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Performance and perception: machine translation post-editing in Chinese-English news translation by novice translators

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Machine translation has become a popular option for news circulation, due to its speed, cost-effectiveness and improving quality. However, it still remains uncertain whether machine translation is effective in helping novice translators in news translation. To investigate the effectiveness of machine translation, this study conducted a Chinese-English news translation test to compare the performance and perception of translation learners in machine translation post-editing and manual translation. The findings suggest that it is challenging for machine translation to understand cultural and semantic nuances in the source language, and produce coherent structural translation in the target language. No significant quality difference was observed in post-editing and manual translation, though post-editing quality was found to be slightly better. Machine translation can help to reduce translation learners' processing time and mental workload. Compared to manual translation, machine translation post-editing is considered as a preferred approach by translation learners in news translation. It is hoped that this study could cast light on the integration of machine translation into translator training programs.

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Introduction

Globalization is leading to an exponential growth in translation which has become a key mediator of intercultural communication (Bielsa, 2005). In this context, news translation has become an indispensable part for the effective information communication. News translation involves capturing cultural nuances and subtleties. As such, McLaughlin (2015) supposed that news translation could be considered as a powerful means to witness individual cultural systems. However, it should be noted that cultural resistance may hinder the intercultural understanding in news translation (Conway, 2010). Close attention should be paid to assess how news information and its translation are assimilated within specific cultural and social contexts (Orengo, 2005). In this respect, it is important to take into account of the cultural and linguistic elements within news translation in order to accurately convey the message to meet the cultural background and preferences of the intended readers.

Speed is an essential part of news translation and an integral element of journalistic excellence (Bielsa and Bassnett, 2011). With the advancement of machine translation, it is believed that machine translation can be used as a useful tool to accelerate the selection and acquisition of news content (Matsushita, 2019). Although machine translation has demonstrated capabilities to overcome the communication barriers and ease interactions among people with different cultural background (e.g., Vieira et al., 2021), it should be emphasized that the performance of machine translation in news translation is far from being perfect. It is particularly unclear about the application of machine translation in news translation by translation learners, who usually aspire to be professionals in the field of translation in the future. Therefore, the purpose of this study is to compare the performance and perception of translation learners in machine translation post-editing and manual translation of news translation to investigate the applicability of machine translation in translation training programs. By doing this, it is hoped that this study could contribute to the development of curricula that equip translation learners with strategies to effectively optimize the use of machine translation, especially in news translation.

Machine translation post-editing in news translation

Peculiarities of news translation. News is typically regarded as informative to be factual and perspective-free, while translation describes linguistic re-expression and adaptation to meet the expectations of readers (Conway, 2015). News translation is a subject of growing significance within the discipline of translation studies. It relates to organizations, agents and texts (Bielsa and Bassnett, 2011). Regarding the text aspect, André Lefevere (1992) describes news translation as a process of rewriting. Bielsa (2016) proposes that news translation entails a series of linguistic transformations, ranging from the use of verbal accounts and visual information to textual transfer from one language into another. Empirical studies into news translation typically take a product-oriented and process-oriented approach. Product-oriented approach commonly takes the form of case studies, where reports contents are compared across national, linguistic and institutional boundaries. For example, Ping (2023) conducted a corpus-based analysis of the original and translated news texts. He found that the style of news translation was influenced by the linguistic features of source language and the conventions of target language. Process-oriented approach works on the process of translation in specific contexts (Kang, 2007). For instance, Sülflow et al. (2019) carried out a laboratory experiment by using eye-tracking measurement to examine participants' attention distribution in news posts selection. The difficulties in translating news are compounded by the complex configurations of linguistic styles and structures. When approaching the task of transferring meanings across languages and cultures, translators have to deal with problems at lexical, syntactic and textual levels (Holland, 2013). In any case, Davier and Doorslaer (2018) suggest that triangulation of research approaches should be considered to provide a comprehensive and multifaceted analysis of the topic in news translation.

