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Original Article

A Structured AI–Human Framework for Machine Translation Post-editing (MTPE) Training

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ABSTRACT: *This research explores AI-human collaboration within a professional translation course for senior Applied English students (N=43), introducing a hands-on MTPE framework designed to foster translator autonomy. Throughout the course, students engaged in small-group weekly Chinese–English and English–Chinese tasks, documenting their interactions with large language models (LLMs) on Moodle. The pedagogical core consists of a structured Standard Operating Procedure (SOP) including source-text analysis, AI-assisted drafting, critical evaluation, iterative refinement, and justification which encourages systematic post-editing practices. Findings reveal that active engagement with AI, facilitated through precise prompting and iterative error detection, produced translations that were both semantically accurate and stylistically appropriate. In contrast, passive reliance on AI outputs led to weaker linguistic awareness and logical flaws. The study suggests that structured human-AI collaboration, anchored in professional standards, significantly enhances metalinguistic awareness and higher-order translation competence. By emphasizing process-oriented assessment and critical interaction with LLM outputs, this research provides a replicable model for modern AI-integrated translator training. This framework ensures that students develop the necessary skills to navigate the evolving landscape of professional translation while maintaining their role as critical decision-makers in the human-machine loop.*

KEYWORDS: *AI-Assisted Translation, Machine Translation Post-Editing, Human-AI Collaboration, Translator Autonomy, Large Language Models.*

1. INTRODUCTION

The rapid development of machine translation and generative artificial intelligence has significantly reshaped translation practice and translator education. Over the past decade, professional translation workflows have evolved from environments primarily supported by Computer-Assisted Translation (CAT) tools to ecosystems increasingly characterized by AI-assisted translation and machine translation post-editing (MTPE) [1, 2].

This technological transformation has prompted renewed discussion regarding the role of AI in translation pedagogy. A central challenge in translator education is integrating AI tools while maintaining students' analytical engagement. Translators' professional identity has shifted from that of an original content creator to a post-editor and quality controller, requiring both technical literacy and metalinguistic competence [3].

The evolution of translation technology can be observed in three main stages. From 2010 to 2015, rule-based and statistical machine translation systems combined with translation memory (TM) tools provided segment-level consistency. Between 2016 and 2020, the shift toward neural machine translation (NMT) enabled sentence-level fluency, positioning translators as post-editors of fluent but sometimes semantically flawed output [2, 3]. By 2021–2025, the rise of transformer-based generative AI and large language models (LLMs) has introduced document-level context awareness and stylistic flexibility. In this environment, the translator acts as a digital curator and prompt strategist, where quality is measured by functional suitability and the mitigation of AI-specific risks such as hallucinations [4, 5].

2. THEORETICAL BACKGROUND

2.1. MACHINE TRANSLATION POST-EDITING IN TRANSLATOR EDUCATION

MTPE has become an increasingly central component of professional translation workflows. As defined by ISO 18587:2017, it entails systematically reviewing and revising machine-generated translations to achieve human-level quality standards [6]. Professional practice differentiates between Light Post-Editing (LPE), focused on ensuring comprehensibility and factual accuracy, and Full Post-Editing (FPE), which aims to produce fluent, stylistically appropriate, and publication-quality translations.

Scholars have emphasized that MTPE training must extend beyond basic error correction. In particular, students should cultivate the ability to critically evaluate the reliability of machine output and determine when human intervention is necessary [1, 7]. This approach situates MTPE competence at the intersection of technical familiarity with translation technology and

critical linguistic judgment [8].

The emergence of LLMs has introduced new dimensions to MTPE. Unlike conventional NMT systems which were the focus of foundational post-editing research [9, 10] LLMs generate translations through probabilistic next-token predictions over massive multilingual datasets [5]. In other words, the system produces translations by estimating which word is most likely to come next according to patterns learned from vast multilingual data. While LLMs produce highly fluent text, this surface-level fluency can obscure subtle semantic inaccuracies. Students may therefore face challenges in detecting errors that would be more apparent in traditional NMT outputs, underscoring the need for the deliberate and structured post-editing practice explored in this study.

