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# Analysis of the Practice of Human-Machine Collaborative Translation from the Perspective of Cognitive Load

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**Abstract:** Artificial intelligence technology has gradually expanded the scope of applications for translation, and at the same time, the cognitive features of translation activities have also changed. Translators no longer complete the translations alone but work with machines. Cognitive Load Theory can be used to study the cognitive processing process of humans and machines in collaboration. Based on the above theory, this paper explores the characteristics of cognitive load for translators in human-machine collaborative translation, traces the application of this theory in translation research, and compares the cognitive differences under different collaboration modes. This paper takes Chen Lei's (2025) eye-tracking data as its reference, shows the gradual changes in cognitive load over time, and explores how translation direction and task difficulty affect cognitive load. Based on the above data, the fixation time and the number of regressions for the human-machine collaboration group were both lower than those of the manual translation group. However, this advantage is due to the quality of the machine's initial output and text difficulty. From the perspective of translation direction, the reduction effect of AI assistance in Chinese-to-English translation is relatively more pronounced than that in English-to-Chinese translation. Based on the above findings, this paper proposes the following three improvements: interface Design, skill training and task management.

**Keywords:** Cognitive load; Human-machine collaborative translation; Post-editing; Eye-tracking; Cognitive resources allocation.

## 1. Introduction

In the 1980s, Sweller put forward the theory of cognitive load, and since then, it has gradually been used to explain how resources in working memory are used by people during information processing. At the bottom of this theory is the idea that the capacity of human working memory is limited. Cognitive overload occurs when the total amount of cognitive processing needed for a task exceeds a person's available resources, and consequently, both the quality and efficiency of the task will be reduced. Translation is a set of sub-tasks that can be carried out in parallel or sequence, such as source-language understanding, code conversion, and target-language generation. This continuously taxes the translator's working memory. Translators have to perform several cognitive operations under the constraint of limited cognitive resources, and the efficiency of resource allocation directly affects the quality and speed of translation.

Recently, with the development of neural machine translation, it has performed well in standard-sentence structure and general-domain translation. However, machine translation is still relatively poor in handling complex sentences, context-dependent paragraphs and expressions with a heavy cultural load [1]. A human-machine collaborative translation model has gradually become the main direction of development for the industry. The model uses machine translation as a support tool, generates an initial translation by the system, and then the translator revises and finalises it. Compared with human translation, the translator in this process needs to complete the translation task and evaluate the quality of the machine-translated text to correct any errors; thus, a change in cognitive processing has occurred.

Research on the translation process has been carried out over time, and now several methods are available, such as think-aloud protocols, eye-tracking and keyboard logging. Eye-tracking technology can be used to determine a person's level of cognitive load, and studies on reading, comprehension and translation have applied it. Based on the actual situation of human-machine collaborative translation, cognitive load has been considered to help understand how translators' brains work when using human-computer interaction tools, and thus offer a path forward for designing translation tools, teaching adjustments and project management systems.

## 2. Cognitive Load Theory and Its Application in Translation Studies

The three types of cognitive load are: intrinsic load caused by the complexity of the information in task materials, extrinsic load caused by poor design of task presentation, and germane load referring to the effort learners put into forming cognitive schemas and achieving automaticity [2]. Specifically, in translation activities, the main sources of intrinsic cognitive load are the language difficulty of the source text, the unfamiliarity with the professional field, and the complexity of sentence structure; all of these affect extrinsic cognitive load, such as the usability of translation tool interfaces, the presentation format of machine translation output, and the efficiency of operational workflows; and the use of professional knowledge by translators and the selection of translation strategies for language conversion and style control are forms of germane load.

