Hybrid Translation Method: Prompt Engineering and Cognitive Integration in Translator Training

Método híbrido de traducción: Ingeniería de prompts e integración del sistema cognitivo en la formación traductora

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Abstract

In this paper, a hybrid translation method is proposed that integrates the translator's cognitive integration and prompt engineering. The primary objective is to enhance translation quality and align translator training with the demands of a professional field increasingly shaped by Generative AI. A three-phase process is outlined: first, the analysis, transfer, and pre-editing of the source text are addressed; second, the focus is placed on the use of prompts, including translator–model interaction and prompt refinement; third, post-editing is incorporated based on quality criteria appropriate to the text type, communicative function, and translation brief. The workflow begins with a cognitive phase where translational and linguistic knowledge guide human–machine collaboration. The process concludes with the translator's evaluation and final decision regarding the output. Additionally, a functionalist template is included for prompt design that considers text type, purpose, audience, and language combination. Through this model, the aim is to support critical thinking, reduce overreliance on automation, and promote an active, reflective role for translators in AI-assisted environments.

Keywords: *hybrid translation method; human-machine collaboration; prompts; pre-editing; post-editing*

Resumen

Se propone un método híbrido de traducción que integra el sistema cognitivo del traductor y la ingeniería de *prompts*. El objetivo principal es mejorar la calidad de las traducciones y alinear la formación de traductores con las exigencias de un campo profesional cada vez más influido por la inteligencia artificial generativa. El proceso se describe en tres fases: en primer lugar, se aborda el análisis, la transferencia y la preedición del texto fuente; en segundo lugar, el enfoque se centra en el uso de *prompts*, incluida la interacción entre traductor y modelo, así como la refinación de instrucciones; en tercer lugar, se incorpora la posedición basada en criterios de calidad apropiados al tipo de texto, su función comunicativa y el encargo de traducción. El flujo de trabajo comienza con una fase cognitiva en la que el conocimiento traductológico y lingüístico guía la colaboración humano–máquina. El proceso concluye con la evaluación del traductor y su decisión final respecto al resultado obtenido. También se presenta una plantilla funcionalista para el diseño de *prompts* que considera el tipo de texto, el propósito, el público destinatario y la combinación lingüística. A través de este modelo, se busca fomentar el pensamiento crítico, reducir la dependencia excesiva de la automatización y promover un rol activo y reflexivo del traductor en entornos asistidos por IA.

Palabras clave: *método de traducción híbrido; colaboración humano–máquina; prompts; preedición; posedición*

Introduction

Generative AI (GenAI) is the new electricity, just as it transformed the industry, so does Generative AI bringing both positive and negative consequences (Stanford Graduate School of Business, 2017). Among the negative effects is what Peterson (2025) refers to as the *collapse of knowledge*, a process through which human knowledge gradually becomes reduced and streamlined over time due to excessive reliance on artificial intelligence. Similarly, the recursive nature of GenAI models —where systems are trained on data they have generated themselves—amplifies biases and simplifies content into standardized versions. Reinforcing the most popular ideas while discarding less common ones diminishes the richness of collective knowledge. This is further compounded by users' tendency to rely on easily accessible information rather than engaging with more in-depth or specialized sources.

This phenomenon also extends to the fields of communication and translation, where it raises concerns about linguistic diversity and intercultural mediation. Hellström (2024) argues that the introduction of Large Language Models (LLMs) may affect four key aspects of human writing: the amount of writing produced by humans, people's ability to write, the value attributed to writing, and trust in the written word. From this perspective, the growing use of generative AI in content production and dissemination may contribute to the reinforcement of dominant language structures and the standardization of idiomatic expression across languages.

This concern is closely related to the notion of knowledge collapse, particularly when AI systems are recursively trained on content generated by previous models rather than on human-origin data. In such scenarios, less frequent linguistic patterns may become increasingly underrepresented, reducing lexical and syntactic variability. Guo et al. (2024) observed a significant reduction in linguistic diversity in texts produced by LLMs across successive recursive training interactions. Even when model outputs do not display obvious errors, they may become increasingly uniform due to the repetition of high-probability patterns, which may contribute to linguistic impoverishment and homogenization over time.

From a technical perspective, Bender et al. (2021) argue that large language models operate primarily by capturing statistical regularities rather than by achieving semantic understanding. This helps explain why GenAI systems tend to perform more effectively with in-domain texts that resemble their training data. When faced with out-of-domain input, such as atypical syntactic constructions, culturally specific references, or novel pragmatic patterns, these systems may produce outputs that are inaccurate, generic, or unnaturally standardized.

These limitations have direct implications for translation. Because AI-generated translations rely on probabilistic patterns, they may favor generic equivalences over contextual nuance, thereby risking the distortion of meaning and the erasure of cultural markers. Consequently, uncritical dependence on AI-generated translations may reinforce biases, homogenize discourse, and weaken the critical interpretive work required for context-sensitive translation.

