The Impact of Technology on Human Translators and Translation Quality: *A Study on Machine Translation and Computer-Assisted Translation Tools*

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Received: January 28, 2024 Accepted: March 1, 2024 Online Published: March 4, 2024

doi:10.5430/elr.v13n1p19 URL: https://doi.org/10.5430/elr.v13n1p19

Abstract

This paper explores the influence of technology, especially computer-assisted translation (CAT) tools, on human translators and the quality of translated texts. the development of machine translation is reviewed, including advancements in neural machine translation (NMT), and various types of CAT tools such as translation memory (TM) systems and terminology management tools. The impact of technology on human translators is analysed, highlighting their evolving role in the digital age, and the effects on translation quality is examined. The article addresses the advantages and challenges associated with technology in translation, emphasizing the need for a balanced approach that combines the strengths of technology with the expertise of human translators.

Keywords: machine translation, computer-assisted translation, neural machine translation, translation memory systems, balanced approach

1. Introduction

The rapid advancement of technology, particularly in the field of language processing, has brought about significant changes in the translation industry. Machine translation (MT) and computer-assisted translation (CAT) tools have emerged as powerful resources that aid human translators in their work. This article aims to explore the impact of technology on human translators and the quality of translated texts, focusing on the use of machine translation and computer-assisted translation tools. By examining the advantages, challenges, and potential implications of these technologies, this study seeks to provide insights into the evolving role of human translators in the digital age and find a balanced approach that combines the strengths of technology with the expertise of human translators.

2. Literature review

2.1 Previous Studies on Machine Translation

Previous studies on machine translation have explored various aspects of the technology, including its development, performance evaluation, and impact on translation quality. Researchers have investigated the historical progression of machine translation, from rule-based systems to statistical and neural machine translation models. They have analyzed the strengths and limitations of different machine translation approaches and compared their performance in terms of accuracy, fluency, and adequacy.

Machine translation is one of the most prominent features of computer assisted translation according to Chen (2013). Zhu (2011) gave a systematic introduction to machine translation which is a real-time translation system that uses a machine (computer) system to transform the translation rules of human languages into computer algorithms, so that the computer can transform a natural source language into another natural target language according to the algorithms. Machine translation can be designed as a bilingual or multilingual translation system. Bilingual translation systems can be designed for one-way translation, such as Japanese to English, or two-way translation. And multilingual translation system can be designed to enable translation among multiple languages in both directions.

Machine translation systems are divided into rule-based, statistics-based, example-based and neural machine system. Dating back to 1993, Brown (1993) firstly introduced the concept of machine translation classification. He divided machine translation into rule-based translation and statistics-based translation. Rule-based machine translation systems can be further divided into three types: grammar-based, semantic knowledge-based and intelligent. Most of the machine translation systems in the world adopt rule-based strategies. The statistics-based machine translation

(SMT) approach considers machine translation as an information transmission process and explains it using a channel model. In SMT, the translation from the source language to the target language is seen as a probability problem, where any target language sentence could be a translation of any source language sentence, albeit with different probabilities. The task of machine translation is to find the sentence with the highest probability. The specific method involves treating translation as a decoding process, transforming the source text into the target text using a model.

On the other hand, the example-based machine translation (EBMT) approach, proposed by the renowned Japanese machine translation expert Makoto Nagao (1984), relies on existing knowledge and experience rather than deep analysis. It translates through analogy principles, without extensive linguistic analysis. The translation process starts by breaking down the source language into sentences, then into phrases. Using analogy, the phrases are translated into corresponding target language phrases, which are then combined to form longer sentences. The main knowledge source for EBMT systems is bilingual example databases. From this perspective, the key challenge lies in maximizing the statistics to build such databases.

Compared with traditional statistical model-based machine translation methods, neural machine translation uses deep neural network models to directly learn the mapping relationship between the source language and the target language, thus achieving more accurate and smooth translation results. It was firstly introduced by Ilya Sutskever, Oriol Vinyals and Quoc V. Le(2014). They propose an end-to-end neural machine translation model based on an encoder-decoder architecture that uses recurrent neural networks (RNN) to model sequential mapping relationships between source and target languages. This research lays the foundation for the subsequent development of neural machine translation. In the contemporary era of rapid development of science and technology, the rise of emerging Internet technologies, neural machine translation has also been upgraded to a certain extent. By obtaining a large number of data sets, introducing pre-trained language models and adopting reinforcement learning methods, neural machine translation has achieved significant improvement in translation quality and efficiency, and has been widely used in practical applications.

