EDICIONES
COMPLUTENSE

Estudios de **Traducción**
ISSN: 2174-047X

MISCELÁNEA

DeepSeek as Generative IA Tool in Specialized Text Translation and Post-Editing

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https://dx.doi.org/10.5209/estr.102953 Recibido: 25 de mayo de 2025 / Revisado: 5 de noviembre de 2025 / Aceptado: 11 de diciembre de 2025

Abstract. This study explores the impact of Generative artificial intelligence (GAI) in specialized translation processes, using DeepSeek-V3 as the primary tool. The research, with an empirical-exploratory and mixed-method approach, focuses on two objectives: first, to analyze the translation skills and strategies used by students employing DeepSeek to translate texts in legal, medical, and scientific fields; second, to describe the post-editing process, evaluating the techniques used to improve the accuracy and cultural adaptation of the final text. The central research question guiding the study is how DeepSeek influences the development of translation skills and what post-editing strategies students apply to enhance their translations.

The methodology involves translation practices with a group of 30 advanced students from the bachelor's degree in Translation at UABC in Mexicali, who translated and post-edited three specialized texts with DeepSeek. These exercises, conducted in three-hour sessions, also included the creation of specific terminological glossaries. A specialized rubric was used to measure translation quality, and Translog-II software recorded the time spent on each activity, assessing the efficiency and accuracy of the process.

Preliminary results indicate improved efficiency in the translation process and the final product quality through AI tools and post-editing. In the final survey, students also reported a positive perception of DeepSeek, highlighting its utility in developing specific translation competencies.
Keywords: artificial intelligence, machine translation, DeepSeek, post-editing, translation competence.

DeepSeek como herramienta de IA generativa en la traducción y posedición de textos especializados

Resumen. El presente estudio explora el impacto del uso de la inteligencia artificial (IA) en el proceso de traducción especializado, utilizando *DeepSeek* como herramienta principal. La investigación, de enfoque empírico-exploratorio y mixto, se centra en dos objetivos: primero, analizar las habilidades y estrategias traductológicas empleadas por estudiantes al usar *DeepSeek* para traducir textos de áreas jurídicas, médicas y científicas; segundo, describir el proceso de posedición, evaluando las técnicas utilizadas para optimizar la precisión y adecuación cultural del texto final. La pregunta central que orienta el estudio es cómo influye *DeepSeek* en el desarrollo de habilidades traductoras y qué estrategias de posedición aplican los estudiantes para mejorar sus traducciones.

La metodología involucra prácticas de traducción con un grupo de 30 estudiantes avanzados de la Licenciatura en Traducción de la UABC, quienes tradujeron y poseditaron tres textos especializados con *DeepSeek*. Estos ejercicios, realizados en sesiones de tres horas, incluyeron también la creación de glosarios terminológicos específicos. Para medir la calidad de las traducciones, se empleó una rúbrica especializada, y el software *Translog-II* registró el tiempo invertido en cada actividad, evaluando la eficiencia y precisión del proceso.

Entre los resultados preliminares, se observa una mejora en la eficiencia del proceso traductológico y en la calidad del producto final mediante el uso de herramientas de IA y posedición. Los estudiantes también

reportaron en el cuestionario final una percepción positiva hacia el uso de DeepSeek, destacando su utilidad en la formación de competencias específicas de traducción.
Palabras clave: inteligencia artificial, traducción automática, *DeepSeek*, posedición, competencias traductológicas.

1. Introduction

Artificial intelligence (AI) has become a transformative and widely discussed phenomenon in recent years, gaining relevance across fields such as health, education, finance, and language technologies. Its rapid development has positioned AI as a disruptive force capable of optimizing complex tasks, supporting decision-making, and creating new opportunities for innovation (Atarchi, Elamari & Marouane 2024). Within this context, the translation industry is no exception, as AI-driven systems increasingly reshape professional and educational translation workflows.

Among the growing ecosystem of AI tools, DeepSeek-V3 was selected for this study due to three key factors: (1) its accessibility in an academic environment, particularly through its free version; (2) its integration of both neural machine translation (NMT) and generative text-production capabilities, which allows students to interact with translation outputs using prompt-based refinements; and (3) its emphasis on transparency and linguistic patterning, which makes it an appropriate tool for teaching specialized translation and post-editing processes. While many large language models (LLMs) exist, such as DeepL or GPT-4, DeepSeek-V3 was chosen because it provides a balanced platform for students to explore translation generation, assessment, and revision without requiring paid access or advanced technical setup—factors relevant in higher-education settings.

According to Alharbi (2023), the emergence of NMT and LLM-based systems has transformed the translation process, enhancing speed and fluency while simultaneously introducing new challenges related to accuracy, terminological consistency, and cultural adaptation. Machine-generated translations—regardless of the tool—have always required human intervention, yet the nature of this intervention has evolved. Modern post-editing now demands a deeper understanding of error patterns in AI outputs, distinguishing between general 'editing' (improving coherence, flow, formatting) and 'post-editing' (correcting semantic, terminological, and pragmatic inaccuracies specific to MT systems). This distinction is essential for readers with both technological and translation backgrounds.