Gile's cognitive load theory is an older theory for studying how to divide people's thinking resources in research. This model breaks down the cognitive process of consecutive interpreting and simultaneous interpreting into several sub-tasks, such as listening comprehension, memory storage and target-language production, and all of them are competing for attention resources. Interpretation errors and omissions are primarily due to a lack of attention resources to meet the demands of all these sub-tasks simultaneously. Research on written translation has also been conducted on cognitive load. Generally speaking, translation is a type of constrained processing, and its cognitive demand is relatively high compared with regular reading or writing. However, a relatively large amount of translation training can be used to improve the efficiency of cognitive resource allocation, gradually automate some processing steps, and thus reduce the total load. A translator's professional experience is expected to reduce cognitive load in other ways. Expert translators can pay attention to the difficulty of a text more reasonably, and novice translators are more likely to be exhausted cognitively.

Now, the idea of cognitive load measurement is less about self-report. The first studies on the translation process were mainly based on verbal-thinking methods and interviews; although they could capture subjective emotions, they were also subject to post-event recall bias. Add Eye-Tracking and keyboard recording devices to acquire more unbiased behaviour data. Through numerous experiments, some indices of eye movement have been found to be closely related to a person's cognitive load during language processing; these include fixation duration, fixation frequency and re-fixation frequency. The frequency and duration of pauses in keyboard recording are also considered to be behavioural expressions of cognitive load [3]. The main direction of research in translation cognition now is mutual verification of multiple methods. Based on the above theoretical system, one can examine the various ways and performance impacts of translators in different environments through the lens of cognitive resource allocation.

## 3. Evolution of the Human-Machine Collaborative Translation Model and Cognitive Characteristics

Under the above theoretical system, the actual forms of human-computer cooperative translation have evolved from computer-assisted translation and machine translation post-editing to AI-assisted post-editing. At the stage of computer-assisted translation, the primary roles of the translation memory bank and terminology bank were retrieval and reference; at this time, the translator had full control. The tools help to standardise the terms and avoid doing this work repeatedly. The appearance of the post-editing mode changed this trend [4]. Translators did not have to start from scratch but rather revised and improved the first translation offered by a machine. This way reduced the translation period but introduced new cognitive problems. At the same time, the translator needed to consider both the original text and what the machine had translated, then adjust the quality of the translation and make modifications. How to distribute attention reasonably among different kinds of texts and translation situations is now a problem that translators need to face.

The Rise of generative AI has brought about new changes. Large Language Models can perform translation and, in some cases, provide reasons for the translation. AI-assisted post-editing (AIPE) is gradually becoming popular, and now people and computers work together this way. Translators' Jobs have changed from implementation to review and collaboration. Li and his colleagues (2026) used 26 graduate students in translation as the subjects of an experiment and, with the help of an EyeLink 1000+ eye tracker and Translog II keyboard recording software, collected data [5]. Based on the above data, it can be seen that in the AIPE mode, translators' efforts in processing the source text, pupil dilation, and attention switching were all reduced, and thus their cognitive load decreased. The focus of translators' work has moved from error correction to evaluation and selection of AI-generated translations, and a relatively high degree of judgment is required for this selection.

However, the effects of the AI-assisted work are not all positive. Although AI generally reduces cognitive load, some studies have shown that the cognitive demands in certain areas are actually higher. The translator needs to carry out all kinds of work in a certain order to evaluate, filter and correct the translation results produced by artificial intelligence. Research on interactive machine translation has also found this. Although the interactive mode can improve the quality of the translation by dynamically adjusting it, it takes more time and effort for the translator to interact with the system in real time, and then repeated evaluations and revisions of the results are needed. Therefore, the cognitive load of human-machine collaborative translation cannot be considered a simple sum or difference. The load characteristics at different stages and nodes are not the same, so a particular case study needs to be carried out.