Machine translation post-editing. Machine translation is the translation from one natural language to another language through using the system of computers without the need of human intervention (Omar and Gomaa, 2020). It is widely recognized that machine translation has achieved great quality improvement over the years, progressing from earlier rule-based, statistical approach to current neural-network systems. Nevertheless, even with the noteworthy advancements, machine translation is far from being a perfect alternative to professional translators (Koponen, 2016). The raw output of machine translation contains more or less errors and inappropriateness, and cannot be adopted directly. Regarding machine translation errors, prior studies have identified and categorized different types of errors. For example, Vilar et al. (2012) presented a hierarchical machine translation error typology, where errors were grouped into missing words, word order, incorrect words, unknown words and punctuation errors. Luo and Li (2012) classified machine translation error patterns into lexical, syntactic and punctuation issues based on English-Chinese translation. Moreover, Daems et al. (2016) have divided machine translation error types into acceptability and accuracy. Acceptability includes grammar and syntax errors, while adequacy includes meaning shifts and word sense errors. Carl and Báez (2019) have adopted machine translation error taxonomies at both phrase level and sentence level. Nevertheless, it could be seen that the typology of machine translation error varies from different research perspectives.

Since machine translation lacks the capacity to understand the intricacies and subtleties of language. It needs different degrees of editing and revisions to improve its usability. Machine translation post-editing has emerged as a process to correct the errors or inappropriateness, so as to improve the quality of machine translation output to an acceptable level (Bowker and Buitrago Ciro, 2019). Post-editing is a complex cognitive activity concerning the procedures of reading the source text, revising the machine translation output and producing the final target text (Yang and Wang, 2023). Based on the requirement for translation quality, post-editing can be classified into light post-editing and full post-editing. Light post-editing involves making the minimum modifications and addressing essential errors of machine translation raw output. Whereas, full post-editing addresses any lexical, syntactical and stylistic problems, and cultural inappropriateness (Vieira, 2019). According to Bowker and Buitrago Ciro (2019), full post-editing is to produce a text that is of comparable quality to a professional translation.

Pym (2011) claims that technology has significantly expanded the scope of cross-cultural situation, leading to alterations in the configuration of culture. Machine translation has significantly impacted the way that translation process is shaped. To investigate the effectiveness of using machine translation, a growth of studies have been conducted on the comparison between manual translation and post-editing, particularly since the introduction of neural machine translation. Krings (2001) has classified the workload of post-editing into temporal, technical and cognitive effort. Temporal effort is related with the time duration in a task. Technical effort is about the labor used in a task. Cognitive effort is related to the mental workload in processing a task. It was found that the involvement of machine translation can have a potential effect on the cognitive process of human translators. For example, Daems et al. (2017a) took an overview of machine translation errors to identify the relationship between machine translation errors and post-editing efforts. In addition, translators with different translation experience may show different attitudes towards using machine translation. It was found that inexperienced translators treated post-editing task as a mainly lexical task, whereas professional translators paid more attention to the coherence and style (Daems et al. 2017b). A survey conducted by Guerberof (2018) showed that translators with post-editing experience were more likely to appreciate the help of machine translation and were more likely to hold a positive attitude towards machine translation post-editing. In addition, Moorkens et al. (2018) found that professional translators tended to favor translation from scratch over post-editing in literary translation, because manual translation allowed them more creative freedom, as opposed to being constrained by machine translation. To further compare the process of human translation and post-editing, Guerberof, Toral (2020) carried out a study based on a fictional story from English into Catalan. They revealed that post-editing might enhance the literary translation productivity of translators. Meanwhile, it was also found that post-editing was faster than human translation in processing technical texts (Yang et al., 2021). Altogether, the efficiency of post-editing performance can be influenced by various factors, such as machine translation systems, text types, and translation experience.

The need for rapid information delivery is a critical consideration in news translation, making machine translation come into being as a practical solution. Machine translation, which has undergone continuous quality improvement, has been tentatively adopted in news translation (Koponen et al., 2021; Krüger, 2022; Ruano, 2021). For instance, Krüger (2022), taking news translation as an example, has compared the quality of machine translation and human translation quality. The primary task in post-editing news translation includes the correction of terminology, avoidance of ambiguity, as well as the cultural and ideological modifications. Feng and Li (2016) have conducted a study on news machine translation post-editing. They offered specific post-editing techniques, such as adjusting word order and dividing sentences. Nevertheless, the complex nature of news translation, coupled with the inherent limitations of machine translation, has created significant challenges for news machine translation post-editing, particularly for translation learners who may lack sufficient expertise to handle the nuances of cultural and ideological bundles. In this regard, it is crucial to investigate the performance and perception of novice translators when they work with machine translation so as to optimize their machine translation use and enhance their translation efficiency.