Given this landscape, the present empirical-exploratory mixed-method study pursues two central objectives: (1) to analyze the translation processes, competencies, and strategies applied by advanced translation students when using DeepSeek-V3 to translate specialized legal, medical, and scientific texts; and (2) to describe the post-editing techniques students employ to improve the accuracy, coherence, and cultural adequacy of AI-generated translations. The study is guided by the following research question: How does the use of DeepSeek influence the development of translation skills, and what post-editing strategies do students apply to improve the final output?

This report is structured as follows: the theoretical framework discusses specialized translation, neural MT systems, and AI-assisted translation tools. The methodology section describes the design, instruments, and procedures employed in the study. The results section presents the quantitative and qualitative findings derived from translation tasks, rubric-based assessments, and students' self-perceptions. The discussion interprets these findings in relation to existing literature, highlighting the pedagogical implications of AI in translator training. Finally, the conclusions and limitations outline key contributions and propose directions for future research.

2. The Role of AI in Specialized translation and Translator Training

Specialized Translation (ST) refers to the process of converting content from one language to another while maintaining the precise terminology, expressions, and linguistic structures specific to a given technical or professional domain. According to Cabré (2020), specialized languages consist of field-specific terms and expressions that facilitate the accurate communication of complex concepts. These languages require precision and clarity to ensure effective knowledge transfer. Consequently, linguistic, textual, and terminological considerations are central to specialized translation, making the identification of appropriate terminological equivalents a critical aspect of the process (Barceló 2017).

The rapid evolution of machine translation (MT) has raised questions about its ability to handle specialized texts effectively. García & Jiménez (2020) highlight notable improvements in accuracy and efficiency, particularly in technical and scientific translation, which has significantly reduced the time required to produce high-quality translations. Additionally, AI-driven MT tools have enhanced post-editing workflows, ensuring greater coherence and overall quality in specialized translations.

As AI-powered translation tools become more integrated into translator education, their impact on translation training and competency development has gained attention. A pilot study by Johnson and Gómez (2022) explored the incorporation of AI-based MT tools into translator training, analyzing their role in skill development and students' perceptions of technology. Their findings suggest that these tools are valuable for managing large-scale projects and improving the technological proficiency required in the professional translation industry. However, they caution that despite their efficiency, MT-generated outputs often fail to meet professional translation standards. This underscores the importance of robust training programs that emphasize post-editing skills and critical evaluation of machine-generated translations.

Successfully incorporating AI-driven tools into translator training necessitates a well-balanced approach that ensures both practical and theoretical understanding. Wang and Schmidt (2024) discuss how AI-driven pedagogical advancements have reshaped translation education, leading to curriculum adjustments that integrate automated tools and post-editing practices. They advocate for continuous professional development among educators to effectively integrate these technologies into teaching, preparing students for both traditional and emerging industry demands.

The rise of AI in translator training presents both challenges and opportunities. Silva & Baxter (2024) conducted an exploratory study on the difficulties educational programs face in adapting to technological advancements. Their research concludes that while AI tools enhance efficiency in managing large translation projects, academic programs must evolve to equip students with the necessary skills for the modern translation industry. The study highlights the importance of adapting training methodologies to keep pace with industry developments.

Post-editing, a critical aspect of AI-assisted translation, involves human intervention to refine machine-generated content for greater accuracy, coherence, and fluency. García (2020) defines post-editing as an essential step in ensuring the quality of machine-translated texts. Similarly, Bertoli & Gavioli (2021) investigated the role of post-editing in computer-assisted translation, finding that it improves both translation quality and productivity. Their research suggests that structured training in post-editing can enhance translation efficiency while reducing turnaround times, positioning post-editing as a key competency in contemporary translation workflows.

Despite advancements in neural machine translation (NMT), post-editing remains indispensable. Koehn (2020) examines the challenges professional translators encounter when refining NMT-generated texts. While recognizing improvements in MT quality, the study underscores that post-editing is essential to ensure linguistic accuracy and fluency in the final product. This research highlights the ongoing necessity of human intervention in maintaining professional translation standards, reinforcing the integral role of post-editing in AI-assisted translation processes.

3. AI-Driven Translation Tools: Insights and Applications

The rapid advancement of AI-driven translation tools has transformed the field of machine translation (MT), enabling faster, more efficient, and contextually aware translations. Tools like DeepL, Google Translate, ChatGPT and DeepSeek have become integral to professional and educational translation workflows. While these systems excel in general and creative texts, their performance in specialized domains and low-resource languages remains an area of active research and development.

AI-driven translation tools have demonstrated significant improvements in handling general and creative texts. For example, Popović (2018) evaluated the performance of neural machine translation (NMT) systems, including Google Translate, and found that they produce fluent and contextually appropriate translations for non-technical content. However, the study also noted challenges in maintaining coherence and terminological accuracy in technical texts. Similarly, Castilho et al. (2017) compared NMT systems to traditional statistical machine translation (SMT) systems, concluding that NMT systems outperform SMT in terms of fluency and readability, particularly for high-resource languages.