## 4. Empirical Findings on Cognitive Load in Human-Machine Collaborative Translation

The above judgments require empirical data for verification. Recently, some researchers have used eye-tracking technology to study the cognitive load of people working together with computers in translation. Chen Lei (2025) took 30 translation master's students as the subjects of a study and used a Tobii Pro Glasses2 eye tracker to collect data. The three levels of difficulty of the cognitive load in manual translation and human-machine collaborative translation were compared in a study [6]. Based on the above results, the gaze duration, number of fixations, total fixations and eye movements in the manual translation group were all higher than those in the human-machine collaborative group, and this difference was even more prominent for complex texts. As the difficulty of the tasks increased, both groups of translators had to fixate and look at something for a longer time; however, the additional cognitive burden imposed on the manual-translation group in complex tasks was more pronounced. This indicates that the human-machine collaboration model can have a greater cognitive burden reduction effect in complex translation tasks. The higher the task difficulty, the more prominent the collaborative advantage becomes.

The above results show that human-machine collaboration has reduced the total load to some extent, and the cognitive load also fluctuates at different times during the translation process [7]. If the first results from machine translation are not good, the person will need to perform more post-editing work, and thus the advantages of collaboration between humans and machines will be reduced. In other words, whether the combination of people and computers can significantly reduce the cognitive load depends on how good the initial machine translation is. High-quality machine translation can reduce the number of revisions required by translators; otherwise, poor-quality machine translation will make the translators have to do more work correcting the errors in the machine translation. Distribution of Cognitive Load at Different Times During Translation. The types of cognitive processing in the source language understanding, quality assessment and target language production stages are different, and the size of the load changes according to the requirements of the task and the quality of the machine's output.

Translation Direction also impacts Cognitive Load. AI-assisted post-editing of Chinese-to-English translation (L1→L2) shows a stronger load reduction effect. The phenomenon of knowledge expertise reversal can be used to explain this: when the task is outside the translator's area of familiarity, the support provided by external tools will be relatively large. AI has reduced the workload for light post-production editing to some extent. In the direction from English to Chinese (L2→L1), translators are more likely to experience a high cognitive load in processing the source text, and this is related to the difference in input processing direction. Cognitive advantages obtained by using humans and computers together generally depend on the direction of translation and the nature of the task.

# 5. Key Factors Affecting the Cognitive Load in Human-Machine Collaborative Translation

Cognitive Load in Human-Machine Collaborative Translation is Affected by Various Factors. The two most direct causes of text complexity and translation direction at the task level are listed above. Experimental data have shown that as the difficulty of the task increases, translators' attention span and the frequency of revisions are both reduced [8]. Complex texts have more specialised terms and more complicated syntactic structures, require accurate understanding in context, and are thus relatively demanding of internal cognitive resources during translation. The Direction of translation is also required. The two directions of translation input and output differ in the distribution of cognitive resources in an organised manner. Researchers have classified the previous allocation models into "all-encompassing" and "local-focused". The former is more suitable for the translation input task, and the latter is more efficient in the translation output task.

Translators' individual attributes are also factors. Experienced translators have undergone extended training and, as a result, developed high-efficiency cognitive schemas; thus, they require fewer cognitive resources for the same-difficulty tasks. Novice translators do not have a prior system and are more susceptible to cognitive overload when facing a difficult text. A translator's language ability and the direction of translation will also affect cognitive load. The quality of the output from the machine-translation system at the technical level will affect how much cognitive effort people need to use. Good machine translation can reduce the number of revisions by translators significantly, and thus the cognitive load will be relatively small. A low-quality machine translation will require frequent re-translation and correction of the content, thus failing to reduce the amount of work and possibly increasing it. The Design of the Interface for Translation Tools also Matters. Information that is too dense and too many steps in the operation will increase the translator's cognitive load.

The technical Design has a problem. A dynamic adjustment of the system can enhance the accuracy of interactive machine translation, but at the same time, continuous interaction between the translator and the system is required to repeatedly evaluate and revise the output. The improved quality is achieved at the expense of extra interaction [9]. The Technical Design needs to balance the demand for "auxiliary benefits" with "interaction costs". If the interaction mechanism is too complex, the reduction in burden may be offset. In this situation, whether human-machine collaboration can play a burden-reducing role largely depends on whether the initial quality of machine translation is reliable enough.

