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# Trends and Divergences in Computational Translation Studies: A Bibliometric Analysis Using CiteSpace

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**Abstract**

This study aims to examine the most dominant aspects of computational translation studies in China and the broader international translation community with the help of CiteSpace. The primary issue addressed in this study is the divergence in research trends between Chinese academia and the global community in computational translation. This study employs CiteSpace to identify the most popular topics in computational translation studies in China and obtain an objective overview. Subsequently, it reviews 40 high-quality papers in the field to reveal the current state of research. The methodology adopted in this study involves bibliometric analysis using CiteSpace, which allows for identifying significant trends in computational translation studies. The findings indicate that contemporary research emphasizes neural networks, machine translation, and post-editing. Furthermore, there is a noticeable divergence in research interests between Chinese scholars and the international academic community. A key finding is that developing new neural models is currently a popular research focus. This study aspires to provide a clear overview of current research trends in computer-based translation studies and to identify potential areas for future exploration. By doing so, it aims to serve as a valuable guide for researchers seeking to understand the landscape of computational translation studies and to investigate emerging aspects of this ever-evolving field further.

**Keywords**: *CiteSpace, Computational translation studies, Literature review*.

## A. Introduction

The field of translation studies is well-known for its flexibility as it constantly evolves together with the development of broader society (Munday, Pinto, & Blakesley, 2022). In the distant past, translation was merely a sub-field of linguistics, where ancient translators engaged in lengthy debates on whether to preserve the form or the message of the original texts, relying solely on experience and practice. However, over the past centuries, it has grown from a branch of pure linguistics into a dynamic discipline, incorporating concepts from fields such as culture and economics, each contributing to its expansion (Jiang & Zhang, 2024). This is also why it has earned the nickname “杂学” in China, which means “the study of many aspects” (Yao & Zhao, 2017).

Thus, when computer science—particularly statistics—emerged as a distinct field, it was no surprise that the translation studies community integrated it as early as the 1950s (Lopez, 2008). This shift empowered researchers to explore the discipline in more sophisticated ways. Today, translation studies are increasingly intertwined with computer science, and recent years have witnessed a surge in papers on computer-oriented translation studies (Li, Feng, & Huang,

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2021). This growing trend is driven by significant technological advancements, including the development of increasingly large translation corpora (Wang, Liao, Peng, Li, & Yin, 2021), the emergence of large language models (LLMs), and the evolution of neural machine translation (NMT) tools, which have introduced a new dimension to research by using machine-generated texts as subjects of study (Dai & Liu, 2023). Some researchers have referred to this shift as the "technological turn" in translation studies (Ren, 2020).

This new point of interest has injected fresh momentum into translation studies, fostering the growth of new research fields. Post-editing, which plays a crucial role in the translation industry, has gained unprecedented attention thanks to the introduction of advanced machine translation tools (Nitzke & Hansen-Schirra, 2021). LLMs now serve as the latest form of machine translation, producing high-quality outputs at remarkable speeds (Jia, 2024). Automated evaluation of translations has also become widespread, allowing for more efficient quality assessments (Jiang & Zhang, 2024). These innovations collectively redefine the field and broaden its research landscape.

Unsurprisingly, the rapid expansion of computational translation studies has resulted in a dense body of research, resembling a complex maze where scholars may struggle to discern the current status of the field due to the overwhelming number of publications released each year (Hou & Hou, 2019). Additionally, many of these studies suffer from quality concerns, as they often lack innovation and contribute little to the field's advancement (Li, 2021).

This is where the present study aims to contribute. It seeks to help researchers gain an objective and accurate understanding of the most significant developments in computational translation studies. To achieve this goal, China's most prominent academic database, CNKI (https://www.cnki.net), along with CiteSpace, is employed to identify the most prevalent research areas within computational translation studies. High-quality papers in these areas are then carefully reviewed. The findings of this study are expected to provide readers with a clearer understanding of the field's current state and inspire future research directions (Feng & Zhang, 2022).

## B. Methods

This study seeks to present an objective overview of the current landscape of the most important areas of computational translation studies. To capture the forefront of research in computational translation studies, this study utilized the CNKI database, which includes virtually all published academic works in China. The search was conducted using the keywords "计算机" and "翻译" (computer and translation), ensuring that relevant studies were retrieved. To maintain the quality of the study, the search results were refined by selecting only core publications from 2019 onward, resulting in approximately 500 papers. The retrieved articles were then exported into CiteSpace, which generated a thematic map based on the frequency of topic occurrences (Figure. 1).