2.2 Previous Studies on Computer-Assisted Translation (CAT) Tools

Despite the speed of machine translation, the quality of translation is not satisfactory. In this case, computer-assisted translation technology has gradually received people's attention to make up for the shortcomings of machine translation. The concept of Computer-Assisted Translation (CAT) was first proposed by Yehoshua Bar-Hillel (1960), an Israeli linguist and mathematician. He discusses the concept of using computers to assist human translation and related theoretical and practical issues. He also analyzes the challenges of machine translation, the design of translation rules, the complexity of language structure, and the limitations of machine translation systems. In 1964, Yehoshua Bar-Hillel, firstly introduced the concept of Translation Support System. This concept emphasizes the auxiliary role of computers in the translation process, including functions such as term management, translation memory, and machine translation. These are the rudiments of the classification of computer assisted translation tools. Then in Chen (2013)’s article, she classifies computer-assisted translation tools into four basic categories: translation memory tools, term management tools, alignment tools and term extraction tools.

In recent years, advances in machine learning and artificial intelligence have also had a significant impact on computer-assisted translation tools. The emergence of Neural Machine Translation (NMT) models has significantly improved the quality of translation. These models enable automatic translation by training large-scale bilingual corpora. Modern computer-assisted translation tools are also increasingly based on cloud-based platforms, allowing translation teams to collaborate and share resources in real time. These tools provide features such as online editing, term management, collaborative reviews, and version control, improving translation efficiency and quality. These categories can be further subdivided and expanded according to specific functions and application areas.

So what are the main functions of the four basic computer assisted translation tools? Translation memory tools are one of the most common CAT tools. They work by saving previously translated sentences or paragraphs so that they can be reused in later translations. When the translator encounters similar or identical text segments, the translation memory tool can automatically provide the corresponding parts of the previous translation, or give suggestions. This improves translation consistency and saves time and effort. Term management tools assist translators and language professionals in managing terminology consistently across different projects. These tools typically include features such as term extraction, term validation, and term glossaries. They help ensure that the correct and approved terms are used consistently throughout the translation process, improving accuracy and reducing ambiguity.

Alignment tools are used to align the source and target language texts in a parallel corpus. Parallel corpora consist of pairs of texts in different languages, where each sentence or segment in one language corresponds to its translation in

the other language. Alignment tools automatically identify corresponding segments and align them, creating a reference for translation and linguistic analysis. These aligned corpora can be used for training machine translation systems, terminology extraction, and comparative linguistic studies. Term extraction tools are designed to automatically identify and extract domain-specific terms from a given text or corpus. These tools analyze the frequency, context, and linguistic patterns of words to identify potential terms. Term extraction is also useful for building terminology databases, creating glossaries, and improving the consistency and accuracy of translations within specific domains or industries.

In conclusion, the continuous development and innovation of computer-assisted translation tools provide translators with more choices and support, and improve the efficiency and quality of translation.

3. Advantages and Challenges of Technology in Translation

3.1 Machine Translation

Machine translation (MT) has gained significant attention and advancements in recent years, presenting both advantages and challenges in the field of language translation. One of the key advantages of machine translation is its efficiency. MT systems can process large volumes of text in a short amount of time, making it highly efficient for translating documents, websites, and other content. This speed enables faster dissemination of information across different languages, facilitating global communication and collaboration.

Another advantage of machine translation is the potential for cost savings. By automating the translation process, machine translation can significantly reduce translation costs, especially for large-scale projects. It eliminates the need for human translators for every task, making it a cost-effective solution for organizations with limited translation budgets.

Consistency is another benefit of machine translation. MT systems can provide consistent translations, ensuring that the same terminology and style are maintained throughout the translated text. This is particularly useful for businesses and organizations that require consistent branding and messaging across different languages.

Machine translation also enhances accessibility to multilingual content. It breaks down language barriers, making information available to a wider audience. This is especially valuable for individuals who may not have proficiency in multiple languages but still need access to information and resources.

However, machine translation is not without its challenges. One of the primary challenges is achieving high translation accuracy. While machine translation systems have made significant progress, they still struggle with complex sentence structures, idiomatic expressions, or ambiguous phrases. Contextual understanding is another challenge, as machine translation often fails to capture the nuances and cultural references present in the source text, leading to inaccuracies or misinterpretations.

Domain-specific knowledge poses another hurdle for machine translation. Technical, scientific, or specialized content often requires domain expertise that machine translation systems may lack. This can result in inaccuracies and a loss of meaning in the translated text.

Language variations also present challenges for machine translation. Each language has unique grammatical structures, vocabulary, and cultural nuances, making it difficult for machine translation systems to accurately handle the intricacies of each language.

