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MACHINE TRANSLATION POST-EDITING TECHNOLOGIES

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The article examines machine translation post-editing (MTPE) technologies in technical documentation translation, with particular attention to productivity, translation quality, and translators' professional experience. The relevance of the study lies in the growing use of MTPE in technical communication, where dense terminology, complex syntax, and functional precision make translation errors especially consequential. The research is based on a mixed-methods design that combines quantitative analysis of post-editing performance with qualitative investigation of translators' decision-making and perceptions. Eleven professional translators working with the English – Ukrainian and English – French language pairs post-edited authentic segments from software user guides, API documentation, and troubleshooting articles. The data included time spent per segment, editing patterns, and final translation quality assessed by independent evaluators. Semi-structured interviews further revealed how translators identify errors, handle technical terminology, and balance productivity and quality. The findings demonstrate that post-editing efficiency varies significantly by content type: API documentation proved the fastest to process, while troubleshooting materials required the greatest effort and, in some cases, were slower to post-edit than to translate from scratch. Although most post-edited segments reached acceptable quality, persistent problems included terminological inconsistency, fluency issues, and subtle semantic distortions. The study also identified MT-induced errors that remained unnoticed because machine-generated solutions appeared plausible. A particularly important result is that technical domain knowledge strongly influences both productivity and quality, as translators with relevant subject expertise performed more effectively and reported greater confidence in MTPE workflows. The article concludes that post-editing in technical translation should be understood not as a purely mechanical correction of machine output, but as a cognitively demanding and professionally complex activity that requires linguistic competence, technological awareness, and domain-specific knowledge.

***Keywords**: machine translation post-editing, technical translation, technical documentation, translation quality, translation technologies.*

Statement of the Problem and Relevance. The transition from human translation to MTPE has posed significant challenges. These challenges extend beyond technical implementation to encompass cognitive, quality management, and professional dimensions. Post-editing refers not only to the *"correction"* of machine output but also to a distinct cognitive task that may require different attention patterns, decision-making processes, and skills than those required in average translation. Research using keystroke logging, think-aloud protocols and eye-tracking reveals that post-editors engage in qualitatively different cognitive processes. For instance, they must quickly assess machine translation quality, determine cost-effective intervention thresholds, navigate the tension between achieving acceptable quality and maximising productivity, and identify errors of varying severity. Therefore, the cognitive load imposed by reading, evaluating, and correcting machine-generated text dramatically differs from composing target-language text de novo. Some studies documented increased mental fatigue, reduced job satisfaction, and concerns about deskilling among professional translators transitioning to MTPE roles.

In technical communication specifically, MTPE presents domain-specific challenges that complicate the human-AI collaboration model. It is worth noting that technical documentation is characterised by dense terminological content, complex syntactic structures, and critical functional requirements where translation errors can render software unusable or create security vulnerabilities (Arenas Guerberof & Moorkens, 2019). Machine translation systems, even state-of-the-art neural models, exhibit systematic weaknesses in handling technical terminology, particularly in emerging technologies where training data is scarce, multilingual term bases are incomplete, and neologisms proliferate faster than translation memory can capture them. For instance, such terms as *"containerization," "microservices architecture," "continuous integration" (CI), "serverless computing," "continuous deployment (CD)," or "zero-trust security model"* present translation challenges involving not just linguistic equivalence but also a conceptual understanding of the underlying technologies (Yamada, 2019). When machine translation systems mistranslate or inconsistently render such terms, post-editors should possess sufficient technical domain knowledge to recognise and correct errors. This requirement may blur boundaries between translators, technical writers, and subject-matter experts.

Analysis of Recent Research and Publications. Post-editing involves different mental processes than traditional translation. Daems et al. (2017) used eye-tracking to study how translators work with machine translation, measuring where and how long they looked at different parts of the text. They found translators spent longer examining MT output and checked back more frequently between source and target texts, indicating increased verification effort. Importantly, they discovered that poor-quality MT requiring extensive revision actually created more cognitive strain than translating from scratch, thus challenging the assumption that any MT output helps productivity.

