Journal of Languages & Translation
P-ISSN: 2716-9359 E-ISSN: 2773-3505
Volume 06 Issue 01 January 2026 pp165-182

Post-editing Machine Translation as a Vital Skill in the 21st Century: A Critical Analysis of the Integration of Artificial Intelligence in University-Level Translation Education

Hafida SLIMANI[1]
Université de Tlemcen – Algérie
hafida.slimani@univ-tlemcen.dz
0009-0000-1459-520X

Rachid SAIM
Université de Tlemcen – Algérie
rachid.saim@univ-tlemcen.dz
0000-0002-7509-6612

Received: *19/05/2025*	**Accepted:** *08/11//2025*	**Published:** *01/01/2026*

Abstract
This study aims to critically examine the integration of post-editing of machine translation (PEMT) in university-level translator training within the context of the growing influence of artificial intelligence. The central research problem concerns the extent to which PEMT is formally incorporated into academic curricula and whether current training programs adequately prepare future translators for professional environments increasingly shaped by AI-driven translation technologies. The study adopts a comparative perspective focusing on three higher education contexts: Algeria, France, and Canada. The research is based on a qualitative and comparative design. The primary methodology consists of a systematic analysis of official curricula, course syllabi, and pedagogical materials related to translator training. This analysis is complemented by a case study approach encompassing both face-to-face and digital learning environments, allowing for an examination of pedagogical practices and technological integration. Analytical criteria derived from translation studies and educational sciences are used to assess the structure and coherence of PEMT instruction. The results reveal significant disparities across the examined contexts. French and Canadian programs demonstrate a relatively structured integration of PEMT, including exposure to professional workflows and translation technologies. In contrast, the Algerian context shows a notable lack of formal pedagogical frameworks and limited institutional recognition of post-editing competences. Moreover, the findings highlight the limited use of standardized machine translation quality assessment metrics, such as Multidimensional Quality Metrics (MQM) and BLEU, within current training programs. The study concludes that translator training curricula require substantial pedagogical updating and recommends the adoption of structured, technology-oriented pedagogical models to better align academic programs with evolving professional demands.
Keywords; Artificial intelligence; Digital skills; Machine translation post-editing; Translator training; Translation pedagogy.

[1] Corresponding author: SLIMANI Hafida / hafida.slimani@univ-tlemcen.dz

Introduction

In recent years, the landscape of translation education has been profoundly reshaped by the rapid development of artificial intelligence (AI), particularly through the rise of Neural Machine Translation (NMT) systems and large language models. These technologies-exemplified by tools such as DeepL, ModernMT, Trados Studio, and ChatGPT-are no longer marginal innovations but have become embedded in both the professional and academic domains of translation. While their diffusion has facilitated access to multilingual content and enhanced productivity, it has simultaneously disrupted traditional training paradigms and prompted a redefinition of the translator's competencies.

Among the emerging professional skills, Post-editing of Machine Translation (PEMT) has gained considerable relevance. Rather than being a supplementary technical skill, PEMT is increasingly regarded as a core competency required of 21st-century translators. It involves the ability to critically interact with machine-generated output, revise it according to linguistic and stylistic standards, and ensure quality comparable to human translation. As such, PEMT training must encompass technological, cognitive, and linguistic dimensions, particularly within university-level curricula.

Despite this global shift, substantial disparities persist in how PEMT is integrated into translation training programs across different educational contexts. In Algeria, for example, university curricula remain heavily anchored in traditional human translation instruction, with limited exposure to CAT and MT tools. In contrast, Canadian and French institutions have progressively embedded PEMT into their translation programs through structured modules, project-based learning, and the use of advanced technologies. This divergence underscores a broader pedagogical and infrastructural gap that risks deepening the digital divide in translator education.

This article presents a critical and comparative analysis of the integration of PEMT (Post-Editing Machine Translation) into university translation programs across three distinct contexts-Algeria, France, and Canada-drawing on curriculum analysis, teaching materials, and translation outputs to assess the current state of PEMT training in these academic systems, propose a structured pedagogical framework based on Bloom's digital taxonomy and task-based methodologies, and offer a comparative case study demonstrating the practical application of PEMT tools (e.g., Trados, DeepL, ChatGPT) while analyzing student interventions in real-world translation tasks.

Through this multidimensional approach, the article seeks to bridge the gap between technological innovation and pedagogical implementation, advocate for the modernization of curricula-particularly in under-resourced contexts-and provide concrete strategies for integrating PEMT into translator education with academic rigor and professional relevance.

1. The Primary Theoretical Framework: Artificial Intelligence and the Transformations of Translation in the Digital Age

1.1. Neural Machine Translation (NMT) and the Evolution of Translation Tools

In recent years, machine translation technologies have undergone a radical transformation, shifting from rule-based models (RBMT) and statistical machine translation (SMT) to neural machine translation (NMT) systems grounded in deep learning and artificial neural networks. These NMT models are distinguished by their growing ability to comprehend complex textual contexts and to produce translations that are notably more fluent and accurate than those generated by previous systems. Tools such as DeepL, Google Translate, and ModernMT have demonstrated high performance levels-particularly with European languages-while still facing challenges when dealing with low-resource languages (Stymne, 2018, p. 20). The integration of NMT into computer-assisted translation (CAT) tools such as SDL Trados and MemoQ represents a qualitative leap in both the professional and technical spheres of translation.

1.2. Human vs. Machine Translation

Although neural machine translation has, in some contexts, begun to approach the quality of human translation, significant differences persist—especially in areas involving cultural nuance, deep semantic meaning, and stylistic adaptation (Pym, 2018, p. 68). The human translator does not merely transfer words;

rather, they interpret and reconstruct meaning within a network of cultural and contextual cues. In contrast, machine translation remains constrained by training algorithms based on pre-existing data, rendering it susceptible to contextual errors or textual incongruity. As such, post-editing has emerged as a practical framework that combines the efficiency of machines with human intuition to ensure high-quality translations.

1.3. Introducing Post-Editing: Concepts, Contexts, and Applications

Post-editing of machine translation (PEMT) is a human-mediated process aimed at correcting and refining machine-generated texts to meet professional publishing standards. This process ranges from "light post-editing," which focuses on basic comprehensibility, to "full post-editing," which aspires to achieve a quality level comparable to human translation (Plitt & Masselot, 2010, p. 185). PEMT is widely employed in specialized fields such as technical, legal, and medical translation, offering an optimal balance between productivity and precision. It has become an integral component of the modern language industry, necessitating its incorporation into university-level translator training programs.

1.4. The Relationship between PEMT and Translator Training: Linguistic, Cognitive, and Technological Competencies

Post-editing requires translators to acquire a multifaceted skill set that transcends traditional linguistic competencies. These include a deep understanding of NMT systems, the ability to analyze machine-generated errors, and proficiency in using collaborative CAT tools effectively. Several studies have indicated that PEMT enhances students' linguistic awareness and can serve as an educational tool for teaching contrastive translation, editing strategies, and quality assessment (Moorkens & O'Brien, 2017, p. 120). In this context, the integration of PEMT into translation curricula is not merely a technical supplement, but a pedagogical necessity aligned with the demands of the digital labor market.

1.5. From Technical Activity to Cognitive Practice: Redefining the Translator's Role in the Digital Age

Over the past few decades, the field of translation has undergone profound transformations due to the accelerating convergence of computational sciences and applied linguistics, particularly following the emergence of neural machine translation (NMT) models. These models represent a significant breakthrough compared to earlier statistical paradigms, relying on deep neural networks that simulate human brain activity in processing language. This has led to notable improvements in fluency, accuracy, and contextual precision, as evidenced by the performance of tools like DeepL and ModernMT (Bahdanau et al., 2014; Bentivogli et al., 2016).