The integration of AI into translator training presents both promising opportunities and significant challenges. As argued by Lévano and Arbildo (2024), although these technologies contribute to improved efficiency and precision in translation processes, it remains essential to recognize that the role of the human translator continues to be relevant and irreplaceable. For this reason, it is important that translators and communication professionals balance the use of GenAI with critical human intervention to preserve linguistic richness and ensure respect for cultural diversity in the transfer of knowledge. Shahmerdanova (2025) emphasizes that although AI-powered translation tools have greatly improved speed and accessibility, they still face important challenges in dealing with idiomatic language, cultural subtleties, and sensitive content. Addressing these limitations calls for an approach that integrates AI's efficiency with the cultural competence and professional judgment of human translators. In response to the rapid evolution of the linguistic services industry, the integration of theoretical frameworks with empirical practice has become a fundamental imperative in translator pedagogy.

AI-assisted translation does not replace human decision-making; instead, it demands greater analytical and adaptive skills. According to Shahmerdanova (2025), the most effective way to address the limitations of AI is through human-AI collaboration, where hybrid translation models bring together the speed and efficiency of artificial intelligence with the contextual insight and cultural sensitivity of human translators. The integration of prompt engineering into translator education offers an opportunity to strengthen skills that have always been essential to the profession: critical thinking, text and context analysis, the ability to infer based on prior knowledge, and the discretion to intervene actively when linguistic or cultural discrepancies arise. In this context, prompting, as Lévano and Arbildo (2024) notice, is an operation in which the translator verbalizes the mental processes involved in understanding the source text and reexpressing it appropriately to achieve high-quality translations in automated and AI-assisted environments. These educational demands are closely connected to the technological conditions of contemporary professional translation. Translator training must prepare students not only to formulate effective prompts, but also to understand how AI-assisted decisions are embedded in broader translation workflows.

Technological integration has profoundly transformed the translation process, evolving into hybrid workflows where human expertise and automated tasks are strategically combined. This shift redefines professional norms by moving beyond the traditional 1990s taxonomy identified by Sánchez-Gijón and Palenzuela-Badiola (2023), which categorized interactions into Machine-Assisted Human Translation (MAHT), Human-Assisted Machine Translation (HAMT), and Fully Automatic Machine Translation (FAMT). In the contemporary digital age, the boundaries between these categories have blurred, giving rise to Translation Editing and Management Systems (TEMS). These platforms serve as the operational backbone for hybridity, centralizing automated assembly functions and facilitating varied levels of human intervention.

The analytical relevance of this hybridity is most evident in the post-editing (PE) phase, where the choice between "light" and "full" PE is determined by the required communicative intent and project constraints. While light PE aims for mere intelligibility, full PE demands a degree of human intervention comparable to traditional translation to ensure stylistic and cultural nuances. To validate the efficacy of these hybrid scenarios, quality assessment moves beyond subjective intuition toward standardized frameworks like the Multidimensional Quality Metrics (MQM). With MQM, professionals can granularly evaluate the output of TEMS, ensuring that the integration of automated tools does not compromise the technical or semantic integrity required for international content export (von Hausen & Muñoz-Ballier, 2025).

This study maintains that the implementation of AI-driven tools, when complemented by human oversight, creates a robust framework for enhancing the performance and qualitative outcomes of translation workflows. While AI translation enables the rapid handling of large volumes of content, human translation contributes precision, contextual understanding, and creativity. Equipping translators with knowledge and skills related to the potential of AI prepares them to operate effectively in an ever-evolving environment. As noted by Soysal (2023), AI can bring multiple benefits to translation processes, including increased efficiency, accuracy, and speed. Thanks to deep-learning mechanisms applied to large pre-trained corpora, ChatGPT has developed powerful semantic analysis capabilities, enabling it to contextualize and comprehend human language.

The LLM is also capable of understanding the correlation between instructions based on the sequential input provided by the user, progressing through combined instructions. This allows it to more effectively perform multi-step, sequential tasks guided by prompts formulated by users drawing on translation theories, models, methods, techniques, and skills tailored to their specific needs. In this regard, designing a hybrid translation method that integrates the translator's cognitive capabilities with the potential offered by LLMs such as ChatGPT would optimize the translation process. The hybrid translation method combines both the translator's cognitive system with prompt engineering to establish a three-phase translation model consisting of analysis, translation, and post-editing.

In the context of Gen. AI, translator training needs to be rebuilt. Operational competencies in both foreign language learning and translation skills development are increasingly being automated. As a result, a new era is emerging in which it is essential to understand the various paradigms and models that guide the translator's interventions to formulate effective prompts. This paper aims to present a hybrid methodology that allows the translator to maintain the nature of its practice (e.g. the value of human communication, the cognitive process, etc.), while making use of new technologies.

1. Translator's cognitive system

Before describing the role of the translator's cognitive system in hybrid translation workflows, this section first clarifies how cognition is understood in relation to translation and why it remains central in AI-assisted environments. In this study, the cognitive system is approached from a cognitive translation studies perspective, which views translation as a problem-solving, inferential, and decision-making activity supported by both general cognitive processes and translation-specific competence.