2.2. AI–HUMAN COLLABORATION AND COGNITIVE ENGAGEMENT

The integration of generative AI into translation pedagogy has transformed the educational landscape. LLMs, functioning as probabilistic predictors rather than task-specific translation engines, often generate text that is linguistically fluent but may include plausible yet semantically inaccurate content [4]. This phenomenon, often referred to as hallucination, can lead to a cognitive bypass, in which students accept AI-generated outputs without engaging in the necessary deep-structure analysis of the source text [4, 11].

In translator education, uncritical acceptance of AI output is particularly problematic for learners developing core competencies. Consequently, pedagogical frameworks must foster active, reflective interaction. Structured instructional designs, such as SOP-guided MTPE workflows, provide a mechanism for cultivating this cognitive engagement. By requiring students to evaluate machine outputs systematically, interrogate translation choices, and justify revisions, AI becomes a collaborative tool that supports analytical reasoning rather than a substitute for human expertise [1, 3].

3. MATERIALS AND METHODS

3.1. PARTICIPANTS AND EDUCATIONAL CONTEXT

The study was conducted in a professional translation course for senior students in an Applied English Department (N = 43). The primary data consisted of weekly translation submissions, screenshots of AI interactions uploaded to Moodle, and instructor evaluations. This instructional environment reflects the evolution from manual translation to workflows combining machine efficiency with human judgment, providing an ideal setting for exploring the impact of technology on translator autonomy.

3.2. TASK DESIGN AND AI COLLABORATION DOCUMENTATION

Students worked in flexible groups (up to five members) on weekly tasks, alternating between Chinese–English and English–Chinese genres. To ensure transparency, students uploaded screenshots of their interactions. These records allowed for the evaluation of the translation process, including prompt engineering and iterative refinement rather than just the final product.

3.3. SOP-GUIDED MTPE WORKFLOW

To ensure clarity for the reader, the SOP stages are presented as follows:

- Source-text analysis: Establishing the communicative purpose and stylistic constraints.
- Initial AI-assisted translation: Generating a draft using an LLM.
- Critical evaluation of AI output: Identifying inaccuracies, omissions, or hallucinations [4].
- Iterative revision and refinement: Collaborative prompt reformulation to improve semantic precision and cultural appropriateness.
- Final evaluation and justification: Providing written reasoning for revisions to demonstrate metalinguistic awareness.

3.4. ASSESSMENT RUBRIC FOR SOP IMPLEMENTATION

To evaluate analytical engagement, a process-oriented rubric was developed, following Massey et al.'s emphasis on MTPE as a specific professional competence [8]. The criterion, description, and grading weight for an assignment are as follows:

- SOP Alignment: Adherence to the analytical focus and systematic workflow steps (30%).
- Prompt Engineering: Effectiveness of iterative prompting and questioning of the AI (20%).
- Error Detection: Accuracy in identifying semantic issues or hallucinations (20%).
- Verification Depth: Evidence of human-led research and fact-checking during post-editing (20%).
- Functional Adequacy: The final translation's suitability for the target context and style (10%).

4. RESULTS AND DISCUSSION

Analysis of the submitted assignments and AI–human collaboration records indicates a clear relationship between students' adherence to the SOP framework and the quality of their translation outputs. Using the process-oriented rubric described in Section 3.4, student groups were classified into two primary interaction patterns.

4.1. ACTIVE AI-HUMAN INTERACTION

Groups that demonstrated strong adherence to the SOP framework consistently engaged in iterative questioning and verification of AI output. Their collaboration logs revealed multiple cycles of prompt reformulation, comparison of alternative translations, and explicit discussions of semantic and stylistic nuances. These groups achieved significantly higher scores in the following categories:

- Identification of semantic discrepancies: Actively detecting hallucinations or omissions in AI-generated content [4].
- Documentation of post-editing verification: Clearly recording the human review process and external fact-checking.
- Contextual adequacy: Producing translations that accurately reflect the communicative intent rather than just the literal meaning.