Nonetheless, human translation continues to excel in rendering the rhetorical, cultural, and functional dimensions of texts-especially in literary and highly specialized professional discourse. Between these two poles, a hybrid model has emerged that combines machine-generated output with human intervention: post-editing of machine translation (PEMT). Over time, PEMT has evolved from a mere "quick linguistic fix" into a complex professional practice requiring advanced linguistic, cognitive, and technological competencies (Graham et al., 2017, p. 661).

PEMT is no longer perceived as a marginal or secondary task within the translation field. Rather, it is increasingly recognized as a viable and future-oriented profession in its own right. Practitioners are expected to master machine translation systems, be familiar with CAT tools, understand the mechanics of machine-generated text, and distinguish among various error types produced by AI systems (Benounane & Naceur, 2020, p. 40). This paradigm shift is reshaping the nature of translational practice across both academic training programs and professional institutions.

In relation to translator education, the theory of translation cognition—or translation process research—offers a valuable lens for understanding how students interact with machine-generated texts. Human involvement in PEMT goes beyond mere linguistic refinement; it entails real-time cognitive decision-making and critical contextual analysis, fostering what some scholars have termed "digital translational awareness" (O'Brien, 2012, p. 110). Such activities contribute to the development of critical thinking, error analysis, and rhetorical sensitivity, positioning PEMT as a powerful pedagogical tool within university translation programs (Krüger & Behrens, 2020).

2. University Contexts and the Teaching of Post-Editing: Between Algeria, France, and Canada

2.1. A Comparative Analysis of Translation Programs in Selected Universities

An analysis of university programs in Algeria, France, and Canada reveals a marked disparity in the extent to which artificial intelligence tools and post-editing practices are integrated into translator training. At the University of Algiers 2 (Department of Translation), the pedagogical approach remains largely centered on traditional human translation, with limited exposure to computer-assisted translation (CAT) tools and no systematic training in post-editing or neural machine translation (NMT) techniques (Khadar, 2024, p. 60). In contrast, the Université de Montréal adopts a more advanced approach, incorporating dedicated modules on "Post-Editing" and "Machine Translation Systems" within its Master's program in Professional Translation. Students are also encouraged to use tools such as Trados Studio, MemoQ, and DeepL as part of their practical training (Université de Montréal, 2023). Similarly, at the Université de Strasbourg, there is a clear integration of linguistic and technological components. The course "Machine-Assisted Translation" includes analyses of neural engine features and hands-on exercises in post-editing machine-generated output (Université de Strasbourg, 2022).

2.2. Integration of AI Tools in University Training

Neural machine translation tools (NMT), such as Google Translate, ModernMT, and DeepL, have become central components in translation education within Western contexts. They are no longer perceived as a threat to the translator's role but rather as essential instruments for enhancing productivity and output quality. Studies such as SEKHRI (2019, p. 230) demonstrate that students trained in post-editing display higher linguistic proficiency and develop a critical awareness of the quality of machine-generated output. In Algeria, however, the integration of such tools remains institutionally and pedagogically delayed, despite individual initiatives and the presence of specialized faculty members who advocate for a gradual incorporation of these technologies (Bouras & Abdelmoumen, 2025, p. 210).

2.3. Skills Required within Curricula: PEMT and CAT Tools

Integrating post-editing of machine translation (PEMT) into university curricula necessitates a set of complex skills, including proficiency in CAT tools such as SDL Trados, OmegaT, and MemoQ, as well as a deep understanding of the features and limitations of neural machine translation systems. These include challenges such as semantic ambiguity and contextual errors. Students are expected to master post-editing techniques and differentiate between levels of intervention—light and full post-editing—according to linguistic and stylistic quality standards. They must also be able to assess translation quality using automated evaluation tools such as BLEU and TER, supported by human judgment (Benounane & Naceur, 2020, p. 40). In both the Canadian and French contexts, these competencies are acquired through specialized coursework that incorporates project-based learning and professional simulations reflective of real-world translation environments. By contrast, the lack of digital infrastructure and qualified personnel in Algeria remains a significant barrier to the effective implementation of PEMT instruction.

2.4. Pedagogical and Technical Challenges

Arab universities face a range of pedagogical and technical challenges in teaching post-editing of machine translation (PEMT). One major issue is the inadequacy of digital infrastructure, particularly due to the absence of official licenses for professional tools like Trados, which limits students' opportunities for practical training. Additionally, there is a pronounced shortage of qualified human resources. AI-related linguistic content is often delivered by instructors lacking sufficient technical background, which adversely affects the quality of training. Moreover, some faculty members exhibit pedagogical resistance, viewing post-editing as a diminution of the translator's role rather than an epistemic and skill-based extension of it (Mellinger & Hanson, 2020, p. 102). These constraints are compounded by the urgent need to redesign educational programs to incorporate PEMT as a standalone transversal competency, rather than relegating it to the status of a peripheral technical elective.

2.5. Post-Editing in Higher Education: A Cross-Border Pedagogical Comparison

2.5.1. Comparative Analysis of PEMT Instruction in Selected Universities

Before addressing specific case studies, it is essential to present a comparative analysis of how post-editing of machine translation (PEMT) is taught across different universities. Such an analysis allows for a better understanding of pedagogical disparities in the integration of this advanced competency into academic curricula. The following table presents a comparison of translation programs at three selected institutions: The University of Algiers 2 (Algeria), the University of Strasbourg (France), and the University of Montréal (Canada).

Table 1: PEMT Teaching and AI Integration in Translation Programs: A Comparative Summary

Item	University of Algiers 2 (Algeria)	University of Strasbourg (France)	University of Montreal (Canada)
Number of Hours Dedicated to PEMT	Concepts of PEMT (Post-Editing of Machine Translation) are integrated within technical translation modules, with approximately 10-12 hours allocated in practical courses. There is no independent course specifically devoted to post-editing.	A dedicated master's course titled "Technical, Editorial, and Audiovisual Translation" is offered, including advanced units on machine translation and post-editing, with about 20-25 hours of practical training on PEMT tools.	The master's translation program includes specialized units on machine translation and post-editing, allocating around 30 hours encompassing practical training and applied projects, alongside opportunities to engage in recognized professional training and certification programs accredited by professional bodies such as OTTIAQ.
Tools Utilized	Tools such as Google Translate and Trados are used in practical training sessions, with limited emphasis on advanced artificial intelligence tools.	The tools employed include DeepL, MemoQ, ModernMT, as well as text analysis software like AntConc, with students trained to use these tools in diverse translation contexts.	The curriculum incorporates advanced tools such as Trados, ChatGPT, DeepL, ModernMT, and MateCat, providing comprehensive training on integrating these tools within translation and post-editing workflows.
Assessment Types	Evaluation is based on the analysis of machine-translated texts, including technical exams to measure students' understanding of machine translation tools and their ability to improve translation quality.	Students are assessed through group translation projects, critical reports, and analyses of machine-translated texts, emphasizing the development of post-editing skills and critical thinking.	Assessment includes editing real texts, oral presentations, and applied projects, focusing on enhancing post-editing competencies and the use of AI tools in translation.
Pedagogical Approach Adopted	The curriculum relies on traditional teaching methods supplemented by technical exercises, without a significant focus on project-based or task-based learning.	A Task-Based Language Teaching (TBLT) approach is implemented, integrating practical projects and hands-on training to strengthen students' post-editing skills.	A project-based learning approach is employed, combining analytical, critical, and technical activities to foster students' abilities in post-editing and the use of AI tools.
Integration of Generative Artificial Intelligence	Limited and informal, relying on basic machine translation tools without systematic integration of generative AI tools within the curriculum.	Generative AI tools such as ChatGPT are incorporated experimentally into educational activities, encouraging students to explore the potentials of these tools in translation contexts.	Generative AI is formally integrated into the curriculum, with training provided on using tools like ChatGPT for translation and post-editing tasks, including analysis of their impact on translation quality.