Given that the articles analyzed in CiteSpace were written in Chinese, the generated thematic map was also in Chinese. The six most prominent topics identified were: 神经网络 (neural networks), 机器翻译 (machine translation), 译后编辑 (post-editing), 翻译教学 (translation teaching), 虚拟现实 (virtual reality), and 翻译转换 (translation shifts), ranked by popularity. These findings align with prior research emphasizing the increasing role of neural networks and deep learning in translation (Li et al., 2020; Niu, Zhong, & Yu, 2021; Wang et al., 2021). To ensure a focused and in-depth investigation, this study concentrated on the top three topics: neural networks, machine translation, and post-editing, which are also among the most widely discussed areas in recent computational translation literature (Dai & Liu, 2023; Hu et al., 2024).

After determining the main research topics, the study identified the most representative papers within each field. The 500 articles were ranked by citation count, a standard metric to assess academic influence (Jia & Sun, 2022). From this, 40 high-quality papers were selected for further analysis. The most frequently cited papers within each category were carefully reviewed, and their core findings are reported in the following sections. The significance of post-editing in machine translation has been extensively discussed in previous studies (Carmo et al., 2021; Geng & Hu, 2023), highlighting the necessity of human intervention to improve machine-generated translations. Additionally, the increasing integration of neural machine translation (NMT) models with artificial intelligence has been noted in Chinese and international research (Liang & Liu, 2023; Shi et al., 2020). Several high-quality foreign studies were also reviewed to provide a comprehensive perspective, as they offer valuable insights that are sometimes underrepresented in Chinese translation research (Chollampatt et al., 2020; Munday, Pinto, & Blakesley, 2022).


**Figure 1.** Thematic Map of Computational Translation Studies Based on CiteSpace Analysis

## C. Findings and Discussion

The above figure shows that neural networks, machine translation (MT), and post-editing are the most prevalent research topics in computational translation studies. With that in mind, this study searched Google Scholar and CNKI with the names of those topics plus "translation," respectively, for the neural network and translation. Over 100 papers were reviewed, and 40 representative ones were cited. The three topics are then discussed in the following subsections.

### 1. Literature Review on Studies Regarding Neural Networks

This realm of translation studies mainly concerns neural network models – the essential component of neural machine translation (NMT), a widely applied form of machine translation. It is worth noting that, though some considered NMT outdated in the face of LLM, NMT is still a potent form of MT since the quality of LLM translations varies greatly depending on the prompt and training materials the LLM received. At the same time, NMT conveniently generates products of stable quality. (Jiang and Zhang, 2024).

From the basics, Hou and Hou (2019) generalized three ways a neural network could be created based on how information is processed. They are rule-based, corpora-based, and mixed. According to their study, there is no simple solution for building a neural network, and each of the three ways prevails under different circumstances. For instance, the rule-based neural networks performed better in low-resource environments, and corpora-based networks won in high-resource language pairs. They paved the way for future research on this subject.

Other studies with this theme are more profound and technical and usually concern innovating NMT models in various ways. Ren (2020) is a case in point. This study proposed using residual and LSTM (Long Short Term Memory) neural networks to improve translation teaching. The author believed that this form of neural network scored the "highest level of satisfaction in practical teaching evaluation" as it learned translation features from teachers and students. Similarly, Wang, Liao, Peng, Li, and Yin (2021) also pointed to LSTM's strength in improving the performance of NMT. Another heated topic of study is the recurrent neural network (RNN). According to Liu and Yu (2019), this is a kind of neural network capable of memorizing, hence its advantage in voice recognition and natural language processing. Liu and Yu explained the underlying principles of this kind of neural network and concluded that applying this model in NMT could enhance the quality and efficiency of translation. A year after Liu and Yu's study, Wang and Yan (2020) made a more penetrating research regarding RNN. Their experiments revealed that, compared to linear translation models, RNN models' BLEU score is 1.51-1.86 higher, demonstrating its strength over traditional NMT models.

Another point of interest in neural networks is the model of attention. Inspired by human biological systems, this is the deep neural network's ability to focus on certain parts of information while processing data (Niu, Zhong & Yu, 2021). In this regard, Shi, Wang, Cheng, and Wei (2020) generalized the underlying principles of the attention model and concluded that the attention model can be mainly used for text classification in natural language processing. In order to explore the depth of natural language processing, Gao, Su, Niu, Zhao, and Fan (2020) used a transformer-based multi-head attention neural network to approach Mongolian-Chinese translation. The results were impressive, with a BLEU score 9 points higher than a LSTM model.