The cognitive system refers to the set of mental processes that allow individuals to acquire, process, store, retrieve, and apply knowledge effectively. In translation, these processes are not equally relevant at every stage. Reasoning and problem-solving are central because they enable translators to identify translation problems, evaluate possible solutions, and make informed decisions. Memory also plays a key role, as translators draw on linguistic, encyclopedic, cultural, and specialized knowledge when interpreting the source text and producing the target text. Attention supports the identification of relevant textual, pragmatic, and cultural cues, while perception contributes to the initial recognition of linguistic and contextual information. Together, these processes allow translators to regulate cognitive effort and intervene critically in human–AI collaboration.

According to Campdesuñer Sarquiz (2010), individuals considered more intelligent tend to display certain characteristics, including the flexible use of learned principles and strategies—enabling them to generalize and apply knowledge to new situations—rapid identification of relevant aspects in problem-solving contexts, the ability to benefit from incomplete learning situations, and the capacity to regulate and allocate cognitive effort and resources effectively. These characteristics are directly relevant to AI-assisted translation, since translators must transfer prior linguistic and translational knowledge to new tasks, identify problematic segments in machine-generated output, make decisions under incomplete information, and regulate their cognitive effort when interacting with automated systems.

During the 1970s and 1980s, cognitive models of translation began to diverge from purely linguistic frameworks by integrating insights from information processing and psychology. To avoid theoretical ambiguity, it is essential to distinguish between the cognitive system and translator competence. The former refers to the universal mental architecture—including mechanisms such as short-term and long-term memory and mental representation—that governs how humans process information. In contrast, translator competence is a specialized, multidimensional construct consisting of the declarative and procedural knowledge required to solve translation-specific problems.

As noted by Xiao and Muñoz Martín (2021), early cognitive theories argued that a purely linguistic approach was insufficient for capturing this distinction. Consequently, researchers began to analyze how the cognitive system's constraints (e.g., memory limits) interact with the specific communicative and pragmatic sub-competencies of the translator. By combining linguistic processing with these psychological constructs, scholars moved toward a more nuanced understanding of translation as a high-level cognitive task that relies on both general cognitive functions and a domain-specific expert competence.

Willis (1996) emphasizes the importance of contextual knowledge and experience in addressing translation problems and dealing with various types of ambiguity. He describes translation as a form of text processing that requires the integration of linguistic, encyclopedic, and specialized expertise, enabling translators to make informed decisions, solve problems, and convey meaning effectively. From the perspective of Relevance Theory, Gutt (2000) emphasizes the role of inference in understanding a text based on its context and communicative intention. Communicative intention determines what elements of the message should be preserved, reformulated, or omitted depending on the reception context. According to Gutt, the decision-making process in translation is not linear but inferential and cognitive. In this framework, the translator evaluates the relationship between the reader's cognitive effort to process the original message and the resulting cognitive effect, that is, how relevant the information is to the reader.

According to the Paris School, linguistic approaches tended to overlook the role of the listener. As explained by Xiao and Muñoz Martín (2021), cognitive translation studies shifted attention toward the mental processes involved in translation, including thought processes, memory, problem-solving, and the communicative situation in both the source and target contexts. From this perspective, ambiguity is not treated merely as a defect in the source text or as a gap in the reader's knowledge, but as a problem that the translator must resolve through inference, contextual analysis, and prior knowledge. Major contributions from the Paris School include the recognition of the deverbalization phase, the importance of prior knowledge, and the incorporation of empirical research. This emphasis on prior knowledge also explains the relevance of Wilks's contribution: expert human translators rely on background knowledge to resolve syntactic and semantic ambiguities, whereas machine systems tend to depend on predetermined mechanical rules and may fail when such contextual inference is required (Wilks, 2009).

According to Zhong (2006), the evolution of raw information into actionable knowledge is a cognitive process structured around three linguistic levels. First, syntactic information provides the grammatical framework; second, semantic information assigns meaning to content; and finally, pragmatic information allows for interpretation based on specific contexts. For example, when translating an informative institutional text, syntactic information helps the translator identify the grammatical relations within the source text, semantic information supports the interpretation of key concepts, and pragmatic information guides decisions about tone, audience, purpose, and cultural adequacy in the target text.

This cognitive transformation relies on both induction and deduction to refine epistemological data into validated scientific knowledge and, ultimately, into "common sense" or intuitive understanding. This progression is vital for the development of intelligence, as it bridges the gap between disorganized information and informed decision-making. As Espinosa Zárate (2023) notes, refining these thinking strategies is essential to mitigate the "rushed or flawed" decisions that often characterize human judgment, replacing impulsive responses with a more structured, cognitively validated approach to problem-solving.