Method

In order to unearth and observe how and to what extent machine translation can help translation learners in news translation, the following research questions will be addressed.

(1) How well does Google Translate perform in Chinese-English news translation through the linguistic and cultural lenses?
(2) What is the performance of novice translators like in post-editing compared to manual translation?
(3) How do novice translators perceive the use of Google Translate in Chinese-English news translation?

The study has employed a mixed-method approach that combines qualitative and quantitative methods. Specifically, the qualitative method aims to gain an understanding of novice translators' perception and attitudes towards machine translation post-editing through interpretive analysis of the questionnaires. Meanwhile, the quantitative approach, including the interpretation of performance data from post-editing and manual translation, enables a systematic evaluation of the performance of machine translation in news translation. It is hoped that the mixed-method approach can cross-validate the findings, which allows for a more comprehensive and in-depth analysis of the feasibility of machine translation in educational settings.

Participants. A total of 24 third-year translation learners volunteered to participate in the present study. All of them are Chinese native speakers and take English as the foreign language. They had translation training experience for about 6 months. Pretest questionnaire was distributed to collect participants' demographic information in order to establish a basic understanding of the participants and identify potential demographic biases that might impact the findings. It was shown that 50% of them have reached College English Test[1]-6 (CET-6) level, 37% were at College English Test-4 (CET-4) level, and others have reached CATTI[2] Level-3. With respect to the computer use literacy, 17% of the participants reported that they were skillful in using computers and the majority (67%) believed that their computer-use ability was at the moderate level. Despite having prior experience with machine translation, none of the participants had received any formal training in post-editing. As such, they were given instructions on how to properly conduct post-editing before the test.

Testing material. Two excerpts were carefully selected from the Report on China's Policies and Actions for Addressing Climate Change in 2019[3]. Government reports can be considered as a type of news (Lehman-Wilzig and Seletzky, 2010). They are documents released by government agencies that contain information about government policies, activities and findings. Although they may not be the same as traditional news produced by independent news organizations, they still play a crucial role in conveying important information to the public. Government reports used as data resource for news translation can be found in prior studies (e.g., Xu et al., 2023).

Translation direction was set from Chinese to English in this study. Text 1 was for manual translation and Text 2 was for post-editing. To ensure the comparability of the two texts, the complexity of Text 1 and Text 2 was carefully manipulated. Common Text Analysis Platform (CTAP, Chen and Meurers, 2016), a web-based text complexity analysis tool, was used to measure the selected text features. Text complexity was evaluated by taking into account both lexical and syntactical features. Lexical measurement included character richness, lexical variation and word frequency. In order to compare the complexity of source text, Type-Token Ratio (TTR) was adopted, which is a widely used indicator for the richness calculation of Chinese characters (Templin, 1957). It is suggested that a higher TTR indicates greater abundance of Chinese characters being used. The syntactical measurement of text complexity included a set of indicators, such as the mean length of prepositional phrases, the mean number of non-phrase, the mean number of verb phrase, and the mean number of simple clause. The lexical and syntactical features were meticulously calculated based on the noted indicators. It was found that Text 1 and Text 2 were largely comparable and could be considered suitable for inclusion in the present study (See Table 1).

Experiment procedure and data analysis. During the test phrase, the participants were instructed to translate Text 1 manually, followed by post-editing the raw output of Text 2 generated by

Table 1 Text complexity analysis.