Source: Haiyudi et al. (2023) , Mellinger & Hanson, (2020) and Daems et al. (2021)

Analysis reveals that University of Algiers 2 integrates the concepts of Post-Editing Machine Translation (PEMT) within technical translation modules without offering a dedicated standalone course. Its training relies on basic tools such as Google Translate and Trados. In contrast, the University of Strasbourg offers an independent master's level course entitled "Technical, Editorial, and Audiovisual Translation," which includes advanced modules on machine translation and post-editing, employing professional tools like DeepL and ModernMT. Meanwhile, the University of Montreal presents an advanced model through specialized modules within its master's translation program, utilizing sophisticated tools such as Trados and ChatGPT, alongside comprehensive training on integrating generative artificial intelligence techniques into the translation and post-editing workflow.

2.5.2. Differences in PEMT Teaching Among the Selected Universities

The comparative table clearly demonstrates that French and Canadian universities, such as Strasbourg and Montreal, significantly outperform University of Algiers 2 regarding the specialization and modernization of their PEMT curricula. These universities allocate between 20 to 30 hours for PEMT instruction, employ cutting-edge tools including DeepL, ChatGPT, and ModernMT, and implement interactive assessment methods based on applied projects and analytical critique. Conversely, University of Algiers 2 offers approximately 10 to 12 hours without a dedicated course and relies on basic tools like Google Translate and Trados, lacking a systematic incorporation of generative AI. Moreover, its pedagogical approach remains traditional compared to the participatory, task- and project-based learning strategies adopted by the other institutions, reflecting a more flexible and rapid response to contemporary market demands and the increasing need for technically qualified translators. Consequently, University of Algiers 2 is called upon to update its curricula, enhance specialization in PEMT, and formally integrate generative AI tools to ensure the training of translators capable of keeping pace with the rapid transformations occurring globally in the translation professions.
Based on a comparative analysis of PEMT curricula at University of Algiers 2, Strasbourg, and Montreal, it is evident that University of Algiers 2 urgently needs to modernize its academic programs to keep up with the swift global developments in artificial intelligence and modern translation tools. Recent literature indicates that integrating tools such as DeepL, ModernMT, and ChatGPT into training improves translation accuracy and accelerates the editing process (Graham et al., 2017, p. 660). Researchers further assert that these tools do not replace translators but rather serve as complements requiring analytical competencies and precise digital skills (Moorkens, 2020, p. 134). Experts recommend adopting project-based learning in PEMT curricula due to its effectiveness in developing realistic professional skills (Bowker & Buitrago Ciro, 2019, p. 85). Similarly, numerous studies emphasize the necessity of including critical evaluation units on machine translation quality through systematic comparisons between human and machine-generated translations (Plitt & Masselot, 2010, p. 185). A recent report highlights the importance of enhancing students' digital and technical skills by training them to use Translation Management Systems (TMS) and modern Computer-Assisted Translation (CAT) tools (Way, 2018, p. 23). Engagement with the labor market is equally vital, as university partnerships with professional bodies positively impact students' readiness for employment (Tawfiq & Boutchacha, 2023, p. 235). Finally, collaboration with international institutions such as the University of Montreal and Strasbourg aligns with contemporary trends aiming to network pedagogical practices in translation teaching on a global scale (Pym et al., 2021, p. 110).

2.5.3. Pedagogical Approaches to Teaching PEMT: From Tasks to Generative Artificial Intelligence

After addressing the technical and pedagogical challenges faced in teaching Post-Editing of Machine Translation (PEMT) at the university level, it becomes essential to review contemporary pedagogical approaches that contribute to the integration of various skills alongside the deployment of modern technologies. In this regard, the pedagogical approaches employed in teaching PEMT have diversified to include project-based and task-based learning methods (PBL – TBL), which enable students to apply what they have learned within practical and professional environments. These approaches are founded on the principle that learning should be interactive and experiential, thereby enhancing the students' capacity for critical and analytical thinking when engaging with modern translation tools.

One of the most prominent approaches involves the integration of generative artificial intelligence within the educational process. Within this framework, generative AI is regarded as a powerful pedagogical tool that enables students to interact with systems such as ChatGPT and DeepL, not merely as auxiliary aids but as integral components of the learning process that reinforce their skills in editing and interpretation. This orientation serves as a means to cultivate students' critical awareness regarding the limitations and errors inherent in machine translation, thereby aiding them in acquiring the critical thinking skills required for effective post-editing.

Through these approaches, students cease to be mere users of technological tools and become active agents in text production, critical analysis, and revision. Consequently, this stimulates the development of their personal translation skills in alignment with the contemporary demands of the labor market.

2.5.4. Reconceptualizing Translator Identity

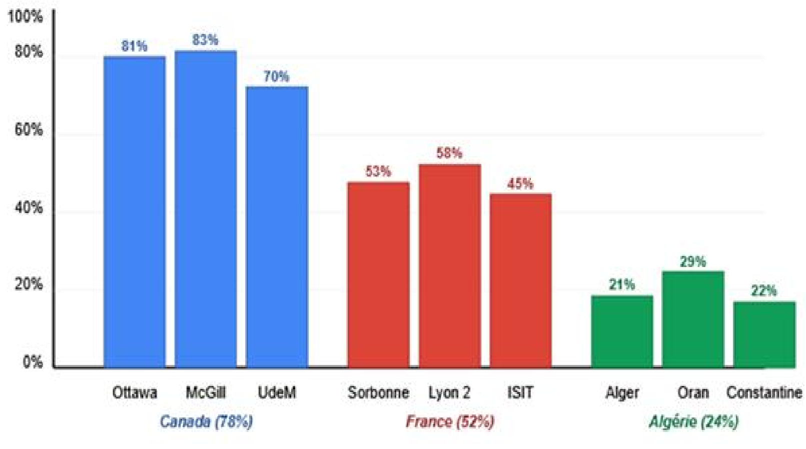
These approaches also seek to redefine the identity of the academic translator, emphasizing the necessity for translators to possess multifaceted skills within a dynamic and complex environment that requires engagement with diverse technologies. Therefore, a profound understanding of the application of artificial intelligence in translation—through advanced machine translation tools—is considered a fundamental step towards enhancing translation quality and ensuring accuracy in produced texts.

3. Case Study: Intercultural Comparison Based on Translation Practices (Canada, France, Algeria)

In this perspective, we propose a comparative case study. To illustrate this perspective, we conducted a comparative case study involving learners and teachers in Canada, France, and Algeria, based on data collected from digital and classroom contexts

The five figures presented offer a comprehensive overview of the current state of Machine Translation Post-Editing (MTPE) integration in higher education. Collectively, they reveal significant geographical disparities, rapid technological evolution, and shifting pedagogical approaches that warrant close examination (Kenny, 2022, p. 30).