The evidence suggests that structured engagement fosters metalinguistic awareness, prompting students to justify translation choices and refine outputs beyond the superficial fluency provided by the LLM.

4.2. PASSIVE AI RELIANCE

In contrast, some groups exhibited minimal interaction with AI outputs beyond the initial machine-generated draft. Their submissions indicated limited prompt modification and few instances of critical evaluation. Although these translations appeared fluent, instructor evaluation revealed persistent issues, including incomplete semantic transfer from the source text, inconsistent use of specialized terminology, and failure to adapt the tone to the target audience.

These patterns suggest that passive reliance reduces opportunities for analytical engagement. This behavior aligns with the concept of cognitive ease, where the surface-level fluency of NMT and LLM outputs leads to a cognitive bypass of the deep-structure analysis required for professional translation [11, 9].

The findings from this study suggest several implications for translation pedagogy, particularly regarding the alignment of classroom practice with international professional standards.

4.3. IMPLICATIONS

First, AI-assisted translation training must incorporate structured workflows that mirror professional quality control. The SOP framework used in this study demonstrates how a step-by-step approach ensures that students engage critically with AI outputs rather than relying passively on machine-generated text. By framing AI outputs as drafts requiring analytical assessment, instructors can cultivate translator autonomy, moving students away from the cognitive bypass often induced by fluent LLM text [11, 4].

Second, process-oriented assessment is essential for capturing the nuances of AI–human interaction. Rubrics that measure both the final product and the depth of interaction as implemented in this course allow instructors to evaluate higher-order translation competence. This includes semantic verification and stylistic refinement, which are core requirements of ISO 18587:2017. This standard defines MTPE as a professional process requiring not just linguistic correction, but context-sensitive judgment [6].

Third, documenting the collaboration through screenshots provides a traceability mechanism. In professional practice, these steps mirror the responsibilities of digital content curators and post-editors, highlighting the importance of combining machine efficiency with human oversight [1, 3]. Aligning classroom practice with these standards reinforces key principles of translation quality control, including differentiating between LPE and FPE based on the intended communicative purpose, prioritizing semantic accuracy over the false fluency often produced by probabilistic LLM architectures [5], and encouraging reflective justification to foster metalinguistic awareness, ensuring students can defend their translation choices against AI-generated alternatives.

In sum, integrating MTPE best practices into pedagogy provides students with both practical skills and a critical framework, preparing them for an AI-augmented professional environment while maintaining human-centered quality standards.

5. CONCLUSION

This study demonstrated that a structured AI–human collaboration framework effectively encourages students to move beyond passive reliance toward critical engagement. By integrating a systematic workflow, educators can help students mitigate the risks of accepting fluent but semantically flawed machine outputs. Beyond the classroom, the professional adoption of these tools must prioritize data security and algorithmic accountability. This involves a shift toward localized language models that protect sensitive information and a commitment to transparency in the translation process. Ensuring that students can trace and justify their interactions with AI not only supports more accurate assessment but also establishes a foundation for professional ethics in an increasingly automated industry.

To prepare the next generation of translators, curricula should treat prompt engineering and digital literacy as essential

competencies rather than optional skills. This evolution requires a multidimensional approach to quality assurance that balances the efficiency of automatic metrics with the nuance of human cultural judgment. Ultimately, the goal of translator education is to harmonize machine capability with human insight. By grounding training in professional standards and iterative workflows, institutions can equip students to become autonomous experts who view AI as a collaborative partner. Future research should continue to refine these procedures across specialized domains to ensure that the human element remains the primary arbiter of quality and ethical integrity in translation.

CONFLICTS OF INTEREST

The author declares that there is no conflict of interest concerning the publication of this paper.

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