Despite their strengths, AI-driven translation tools often struggle with specialized domains such as legal, medical, and technical translation. Forcada (2017) highlighted the challenges of using NMT systems in professional translation tasks, noting that while these tools deliver fast and fluent translations, they frequently require post-editing to ensure terminological consistency and accuracy. This is particularly true for low-resource languages and highly specialized fields, where training data is limited. Zaretskaya et al. (2015) also emphasized the limitations of NMT systems in legal translation, pointing out that errors in terminology and syntax can have significant implications for the accuracy and reliability of translations.

The integration of AI-driven tools into modern translation workflows has been a focus of recent research. Moorkens et al. (2018) examined the role of post-editing in MT workflows, highlighting the importance of human intervention to refine machine-generated translations. Their study found that while tools like Google Translate and DeepL can significantly reduce turnaround times, they cannot fully replace human translators, especially in complex and nuanced translations. Similarly, Bentivogli et al. (2016) discussed the potential of NMT systems to enhance productivity in translation workflows but cautioned against over-reliance on these tools, particularly in specialized domains where contextual understanding and terminological precision are critical.

The limitations of AI-driven translation tools have been well-documented in the literature. Way (2018) argued that while NMT systems have made significant strides in recent years, they still struggle with issues such as domain adaptation, handling rare words, and maintaining consistency in long texts. Toral et al. (2018) also highlighted the challenges of using NMT systems for low-resource languages, noting that the quality of translations often deteriorates when training data is scarce. These limitations underscore the importance of human oversight in ensuring the accuracy and reliability of machine-generated translations.

Additionally, it is important to distinguish that the type of post-editing required for neural machine translation output is frequently 'heavy post-editing,' as described in the MT literature. This involves correcting not only surface-level stylistic issues but also deep structural, semantic, and terminological inconsistencies that AI systems still struggle with (Forcada 2017). Heavy post-editing is especially critical in specialized domains such as legal and medical translation, where inaccuracies may lead to serious misinterpretations or professional risks.

Given these limitations, selecting DeepSeek-V3 for this study allowed students to engage directly with the strengths and weaknesses of contemporary LLM-based MT. Its accessible platform and integration of generative capabilities provided an ideal environment to analyze translation workflows while also revealing the necessity of rigorous human intervention and domain knowledge.

4. Students' Perceptions and Acceptance of AI in Translation

Artificial intelligence has significantly influenced various fields, including translation and language education. The increasing integration of AI-powered machine translation tools has sparked growing interest in academia, particularly regarding their role in translator training and students' attitudes toward these technologies. As a result, multiple studies have investigated how students perceive and adopt AI tools in their learning processes.

Khairuddin et al. (2024) examined students' perspectives on AI tools as academic aids, concluding that these technologies enhance efficiency in written production and text comprehension across different languages. Their findings indicate that students value the immediacy and accuracy of AI-generated outputs but also express concerns about over-reliance on these tools. Additionally, they emphasize the importance of developing critical thinking skills to assess AI-generated translations effectively.

Similarly, Wang, Xu & Liu (2024) applied the Unified Theory of Acceptance and Use of Technology (UTAUT) model to analyze students' acceptance of ChatGPT as a translation tool. Their research identified key factors influencing adoption, including ease of use, perceived usefulness, and confidence in the translation quality. The study also highlights the impact of students' familiarity with technology and prior training in translation strategies on their interactions with AI.

Further contributing to this discussion, Le (2023) investigated the application of AI in English language instruction, revealing that students consider these tools beneficial for developing linguistic skills, particularly in writing and text comprehension. In a related study, Burkhard (2022) explored students' perspectives on AI-driven writing tools, emphasizing their potential to support personalized teaching strategies.

Collectively, these studies underscore the increasing role of AI in translator education. While these tools offer significant advantages by streamlining certain aspects of the translation process, they also present challenges in professional training. The findings highlight the need for students to develop critical competencies in post-editing and evaluating AI-generated translations, ensuring their ability to produce high-quality, contextually appropriate translations in professional settings.

Furthermore, these perspectives align with broader research on translator competence development, highlighting those affective and attitudinal dimensions—such as confidence, perceived usefulness, and self-regulation—directly influence students' willingness to rely on AI tools. This connection is essential because perceived competence often shapes actual performance in translation tasks, as noted in studies on competence-based translator education.

5. Methodology

This study falls within the realm of empirical-exploratory translation studies and employs a mixed-methods approach. Qualitative data were gathered through a structured self-evaluation (revise annex) designed to examine students' experiences and self-perceptions concerning the translation process and the outputs produced by AI-driven translation tools. Meanwhile, quantitative data were derived from three specialized translation tasks around completed by the participants, covering legal, medical, and scientific domains. Each text was around 1200-1300. These translations were assessed using a rubric specifically designed for evaluating specialized translation quality. The translations were conducted using the free version of DeepSeek-V3.

Legal example:

H E C H O S:

PRIMERO.- La suscrita y mi ahora demandado tuvimos un noviazgo a partir del año 2008 y producto de ésta relación resulte embarazada de mi primer hijo, teniendo seis meses de embarazo decidimos casarnos pero la de la voz le marque para cancelar la boda y nunca se llevó a cabo, a lo largo de estos años hemos tenido una relación muy inestable, pues ha sido intermitente, es decir, vivimos juntos dos meses, nos separamos otros seis meses, y la pensión alimenticia es condicionada a si estoy con él si aporta pero si estamos separados no aporta para los alimentos, hace cuatro meses que decidí ya no estar con él y durante éste tiempo él no se ha hecho responsable de aportar una pensión que cubra los gastos de nuestro hijo, por eso me veo en la imperiosa necesidad de garantizar esta pensión a través de la presente demanda.