Figure 1. Comparative Histogram: Rate of MTPE Integration in University Curricula (2023)

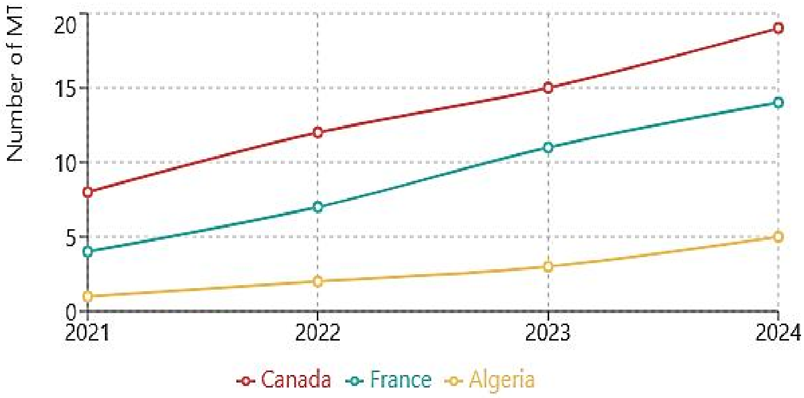


Source: (Kenny, 2022) and (Torres-Hostench & Sánchez Ramos, 2023), (Puchała-Ladzińska, 2025). (Nguyen et al. , 2025).

Figure 1 highlights marked disparities in the rate of MTPE integration within university programs in 2023 across Canada, France, and Algeria. In Canada, the integration rate is high (78–80%) due to

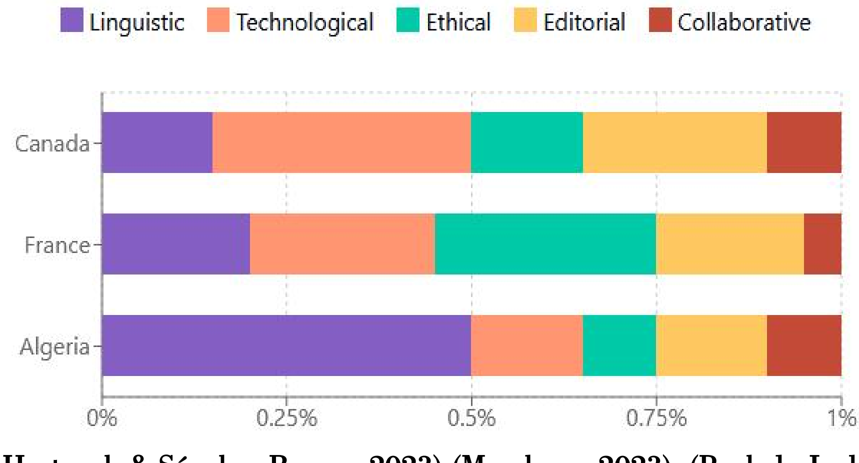
proactive educational policies, strong industry partnerships, and the use of advanced tools. In France, integration is moderate (50–55%), typically embedded within broader computer-assisted translation (CAT) frameworks without autonomous recognition. Algeria lags significantly behind (<30%), offering limited training and exposure to MTPE tools. These gaps reflect the influence of institutional policies and resource availability on the adoption of MTPE in higher education.
Figure 2 depicts the differing trajectories of MTPE integration between 2021 and 2024 in the three countries. In Canada, a steady increase is observed, particularly after 2022, driven by the rise of generative AI and a university environment conducive to pedagogical innovation. In France, a more moderate growth trend is seen, with a peak between 2022 and 2023 reflecting a structured phase of experimentation (notably with ChatGPT and DeepL), informed by ethical concerns. In Algeria, progress remains minimal until 2022, followed by a slight rise linked to local pilot projects. These contrasting dynamics reflect distinct institutional strategies: proactivity and flexibility in Canada, cautious openness in France, and an initial phase of engagement in Algeria (Torres-Hostench & Sánchez Ramos, 2023, p. 83).

Figure 2. Temporal Evolution (2021–2024) of MTPE Introduction by Country



Source: (Torres-Hostench & Sánchez Ramos, 2023), (Puchała-Ladzińska, 2025). (Nguyen et al. , 2025) and (Moorkens, 2023)

Figure 3. Area Chart: Distribution of Targeted Skills in MTPE Modules

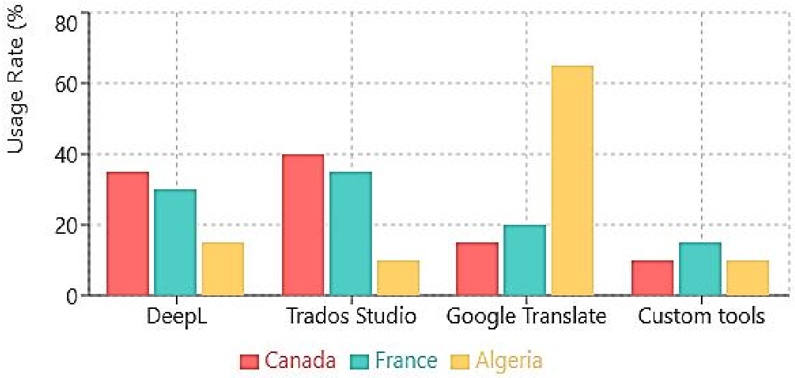


Source: (Torres-Hostench & Sánchez Ramos, 2023) (Moorkens, 2023), (Puchała-Ladzińska, 2025) and (Nguyen et al. , 2025).

The area chart (Figure 3) reveals diverging curricular priorities in MTPE instruction. Canada emphasizes technological and editorial skills with a clear professional orientation. France promotes a balance between technical and ethical competencies, while Algeria focuses primarily on linguistic skills,

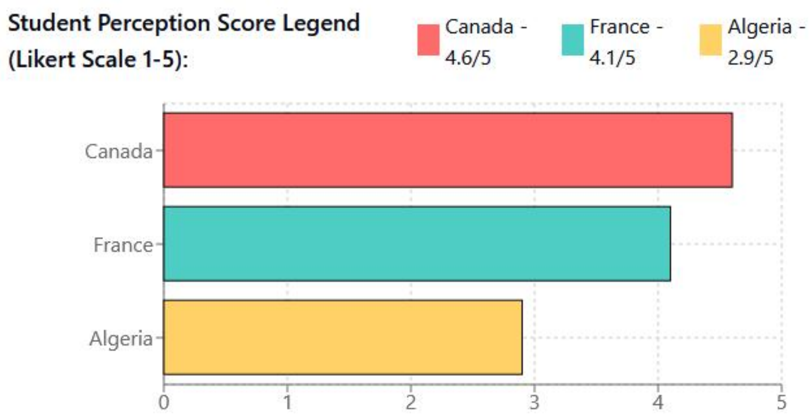
indicating a more traditional educational approach. These differences reflect country-specific educational philosophies and socio-professional expectations (Daems & Vandepitte, 2021, p. 305).
Figure 4 presents, through a dual-ring pie chart, the relationship between selected AI technologies and the pedagogical competencies they support within language education. The inner ring identifies four key tools - Trados, DeepL, ChatGPT, and Google Translate - while the outer ring links each tool to a specific skill: Trados enhances editorial proficiency (structured editing and segmentation); DeepL supports linguistic competence (fluency and reformulation); ChatGPT fosters critical and collaborative skills (contextual writing and assisted revision); and Google Translate is typically associated with basic technological initiation, often lacking structured pedagogical support (Moorkens, 2023, p. 15). The comparative analysis underscores geographic disparities: in Canada and France, Trados and ChatGPT are generally integrated into guided didactic frameworks, promoting reflective engagement with the tools. In Algeria, however, the predominant use of Google Translate without critical pedagogical anchoring limits the development of assisted editing skills and diminishes the formative potential of AI in language classrooms.