# 6. Practical Approaches to Optimizing the Cognitive Load of Human-Machine Collaboration in Translation

Given the above reasons, how to deal with them effectively is the problem now at hand. The development of translation tools must be based on the idea that they are to reduce the work of translators, not to create new problems. The output quality of the machine translation system should be continuously improved to reduce the workload of error correction and identification for translators. In terms of interface Design, the displayed information should be simple and the operating steps not too complicated; otherwise, translators will expend energy on the tool itself before they can begin translating [10]. A large language model can provide a translation suggestion and a reasoning process, but the way it is presented needs to be decided; otherwise, it may be overly helpful and thus distracting. A better way is to match the level of help with the difficulty of the text and translator needs, use the strengths of AI, and avoid information overload. Ultimately, the technical design should be centered on people, and machines are to assist in compensating for human weaknesses rather than replacing human judgment.

Training needs to adapt to changes in technology at the same time. Translation teaching should also help students recognise their own cognitive features and learn to allocate attention reasonably in the context of human-computer collaboration, rather than just teaching language translation skills. Different translation directions have different requirements for cognition, and teaching and training should be designed in accordance with them [11]. Post-editing is now the norm, and students need to be able to critically evaluate machine translation; they should quickly recognise typical errors and know when to rely on a machine or when to correct it themselves. Help students learn about how the difficulty of the text affects cognitive load and adapt their study strategies accordingly in practice.

Consider Cognitive Factors in the Management of the Industry. If project scheduling and personnel allocation only consider time and cost, without taking into account the cognitive endurance capacity of translators, both the quality and efficiency of the work will gradually decline. Complex texts are more demanding on the brain, so the project arrangement should allow for more processing time. At the same time, the difficulty of the text, the direction of translation and the translator's experience should be considered in task distribution. AI can help with some light-to-medium post-editing work; therefore, some of these tasks are now automated. In the future, a monitoring and feedback system for cognitive load will be introduced to promptly detect any problems of excessive fatigue and, by ensuring that translators are healthy and energetic enough to work, maintain the quality of translation. Technological empowerment and the sustainability of the people must be harmonised.

# 7. Conclusion

Based on cognitive load theory, this paper will discuss the problems of cognitive overload in human-machine translation. Cognitive Load Theory can be used to study the cognitive load that translators face in their work in a human-computer interaction environment. The Effect of Human-Machine Cooperation on Cognitive Load is Not Uniform. There are differences in the distribution of the load at different times and across various links; thus, human-machine collaboration is not the same as traditional human translation.

Eye-tracking data show that in human-machine cooperation, the duration of fixation is reduced and the number of regressions is lower. This advantage will be more obvious in the case of a difficult text. AI assistance also changes the cognitive model of translators. Translators are no longer the main recipients of the source language and producers of the target language. Instead, they have to spend a lot of time determining how good the machine translation is and whether to use it. The Direction of translation also has an effect. In the case of translating from Chinese to English, the impact of AI reducing the workload is more pronounced, and this may be due to different levels of control translators have over their native language and second language proficiency. These variables are not independent but are also related to one another: Text difficulty, the initial quality of the machine, and translator experience all interact. They cannot be analysed in isolation to find out how they affect others.

Based on the above results, this paper puts forward three types of recommendations for improvement: technology, teaching and management. The technical part presents the design rules for guidance tools based on cognitive ergonomics. Teaching aims to incorporate cognitive load management in the course of translation. The Industry aspect can be added to the list of requirements for translators in the project plan.

Some deficiencies in the current study will also be presented. Eye-tracking data can show how much cognitive load different tasks place on people, but its methods of collection are not ideal, and we don't know precisely why that change happens. Other ways for future research include electroencephalography and near-infrared brain functional imaging. In addition, most of the current studies on this topic are experiments in Chinese-English translation; the performance of other languages and text types has not yet been widely explored. There are still many areas of research in the cognitive study of human-machine cooperative translation.

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