SEGUNDO.- Como lo he manifestado en el punto anterior, mi ahora demandado económicamente se hace cargo pero sólo en las temporadas en las que estamos viviendo juntos y depende de su consideración y no de lo que se encuentra apegado a derecho como debe de ser para garantizar los alimentos del hijo que se encuentra bajo mis cuidados y al ver que mi demandado tiene un trabajo estable en donde sus precepciones son seguras y de manera quincenal es por lo que pido se condene al demandado al

Medical example:

updates

Immune checkpoint inhibitors-associated cranial nerves involvement: a systematic literature review on 136 patients

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Received: 13 July 2024 / Revised: 20 August 2024 / Accepted: 22 August 2024
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Abstract
Objective Describe the demographic data and clinical phenotype of cranial palsy induced by immune checkpoint inhibitors (CNP-ICI).
Methods A systematic literature review of the literature was performed in Pubmed, Web of Science, and Embase, including 68 articles and 136 patients (PROSPERO no. CRD42024517262).
Results Out of the 1205 articles screened, 68 articles were included after fulfilling the inclusion criteria, for a total of 136 patients. All articles were case reports and case series. In the cohort studied, 52% of patients were treated with anti PD-1/PDL-1 therapies, 14% with anti CTLA-4 therapies, and 34% with a combination of anti CTLA-4 and anti PD-1/PDL-1 therapies. The facial nerve was the most affected cranial nerve, involved in 38% of cases, followed by the optic nerve (35%), the cochleovestibular nerve (12%), and the abducens nerve (10%). The median time from the initial immune checkpoint inhibitor (ICI) injection to the onset CNP-ICI was 10 weeks (IQR 4–20). Magnetic resonance imaging demonstrated contrast enhancement or abnormal signal of the affected nerve in 43% of cases. Cerebrospinal fluid analysis indicated lymphocytic pleocytosis in 59% of cases. At the onset of immune-related adverse events, 89% of patients discontinued immunotherapy, and 92% received treatment for CNP-ICI. Treatment regimens included corticosteroids in 86% of cases, intravenous immunoglobulin in 21%, and plasma exchange in 5.1%. Among the whole population, 33% achieved recovery, 52% showed clinical improvement, 16% remained stable, and 3% experienced worsening of their condition. Rechallenge with immunotherapy was significantly associated with the emergence of new immune-related Adverse Events (irAEs).
Conclusion ICI therapy may lead to cranial nerve involvement, particularly affecting the facial nerve, typically presenting around 10 weeks after treatment initiation. While corticosteroid therapy often resulted in patient improvement, rechallenging with ICIs were associated with new irAEs.

Keywords Immune checkpoint inhibitors · Nivolumab · Pembrolizumab · Ipilimumab · Immune-related adverse events · Cranial palsy

Scientific example:

A systematic literature review on machine learning applications for agile project management

Una revisión sistemática de la literatura sobre aplicaciones del aprendizaje automático para la gestión ágil de proyectos

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Abstract

Since the rise of agile methods, it has become important to maintain their management and monitoring to succeed in the transformation process from a traditional approach to an agile one. Several authors have used Machine Learnig models to support prediction or estimation processes in the project management framework. However, there are current challenges and areas of opportunity in relation to Agile Project Management in combination with Machine Learning. Therefore, in this paper, we have conducted a Systematic Review of the Literature to understand the current state of Machine Learning applied to Agile Project Management, in order to identify which techniques are currently the most used and thus detect new areas of opportunity.
Keywords: Project management, agile approach, machine learning, systematic review, traditional approach.

Resumen

Desde el surgimiento de los métodos ágiles, se ha vuelto importante mantener su gestión y monitoreo para tener éxito en el proceso de transformación de un enfoque tradicional a uno ágil. Varios autores han utilizado modelos de aprendizaje automático para apoyar procesos de predicción o estimación en el marco de gestión de proyectos. Sin embargo, existen desafíos actuales y áreas de oportunidad en relación con la gestión de proyectos ágiles en combinación con el aprendizaje automático. Por lo tanto, en este documento, hemos realizado una revisión sistemática de la literatura para comprender el estado actual del aprendizaje automático aplicado a la gestión de proyectos ágiles, con el fin de identificar qué técnicas son actualmente las más utilizadas y así detectar nuevas áreas de oportunidad.
Descriptores: Gestión de proyectos, enfoque ágil, aprendizaje automático, revisión sistemática, enfoque tradicional.

5.1. Characteristics of the sample

The study involved a group of 30 students in the final phase of their Bachelor's Degree in Translation, all of whom were enrolled in the elective course AI Applications in Translation, an integral part of the program's curriculum. These students had already completed core coursework aimed at developing their proficiency in translation support tools, including terminology database management, corpus linguistics, and machine translation. Their working languages consisted of Spanish as their native language and English as a second language, with all translation tasks being carried out in a direct translation format (English to Spanish).