Establishing appropriate quality standards for post-edited content remains challenging. Moorkens and O'Brien (2017) argued for "fit-for-purpose" quality frameworks that adjust post-editing effort based on how content will be used. Their research showed that organisations were increasingly distinguishing between content requiring full post-editing (user interfaces, installation guides) and content suitable for light post-editing (internal specifications, developer comments). However, implementing such systems requires clear quality specifications and consistent training (Vieira, 2020).

Rossi and Chevrot (2019) studied how post-editors handle new technology terminology through think-aloud protocols with 12 technical translators. They identified four strategies: accepting MT translations when plausible, consulting other texts to verify usage, creating new translations, and keeping English terms when target-language equivalents weren't established. Notably, 73% of post-editors retained English terms for cutting-edge concepts such as "containerization" and "microservices," fearing that premature localisation might confuse audiences familiar with English terminology.

Understanding systematic error patterns helps develop targeted strategies. Daems et al. (2017) created an error classification system for post-editing, categorising mistakes by type (lexical, syntactic, semantic, stylistic, terminological) and severity (critical, major, minor). Analysing 10,000 post-edited segments, they found that while NMT produced fewer critical errors than older systems, minor and major errors – especially terminology, register, and cultural appropriateness – remained common. Significantly, post-editors often failed to correct minor errors under time pressure, suggesting that productivity incentives may systematically bias work toward comprehensibility rather than professional standards.

Purpose and Objectives of the Article. The purpose of the article is to examine the effectiveness of machine translation post-editing in the translation of technical documentation by combining quantitative assessment of post-editing performance with qualitative analysis of translators' experiences and decision-making processes. To achieve this purpose, the study addresses the following **objectives:** to compare post-editing productivity and quality across different types of technical documentation; to identify the error patterns that remain in post-edited technical texts; and to explore how professional translators perceive, manage, and adapt to MTPE workflows in technical communication contexts.

Summary of the Main Research Material. Participants were recruited through professional translator networks and language service providers specialising in technical translation. Recruitment criteria required: (1) minimum two years of professional translation experience, (2) regular work translating IT/software documentation, and (3) current use of machine translation with post-editing in their workflows. It is worth noting that no specific MTPE training was required, as the study aimed to capture diverse post-editing approaches, including self-taught practices.

Recruitment occurred through announcements in professional translator platforms and forums, direct contact with two language service providers offering localisation services, and referrals from initial participants. The recruitment message emphasised that the study examined typical working practices rather than testing translator competence and that all data would be anonymised.

The final participant group consisted of 11 professional translators working across three language pairs: English-Ukrainian (n=6) and English-French (n=5). These pairs were selected based on their commercial importance in software localisation and the researcher's language competencies for quality assessment. Participants included freelance translators (n=7) and language service provider staff (n=4), with translation experience ranging from 2 to 10 years. Six participants (55%) received some formal training in post-editing, either through university coursework or professional development workshops, whereas 5 participants were self-taught in MTPE practices.

The study used 90 segments of authentic technical documentation representing three common content types: (1) software user guides explaining key procedures and features (n=30 segments), (2) API reference documentation describing parameters and programming interfaces (n=30 segments), and (3) troubleshooting articles providing solutions to common technical problems (n=30 segments). These categories were selected for their prevalence in localisation projects and for their representation of numerous linguistic challenges. These challenges comprised the following: user guides require clarity for non-technical audiences, API documentation requires terminological precision, and troubleshooting content combines problem-solving logic and procedural instructions.

Source documentation was drawn from publicly available materials for widely used open-source software, including PostgreSQL, WordPress, and Visual Studio Code, to ensure that all participants would encounter standard terminology and familiar technical concepts. Segments ranged from 50 to 200 words, with an average length of 155 words, which is typical of translation project segmentation in different computer-assisted translation tools.

All selected source segments were machine-translated into Ukrainian and French using Google Translate and DeepL, creating machine translation output that participants would post-edit. Using a single, widely available MT system ensured consistency and reflected common industry practice, as Google Translate and similar general-purpose engines remain prevalent in technical translation workflows despite specialised alternatives (Yamada, 2019). Every participant received 15 segments: 7 user-guide segments, 5 API-documentation segments, and 3 troubleshooting segments, randomly assigned to ensure variety while keeping the workload manageable (approximately 2,000 words per participant).