Measurement	Indicators	Text 1	Text 2
General level	Number of characters	265	271
	Number of sentences	7	6
	Average sentence length	37	45
Lexical level	Character richness (TTR)	0.49	0.50
	Lexical variation (Verb)	10.77	10.73
	Number of characters appear only once	53	67
Syntactical level	Mean length of prepositional phrases	10.5	13.0
	Mean number of non-phrase per simple clause	4.9	1.28
	Mean number of verb phrase per simple clause	2.7	2.14
	Mean number of simple clauses per sentence	1.43	2.33

the Google translate. Online resource was allowed to ensure maximum simulation of authentic translating scenarios. Screen recordings were used to capture detailed processing information and to detect any plagiarisms. Students were provided with specific post-editing guidelines and required to diligently identify and correct any errors or inappropriateness in the raw output of machine translation. After they have completed the manual translation and post-editing task, the participants were immediately administered a post-test questionnaire to collect their perception on the respective task conditions.

The post-test questionnaire consisted of NASA-Task Load Index (Hart and Staveland, 1988) and performance self-assessment, to gauge the participants' perception of workload and self-assessment of their respective task performance. To assess the quality of translation in terms of acceptability and adequacy, we followed the assessment approach outlined in the study conducted by Daems et al. (2013). Two raters were invited and given explicit instructions to evaluate the quality of manual translation and post-editing tasks. The obtained data was analyzed by social statistical software SPSS 17.0. The mean score distribution for both manual translation and post-editing tasks were analyzed using descriptive analysis. Due to the small sample size, Wilcoxon signed ranks test was conducted to determine any significant differences between the two task modes.

Results

Machine translation quality analysis from linguistic and cultural lenses. In order to obtain an error profile of machine translation raw output, a machine translation error taxonomy was developed based on the error classification system proposed by Daems et al. (2013). Lexical and syntactical errors were found to be the most common types of errors present in the machine-generated output in the present study. Further analysis showed that among the lexical errors, mistranslation was the most prominent error type, particular in relation to noun phrases and conjunctions. The subsequent examples were provided to facilitate a more comprehensive understanding of the performance of machine translation. Particular attention has been directed towards lexical translation, structural translation and tense and modality translation.

(1) **Lexical translation**

Example 1: 基本国策

Machine translation: basic national policy

Official translation: basic state policy

The term "基本国策" (basic state policy) was translated by machine translation as the "basic national policy". "Nation" and "state" were often used interchangeably, despite their distinct connotations. "Nation" is an ideological construct and "state" is an administrative term. "Nation" pertains to a sociocultural entity, characterized by shared ideals, values, and traditions, while "state" refers to a legal and political entity with legitimate authority over a defined territory and population (Kuijper, 2022). Nonetheless, the practical separation of the two concepts has proven to be a challenging task, as machine translation still faces difficulties in accurately conveying the subtle nuances.

Example 2: 应对气候变化问题

Machine translation: the problem of picking climate change

Official translation: to promote the response to climate change

In this example, machine translation translated "问题" as "problem" in a literal and inappropriate manner, leading to a mistranslation of the phrase as "the problem of picking climate change". As noted by Song (2020), an effective word-level translation requires an intricate understanding of the sociopolitical context and cumulative meaning of a word. It is important to point out that machine translation still struggles to comprehend the underlying semantic connotations and associations woven in the source text, despite its capacity to generate moderately comprehensible translations.

(2) **Structural translation**

Example 3: 它既受自然因素影响, 也受人类活动影响, 既是环境问题，更是发展问题，同各国发展阶段…等因素密切相关

Machine translation: It is not only affected by natural factors, but also by human activities. It is not only an environmental issue, but also a development issue…

Official translation: It is associated with both natural factors and human activities. It is an environmental issue, but also, and more importantly, a development issue…

Lengthy and complex sentences are typically considered challenging for machine translation, due to the potential for ambiguity. According to Choi (2013), conjunction errors may come from the failure to understand the deep link and relationship between sentence segments. In example 3, the sentence is structured with conjunctions and errors may appear from the omission or misunderstanding of the conjunctions by machine translation. The raw outputs generated by machine translation are quite literal and neglect the intricate structures of the sentences, as observed through its comparison with the official translation. Machine translation may falter in capturing the logical connections between segments of the sentence. The official translation includes adjustments like the addition of phrases, such as "and more importantly", to reflect the deep structure of the sentence.

