development needs of the translation industry in the new era.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Boyang Liu wrote the paper; Huiying Yang was

responsible for revising the paper; both authors had approved the final version.

FUNDING

This research was funded by Shaanxi Social Science Foundation, grant number 2023K022.

REFERENCES

[1] E. Pavlick, "Semantic structure in deep learning," *Annu. Rev. Linguist.*, vol. 8, 2022.
[2] H. Wang and Z. Li, "A survey on the application of translation technology by translators in the age of artificial intelligence: Status quo, findings, and suggestions," *Technol. Enhanc. Foreign Lang. Educ.*, no. 6, 2019.
[3] Q. Li, "Research on AI empowerment and impact from the perspective of the publishing industry," *Sci.-Technol. Publ.*, no. 2, 2024.
[4] F. Marconi, *Newsmakers, Artificial Intelligence and the Future of Journalism*. New York: Columbia Univ. Press, 2020.
[5] B. Jones, R. Jones, and E. Luger, "AI 'everywhere and no-where': Addressing the AI intelligibility problem in public service journalism," *Digit. Journalism*, 2022.
[6] S. Liu, "Artificial intelligence translation and international communication: Status quo, problems and prospects," *Foreign Lang. Res.*, no. 3, 2025.
[7] WIPO. (2025). Transformation of the translation labor market. p. 15. [Online]. Available: https://www.wipo.int/portal/en/index.html
[8] CSA Research. (2024). Language technology market concentration report. [Online]. Available: https://csa-research.com/Blogs-Events/Data-Center
[9] Stanford HAI. (2025). Liability avoidance in AI terms of service. [Online]. Available: https://hai.stanford.edu/
[10] X. Yuan and Q. Luo, "Artificial intelligence and the future of literary translation: Reflections based on comparative studies of human and machine literary translation," *Foreign Lang. Their Teach.*, no. 2, 2025.
[11] S. Lao, *Camel Xiangzi*. Chengdu: Sichuan People's Publishing House, 2019.
[12] S. Lao, *Rickshaw Boy*, H. Goldblatt, Trans. New York: Harper Collins Publishers, 2010.
[13] S. Lao, *Rickshaw: The Novel Lo-t'o Hsiang Tzu*, J. M. James, Trans. Honolulu: The Univ. Press of Hawaii, 1979.
[14] M. Peeters *et al*., "Hybrid collective intelligence in a human-AI society," *AI Soc.*, no. 1, 2021.
[15] S. Wang and Y. Zhu, "When translation meets the metaverse: An analysis of the translation practice landscape in the digital society," *J. Beijing Int. Stud. Univ.*, vol. 45, no. 2, pp. 33–47, 2023.
[16] X. Wang, X. Li, and G. Chen, "A comparative study of human translation revision and machine translation post-editing: Evidence from keystroke logging, retrospection and questionnaires," *Foreign Lang. Learn. Theory Pract.*, no. 5, pp. 88–97, 2024.
[17] W. Zhang, "Challenges and solutions for translation programs in the age of artificial intelligence: Analysis based on a large-scale social survey," *Chin. Transl. J.*, vol. 45, no. 5, 2024.
[18] W. Ren, "Translation practice and education in the era of generative artificial intelligence: From instrumental action to communicative action," *Chin. Transl. J.*, vol. 45, no. 6, 2024.