Data Collection

Phase 1: Post-Editing Tasks

Participants completed post-editing assignments using their own computer-assisted translation (CAT) tools and working environments to maintain naturalistic conditions. The most common tools were SDL Trados Studio (n=5 participants), MemoQ (n=3), and MateCat (n=3). Rather than requiring specific software, this approach showed how translators actually work with the tools they use on a constant basis.

Participants were instructed to post-edit the machine-translated segments to professional-quality standards they would apply to paid client work, with no time limit. They had access to terminology databases, internet resources, and reference materials as they would in normal working conditions. Screen recording software (OBS Studio or Camtasia, depending on participant preference) captured their work, recording time spent per segment, pauses, and editing patterns. Participants worked at their own pace over a two-week period, with most completing the assignment in 2 or 3 sessions.

This phase generated quantitative data, including total time per segment, editing approach (incremental modifications versus complete rewriting), and final word count differences between raw machine translation and post-edited versions. Furthermore, participants noted segments in which they encountered significant difficulties or made significant decisions, which later informed interview discussions.

Phase 2: Quality Evaluation

Post-edited translations were evaluated by two independent assessors, professional translators with technical translation experience in the relevant language pairs who did not participate in the post-editing phase. Evaluators assessed a representative sample of 25 segments from each participant using a simplified quality rubric adapted from industry standards (Daems et al., 2017). The rubric assessed four dimensions on a three-point scale (inadequate/acceptable/excellent): (1) accuracy – whether the translation correctly conveyed the source meaning, (2) terminology – whether technical terms were correctly translated and used consistently, (3) fluency – whether the target text read naturally and was grammatically correct, and (4) usability – whether the translated documentation would enable users to accomplish technical tasks.

Error analysis categorised all the remaining mistakes by type (terminology error, grammar issue, mistranslation, awkward phrasing) and severity (critical errors preventing comprehension or causing incorrect actions, minor errors affecting style but not understanding). This analysis identified which types of machine translation errors post-editors most frequently missed or inadequately corrected.

Phase 3: Interviews

Semi-structured interviews lasting 20-35 minutes were conducted via video call (Zoom) with all 11 participants within 2 weeks of completing their post-editing assignments. Interview questions explored: How do you decide whether to accept, modify, or completely rewrite machine-translated segments? What types of errors do you consider most challenging to identify and correct? How do you tackle technical terminology when machine translation provides plausible but potentially incorrect translations? How has post-editing influenced your translation workflow and professional identity? What are your main frustrations or concerns with MTPE in technical translation?

Interviews were audio-recorded and transcribed. The conversational format allowed participants to elaborate on their experiences and raise issues not anticipated in the interview guide. Several participants referenced specific segments from their post-editing work to illustrate their points, which the researcher could review from screen recordings to understand the context of their comments.

In contrast, **User Guide segments** required more extensive intervention, averaging 12.7 minutes per segment (range: 7.2-21.4 minutes), equivalent to approximately 732 words per hour – only an 8.5% improvement over translation from scratch. The increased time reflected the need to adapt explanations for clarity, adjust register for non-technical audiences, and correct subtle semantic issues that could confuse users.

Troubleshooting articles presented the greatest challenge, averaging 15.4 minutes per segment (range: 9.8-26.7 minutes), or approximately 604 words per hour – actually 24.5% *slower* than participants' reported translation-from-scratch speed. This unexpected finding contradicts assumptions that any MT output improves productivity and aligns with Daems et al.'s (2017) observation that poor-quality MT requiring extensive revision can impose greater cognitive load than translation from scratch.

Statistical analysis confirmed that content type significantly predicted post-editing time ($F(2,88) = 18.47$, $p < .001$). Post-hoc comparisons revealed that troubleshooting segments required significantly more time than both API documentation ($p < .001$) and user guides ($p = .003$), while API documentation was significantly faster than user guides ($p = .007$).