(3) **Tense and modality translation**

Example 4: 中国高度重视和积极推动科学发展观

Machine translation: China attaches great importance to and actively promotes scientific development concept

Official translation: China attaches great importance to and has actively promoted scientific development

Tense and modality are important features in natural languages, yet they are largely absent in Chinese, which lacks grammaticalized tense and modality forms. These features are typically expressed at the discourse level, often through the use of time expression lexical words or through the reliance on contextual information (Wu, 2022). To this regard, machine translation may struggle to consistently and accurately transfer the tense issue in Chinese-English translation, due to its insensitivity to the lexical and contextual nuances. In example 4, machine translation seemed to have used the present tense, which produced a comprehensible but inappropriate translation. By contrast, the official translation has adopted the present perfect tense of "has actively promoted" to emphasize the duration of a past-to-present action, thereby underscoring the significance and involvement devoted to the scientific development. Incorporating the subtle differentiation in tense is critical to accurately convey the intended meaning and emphasis of the source text.

Performance analysis of machine translation post-editing. To assess the quality of translation, two raters were given rating guidelines and instructed to evaluate the manually translated Text 1 and the post-edited Text 2 separately. Inter-rater reliability was calculated for rating bias consideration. According to Goodwin (2001), the correlation coefficient can indicate the extent of linear association between the raters' rating data. The findings suggested that Pearson correlation coefficient was 0.66 for Text 1 and 0.40 for Text 2, suggesting the inter-rater reliability was merely acceptable. Descriptive analysis showed that the mean score for Text 1 was 84.20 (SD = 4.66) and 84.58 (SD = 2.39) for Text 2. No significant difference was observed regarding quality performance between manual translation and post-editing. In order to have a deep look into the post-editing performance by novice translators, error identification rate and modification rate of machine translation errors were described in Table 2.

The findings indicated that the novice translators demonstrated a relatively high proficiency in identifying the lexical errors (61.29%), displaying an insufficient capability to identify syntactic errors (38.71%), and low proficiency in identifying the grammatical errors (19.35%) and the style errors (12.9%). Compared to the error identification rate, error correction rate in post-editing was even lower. It was found that the top error correction rate went to syntactic error, only accounting for 29.03%. Following syntactic errors, lexical error correction rate and grammatical error correction rate were exhibited with 19.35% and 16.13%, respectively. The correction rate of style errors was placed as the lowest one (6.45%), the same to its identification rate. It could be seen that the ability of novice translators to recognize and rectify machine translation errors was inadequate in Chinese-English news translation.

Perception analysis of using machine translation post-editing. After the participants have completed the whole test, they immediately received a post-test questionnaire to collect their perception of using machine translation. The questionnaire focused particularly on the self-assessment of performance and workload in machine translation post-editing and manual translation, based on a 5-point rating scale (1 point as the poorest and 5 points as the best for quality assessment, 1 point as the least and 5 points as the highest for mental workload).

Self-assessment of the production quality. In order to collect the perception data, participants were required to assess the performance of machine translation, their manual translation and machine translation post-editing. The findings suggested that 70.83% students believed that the quality of machine translation was at the average level of 3, and 29.17% regarded machine translation quality as 4. Generally, they thought the machine translation output was acceptable. In terms of their machine translation post-editing performance, 20.83% students evaluated their performance at the poor level of 2 points, 54.17% as the average level of 3, and 25% as the quite good level of 4, suggesting even though they believed that machine translation quality was quite acceptable, they still lacked confidence in their ability to perform machine translation post-editing. Nevertheless, it was interesting to find that participants' self-assessment of manual translation performance was quite complicated. 25% students reported their performance was at the poor level of 2 points. 66.67% believed their performance was at the average level of 3 and only 8.33% thought their manual translation performance was good. This indicated that most students were not satisfied with their translation competence. In comparison to manual translation, 96% students preferred to use machine translation post-editing. Please see Fig. 1.

Table 2 Statistics of error identification and correction rate in post-editing.