Additionally, machine-translated content often requires post-editing by human translators to improve the quality, style, and overall coherence of the translation. This additional step adds time and effort to the translation process.

3.2 Computer Assisted Translation Tools

Computer-assisted translation (CAT) tools have revolutionized the translation industry, providing numerous advantages while also presenting certain challenges.

One of the key advantages of CAT tools is increased productivity. These tools automate repetitive tasks, such as sentence matching and terminology management, allowing translators to work more efficiently. By leveraging translation memory, which stores previously translated segments, CAT tools can suggest or automatically translate similar or identical segments, saving time and effort.

CAT tools also enhance consistency in translations. They enable the creation and management of terminology databases, ensuring the use of consistent terminology across multiple projects and translators. This consistency is particularly important for companies and organizations that require brand consistency and adherence to specific industry terminology.

Another advantage is improved collaboration and workflow management. CAT tools enable multiple translators to work on the same project simultaneously, facilitating collaboration and reducing turnaround times. Project managers can assign tasks, track progress, and coordinate translation efforts more effectively, resulting in streamlined workflows and increased productivity.

CAT tools also contribute to quality assurance. They include features such as spell-checking, grammar checking, and quality control checks, which help identify errors, inconsistencies, and potential translation issues. This ensures that the final translation is of higher quality and meets the desired standards.

Cost savings are another benefit of CAT tools. By leveraging translation memory and reusing previously translated content, CAT tools reduce the amount of new translation required, resulting in cost savings for clients. Additionally, the automation of certain tasks reduces the need for manual labor, further reducing costs.

However, CAT tools also come with their share of challenges. One of the main challenges is the initial learning curve. Translators need to familiarize themselves with the specific CAT tool they are using, as each tool has its own interface, features, and functionalities. This learning process can require time and effort, especially for translators who are new to CAT tools.

Another challenge is the reliance on the quality of the translation memory. If the translation memory contains inaccurate or poorly translated segments, it can negatively impact the overall quality of the translation. Therefore, maintaining and updating high-quality translation memory is crucial for achieving accurate and consistent translations.

CAT tools may also face difficulties when dealing with highly creative or literary texts. These texts often require a more nuanced and subjective approach, which can be challenging for CAT tools that primarily rely on algorithms and statistical models.

Furthermore, CAT tools may struggle with handling complex formatting, such as tables, charts, or graphics, which can result in formatting issues in the translated documents. Translators may need to manually adjust the formatting to ensure the final output is accurate and visually appealing.

4. Integration of the Advantages of Technology with the Expertise of Human Translators

4.1 Translation Accuracy

Although machine translation and CAT tools enjoy advantages over human translation in many aspects, they still need human expertise to support translation accuracy. Peter F. Brown (1990) introduced a statistical model-based machine translation method, which combines machine translation with human expertise to train translation models through a large-scale bilingual corpus. As we know that accuracy is a crucial factor in achieving high-quality translations, and it can be enhanced by combining the power of machine translation (MT) technology with the expertise of human translators.

One way to enhance accuracy is to make use of both machine translation and human expertise through computer-assisted translation (CAT) tools. These tools provide features such as translation memories, terminology databases, and alignment tools to assist human translators. Translation memories store previously translated segments, allowing translators to reuse them for consistency and efficiency. Terminology databases ensure the correct usage of domain-specific terms, while alignment tools help align the source and target texts for better quality control.

Collaboration between human translators and machine translation systems can also involve interactive translation. In this approach, the translator actively interacts with the machine translation system during the translation process. They can make use of real-time suggestions and feedback from the system to improve the accuracy and efficiency of their translations. This iterative process allows the translator to benefit from the strengths of the machine translation system while applying their linguistic expertise to produce accurate and contextually appropriate translations.

4.2 Cultural and Linguistic Nuances

Combining machine translation and human expertise represents a powerful synergy that navigates the complexities of cultural and linguistic nuances. Machine translation, powered by AI algorithms, offers efficiency and speed in rendering text across languages. Recent years machine translation systems have made significant advancements, leveraging statistical and neural models to automatically translate large volumes of text. These systems excel at handling repetitive and straightforward content, providing quick and cost-effective translations. However, they often struggle with capturing the nuances of language, understanding context, and producing culturally appropriate translations. This is where human expertise comes into play.

Human translators bring a nuanced understanding of context, culture, and idiomatic usage, making them indispensable in refining machine-translated content. They possess the ability to decipher the intricacies of language, accounting for cultural nuances that machines might overlook. For instance, idioms, jokes, or culturally specific references often require human intuition to be accurately translated. They also possess a deep understanding of language, culture, and context, allowing them to accurately interpret and translate texts. They bring their linguistic skills, cultural awareness, and subject matter expertise to ensure that the translation conveys the intended meaning accurately. By combining their expertise with machine translation technology, the translation process can be significantly improved.