Finally, some studies are concerned with improving the performance of neural networks in low-resource language pairs. The problems of neural networks in this aspect tend to be incorrect grammar, and a solution could be unsupervised machine translation (Hu, Ye, Zhang & Cai, 2024). Another solution is to "filter" the training materials for the neural network and create "pseudo parallel texts" by back-translation (Zhao et al., 2019). This is echoed by Li, Feng, and Huang (2021), where different ways of enhancing neural networks were compared.

## 2. Literature Review on Studies Regarding Machine Translation

This is a relatively old topic of research in comparison with the neural network, and it was listed in China's strategic plans for scientific development as early as 1957 (Yao & Zhao, 2017). In recent decades, MT has evolved from the initial rule-based approach to statistical MT to the more sophisticated NMT and LLM (Okpor, 2014; Lopez, 2008). Today, the prevalent forms of MT are NMT and LLM, and to distinguish between sections 2.1 and 2.2, this section will not engage in neural networks as a single component of NMT but MT as a whole, including both NMT and LLM.

For starters, there are studies relating to the impact of MT use on students or professionals, though this kind of study is declining in number. Wu's (2024) study found that low- to middle-degree assistance from MT is more beneficial to middle- and high-level English students, and a high-degree reliance on MT is not helpful for all students. Following a different design, Lee (2020) showed that students learning English who corrected their assignments with the help of MT after they had done them independently scored better writing outcomes with fewer lexicogrammatical errors. Some studies also claimed that existing MT tools can be improved to better support students (Urlaub & Dessein, 2022).

Most research in MT is more practical and question-oriented. Classically, they often begin with a question in mind and tamper with MT in one way or another to see how the outcome changes. This kind of study dominates research in this direction. For example, Zhou, Duan, Yu, and Zhang (2021) proposed a "knowledge distillation" method to compress enormous NMT models into simple, flexible ones for better performance. Similarly, Li, Li, Liu, and Zhang (2020) also proposed a new way of knowledge distillation without sacrificing prediction accuracy, which often accompanies high-ratio compression.

Many studies also concern the comparison between MT products and human translations. For instance, Liang and Liu (2023) established two corpora consisting of MT and human translations and compared them with statistics software to see where divergences lie. They concluded that human translators have an edge in precise bilingual conversion using context and general knowledge, reader-centered expression, textual coherence, and circumstance-appropriate language. Also pointing to MT's inadequacy is Li's (2021) study, where a comparison of five different online machine translation systems indicated that their products were acceptable but unsatisfactory. Likewise, it is also observed that MT is somewhat applicable in literary translation but could certainly be further improved (Qin, 2024). Researchers seem to agree that MT has made a huge step forward in terms of quality but still falls short of human translators in one way or another.

Approaching the end of this section, the most common type of MT research centers around the application of MT to deal with a specific task, and some applied MT in novel ways to facilitate this process. Wu, Wand, and Huang's (2024) study availed a tinkered MT to translate ancient Chinese agricultural books and build a corpus, which was then transformed into a map of ancient agricultural wisdom with the help of manual annotation. Bian (2024) researched the possibility of applying interactive MT in translating children's books and deemed that more extensive training data led to better translations and MT model performance. Furthermore, there are attempts to fine-tune MT so that it can be used to translate traditional Chinese idioms (Li & Hou, 2024).

Ultimately, some general papers do not touch on the technical aspect of MT. Wang (2024) believed that over-reliance on MT is detrimental to a range of parties, including students, teachers, readers, and professionals, and that MT could harm language diversity and student creativity. Thus, we must utilize MT cautiously to avoid risks. Dai and Liu (2023) generalized MT's development course and believed that MT could be further improved. Feng and Zhang (2022) also voiced the need for cooperation between MT and human translators.

## 3. Literature Review on Studies Regarding Post-editing

In a broad sense, post-editing is, in essence, a link in MT. However, given the large number of studies specializing in this regard, this study singled it out as an independent topic, and the preceding section pertains to direct MT in its pure form.