Error type	Identification rate (%)	Correction rate (%)
Lexical error	61.29	19.35
Grammatical error	19.35	16.13
Syntactic error	38.71	29.03
Style error	12.90	6.45

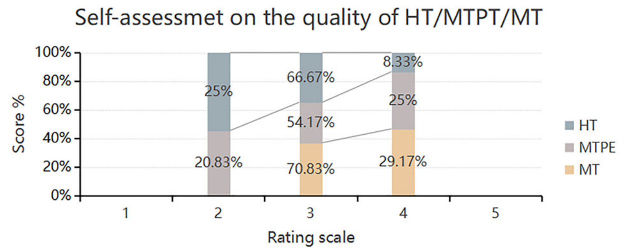

Fig. 1 Ratings of the performance. Differences are shown for individual ratings of the translation quality in human translation, machine translation post-editing and machine translation. HT manual translation, MTPE machine translation post-editing, MT machine translation.

Questionnaire on translation difficulties was distributed to the participants to further identify the difficulties in manual translation. The findings showed that students put lexical issue at the biggest challenge (33%), followed by semantic expression (29%), terminology (17%), background information (17%) and structural issue (5%). The students perceived that the most significant challenge in their manual translation was related to their comprehension and use of lexical content. Furthermore, insufficient knowledge of the terminologies and background information of the text may further impede their translating process. Please see Fig. 2.

In comparison with manual translation, it was found that students' attention distribution pattern was quite different in machine translation post-editing. In post-editing, they paid much attention to the structural cohesion (92%), compared to semantic expression (84%), grammatical and lexical issue (68%) and punctuation (36%). This implies that students tended to pay more attention to prioritize the macro-level language issues in their post-editing process, with particular emphasis on enhancing structural cohesion and semantic expressions. To put it another way, it could be interpreted that machine translation could effectively help students improve the lexical understanding of source text in the post-editing process.

Self-assessment of the mental workload. Descriptive analysis was conducted regarding the mean value and standard deviation of the workload in human translation and post-editing. As shown in Table 3, it was found that the mean values of time demand, physical demand, mental demand and frustration in manual

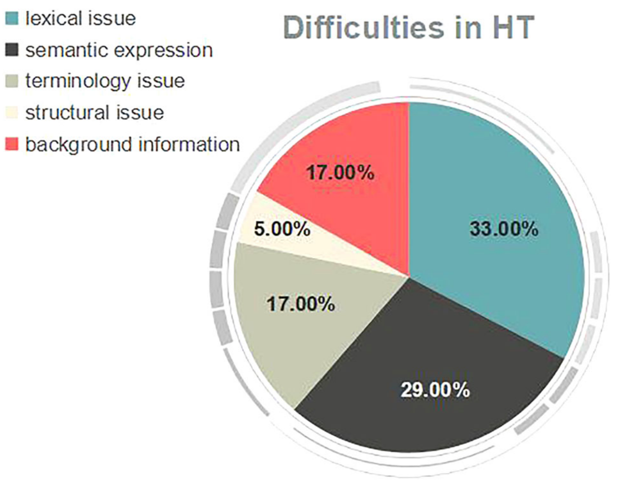

Fig. 2 Difficulties in human translation. Perceived challenges in human translation include difficulties related to lexical issue, semantic expression, terminology issue, structural issue, and background information.

Table 3 Descriptive analysis of workload in manual translation and post-editing.

Task	Workload							
	Time demand		Physical demand		Mental demand		Frustration	
	M	SD	*M*	SD	*M*	SD	*M*	SD
HT	4.12	0.64	3.04	0.95	4.13	0.61	3.33	0.76
PE	3.71	0.81	2.71	0.91	3.83	0.92	3	0.78

translation were all higher than those in post-editing. This suggests a higher degree of frustration encountered by translation learners in manual translation as opposed to post-editing. A Wilcoxon signed-ranks test was conducted to confirm whether there was a significant difference between manual translation and post-editing regarding these workload indicators. The findings indicated that a significant difference was observed between manual translation and post-editing with respect to time demand ($Z = -2.65$, $p < 0.05$) and physical demand ($Z = -2.53$, $p = 0.01$). Marginal significant differences were identified on mental demand ($Z = -1.94$, $p = 0.05$) and frustration ($Z = -1.89$, $p = 0.06$). The findings revealed a great advantage of post-editing compared to human translation in terms of the reduction of processing time and labor effort. In addition, the findings were also supported by the screen-recording data. For example, recording data suggested that it roughly took about 30 min for manual translation and 20 min for post-editing by translation learners. Collectively, the obtained findings support the notion that machine translation post-editing could be an effective means in Chinese-English news translation by translation learners in reducing the processing time and mental workload.