5.2. Translation practices, their assessing and mixed data recollection

Participants engaged in three translation tasks using DeepSeek-V3 as a machine translation tool, followed by a structured post-editing process. Additionally, they were required to compile specialized terminological glossaries based on the terminology encountered in the translated texts. The focus areas for these tasks were legal, medical, and scientific translation, with each task allocated a three-hour period, ensuring an even distribution of time between translation and post-editing phases.

Prior to commencing these activities, students received comprehensive training on the functionalities of DeepSeek, including its applications in machine translation. Once the translations were completed, they were evaluated using a specialized translation rubric, which provided structured criteria to assess both the process and final product in accordance with the standards of each discipline.

To further analyze the translation workflow, the Translog-II software was employed to track the time spent on active translation, terminological searches, and the use of consultation tools. This data collection aimed to quantify the duration of each activity, particularly the post-editing phase, ensuring that no session exceeded the designated 180-minute time frame.

Finally, at the conclusion of the course, students completed a structured questionnaire consisting of ten questions, designed to capture their reflections on the translation and post-editing experience. This qualitative instrument provided valuable insights into students' perceptions and the learning outcomes gained throughout the course.

In accordance with methodological standards in translation studies, the questionnaire and rubric used in this study underwent expert validation prior to implementation. Two faculty members specializing in translation pedagogy and assessment reviewed the instruments for content relevance, clarity, and alignment with the competencies targeted in specialized translation courses. Minor adjustments were made to improve consistency in the phrasing of items, ensure that all criteria reflected measurable behaviors, and eliminate redundancies.

Although the complete rubric is provided in Annex 1, the methodology section benefits from a synthesized description of its structure. The rubric evaluated twelve criteria across linguistic, socio-cultural, and translation-process dimensions. These included accuracy, terminological adequacy, textual cohesion, register, punctuation, orthotypography, sociocultural adaptation, false or misleading senses, omissions, additions, thoroughness of revision, and reproduction of original formatting. Each criterion was scored on a four-point scale, allowing a maximum of 48 points per translation task.

Furthermore, the distinction between editing and post-editing is crucial within the methodological design. Editing referred to adjustments in formatting, coherence, and typographic features, while post-editing consisted of addressing semantic, terminological, and pragmatic errors produced by DeepSeek. This conceptual distinction was explicitly communicated to students during training sessions to ensure procedural consistency.

Finally, the choice of DeepSeek-V3 for this intervention is methodologically grounded. The model's free version offered sufficient generative and MT-related capabilities for academic use while allowing researchers to observe limitations inherent to non-premium systems. These constraints—such as inability to upload full documents or fine-tune domain outputs—were treated as natural variables influencing students' post-editing strategies.

6. Data Analysis and Results

This section presents the results obtained after the implementation of the methodological phase of this study. Given the nature of this research, the data analysis and presentation of results are structured in two sections: quantitative data and qualitative data, in that order.

To support readers without a background in translation studies, the distinction between editing and post-editing is essential for interpreting the results. Editing refers to adjustments involving formatting, cohesion, surface-level style, and orthotypography. Post-editing, in contrast, focuses on correcting errors produced specifically by AI or MT systems—such as semantic inaccuracies, terminological inconsistencies, mistranslations, cultural mismatches, or structural distortions intrinsic to neural MT output. This distinction is relevant when interpreting the time distribution shown in Table 2, where post-editing constitutes nearly half of total task time.

Consistent with MT literature, the type of post-editing required for the DeepSeek-generated texts should be classified as heavy post-editing (Forcada 2017). This classification reflects the need for terminological verification, restructuring of sentences, pragmatic adjustments, and correction of domain-sensitive meanings. This reinforces the importance of human intervention even when AI-generated output appears fluent.

Translation activity evaluation

A specific guideline was used to obtain the evaluation data of the translation activities, including accuracy, fluency, use of translation tools, post-editing and proofreading, quality of the terminological glossary, format, and spelling. Following the assessment of the translations performed by the participants, the results are organized in the chart below.

Table 1. Specialized translation scores and averages.

Participant	Scientific trans.	Medical trans.	Legal trans.	Individual average
P1	100	99	99	99.3
P2	99	100	100	99.6
P3	97	98	98	97.6
P4	98	99	99	98.6
P5	96	97	97	96.6
P6	99	98	98	98.3
P7	100	100	100	100
P8	95	96	96	95.6
P9	97	97	95	96.3

Participant	Scientific trans.	Medical trans.	Legal trans.	Individual average
P10	96	94	97	95.6
P11	89	96	96	93.6
P12	90	91	89	90
P13	99	98	90	95.6
P14	100	100	99	99.6
P15	97	98	100	98.3
P16	100	99	99	99.3
P17	99	100	100	99.6
P18	97	98	98	97.6
P19	98	99	99	98.6
P20	96	97	97	96.6
P21	99	98	98	98.3
P22	100	100	100	100
P23	95	96	96	95.6
P24	97	97	95	96.3
P25	96	94	97	95.6
P26	89	96	96	93.6
P27	90	91	89	90
P28	99	98	90	95.6
P29	100	100	99	99.6
P30	97	98	100	98.3
Overall average	96.8	97.4	96.8	97.02

Note. Scores reflect rubric-based evaluations of legal, medical, and scientific translations. Higher scores indicate greater accuracy, terminological adequacy, and textual cohesion.