The study of human cognition is inherently interdisciplinary, requiring a convergence of linguistic, psychological, and neurological perspectives. Central to this field is the evolving relationship between cognitive science and Artificial Intelligence (AI). Rather than being disparate domains, they share a functional synergy: cognitive science seeks to decode the architecture of human thought, while AI aims to emulate and extend those capabilities through computational models. As Xiao and Muñoz Martín (2021) explain, this relationship is best understood through the lens of augmented cognition, where technological tools are not mere external aids but are integrated into the translator's mental workflow to expand processing limits and memory capacity.

This integration transforms the translation process from a purely internal mental task into a distributed cognitive system, where AI manages large-scale linguistic patterns while the human translator focuses on high-level nuances. According to Espinosa Zárate (2023), this "cognitive assistance" is formalized in computer science through Decision Support Systems (DSS). These systems bridge the gap between raw data and intelligent choice, which is critical in specialized domains like legal translation. In high-stakes scenarios—such as the translation of asylum requests, visa applications, or judicial contracts—the DSS does not replace the translator; instead, it serves as a cognitive safeguard. By managing terminology and technical consistency, the system allows the human expert to dedicate their cognitive resources to what He (2024) identifies as the essential management of legal subtleties and cultural originality, ensuring that the final output is both legally accurate and pragmatically appropriate

However, the implementation of systems designed to enhance cognitive processing through automation has also raised concerns in the literature about the possible weakening of human cognitive engagement when users develop excessive dependence on machines. Xiao and Muñoz Martín (2021) point out that while language provides a framework for communication, it often fails to fully encode the broad range of meanings associated with words, meanings that draw upon diverse forms of knowledge and personal experience. A translator with strong grammatical competence can readily distinguish between standard (in-domain) structures and complex (out-of-domain) syntax. By identifying these unusual constructions, the translator can apply necessary syntactic shifts to resolve ambiguities, ultimately minimizing errors that the automated system might overlook. Timely intervention at the pre-editing stage can reduce the need for post-editing and improve the accuracy of the target text (TT). In this context, Gu (2025) conducted a study aimed at improving machine translation by integrating linguistic theories with neural methods. The research focused on the translation of attributive clauses from Japanese into Chinese, analyzing how the semantic roles of modified nouns influence translation choices. The study found that prompts grounded in linguistic theory improved the quality, robustness, and consistency of Chinese translation in structurally complex sentences. Consequently, knowledge of linguistic systems enables translators to recognize source-language structures with low perplexity—those that closely resemble the model's training patterns—thereby increasing the likelihood of better outcomes when processed automatically.

Having theoretical knowledge in textual, communicative, and cultural aspects facilitates problem-solving and helps manage hallucinations produced by LLMs. As Vidal Claramonte (2009) argues, theory significantly supports translation practice by encouraging critical reflection on the challenges posed by a text, leading translators to consider questions such as who commissioned the translation, who the target audience is, and why they, in particular, were chosen to carry out the task. In the context of the hybrid translation method proposed in this study, this theoretical knowledge becomes the basis for the translator's cognitive intervention before, during, and after interaction with GenAI. It guides the analysis of the source text, the formulation of prompts aligned with the translation brief, and the post-editing decisions required to ensure that the final output fulfills its communicative purpose. Thus, the translator's cognitive system functions as the organizing principle of the hybrid model, preventing prompt engineering from becoming a merely technical operation and reaffirming the translator's role as an informed decision-maker in AI-assisted translation workflows.

2. Prompt Engineering

DAIR.AI (2025) identifies the four core elements of a prompt as follows: instruction, which clearly defines the task the model is expected to perform; context, which provides additional background information to guide the response; input data, meaning the specific textual content to be processed; and output data, which specifies the format, style, or type of response expected. Similarly, IBM (2026) proposes a comparable classification, identifying the following components: instruction, context, examples, and cue. Although the terminology differs, both frameworks refer to the same structural principles: defining the task, providing guidance, offering concrete input, and establishing clear criteria for how the model should deliver its response. For the hybrid translation model proposed in this study, DAIR.AI's four-part structure—instruction, context, input data, and output data—is adopted because it aligns more directly with the stages of a translation task: defining the translation brief, contextualizing the communicative situation, providing the source text, and specifying the expected target-text format and quality criteria.

In addition to understanding the structural components of a prompt, it is essential that translators become familiar with and master various prompting techniques. Park and Choo (2024) emphasize that achieving accurate and contextually appropriate responses requires a specific set of skills, methods, and strategies. According to Gadesha (2026), some of the most commonly used techniques include:

- *Zero-shot prompting*: This technique involves asking the model to perform a task without providing any input data or prior examples. It relies on the model's ability to infer the appropriate response directly from the instruction. In translation tasks, it may be useful for producing a first draft when the text is relatively straightforward and the translation brief is clearly defined.

- *Chain-of-thought prompting*: This technique prompts the model to carry out a step-by-step reasoning process before producing an answer, encouraging structured analysis. In translation tasks, it may support the analysis of ambiguous segments, terminology choices, register, and syntactic reformulation before generating or revising the target text.