Conclusion. Quality analysis revealed that while 78% of the post-edited segments achieved acceptable or excellent ratings, systematic error patterns persist – particularly terminology inconsistencies (34% of errors), fluency issues (23%), and subtle semantic distortions (19%) that compromise professional standards even when basic comprehension remains intact. Significantly, the study documented “MT-induced errors” in which post-editors failed to detect plausible but incorrect translations, especially in technical terminology, due to domain knowledge gaps that prevented them from recognising inaccuracies. This pattern underscores that post-editing effectiveness depends not merely on linguistic competence but on technical domain expertise – a requirement that blurs traditional boundaries between translator, technical writer, and subject matter expert roles. The critical importance of technical domain knowledge emerged as perhaps the study's most consequential finding. Post-editors with software development or technical backgrounds achieved substantially higher productivity (averaging 7.9 minutes per segment versus 16.3 minutes) and quality (94% versus 68% acceptable ratings) compared to linguistically skilled but technically inexperienced colleagues. Moreover, technically knowledgeable participants reported greater professional satisfaction, viewing MTPE as an appropriate division of labour between machine efficiency and human expertise, while those lacking technical confidence experienced frustration and uncertainty about their quality judgments.

Future research should investigate several critical gaps. Longitudinal studies tracking the evolution of MTPE quality as neural machine translation continues to improve would clarify whether identified error patterns persist or diminish over time. User experience research examining how end-users perceive and interact with post-edited versus human-translated documentation would provide essential usability validation currently absent from translator-focused studies.

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ТЕХНОЛОГІЇ ПОСТРЕДАГУВАННЯ МАШИННОГО ПЕРЕКЛАДУ

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У статті розглянуто технології постредагування машинного перекладу у перекладі технічної документації з особливою увагою до продуктивності, якості перекладу та професійного досвіду перекладачів. Актуальність дослідження зумовлена зростанням використання MTPE у технічній комунікації, де насиченість термінологією, складний синтаксис і функціональна точність роблять перекладацькі помилки особливо значущими. Дослідження ґрунтується на змішаному дизайні, що поєднує кількісний аналіз ефективності постредагування з якісним вивченням рішень і сприйняття перекладачів. Одинадцять професійних перекладачів, які працювали з мовними парами англійська – українська та англійська – французька, здійснювали постредагування автентичних фрагментів посібників користувача програмного забезпечення, API-документації та статей із усунення технічних несправностей. Зібрані дані охоплювали час, витрачений на кожен сегмент, моделі редагування та підсумкову якість перекладу, оцінену незалежними експертами. Напівструктуровані інтерв'ю додатково дали змогу з'ясувати, як перекладачі виявляють помилки, працюють із технічною термінологією та оцінюють баланс між продуктивністю та якістю. Результати засвідчують, що ефективність постредагування істотно варіюється залежно від типу контенту: API-документація виявилася найшвидшою в опрацюванні, тоді як матеріали з усунення несправностей потребували найбільших зусиль і, в окремих випадках, постредагувалися повільніше, ніж перекладалися з нуля. Хоча більшість постредагованих сегментів досягла прийнятного рівня якості, стійкими проблемами залишалися термінологічна неузгодженість, порушення плавності викладу та тонкі семантичні спотворення. У дослідженні також виявлено помилки, зумовлені машинним перекладом, які залишалися непоміченими, оскільки згенеровані машиною варіанти видавалися правдоподібними. Особливо важливим результатом є те, що знання технічної предметної галузі суттєво впливають як на продуктивність, так і на якість, оскільки, перекладачі з релевантною фаховою підготовкою працювали ефективніше й демонстрували вищу впевненість у процесах MTPE. У статті зроблено висновок, що постредагування у технічному перекладі слід розуміти не як суто механічне виправлення машинного результату, а як когнітивно напружену й професійно складну діяльність, що вимагає мовної компетентності, технологічної обізнаності та предметно-галузевих знань.

Ключові слова: *постредагування машинного перекладу, технічний переклад, технічна документація, якість перекладу, перекладацькі технології.*

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