As shown in Table 1, the students achieved high average scores, based on a scale from 0 to 100, where 95 indicates a translation with slight errors that can be corrected in a new editing process. The overall average for the group is 96.80, with the medical translation having the best performance. In contrast, the lowest averages were recorded in the areas of scientific and legal translation, with a lower percentage of 0.6 points compared to the overall average. Consequently, it is possible to point out that the participants, at this final stage, can present high-quality products and demonstrate solid translation competence. Nevertheless, it is imperative to encourage students to dedicate time to the final editing of the document and slightly review the sources of documentation, since according to the manual review of the guidelines, an opportunity for improvement was detected in these two areas.

Table 2. Average time in minutes for translation, post-editing, and editing.

Participant	Effective Trans. (min)	Edition (min)	Post-editing (min)	Total (min)
P1	54	65	42	161
P2	45	87	44	176
P3	34	34	90	158
P4	40	28	87	155
P5	30	29	83	142
P6	34	37	96	167
P7	27	36	110	173
P8	29	29	84	142

Participant	Effective Trans. (min)	Edition (min)	Post-editing (min)	Total (min)
P9	36	12	86	134
P10	35	34	87	156
P11	33	54	86	173
P12	37	64	82	183
P13	36	45	85	166
P14	32	54	94	180
P15	29	57	94	180
P16	54	65	42	161
P17	45	87	44	176
P18	34	34	90	158
P19	40	28	87	155
P20	30	29	83	142
P21	34	37	96	167
P22	27	36	110	173
P23	29	29	84	142
P24	36	12	86	134
P25	35	34	87	156
P26	33	54	86	173
P27	37	64	82	183
P28	36	45	85	166
P29	32	54	94	180
P30	29	57	94	180
Overall Average	35.4	44.33	83.33	163.06

Note. Post-editing time includes terminological searches and corrections required to address MT-generated errors.

As shown in Table 2, there is a predominant trend in the use of time spent on the post-editing activity. This stage, characterized by the editing of a text generated by an automatic translation system such as DeepSeek, plays a main role in the process. Notably, the group spent an average of 83.3 minutes on this activity, which is equivalent to 46.2% of the total time spent on the translation exercises. It should be noted that the time invested in the terminology search, corresponding to the terms that the automatic translation system was unable to resolve, was integrated into the calculation of the time spent on post-editing the text.

Regarding the average time spent editing the text, the group invested 44.3 minutes, which represents 24.6% of the total time. The activities considered in this stage include reproducing the original format, re-reading the text, terminological association, and both textual and image editing. The use of an automated translation system, such as DeepSeek, makes it possible to reduce the time required for editing, as reflected in the data presented in Table 2. However, editing remains a fundamental stage in the translation process, especially in the context of student training, since it contributes significantly to guaranteeing the quality of the translation service.

The concept of *practical translation*, used by Andrade and Cortez (2022, 2024), refers to the time dedicated exclusively to transferring content from a source to a target language system. This concept and indicator are particularly valuable since they make it possible to quantify and analyze the time specifically allocated to this activity within the studies on translation procedures.

In the present study, the group spent an average of 35.4 minutes, equivalent to 19.6% of the exercises, using the DeepSeek tool to perform the translation task. Since this tool, based on text-generating artificial intelligence, was used in its free version 3.0; it has limitations, such as the impossibility of attaching complete documents. Therefore, users must resort to copy and paste large volumes of text to complete the translation. Despite these restrictions, DeepSeek proves to be an effective tool that contributes significantly to the optimization of the translation process. Table 3 shows the final score obtained in the course.

Table 3. Final student scores of the course

Participant	Score
P1	93
P2	100
P3	93
P4	100
P5	89
P6	94
P7	100
P8	99
P9	94
P10	89
P11	80
P12	93
P13	89
P14	100
P15	100
P16	93
P17	100
P18	93
P19	100
P20	89
P21	94
P22	100
P23	99
P24	94
P25	89
P26	80
P27	93
P28	89
P29	100
P30	100
Overall Average	97.02

As shown in Table 3, the students obtained an overall average score, as a group, of 97.02, which means that the group's performance was good, with slight opportunities for improvement. Nevertheless, they are competent to work on specialized translations with specific terminology using AI-powered tools.

Regarding Table 3, the inclusion of students' final course grades provides contextual information about participants' overall academic performance in the course. While not directly tied to translation-product quality, it offers a complementary indicator of student engagement and competence. However, in interpreting the experimental results, translation-task scores remain the primary metric of interest.

The quantitative data indicate that the students were able to achieve acceptable translations using DeepSeek, as well as to allocate specific times, which were obtained through Translog-II. However, to go deeper into the activity performed, and as previously mentioned, it is important to know the perception and self-perception of the students about this exercise, as well as the use of AI applications incorporated in their training as translators, so now we proceed to investigate the most relevant results and findings through the final satisfaction questionnaire of the course AI Applications in Translation.