- *Tree-of-thought prompting*: This technique leads the model to explore multiple lines of reasoning or perspectives to address a given task. It is particularly useful for complex problems, as it allows the model to evaluate possible solutions from different angles. In translation tasks, it may be useful for comparing alternative renderings of culturally marked expressions, idioms, specialized terminology, or segments with more than one plausible interpretation.

According to Ye et al. (2024), the primary goal of prompt engineering, from a theoretical perspective, is to design instructions that enable large language models to produce the most effective output based on a given set of inputs. In other words, a prompt's effectiveness is not determined solely by its linguistic clarity, but by its ability to generate responses that align with the user's objectives in specific contexts. This requires ongoing revision and refinement of the prompt design, evaluation of its impact on the model's output, and the application of strategies such as contextualization, domain delimitation, and the use of representative input examples.

Gu (2025) found that incorporating linguistic elements into a prompt significantly improves the translation quality, indicating that the user's linguistic and discursive knowledge directly influences prompt effectiveness. Therefore, translators—who already possess advanced competence in language structure and use, as well as familiarity with techniques for managing cross-linguistic discrepancies—have an advantage that allows them to design prompts that guide the model toward more accurate and natural output. Their ability to interpret implicit meaning, recognize cultural nuances, and reformulate expressions according to context and register allows them to strategically refine prompts and thereby optimize the quality of GenAI-generated translations.

He (2024) and von Hausen et al. (2024) suggest that deepening our understanding of prompt engineering in the context of translation may help reshape the way translator training is approached in an evolving professional landscape. Since one of the core pillars of prompt generation is the understanding of structural and functional differences between languages, designing effective prompts and megaprompts requires translators to possess a solid foundation in contrastive linguistics. Translators frequently encounter texts with varying styles, syntactic structures, and distinct ways of constructing coherence. Therefore, translation students should be able to:

- Recognize complex adjectival clauses: Accurate identification of these structures facilitates the formulation of prompts that minimize errors when translating highly descriptive phrases.

- Identify ambiguous sentences: Syntactic and semantic ambiguity can lead to multiple interpretations. To optimize prompt design, it is essential for future translators to learn how to detect and reformulate ambiguous sentences to enhance translation accuracy.

- Determine the actual logical connections within the text: Analyzing cohesive devices and logical links allows translators to provide the system with explicit context, ensuring that the machine-generated output maintains the original argumentative flow.

Secondly, the translator must possess knowledge of translation theory. The principles and approaches within this field help structure prompts that accurately reflect the original text's intent and communicative functions. Among the most relevant aspects are:

- Textual aspects related to source and target contexts: A well-crafted prompt should account not only for linguistic content, but also for the cultural, pragmatic, and discursive context surrounding the text.

- Genre-specific characteristics: Each text type (scientific, literary, technical, advertising, etc.) presents unique features that should be reflected in the prompt to appropriately guide the translation process.

- Translation method: Depending on the purpose of the translation, it is necessary to indicate whether a literal, adapted, dynamic, or creative translation is preferred.

- Function of the translation: Defining the intended purpose of the target text is essential, as a translation aimed at general audiences may require different strategies than one intended for specialists.

- Translation brief: It is essential to define clear instructions that inform the translator about the source text, its purpose, context, and intended goals, ensuring consistency with the expectations of the client or requester.

According to Stoltz (2023), a megaprompt is a composite prompt made up of multiple interconnected parts. For instance, the process may begin with a preprompt that assigns a specific "persona" or role to the LLM and ensures it remains consistent throughout the task. This is followed by the main prompt, which includes all the details from the translation brief, along with textual, typological, methodological, and functional elements relevant to the translation task. Finally, postprompts are used to adjust specific segments or translation subunits that require additional attention due to their failure to meet the criteria established in the main prompt. Lin (in press) notes that a well-structured prompt can produce answers that are accurate, coherent, and relevant, thereby significantly improving the model's performance. In contrast, poorly formulated instructions often lead to inaccurate, erroneous, or irrelevant results.

3. Hybrid translation process

Despite technological advancements, AI and machine translation (MT) continue to require human collaboration to optimize the translation process. According to Bekouche (2024), although machine translation has made significant progress, human expertise remains essential at every stage—particularly during pre-editing and final revision—where human involvement is crucial to ensuring high-quality translations.

From the perspective of developments in translation studies, strengthening the synergy between humans and machines to achieve professional translation goals is essential. According to He (2024), human-AI collaboration can become a powerful strategy: humans focus on tasks that require nuance and creativity, while AI handles repetitive operations or produces preliminary drafts that are later refined by human translators.

According to Liu and Asfaal (2021), AI-generated translations can function as a preliminary stage in the translation process, where the system provides an initial draft that is subsequently reviewed and corrected by human translators. This collaborative approach positions AI as a supportive tool rather than a replacement for human expertise. Mosqueira-Rey et al. (2023) describe the interactions between humans and machine learning algorithms as a "*human-in-the-loop*" approach, in which humans and AI models work together in both learning and content creation processes.