Core publications on post-editing in recent years are mainly prescriptive. There are only a handful of descriptive studies, for instance, Wang and Wang (2024), where four ways of measuring cognitive effort were theorized, echoing Munday's opinion that translation studies are in urgent need of descriptive research (Munday, Pinto, & Blakesley, 2022). Among them, a small number are concerned with post-editing teaching in universities or professional training. For instance, Zhong and Shu's (2020) research concerns university post-editing teaching. After analyzing post-editing teaching in foreign universities, their study divided the post-editing competence into pre-translation text processing ability, post-translation text processing ability, and general ability, and based on this, they sought to improve post-editing teaching in China in terms of teaching goals, teaching models and teaching design. Similar studies include Wang and Wang (2023)'s. In this study, the researchers proposed a novel post-editing teaching method involving ChatGPT, and their experiments showed that students who attended classes adopting this new design scored much better than those who did not. In the professional setting, attempts were made to apply ChatGPT to assist translators in post-editing (Jia, 2024), enhancing work efficiency.

An important part of post-editing is the research on cognitive load, which may relate to the difficulty in the post-editing process. This refers to the translator's mental working process during post-editing. For example, Wang and Wang (2024)'s research discussed the concept in detail, as well as the four main ways used to measure it. It then reflected the inadequacies present in existing studies on this topic and suggested ways of future improvement. Following a similar structure, Sun (2019) also clarified the definition of the term "cognitive load" before reviewing research into difficulties in post-editing and translation. Also relevant is Jia and Sun's (2022) study, where it is demonstrated that post-editing difficulty is mainly associated with the source text, the individual condition of the translator, and the tool applied in post-editing.

Missing in the domestic research community is the risk management in post-editing. With business implications, this topic mainly concerns possible risks the post-editing process may carry. Possible risks include data breaches, loss of control of processes, uncertain liability modalities, the translator's low opinion towards the post-editing model, and quality issues (Nitzke, Canfora, & Hansen-Schirra, 2019). The authors further refined their study and proposed a translation competence model, emphasizing translators' MT and post-editing capabilities(Nitzke & Hansen-Schirra, 2021).

Though counter-intuitive, studies exploring automatic post-editing abound. For instance, when asked to refine and improve the Chinese-English and English-Chinese translations it had done, ChatGPT performed extraordinarily in terms of Chinese-English translations but only performed not so impressively in English-Chinese translations (Geng & Hu, 2023). NMT's role in automatic post-editing is also recognized, boasting such advantages as cost-effectiveness and time-saving (Carmo et al., 2021). Another successful attempt at applying NMT to improve English-German translations is Chollampatt, Susanto, Tan, and Szymanska's (2020) research, which demonstrated with a corpus that NMT could enhance human translations.

## D. Conclusion

The field of computational translation studies was born out of the marriage between conventional translation studies and the development of computer technologies, which opened up new horizons for research. In this study, we reviewed the latest fruits in the three largest branches of computational translation studies to determine the current status. To ascertain the research hot spots in an objective manner, 500 core papers from the last 5 years concerning computational translation studies were exported from CNKI and put into CiteSpace for analysis, revealing the current research interest. Several quality studies in the corresponding fields at home and abroad were then obtained from CNKI and Google Scholar and reviewed.

Through careful study, it is evident that researchers in neural networks mainly focus on adjusting them in often deeply technical ways to improve performance. This could be achieved by adjusting the underlying model of NMT, adjusting how the network processes information, or simply more effectively availing training resources. RNN and other advanced neural models are a particularly popular research topic there. In the realm of machine translation, almost all studies were prescriptive. Some use MT for practical reasons in one way or another, for example, education, usually with a warning that over-reliance hinders the students' growth. Others frequently pertain to comparisons between humans and MT. Few descriptive studies were found. Regarding post-editing, research interest mainly relates to post-editing teaching, difficulty investigation, and automatic machine post-editing. Foreign researchers also delved into the risks involved in post-editing, which is lacking in the domestic academic community. Automatic post-editing is trending as well.

Another interesting finding is that, though academia is no stranger to LLM, NMT still holds relevance, as several studies focus on developing neural networks even after the emergence of LLM. The fact that papers concerning neural networks outnumber machine translation, which includes LLM, also testifies to this conclusion. Furthermore, the number of descriptive studies is dwarfed by the number of prescriptive studies, which is a shame. To conclude, research into neural networks is pretty advanced, with a staggering degree of complexity. Those in MT are now concerned with NTM and LLM and are not as technical. Many still follow an almost ancient pattern of translate-and-test. Regarding post-editing, a new trend of applying LLM and NMT to automate the process can be observed, and a certain amount of attention has been paid to teaching, just like MT. Under such circumstances, future research into computational translation studies may consider the following aspects: innovating neural networks to further NMT performance, novel ways of improving MT products, and automatic post-editing. Moreover, descriptive studies are always needed. This way, academia can establish a more advanced and balanced study framework.

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