Self-perception of the course and mastery of applications with AI

Student self-perception is a meaningful construct in translation pedagogy because it reflects learners' confidence, metacognitive awareness, and perceived ability to manage specialized tasks—factors that directly influence performance outcomes (Kelly 2005, González-Davies 2017). It constitutes a relevant indicator for identifying opportunities for improvement in both course design and pedagogical strategies implemented within the bachelor's degree in Translation program at the Autonomous University of Baja California, Mexicali campus. For this purpose, the self-evaluation consisted in 12 criteria assessing the perception of individual performance using a five-point Likert scale, where 1 represented "very low" performance and 4 "excellent" performance giving a maximum of 48 points.

The results revealed that 71.4% (n=10) of the students evaluated their performance with a rubric-assessed score of 4/5, while 28.6 % (n=5) self-evaluated themselves with a 5/5, corresponding to an "excellent" performance. When comparing these self-evaluations with the final scores obtained in the course, it was observed that those students who reported "excellent" performance achieved scores within the range of 97-100/100. These findings suggest a positive correlation between self-perception of performance and objective academic results, which reinforces the usefulness of self-evaluation as a diagnostic tool to optimize both the teaching-learning processes and the formative experience of students.

A five-point Likert scale was applied to the mastery of the applications used in the course and their ease of use and management, where 1 represented "Strongly Disagree" and 5 "Strongly Agree". The results indicated that 57.1% (n=9) of the students evaluated their mastery with a score of 4/5, while the remaining 42.9% (n=6) selected 3/5. These data suggest that a significant proportion of the participants faced certain difficulties in handling the digital tools incorporated during the course.

Although the students had previous experience with machine translation systems, the integration of tools based on generative artificial intelligence represented an additional challenge. The convergence of multiple digital technologies (each with specific functionalities) raised the learning curve, especially when applied to complex translation tasks. This finding underscores the importance of designing more structured pedagogical strategies and providing specific training that facilitates the transition to the effective use of advanced technologies in the field of translation.

Students were also questioned, based on the same scale, as to whether applications such as DeepSeek have significantly improved their translation products. To which the group reported 57.1% (n=9) total agreement that the tools are easy to use and incorporate into translation work. This was followed by 28.6% (n=4) of students who selected agree (4/5), while a smaller percentage of 14.3% (n=2) selected 3/5 on the scale, indicating that they have a medium opinion regarding the difficulty of using the AI applications and DeepSeek commands seen in class.

Students' perception of whether tools such as DeepSeek have significantly improved their translation products was also assessed using the same five-point Likert scale. The results showed that 57.1% (n=9) of the participants selected "Strongly Agree" (5/5), indicating that they consider these tools to be easy to use and easy to integrate into translation tasks. 28.6% (n=4) expressed agreement (4/5), while 14.3% (n=2) reported a medium rating (3/5), suggesting a more neutral perception regarding the ease of use of the artificial intelligence applications and DeepSeek commands presented during the course.

These findings reflect that, although most students positively rate the functionality of these tools, a smaller percentage still encounter some difficulty when using them. This highlights the need to continue to optimize training in the use of emerging technologies to ensure their effective and widespread adoption in the translation field.

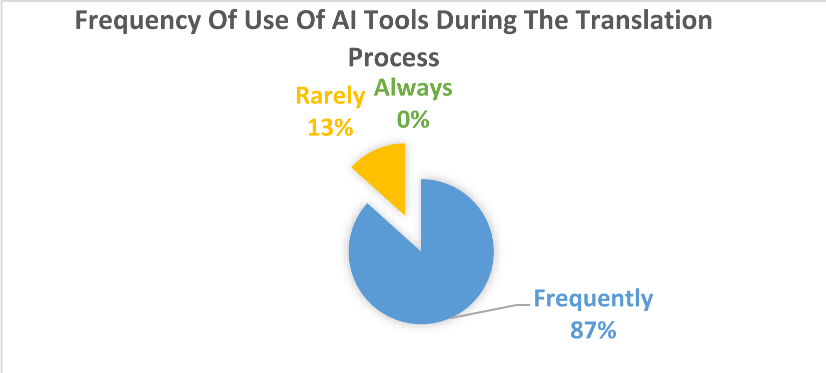
On the other hand, the students' perception of the quality of the translations generated by DeepSeek was explored. None of the participants selected "Strongly Agree" (5/5) on the rating scale. However, 57.1% (n=9) indicated agreement (4/5) that DeepSeek produces quality translations in specialized areas, while the remaining 42.9% (n=6) selected a medium rating (3/5). These results suggest that, although students recognize the potential of the tool, they do not consider it to be completely infallible.

In other sections of the questionnaire, participants noted that the translations generated by DeepSeek are generally of good quality, as they do not require in-depth post-editing, which reduces the effort required at this stage. In addition, they highlighted the accuracy in the automatic generation of glossaries of specialized terms, which optimizes both the terminology search time and the translation process in general. This optimization allows students to focus most of their time on post-editing, previously identified as the most demanding phase of their translation assignments.