The rise of collaborative work between various actors—such as translators and clients, and humans and technology—led to the development of ISO standard 17100, aimed at ensuring that translation services are consistent, reliable, and of high quality. The standard outlines four key phases in the translation process: (1) preparation or initial assessment of the brief and selection of necessary resources; (2) production of the translation; (3) revision to verify the accuracy and appropriateness of the translated text; and (4) editing and proofreading to ensure final quality, followed by validation or confirmation that the final product meets the client's specific requirements prior to delivery.

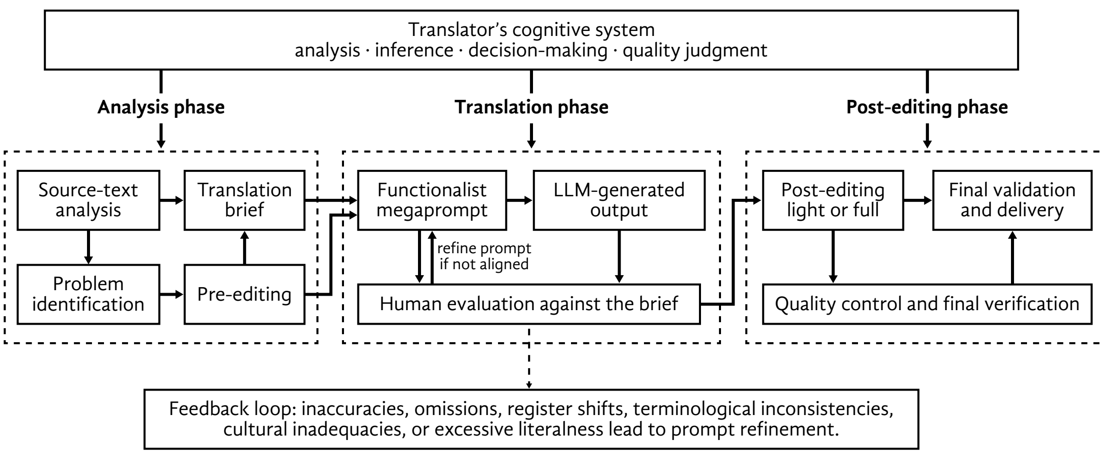
Kornacki and Pietrzak (2024) propose a framework for the collaborative integration of human translation skills and artificial intelligence to enhance both quality and efficiency. For this synergy to succeed, training must go beyond technical mastery to strengthen ethical reflection and the translator's metacognitive abilities—such as self-efficacy, self-regulation, and self-conceptualization. By fostering these personal resources, students can engage more proactively in the learning process, reducing the risk of overreliance on automated tools. Ultimately, this approach builds digital resilience, equipping future professionals with the critical judgment necessary to navigate the complex and evolving demands of an AI-enhanced environment.

Lévano and Arbildo (2024) argue that translator training should be structured around three key pillars: developing critical thinking to support the appropriate integration of technology into training, promoting the functional use of prompts to optimize the application of AI models in translation, and encouraging reflection on utilitarian ethics and translation-related decision-making. In line with this perspective, the following phases are proposed as part of the hybrid translation process:

To clarify the operational sequence of the proposed model, Figure 1 presents the hybrid translation workflow as a recursive process in which the translator's cognitive system guides each stage of human–AI collaboration. The model begins with source-text analysis and pre-editing, continues with prompt formulation and iterative interaction with the LLM, and concludes with post-editing and final quality assessment. Although the stages are presented sequentially, the process allows for feedback loops, since the translator may return to prompt refinement or source-text analysis whenever the generated output does not meet the requirements of the translation brief.

Figure 1

Hybrid translation workflow integrating the translator's cognitive system and GenA



Note. Own elaboration. The figure presents the hybrid translation workflow proposed in this study.

Analysis phase:

According to Alves and Limpo (2015), translation should not be reduced to the mere retrieval of information; rather, it requires a holistic interpretation of the source text, accounting for its structural, semantic, and contextual intricacies. Consequently, analyzing the communicative and intratextual situation is essential for formulating effective prompts. As Nord (2018) explains, the primary purpose of drafting a translation brief prior to initiating a translation task is to encourage critical reflection on the original text and to assess whether the translated version is appropriate for the intended target audience. Examining the source—including when, how, where, and from whom it is received—can reveal implicit assumptions that may not apply to the recipient culture. Considering the original's purpose and function in the context of the target reader makes it possible to anticipate challenges and limitations before investing resources in the translation process. Colina (2003) highlights that a well-designed translation brief can help improve translation quality by preventing misinterpretations that arise from surface-level analysis, while also specifying how portions of the source text are used, its communicative goals, and the intended outcomes.

According to Research Institute for United States Spanish (2009), after completing the situational analysis, the translator must identify potential translation problems and consider how to address them throughout each phase of the process. This includes gathering information about the purpose and function of the source text, determining its type and any specific requirements, identifying cultural biases that may need to be replaced with target-culture conventions, and detecting translational challenges as well as low-quality source texts that could hinder the translation process. With this information, the translator can then formulate a set of guiding instructions to support decision-making throughout the task.