Figure 4. Technology Usage in MTPE Modules by Country



Source: (Moorkens, 2023) and (Bowker, 2021), (Puchała-Ladzińska, 2025) and (Nguyen et al. , 2025).

Figure 5. Horizontal Bar Chart: Student Perception of MTPE Relevance



Source: (Moorkens, 2023) (Puchała-Ladzińska, 2025). (Nguyen et al. , 2025) and (Bowker, 2021)

The bar chart reveals national differences in students' perceptions of MTPE. Canadian students view it as a valuable skill (4.6/5), supported by appropriate training and employment prospects. In France (4.1/5), perceptions are also positive but tempered by concerns about automation. In Algeria, the low average (2.9/5) reflects a lack of instructional support and career relevance. These findings highlight the importance of structured and critical MTPE training to foster pedagogical engagement and student buy-in.

The analysis reveals structural disparities in MTPE integration, shaped by educational policies and resource allocation. Canada demonstrates innovation, France remains cautious, and Algeria shows stagnation (Bowker, 2021, p. 12). This heterogeneity underscores the urgent need for harmonized curricula to mitigate North–South inequalities.

The study advocates for the mandatory inclusion of MTPE modules at the Master's level, combining traditional tools with recent AI technologies. It stresses the importance of continuous and critical teacher training, hybrid (automated and human) skill assessments, and the development of technological infrastructure in emerging contexts such as Algeria. Real-world, multilingual project-based learning is recommended. Future research should address the long-term impact of MTPE, trainer education, comparative tool evaluation, cognitive modeling, and ethical considerations. MTPE is emerging as a strategic challenge for translator training, requiring a balance between innovation and academic rigor.

4. Proposed Pedagogical Framework for Integrating Post-Editing of Machine Translation (PEMT) into University Translation Programs

4.1 Introduction to the Pedagogical Framework

Amidst the rapid technological transformations witnessed in the field of translation, it becomes imperative to update curricula to incorporate contemporary tools and techniques such as artificial intelligence. Post-editing of machine translation (PEMT) constitutes a fundamental component of this evolution, enabling students not only to enhance their translation skills but also to engage actively with technologies that dominate today's market. Therefore, the proposed pedagogical framework should be founded on the principle of blended learning, effectively integrating traditional education with modern technologies. This encompasses learning technological tools, developing critical thinking towards machine-translated texts, and applying contemporary techniques within an academic environment.

4.2 Curriculum Design: Integrating Artificial Intelligence within Translation Programs

To develop an effective academic curriculum for teaching PEMT, it is essential first to include dedicated instructional units focusing on machine translation technologies such as Neural Machine Translation (NMT) and Computer-Assisted Translation (CAT) tools like SDL Trados and MemoQ. This should involve practical sessions on how to utilize these tools, analyze machine translation errors, and correct them (Plitt & Masselot, 2010, p. 188). Moreover, hands-on workshops must be allocated to test students in varied domains-legal, medical, and technical translation-which demand greater precision in post-editing.

The curriculum should also incorporate theoretical components to familiarize students with the foundations of artificial intelligence in translation, including distinctions between deep learning and machine learning, and how these technologies influence the translation process (Stymne, 2018, p. 21). Interactive activities should be designed to motivate students to evaluate the quality of machine-translated outputs by analyzing automatically generated texts and making necessary adjustments to achieve the desired quality.

4.3 Post-Editing Skills (PEMT) and Integrated Competencies

To become effective post-editors of machine translation (PEMT), students must acquire a comprehensive skill set that goes beyond the basic use of AI tools. This includes the development of linguistic competencies, such as the ability to faithfully comprehend source texts and interpret nuanced meanings within varied cultural contexts. Equally important are cognitive skills, which enable students to critically analyze typical machine translation errors-ranging from syntactic inconsistencies to culturally inappropriate renderings-and to make the necessary adjustments to achieve the desired quality. In addition, students must build technological proficiency in using advanced tools like DeepL and Google Translate, as well as develop a strategic understanding of how to optimize machine translation workflows.

When effectively integrated, these linguistic, cognitive, and technological abilities empower students to evolve from traditional translators into specialized post-editors, capable of operating confidently within increasingly complex digital translation environments.

4.4 Practical Application: Case Studies and Training Programs

It is crucial to include case studies that allow students to engage with real-world challenges in translation. For example, students can work on machine-translated texts from widely-used software like ModernMT or Trados in diverse contexts (e.g., legal or technical translation), subsequently performing post-editing based on professional quality standards.

Additionally, university programs should incorporate internships or collaborative training schemes with industry partners such as translation agencies or technology firms developing translation tools. Through these programs, students can work in teams on authentic projects, applying PEMT techniques in professional settings.

4.5 Performance Evaluation and Analysis

Within this new curriculum, it is essential to develop novel assessment methods that consider the quality of improvements made to machine-translated texts. Evaluation should measure the accuracy of post-editing, the quality of the final text, and the ability to analyze and effectively rectify machine translation errors. Self-assessment and peer evaluation can also be integrated into the process, aiding students in cultivating critical analytical skills and identifying weaknesses in their work (Moorkens & O'Brien, 2017, p. 122).

5. Towards a Pedagogical Framework for Post-Editing Machine Translation Skills (PEMT)

5.1 A Methodological Proposal for Teaching PEMT in the University Context

In light of the rapid expansion in the use of Neural Machine Translation (NMT), it has become imperative for university curricula to adapt to the evolving demands of the professional landscape by integrating dedicated modules on post-editing machine translation (PEMT). Numerous scholars (O'Hagan, 2020, p. 15) support the development of a pedagogical model that merges critical practice with interactive editing, structured into three interconnected phases. The first is the Theoretical Awareness Phase, in which students are introduced to core concepts of NMT and PEMT, including the distinctions between post-editing and translation revision, as well as the varying degrees of post-editing (light versus full). The second phase, Practical Simulation, engages learners with authentic editing tasks using widely adopted tools such as Google Translate, Trados, DeepL, and ChatGPT, enabling them to apply post-editing techniques across diverse text types and contexts. The final stage, Self-Assessment and Analytical Critique, encourages students to reflect on their own editing decisions, compare machine-generated outputs with human translations, and develop a critical understanding of quality standards and error analysis. This tripartite framework fosters not only technical proficiency but also critical thinking and evaluative skills essential to contemporary translation practice.

5.2 Integrating Analytical, Critical, and Technical Activities

To achieve pedagogical effectiveness in teaching PEMT, it is insufficient to focus solely on technical aspects; rather, the instructional process must incorporate a critical and analytical dimension. Bowker and Buitrago Ciro (2019, p. 97) recommend integrating comparative discourse analysis, typologies of errors generated by NMT systems (semantic, syntactic, idiomatic, contextual), and targeted activities that highlight points of human intervention in the machine-generated output. In this context, student competencies can be significantly enhanced through guided post-editing tasks, collaborative review sessions comparing multiple translation outputs, and evaluations aligned with established quality assessment frameworks such as MQM (Multidimensional Quality Metrics) and TAUS, fostering both critical reflection and editorial precision.

5.3 The University Lecturer's Role in Developing Linguistic and Digital Competencies

The university instructor plays a central role in bridging the gap between theoretical instruction and professional training, particularly in the context of translation education shaped by digital transformation. As Guichon and Hauck (2020, p. 44) emphasize, the instructor acts as a pedagogical mediator, guiding students not only in mastering linguistic precision but also in developing critical awareness of stylistic nuances and deviations. This dual responsibility requires educators to possess both disciplinary expertise in translation and technical proficiency in digital editing tools, such as Computer-Assisted Translation (CAT) software, machine translation systems, and collaborative platforms. Moreover, instructors must cultivate in learners a strong ethical sensibility concerning the implications of automation and artificial intelligence in translation, thereby equipping future professionals with the reflective and technical competencies needed to navigate the evolving demands of the language industry.