Discussion

This study aimed to investigate the performance and perception of translation learners in machine translation post-editing. It focused on a case study of Chinese-English news translation, using a small sample of translation learners. The quality of machine translation for news reports was first analyzed. The findings indicated that it was difficult for machine translation to deal with semantic connotations, deep logic of sentences, as well as the tense and modality. Machine translation commonly struggles with sentence comprehension, failing to understand the underlying semantic connotations (Yu, 2022). According to Popovic and Ney (2011), syntactic errors can result from errors in conjunctions, prepositions, syntactic order, and word category. It can be observed that the machine translation errors described in the present study generally align with prior studies. Nevertheless, it should be noted that the semantic connotation and degree of formality of the equivalent forms can vary depending on the specific language contexts. Hence, there is still a need for careful interpretation of the machine translation errors identified in the current study.

Regarding production quality, post-editing was found to be better than manual translation, though no significant difference was observed. This basically supported the findings by Garcia (2011). Translation learners have found that using lexical and semantic expressions can be challenging in manual translation, especially when translating terminologies. This is because translating terminology requires a specific and specialized understanding. Translation learners considered the quality of machine translation to be acceptable on the whole. However, their rate of identifying errors and correcting them was quite low, which was in line with the findings of Yamada (2019). This has reinforced the need to integrate instructional modules on machine translation post-editing into translation curriculum (Yang and Wang, 2022).

Machine translation post-editing can save the processing time and reduce mental workload of translation learners, which was consistent with the findings by Elming and Carl (2014). This is understandable since the majority of the translation work has been completed by machine translation, leaving minor editing and correction work in the post-editing process. In contrast to the process of machine translation post-editing, translation learners were required to manually translate news texts without the aid of machine translation, resulting in a more labor-intensive endeavor. As such, participants reported experiencing less frustration during the post-editing process compared to manual translation. Additionally, they expressed greater confidence in their post-editing performance when compared to their manual translation. This finding has provided an explanation for the inclination of most translation learners towards post-editing and their overall positive attitude towards the use of machine translation in news translation. Nevertheless, machine translation still has constraints regarding its capability in cultural translation (Song, 2020). Despite certain reservations and skepticism regarding the quality of machine translation, it is important to acknowledge that machine translation has made significant advancements to the point where its output quality maybe comparable to, or even exceed the translations produced by human translators. By conducting an investigation into the role of machine translation in news translation, novice translators can acquire valuable insights into the advantages and disadvantages of utilizing machine translation. By acquiring the necessary skills and knowledge, they can enhance their readiness to enter the translation industry and effectively address the increasing need for multilingual communication.

Conclusion

This study was conducted to investigate how translation learners perform and perceive in machine translation post-editing compared to the manual approach in news translation. As a preliminary step, an analysis was conducted to examine the errors generated by Google Translate in Chinese-English news translation. This analysis aimed to provide insights into the performance of the selected machine translation system. The findings suggest that machine translation faces difficulties in capturing semantic connotation, maintaining structural cohesion, and accurately rendering tense and modality. It has been determined that translation learners in manual translation encounter significant difficulties primarily related to lexical and semantic challenges. They have not given sufficient consideration to translation style, tense and modality issues, as well as structural coherence. Translation learners believed that their post-editing performance was superior to their manual translation performance, though no significant translation quality difference was observed. They expressed satisfaction with the performance of Google Translate for the most part. The utilization of machine translation can expedite the translation process and reduce the labor effort of translation learners. Based on the available evidence in the present study, a preliminary inference can be made that machine translation could potentially offer benefits to translation learners in the context of news translation.