According to Sánchez-Gijón and Palenzuela-Badiola (2023), when the source text is flawed, pre-editing becomes a key stage, as it allows for adjustments that improve the quality and accuracy of machine translation output. This activity ensures the appropriate preparation of the source text to achieve better results. Pre-editing tasks may include lexical and syntactic simplification. From a linguistic standpoint, this process can be approached through the lens of controlled language—a set of rules applied in the drafting of technical texts to minimize lexical and semantic ambiguity and to avoid complex grammatical structures, thereby enhancing readability and user comprehension. This also facilitates the effective use of technologies such as translation memories (TM) and machine translation (MT).

As noted by O'Brien (2003), this approach focuses on vocabulary and grammar, and is typically designed for very specific domains or even for particular tasks. Finally, this stage also involves identifying orthotypographic elements —the set of rules governing the correct use of typography, punctuation, and formatting symbols in a given language—that could potentially lead to errors in LLM-generated translations.

Translation phase:

It is at this stage that the LLM-based generative AI system executes the commands provided through the megaprompt designed by the translator. In this study, the term LLM refers specifically to large language models used as generative AI tools for translation tasks, rather than to AI systems in general. The translator is responsible for verifying that the instructions embedded in each prompt are properly followed by the model. Although the initial translation output is primarily generated by the LLM, this phase requires continuous interaction between the translator and the system to ensure effective human–AI collaboration.

This interaction develops iteratively. First, the translator submits a prompt that includes the translation brief, the source text, the target audience, the communicative purpose, the expected register, and any relevant terminological or stylistic constraints. The resulting output is then examined in relation to the criteria established in the brief. If the output presents inaccuracies, omissions, register shifts, terminological inconsistencies, cultural inadequacies, or excessive literalness, the translator reformulates the prompt by adding more explicit contextual information, narrowing the task, specifying the desired translation strategy, or requesting alternative renderings for problematic segments. This process may involve successive rounds of prompting until the output becomes sufficiently aligned with the intended function of the target text.

The result can be considered satisfactory when it preserves the meaning and communicative function of the source text, follows the genre conventions of the target language, uses appropriate terminology and register, addresses the needs of the intended audience, and does not introduce unsupported information or distortions. At this point, the translator may move from prompt-based interaction to the post-editing phase, where the output is revised in greater detail according to the required quality level and the specific conditions of the translation brief.

Post-editing phase:

Post-editing can be understood not as revision in the traditional sense, but rather as a form of human intervention applied to the output generated by a machine translation system. This intervention involves modifying machine-generated text in order to improve its form, meaning, fluency, accuracy, and suitability for the intended communicative purpose. As early work on machine translation post-editing shows, the extent of this intervention depends on the type of document, the expected quality level, and the needs of the final users (Laurian, 1984). More recent approaches also describe post-editing as a practice located between translation technology and professional translation, requiring both technical awareness and human decision-making (Guerberof Arenas, 2019).

According to the Spanish Association of Translators, Copyeditors, and Interpreters (Asetrad, 2021), there are two types of post-editing: light or partial post-editing and full post-editing. The former involves minimal intervention and aims primarily at ensuring that the text is comprehensible, without improving its style or fluency. Typically, the changes focus on grammar and terminology. Full post-editing, on the other hand, entails more substantial revisions to achieve a high-quality translation, emphasizing not only semantic accuracy but also naturalness. The choice between these two types depends on the client's expectations for the translation task—ranging from internal-use documents, which may only require light post-editing, to publishable materials, such as academic articles, institutional reports, technical manuals, websites, marketing content, or other texts intended for external circulation, which demand full post-editing.

According to the Spanish standard UNE-ISO 18587:2017 (International Organization for Standardization, 2017), the post-editing process is structured into two fundamental stages: production (full post-editing) and post-production (final verification). During the production stage, a professional post-editor must revise the machine-generated output to achieve a quality level comparable to human translation. This task requires strict adherence to client-approved glossaries, reference materials, and domain-specific terminology to ensure consistency. Furthermore, the post-editor is responsible for respecting all orthographic, syntactic, and punctuation conventions of the target language, while ensuring the final document maintains the original format and complies with relevant style guides and local regulations.

In the post-production stage, the focus shifts to quality control and thorough verification to guarantee that the final output meets professional standards before delivery. This phase ensures that the translated content is fully appropriate for its intended audience and fulfills all prior agreements made with the client. Additionally, the standard encourages a feedback loop, where post-editors provide technical evaluations on the performance of the machine translation engine. This systematic verification helps ensure that the hybrid process results in a product that meets professional quality standards and approaches the level of adequacy, fluency, and reliability expected of a human translation.