.5.4 How Does Artificial Intelligence Reshape the Identity of the University Translator?

Artificial intelligence does not threaten the translator but rather reconfigures their professional and academic identity. The contemporary translator is no longer merely a conveyor of texts but has evolved into a digital linguistic editor, a decision-maker, and a multi-skilled analyst. Pym and Torres-Simón (2021, p. 60) contend that the translator's future professional identity centers on *supralinguistic competence*, encompassing editing, contextual understanding, and adaptability to AI.
In this framework, university translation education shifts from the mere transmission of linguistic skills to the development of integrated technological and editorial competencies. Consequently, PEMT emerges as a new pedagogical domain intersecting linguistic, digital, and critical dimensions, necessitating a rethinking of pedagogical roles, assessment methods, and professional outcomes.

6. A Model of a University Teaching Unit for Post-Editing Machine Translation

To consolidate the teaching of the post-editing skill of machine translation (PEMT) within university curricula, it is proposed to design an integrated teaching unit that addresses this theme from multiple perspectives. The aim of this unit is to enable students to analyze the quality of machine translation output and to intervene in its results so as to ensure the achievement of the communicative and semantic standards of the target text. The unit includes clear educational objectives, such as training students to use post-editing tools (e.g., Trados and ModernMT) and to evaluate translations based on quantitative and qualitative indicators. Regarding content, the unit covers the principles of machine translation, PEMT strategies, and applied case studies. The unit also integrates the use of various artificial intelligence tools (Google Translate, DeepL, ChatGPT), alongside evaluative activities such as group comparisons, individual editing tests, and analytical presentations.

It is recommended that the unit align with competency-based teaching standards prevalent in European and Canadian contexts (Bowker & Buitrago Ciro, 2019, p. 57; Rico & Torrejón, 2020, p. 49). Moreover, the provision of adequate digital resources and a sufficient number of hours balancing theoretical and practical aspects is advised (Läubli & Orrego-Carmona, 2020, p. 111).

6.1. Designing Digital Learning Activities According to Bloom's Digital Taxonomy

To enhance the effectiveness of teaching PEMT in university environments, Bloom's Digital Taxonomy can be adopted as a reference framework for designing pedagogical activities. This taxonomy assists in organizing activities according to higher-order thinking levels, ranging from analysis to creativity and evaluation. Within this framework, students can be trained to analyze differences between machine translation outputs generated by different engines (e.g., Google Translate and ModernMT) and to post-edit translated segments in accordance with stylistic and semantic quality standards, which corresponds to the creativity level. Evaluation activities based on metrics such as BLEU, HTER, and MQM are also included to measure the accuracy of students' editorial interventions (Benounane & Naceur, 2020, p. 41).

Tools such as ChatGPT and Trados Studio are leveraged as interactive pedagogical media that foster the development of technical skills within a dynamic educational environment, particularly in light of contemporary calls to shift towards digitally skill-based education (Kiraly, 2000, p. 131; Massey & Ehrensberger-Dow, 2022, p. 28).

6.2. Transformations of the University Translator's Identity in the Age of Artificial Intelligence

Artificial intelligence is reshaping the contours of the academic translation profession, necessitating a reconsideration of the role of the student translator within higher education institutions. Previously, the translator was viewed primarily as a "meaning conveyor," concerned with transferring the content of the source text to the target language. Today, this role has evolved to encompass editorial, technical, and analytical dimensions that require complex competencies.

The university translator now works with sophisticated tools and is required to intervene in non-human generated outputs according to rigorous standards that exceed mere linguistic comprehension. Within this context, the concept of the "intelligent editor" emerges as a central actor capable of interacting with neural machine translation systems and making editorial decisions based on contextual analysis and linguistic critique.

Recent literature advocates redefining the university translator as a strategic practitioner and a digital linguistic critic (Castilho et al., 2017, p. 110; Boukhelef, 2020, p. 30). This calls for curricula to reconceptualize the translator as a multi-skilled professional positioned at the intersection of technology, language, and critical thinking.

6.3. A Practical Pedagogical Model Based on Bloom's Digital Taxonomy

Below is a proposed practical pedagogical model for teaching the post-editing of machine translation (PEMT) skill in university education, grounded in Bloom's Digital Taxonomy and attentive to linguistic, technical, and critical competencies. The model clearly links educational objectives, activities, tools used, and assessment methods:

Table 2: A University Pedagogical Model for Teaching PEMT Based on Bloom's Digital Taxonomy

Digital Bloom's Taxonomy Level	Proposed Learning Objective	Practical Activity	Digital/ Technological Tool	Assessment Method
Remembering	Introducing students to the concepts of CAT (Computer-Assisted Translation), machine translation tools, and standards	Digital terminology flashcards; interactive short quiz	Quizlet, Google Forms	Automated quiz
Understanding	Explaining the difference between machine translation and human post-editing	Interactive presentation and analysis of various translations	Google Translate, DeepL	Descriptive analysis
Applying	Applying post-editing steps on machine-translated texts	Editing preliminary technical and literary texts	Trados Studio, ModernMT	Individual edited file
Analyzing	Comparing the performance of machine translation tools according to text type	Group analytical activity plus graphical representation	HTER, BLEU, Excel	Analytical report
Evaluating	Assessing the quality of machine translation according to defined criteria	Group review with critical discussion	MQM, Trados Quality Model	Group evaluation rubric
Creating	Producing a final human-quality revised translation	Final post-editing project with critical commentary	ChatGPT, DeepL + text editing tools	Group presentation and collaborative assessment

Source: (Castilho et al., 2017), (Boukhelef, 2020), (Kiraly, 2000), (Massey & Ehrensberger-Dow, 2022) and (Benounane & Naceur, 2020).

6.4. Pedagogical Notes:

It is recommended that this framework be implemented within a teaching unit lasting approximately 20 to 30 hours. This duration allows sufficient time to cover all fundamental aspects related to teaching machine translation post-editing. Integrating the activities within a project-based or task-based learning approach is encouraged, as it enhances students' capacity for practical application and the use of technological tools in authentic contexts. Furthermore, employing the digital Bloom's taxonomy serves as an effective instrument to shift instruction from mere knowledge transmission toward the development of higher-order competencies such as analysis, creativity, and evaluation. This approach strengthens critical thinking skills and promotes active engagement with the instructional content.

7. Post-Editing Tools in Academic Practice

7.1. Critical Analysis of Tools Used in Post-Editing

In recent decades, neural machine translation (NMT) tools have become central to both academic and professional translation practices. These tools vary in accuracy, editability, and integration with professional translation platforms. For instance, Google Translate demonstrates broad capabilities in high-resource languages but continues to exhibit semantic inconsistencies in less-resourced languages such as Arabic, particularly in specialized contexts (SEKHRI, 2019, p. 231). In contrast, DeepL offers a more natural and precise style of expression, especially in European language pairs; however, its performance in translation into Arabic remains limited compared to its Arabic-to-other-languages output (Groves & Mundt, 2021, p. 18).

ChatGPT provides translation and contextualization through a large-scale language model (LLM) that relies on contextual understanding rather than mere statistical alignment. Nevertheless, its non-specialized nature may lead to stylistic deviations or terminological errors in specialized texts (Darif M., & Shoshani, 2024, p. 50). Trados Studio remains the most integrated tool within the post-editing environment, enabling translators to work in a comprehensive CAT environment, supporting terminology databases, translation memories, and quality assessments. Meanwhile, ModernMT is distinguished by its interactive learning capability from the editor, which reduces repetitive errors and enhances contextual adaptation (ModernMT, 2022).