However, it is important to note that the research findings should be interpreted with caution due to certain limitations. First, the findings were obtained based on a case study involving a limited number of translation learners. This limitation may give rise to concerns regarding the applicability and generalizability of the results. Thereby, it is necessary to validate the findings through replicating the study using larger and more diverse population-based cohorts. News translation entails the ongoing tensions between the requirement for accurate portrayal of the source culture and the necessity for efficient and understandable communication with the intended audience (Holland, 2013). It is more than just a linguistic act of rendering material from one language into another, but an intra-linguistic and inter-semiotic translation. When government reports are translated into another language and used by news outlets to inform their audience about the government performance, this practice can be regarded as a type of news translation. Government reports can serve as valuable resources for news translation due to their official nature, primary source status, transparency, and credibility. They offer significant contextual information and data to effectively communicate news across different languages. However, it should be pointed out that the selected excerpts may not fully represent the overall quality of news translation. Certain linguistic and contextual features may be absent or insufficiently represented in the chosen excerpt. Therefore, the obtained findings cannot be considered conclusive in reflecting all aspects of news translation. Additionally, machine translation systems may have unique features and approaches to handle different types of language pairs, resulting in varying levels of translation accuracy and fluency. It is risky to rely solely on Google Translate to provide a comprehensive view on the machine translation capabilities. To this end, the performance of Google Translate reported in this study should be approached with caution, and cannot be extrapolated to other machine translation systems.

Taking all things into account, it is evident that machine translation has become a crucial technology in the field of news translation, given its ability to facilitate the exchange of multilingual information. The fast speed and labor-saving nature of machine translation may present a promising opportunity to facilitate the news circulation worldwide. Yamada (2015) supposed that given the growing demand of machine translation post-editing, it could be judicious to evaluate translation learners as potential post-editor candidates. The findings of the present study have roughly confirmed this statement. Post-editing is a unique and distinct process that bears similarities to, yet different from manual translation. It involves an interactive collaboration between translators and machine translation, which necessitates specific skills and strategies. The findings obtained from the study indicate that rates of identification and correction of errors in machine translation were found to be unsatisfactory. It is evident that the proficiency level of translation learners has not yet attained the desired standard of quality. In such a scenario, the primary objective would be to equip translation learners with the necessary abilities to effectively and proficiently utilize and improve machine translation output. The suggestion to incorporate a post-editing module into translator training programs has been put forth by scholars (e.g., Łoboda and Mastela, 2023; O'Brien, 2022). It is suggested that translation education community should prioritize imparting adequate post-editing knowledge and techniques for post-editing. This includes the implementation of effective error detection strategies, the utilization of appropriate editing strategies, and the cultivation of critical thinking skills. Nevertheless, it is hoped that the exploratory findings of this study will empower translation learners to effectively navigate the changing translation landscape and successfully address its demands and challenges.

Data availability

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Notes

1 CET (shorted for College English Test) is to examine the English proficiency of undergraduate students in China and ensure that Chinese undergraduates reach the required English levels specified in the National College English Teaching Syllabus (NCETS). It consists of three tests: Band 4 (CET-4), Band 6 (CET-6), and the CET-Spoken English Test (CET-SET).

2 CATTI (shorted for China Accreditation Test for Translators and Interpreters) is a state-level vocational qualification examination entrusted by the Ministry of Human Resources and Social Security (MHRSS) of the People's Republic of China and implemented and administrated by the China International Publishing Group (CIPG). It is designed to assess the proficiency and competence of candidate translators and interpreters and is divided into four levels: Senior Translator, Level 1, Level 2, and Level 3.

3 https://www.mee.gov.cn/ywdt/hjnews/201911/W020191127531889208842.pdf.

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Author contributions
Conception and design of the work: Y.Y. Original draft: Y.Y. Revising and editing: R.L. and X.Q. Data collection and analysis: Y.Y. and J.N.

Competing interests
The authors declare no competing interests.

Ethical approval
The study was approved by Ethics Committee of Nanjing Agricultural University.

Informed consent
A consent form was distributed to the participants. The aim and procedures were explained to the participants. The participants were allowed to ask any questions during the experiment.

Additional information
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