4. Proposal of a functionalist prompt structuring

To complement the principles previously discussed, this section presents a functionalist approach to prompt construction. This framework is grounded in the tenets of Skopos theory

(Reiss & Vermeer, 2014), which prioritizes the purpose of the translation and its function in the target culture. Within this approach, prompt formulation is framed as a translational task in itself. It requires the translator to encode contextual, textual, and functional information into the system to reflect the original brief and communicative goals of the source text.

This structure encourages translators to treat prompt generation as a professional decision-making process rather than a purely technical command. By mirroring traditional workflows, the translator ensures that AI-generated output aligns with the intended audience, text type, and specific purpose. Crucially, this process must also account for the contrastive features between specific language pairs, such as information structure and formality conventions. Consequently, specifying the exact language combination—for example, Spanish into British English—becomes an essential component of the prompt strategy to guide the model's idiomatic usage and stylistic accuracy. The template below outlines a structured megaprompt designed according to functionalist principles. Each component reflects one or more dimensions of the translation brief, including source and target languages:

Figure 2

Functionalist megaprompt template with applied example for hybrid translation tasks

	Megaprompt segment	Applied example
1. Role and language pair	You are a professional translator working from [source language] into [target language], with expertise in [domain or subject area]	You are a professional translator working from Spanish into English, with expertise in academic communication and translation studies
2. Target audience and context	Translate the following text for [target audience], to be published in [medium or context]	Translate the text for undergraduate translation students, to be published in a university teaching handout
3. Communicative purpose	The purpose of the translation is [communicative function: e.g., informing, persuading, instructing]	The purpose is to inform readers about how generative AI affects translation workflows
4. Text type and cultural adaptation	Preserve the conventions of [text type: e.g., legal, literary, technical], and adapt language and cultural references to suit the target audience	Preserve the conventions of an academic explanatory text and adapt terminology to an English-speaking academic audience
5. Language variant, register, and style	Use [language variant: e.g., British English], maintain a [formal/informal/neutral] register, and ensure idiomatic clarity and inclusivity	Use academic English, maintain a formal register, and ensure idiomatic clarity and inclusive language
6. Institutional or style conventions	Adhere to [style guide or institutional convention, if applicable]	Follow APA 7 style conventions for terminology, capitalization, and academic tone where applicable
7. Source text	The source text is as follows: [source text]	La inteligencia artificial generativa transforma la labor del traductor, pero no sustituye su juicio profesional

Note. Own elaboration based on functionalist translation principles and the components of the translation brief. The applied example illustrates how the template can be used to formulate a prompt for translating a brief academic text from Spanish into English.

This model foregrounds the translator's agency by allowing them to encode genre-specific features, cultural nuances, language-pair constraints, and pragmatic intentions directly into the prompt. It promotes a reflective approach to prompt design, ensuring that students learn to assess the needs of a translation task before engaging with automated tools. In doing so, it reinforces a central tenet of functionalist theory: that translation decisions must be determined by purpose, context, and language combination—not by surface-level correspondences alone.

The proposed hybrid method is intended for both translator training and professional translation practice, although its primary orientation is pedagogical. In academic contexts, the model can be used to train students to analyze source texts, formulate translation briefs, design functionalist prompts, evaluate LLM-generated outputs, and justify post-editing decisions. In professional contexts, the same workflow can support AI-assisted translation tasks that require human oversight, especially when terminological consistency, cultural adequacy, communicative purpose, and quality control are central requirements. Therefore, the method should not be understood as a fully automatic translation procedure, but as a structured framework for human-led decision-making in AI-assisted translation environments

Conclusions

In the era of Generative AI (GenAI), the translator's cognitive system may contribute to safeguarding for accurate, context-sensitive, and ethically grounded decision-making. With the integration of linguistic, textual, and pragmatic knowledge, translators move beyond technical operation to interpret and refine AI-generated outputs, ensuring communicative adequacy in increasingly high-stakes scenarios. Within this framework, prompt engineering—when rooted in translational competence—functions as a strategic extension of professional judgment rather than a mere technical skill. Prompt construction that reflects genre conventions and specific translation briefs reinforces the professional's role as an expert mediator in human–AI collaboration.

The central contribution of this study is the proposal of a systematic hybrid translation workflow that aligns technological tools with functionalist principles. Unlike approaches that focus primarily on post-editing or on the technical formulation of prompts, this model integrates three dimensions within a single pedagogical and professional framework: the translator's cognitive system, functionalist prompt design based on the translation brief, and quality-oriented post-editing. In this sense, the proposal contributes to AI-assisted translation studies by positioning prompt engineering as a translation-specific decision-making activity rather than as a generic technical procedure.

The model—structured through stages of analysis and pre-editing, brief-tailored prompt formulation, interaction with Large Language Models, and post-editing—also seeks to reinforce the translator's cognitive and ethical agency in human–AI collaboration. However, this study has limitations. As a theoretical and methodological proposal, it does not include empirical validation with professional translators, students, or specific language pairs. Future research should therefore test the model in classroom and professional settings, compare its effectiveness across text types and language combinations, and assess its impact on translation quality, translator autonomy, and critical engagement with GenAI systems.

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