7.2. Differences Between Types of Post-Editing: Light vs. Full Post-Editing

The type of required post-editing depends on the translation's purpose. Light post-editing aims solely to improve text acceptability and grammatical correctness, without focusing on stylistic refinement, and is commonly used for internal translations or provisional documents. Conversely, full post-editing involves thorough rephrasing to ensure the highest levels of quality and stylistic accuracy, demanding that the output be equivalent to a first-rate human translation (Plitt & Masselot, 2010, p. 186).

7.3. Educational Analysis of a Sample Machine Translation

Based on an analysis of translation samples generated by the aforementioned tools, the following
example is presented: ***Original sentence (English)" :***
The economic outlook remains uncertain despite recent policy measures".

Google Translate output:
"لا يزال التوقع الاقتصادي غير مؤكد على الرغم من الإجراءات السياسية الأخيرة."
Educational observations:
The term "التوقع الاقتصادي" (economic expectation) is inaccurate; the correct term is "الآفاق
الاقتصادية" (economic outlook.).
"الإجراءات السياسية"is a literal mistranslation of "policy measures," which should be rendered as
"الإجراءات السياساتية"or"التدابير الاقتصادية."

DeepL output:
"لا تزال الآفاق الاقتصادية غير واضحة رغم التدابير الأخيرة التي اتُّخذت."

Observations:
The phrasing is more natural, and the terminology is closer to the economic context, though it requires grammatical improvement ”اتُّخذت“) lacks a clear subject.(
ChatGPT output:
"رغم التدابير الأخيرة، لا تزال الآفاق الاقتصادية غامضة."
Observations:
7.4. Critical Analysis of Translation Accuracy and Student Editor Intervention
7.4.1. Technical Criteria for Evaluating PEMT Tools
This table summarizes the key technical metrics used to assess the quality of Post-Editing Machine Translation (PEMT) tools. Indicators such as HTER, BLEU, and MQM provide objective frameworks for measuring the performance of machine translations against human references. These criteria are increasingly incorporated into translation training programs to enhance students' analytical skills (Benounane & Naceur, 2020).

Table 3. Technical Criteria for Evaluating PEMT Tools

Metric	Full Name	Description
HTER	Human-targeted Translation Edit Rate	Measures the proportion of edits required to correct a machine-translated text compared to the reference human translation.
BLEU	Bilingual Evaluation Understudy	Evaluates machine translation accuracy based on word and phrase overlap with a reference translation.
MQM	Multidimensional Quality Metrics	A comprehensive framework assessing translation quality across dimensions such as linguistic accuracy, terminology, fluency, and style.

Source: (Benounane & Naceur, 2020), (Puchała-Ladzińska, 2025). (Nguyen et al. , 2025).

The technical metrics (HTER, BLEU, MQM) enable standardized evaluation of machine translation quality. Their inclusion in translation training reflects an effort to align student competencies with industry standards while fostering a critical approach to PEMT tools.

7.4.2. Evaluation of Student-Edited Outputs in PEMT Training
This table highlights the core focus areas for evaluating student-edited outputs in PEMT training. It emphasizes the identification of errors, the decision-making process for human intervention, and the assessment of editorial proficiency. These elements aim to prepare students for the professional demands of post-editing in the translation industry.

Table 2. Evaluation of Student-Edited Outputs in PEMT Training

Evaluation Focus	Definition	Objective in Pedagogy
Error Types	Identification of linguistic, stylistic, and contextual errors in machine output.	Train students to recognize the scope and nature of MT errors.
Need for Human Intervention	Determination of which segments require human correction.	Teach judgment and prioritization in editing.
Editorial Proficiency	Evaluation of the quality and accuracy of student revisions.	Assess editing techniques and alignment with professional standards.

Source : (Benounane & Naceur, 2020), (Puchała-Ladzińska, 2025). (Nguyen et al. , 2025).

The evaluation of student work in PEMT training focuses on three key dimensions: error detection, editorial decision-making, and revision quality. This pedagogical approach aims to develop practical skills while encouraging reflection on the limitations and potential of machine translation.

7.4.3. Ethical Issues in the Academic Use of PEMT Tools

This table explores the major ethical concerns associated with the academic use of PEMT tools. Issues such as confidentiality, authenticity, and assessment integrity are examined, underscoring potential risks and challenges for the responsible integration of these technologies in educational settings.

Table 3. Ethical Issues in the Academic Use of PEMT Tools

Ethical Concern	Question Raised	Implication
Confidentiality	Can PEMT tools ensure secure handling of sensitive texts?	Risk of data leakage in medical, legal, or academic documents.
Authenticity	Does using AI compromise the originality of student work?	Raises concerns on plagiarism, authorship, and creative ownership.
Assessment Integrity	How can PEMT use affect fair student evaluation?	Over-reliance may undermine the development of fundamental translation skills.

Source : (Benounane & Naceur, 2020), (Puchała-Ladzińska, 2025). (Nguyen et al. , 2025).

The ethical issues raised in this table highlight the tensions between technological innovation and academic integrity. Data confidentiality, the authenticity of student work, and fair assessment practices are major challenges that require regulatory frameworks and best practices to address effectively.

Academic practice in post-editing machine translation reveals significant variation in student intervention levels. A study by Moorkens and O'Brien (2017, p. 90) found that students trained in post-editing made more precise qualitative corrections compared to those without PEMT (post-editing of machine translation) backgrounds. This difference is attributed to the intersection of cognitive, linguistic, and technological skills, especially in addressing subtle stylistic errors.

Ideal post-editing intervention requires that the student not only identify unclear contextual errors but also apply rigorous editing standards, such as the use of specialized glossaries and the verification of syntactic functions. Moreover, students must learn to strike a balance between preserving the structure generated by the machine and adapting the output to meet the stylistic and idiomatic expectations of the target language.

Conclusion

The analysis results concerning the integration of Post-Editing of Machine Translation (PEMT) into higher education reveal a profound transformation driven by the advancement of digitalization and the utilization of artificial intelligence. Initially confined to correcting errors produced by machine engines, this practice has evolved into an essential skill that requires translator-students to deploy intertwined linguistic, cognitive, and technical competencies. It has surpassed mere error correction to become an intelligent practice necessitating deep critical and analytical thinking, amidst the ongoing evolution of neural machine translation models. The study also identified disparities between university programs in Algeria, France, and Canada regarding the incorporation of PEMT within academic curricula, with many Algerian universities lacking structured educational units dedicated to this practice. On a practical level, the analysis of translation tools such as DeepL, Trados, and ChatGPT revealed variability in accuracy and the necessity for human intervention, underscoring the importance of employing evaluation metrics like BLEU and MQM to assess translation quality. Accordingly, the study recommends updating university curricula to include a dedicated PEMT instructional unit that harmonizes theoretical and practical dimensions, encompassing students' technical, critical, and linguistic skills. Furthermore, the adoption of project-based and task-based learning methods (PBL-TBL) is advised, alongside curriculum updates to integrate modern translation tools such as ChatGPT and ModernMT.

References

Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*.

Benounane, H. M., & Naceur, D. (2020). Neural vs. statistical machine translation: A comparative study of Google Translate and Reverso. *Academic Review of Social and Human Studies, 12*(2), 38–47. https://asjp.cerist.dz/en/downArticle/552/12/6/123463

Bentivogli, L., Bisazza, A., Cettolo, M., & Federico, M. (2016). Neural versus phrase-based machine translation quality: A case study. *Proceedings of EMNLP*, 257–267.