Another method involves collaborative translation, where human translators work alongside machine translation systems. They guide the system, correcting its errors and fine-tuning the output. Through this process, the machine learns from the human corrections, gradually improving its accuracy and understanding of nuanced language usage.

Moreover, establishing clear guidelines and quality checks is vital. Human expertise comes into play not just during translation but also in designing protocols for post-editing, ensuring consistency, and maintaining the authenticity of the translated content.

4.3 Post-Editing and Quality Assurance

Post-editing and quality assurance play pivotal roles in combining machine translation and human expertise to achieve high-quality and accurate translations. The integration of technology and human skills in these processes is crucial for refining machine-generated content and ensuring that it meets the standards of fluency, context, and cultural sensitivity.

Post-editing involves human translators reviewing and enhancing machine-generated translations. It serves as a bridge between the efficiency of machine translation and the nuanced understanding of human linguists. During post-editing, translators focus on correcting errors, improving coherence, and adapting the content to cultural and contextual nuances. This step requires linguistic expertise to address the intricacies that machines might misinterpret, such as idiomatic expressions or subtle cultural references.

Quality assurance is equally important and involves a systematic approach to verifying the accuracy and overall quality of translations. This can include linguistic validation, consistency checks, and adherence to style guides. Human linguists play a critical role in developing and implementing quality assurance processes, leveraging their expertise to ensure that the final output aligns with the intended meaning and cultural nuances.

Technology supports these processes by providing tools for automated checks, terminology consistency, and alignment with established guidelines. However, it's the human touch that adds the finesse necessary for crafting translations that resonate with the target audience. Human translators bring cultural awareness, creativity, and a deep understanding of language nuances, enabling them to refine machine-generated content in a way that goes beyond literal translation.

Effective collaboration between technology and human expertise involves continuous feedback loops. As translators post-edit machine-generated content, the system learns from these corrections, improving its performance over time. This iterative process enhances the capabilities of machine translation systems and contributes to a more refined, efficient, and contextually accurate translation output.

5. Conclusion

In concluding the pursuit of a harmonious integration of technology and the expertise of human translators, it's evident that a balanced approach capitalizes on the unique strengths of each while mitigating their respective limitations. The fusion of technology and human proficiency in translation endeavors not only augments efficiency but also elevates the quality and cultural relevance of the final output.

Technology, specifically machine translation, offers unparalleled speed and scalability in handling vast volumes of content. Its ability to swiftly process information serves as a foundational pillar, laying the groundwork for the translation process. However, its inherent limitations in understanding context, idiomatic expressions, and cultural nuances underscore the indispensable role of human expertise.

Human translators bring an irreplaceable depth of understanding to the table. Their nuanced grasp of language, cultural intricacies, and the ability to discern contextual meanings remain unmatched. The human touch ensures that translations resonate authentically with the target audience, conveying not just words but the intended emotions, nuances, and cultural sensitivities.

A balanced approach necessitates a symbiotic relationship between technology and human translators. Machine-generated translations can serve as a preliminary step, providing a rapid framework that human experts can refine. Post-editing and quality assurance steps allow for the meticulous review and enhancement of the translated content, ensuring linguistic accuracy, style coherence, and cultural relevance.

Moreover, continuous collaboration fosters improvement. Human translators contribute their insights, corrections, and refinements during post-editing, refining machine algorithms and enhancing their understanding of linguistic complexities and cultural contexts. This feedback loop perpetuates a cycle of growth, enhancing the capabilities of machine translation systems while harnessing the nuanced expertise of human translators.

In essence, the balanced integration of technology and human expertise is not about replacing one with the other but harnessing their collective potential. This approach optimizes efficiency without compromising the essence and accuracy of translation. It represents a fusion where technology serves as a supportive tool, enhancing the capabilities of human translators, and together, they produce translations that bridge linguistic divides while honoring cultural nuances. This collaborative synergy not only meets the demands of a globalized world but also upholds the integrity and authenticity of communication across diverse cultures and languages.

Acknowledgments

Not applicable.

Authors contributions

Stu. Yixin Wang was responsible for study design and revising. Stu. Yixin Wang was responsible for data collection. Stu. Yixin Wang drafted the manuscript and Stu. Yixin Wang revised it.

Funding

Not applicable.

Competing interests

I declare that I have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Sciedu Press.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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