Boukhelef, F. (2020). The impact of modern technologies on the content of translator training and the importance of technical competence to keep pace with the translation market. *Academy of Social and Human Studies, 12*(3), 28–33. https://asjp.cerist.dz/en/article/109304

Bouras, S., & Abdelmoumen, A. (2025). Machine translation: Its prospects, difficulties, and the efforts of Arab scholars in this regard. *Al-Umda in Linguistics and Discourse Analysis, 9*(1), 206–216. https://asjp.cerist.dz/en/article/262489

Bowker, L. (2021). Promoting linguistic diversity and inclusion: Incorporating machine translation literacy into information literacy instruction for undergraduate students. *International Journal of Information, Diversity & Inclusion, 5*(3), 127–151. https://doi.org/10.33137/ijidi.v5i3.36159

Bowker, L., & Buitrago Ciro, J. (2019). *Machine translation and global research: Towards improved machine translation literacy in the scholarly community*. Emerald Publishing.

Castilho, S., Moorkens, J., Calzada, F., Lin, H., & Way, A. (2017). Towards ethical guidelines in machine translation. *Proceedings of AMTA 2018*, 105–117.

Daems, J., & Vandepitte, S. (2021). Post-editing training and the development of professional identity. *Meta, 66*(2), 299–316.

Darif, M., & Shoshani Obaidi, M. (2024). Evaluating the translation of ChatGPT: A comparative study of a simplified scientific text. *Maalem, 14*(2), 41–56. https://asjp.cerist.dz/en/article/240141

Gaspari, F., Toral, A., Naskar, S., & Way, A. (2022). A survey of human evaluation in machine translation. *Computational Linguistics, 48*(1), 1–36. https://doi.org/10.1162/coli_a_00428

Graham, Y., Baldwin, T., Bond, F., Carpuat, M., & van Genabith, J. (2017). A pilot study of human evaluation for machine translation. *Natural Language Engineering, 23*(5), 653–673. https://doi.org/10.1017/S135132491600015X

Groves, M., & Mundt, K. (2021). DeepL versus Google Translate: A case study in translation accuracy and user perception. *Translation & Interpreting Studies, 16*(2), 10–29.

Guichon, N., & Hauck, M. (2020). Teacher education in the age of artificial intelligence: Opportunities and challenges. *ReCALL, 32*(1), 40–59.

Haiyudi, H., Pratama, Y. B., & Art in, S. (2023). Post Editing Machine Translation (PEMT) as the preferred method for university students in Indonesia. ELT Forum Journal of English Language Teaching, 12(2), 90 97. https://doi.org/10.15294/elt.v12i2.67163

Kenny, D. (2022). The impact of AI on translation pedagogy. *Translation Spaces, 11*(1), 27–41.

Khadar, M. (2024). The position of the translator in the digital environment: Reality and challenges. *Maalem, 14*(2), 57–72. https://asjp.cerist.dz/en/article/240142

Kiraly, D. (2000). *Authoring and tutoring in the foreign language classroom: A social constructivist approach*. Narr Francke Attempto Verlag.

Krüger, R., & Behrens, B. (2020). Post-editing and translation competence: A pedagogical perspective. *The Journal of Specialised Translation, 34*, 136–157.

Läubli, S., & Orrego-Carmona, D. (2020). When Google Translate is better than some human colleagues, those people are no longer colleagues. *Journal of Specialised Translation, 34*, 100–123.

Mahboubi, R. (2024). The tendencies of higher education professors in Algeria towards using artificial intelligence applications to achieve quality standards in the educational process - A field study at the

University of May 8, 1945, Guelma. *Atras Magazine*, *5*(Special Issue on Artificial Intelligence, Education and Distance Education), 762–779. https://asjp.cerist.dz/en/downArticle/880/5/3/253683

Massey, G., & Ehrensberger-Dow, M. (2022). Competence and cognition in translator training: A study of learning outcomes. *The Interpreter and Translator Trainer*, *16*(1), 24–41. https://doi.org/10.1080/1750399X.2021.2008559

Mellinger, C. D., & Hanson, T. A. (2020). *Translation and technology: A guide for the 21st century translator*. Routledge.

ModernMT. (2022). *Adaptive neural machine translation in real time*. https://www.modernmt.com

Moorkens, J. (2023). Ethical considerations in MTPE and AI use in translation. *Translation Studies*, *16*(1), 10–25.

Moorkens, J., & O'Brien, S. (2017). Assessing user interface needs of post-editors of machine translation. *Translation & Interpreting Studies*, *12*(2), 111–133. https://doi.org/10.1075/tis.12.2.05moo

Nguyen, T. N. N., Tran, T. T., Nguyen, N. H. A., Lam, H. P., Nguyen, H. M. S., & Tran, N. A. T. (2025). The Benefits and Challenges of AI Translation Tools in Translation Education at the Tertiary Level: A Systematic Review. International Journal of TESOL & Education, 5(2), 132-148. https://doi.org/10.54855/ijte.25527

O'Brien, S. (2019). The future of translation and interpreting in the age of artificial intelligence. In *The Routledge handbook of translation and technology* (pp. 14–29). Routledge. https://doi.org/10.4324/9781315642300-2

O'Hagan, M. (2020). *The Routledge handbook of translation and technology*. Routledge.

Plitt, M., & Masselot, F. (2010). A practical guide to the design of a post-editing course. In *Translation and interpreter training* (pp. 183–194). Routledge.

Puchała-Ladzińska, K. (2025). Translator1 Training: Teaching Translation and Interpreting in the 21st Century. Heteroglossia, 18. Wydawnictwo Uczelniane Wyższej Szkoły Gospodarki. https://www.wsg.pl

Pym, A. (2018). What technology does to translating. *Translation Spaces*, *7*(1), 61–82. https://doi.org/10.1075/ts.7.1.04pym

Pym, A., Malmkjær, K., & Plana, M. del M. (2021). *Traduction et technologie: Nouvelles approches didactiques*. Presses Universitaires de Rennes.

Rico, C., & Torrejón, E. (2020). Integrating post-editing competence into translator training. *InTRAlinea, Special Issue: Post-editing in the Wild*. https://www.intralinea.org/specials/article/integrating_post_editing_competence_into_translator_training

Sekhri, O. (2019). Machine translation and the problems of translating cultural terms in the Arab world. -AL-MUTARĞIM, 19; (2), 239–261. https://asjp.cerist.dz/en/article/115183

Specia, L., Scarton, C., & Paetzold, G. H. (2018). *Quality estimation for machine translation*. Morgan & Claypool Publishers.

Stymne, S., Tiedemann, J., & Ahrenberg, L. (2018). Explaining neural machine translation. *Machine Translation*, *32*(1), 1–26. https://doi.org/10.1007/s10590-018-9213-y

Tawfiq, M., & Boutchacha, J. (2023). The role of translation in establishing community convergence: Hotel website translation as a strategic tool for effective cross-cultural promotion. *Maalem*, *14*(1), 231–246. https://asjp.cerist.dz/en/article/222152

Torres-Hostench, O., & Sánchez Ramos, M. (2023). Curricular adaptations in MTPE training in Europe. *The Interpreter and Translator Trainer*, *17*(1), 70–88.

Université de Montréal. (2025). *Maîtrise en traduction*. Faculté des arts et des sciences. https://admission.umontreal.ca/programmes/maitrise-en-traduction/

Way, A. (2018). Quality expectations of machine translation. In *Machine translation: What it is and what it isn't* (pp. 17–34). Springer.