Another relevant data refers to the evaluation of the students' satisfaction with the final translation product obtained with DeepSeek, the post-editing process, and the subsequent editing. For this analysis, the Likert scale was used again, where 5 represented "very satisfied" and 1, "not at all satisfied". 71.4% (n=11) of the students reported a score of 4/5, suggesting that they were satisfied with the translated product. On the other hand, 28.6% (n=4) indicated that they were totally satisfied with the quality of the translations delivered as part of the course assignments. This result is a significant indicator since the students' perception of the quality of their work seems to be closely linked to the performance reflected in the scores obtained during the course.

Regarding the frequency of use of AI tools, besides DeepSeek, students were questioned about the frequency of use of this tool, where the options were always, frequently, and rarely. Figure 1 shows the percentages obtained by the 15 participants in the study.

Figure 1. Frequency of the use of AI tools during the translation process.



As can be seen in the graph above, 87% of the participants in this study report the constant use of tools, while 13% state that they do not use them during their translation process. In the same way, they were asked about the AI tools they used to elaborate their translations during their training, and they mentioned some of them: Wordfast (in its different versions), SDL Trados, Microsoft Copilot, and DeepSeek. It is interesting that from this course, the students argue that learning to design specific prompts or focus on translation, editing, and post-editing in a text-generative AI, such as DeepSeek, achieved better results and reduced translation and post-editing time. It should be noted that this type of activities was carried out in the last unit of the course, with the intention that the students could compare the importance of *prompt* design and how they can improve their results by requiring higher specifications.

Interestingly, due to this course, students acknowledged that learning to design specific prompts focused on translation, editing, and post-editing in a generative text AI like DeepSeek allowed them to achieve better results and significantly reduce the time spent on these tasks. These activities were implemented in the course's final unit to enable students to compare the importance of prompt design and how, by requiring greater specifications, it is possible to improve the quality and efficiency of their translations.

Perception and satisfaction regarding the use of DeepSeek and the course

This section focuses on the students' perception regarding the use of DeepSeek and the course *AI Applications in Translation* based on the results obtained from the previously mentioned questionnaire. Firstly, when asked about which tools posed the greatest challenge to integrate into their translation projects, students pointed out that SDL Trados and MultiTerm were the most challenging. They indicated that the interfaces of both tools are complex; the wide range of options they offer and the necessary processes to use their features posed a significant challenge. However, after continuously using the tools and working on several additional translation projects, they managed to functionally master them. Despite this, students mentioned that while they find these tools useful, they require considerable experience to work optimally with them.

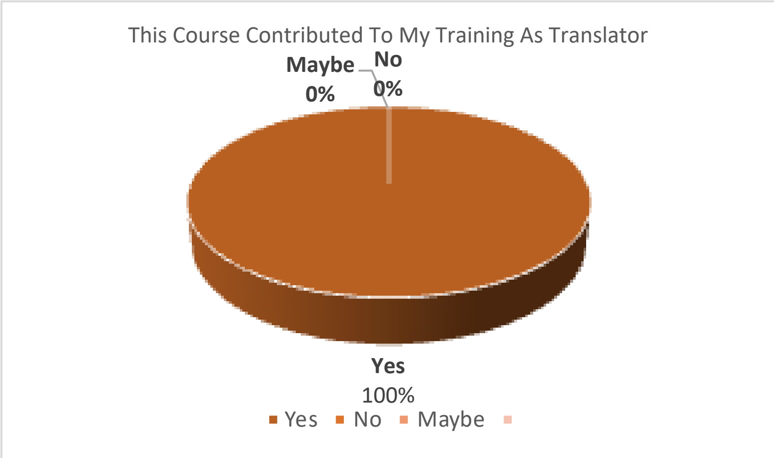
Participants were also asked to describe the positive aspects of using DeepSeek in their translation activities. From their responses, three key points were identified: 1) orthotypographic and stylistic corrections, which significantly facilitate the final editing process; 2) The ability of DeepSeek to offer diverse translation options while largely respecting the context and fidelity of the original text, which allows users to select or construct fragments from the generated suggestions; and 3) ease of use and the speed at which translations are processed, optimizing the user's workflow.

Among the positive experiences reported by students regarding DeepSeek as a translation assistance tool, the generation of "good translations" in semi-specialized fields stood out. Nevertheless, a thorough terminological review was necessary to ensure precision when faced with more complex terminology. Moreover, the grammatical and stylistic accuracy of general text translations was valued, as the system provided satisfactory results. Overall, these observations concluded that the tool significantly contributes to optimizing the various phases and processes involved in translation work.

On the other hand, the group was asked to identify negative experiences related to the use of DeepSeek as a translation tool. Their responses can be summarized as follows: firstly, the system does not reproduce the original text format, requiring additional work for subsequent adjustments. Secondly, some participants pointed out that the need to specify orders and commands in detail created complications, as it demanded time and was perceived as tedious. Also, a limitation of the free version was highlighted: the inability to process complete documents, which forced users to work fragment by fragment, translating paragraph by paragraph.

The final two questionnaire questions aimed to collect students' general opinions about the course. Specifically, they were asked if they considered the course *AI Applications in Translation* had contributed to their training as future translators. Figure 2 shows the responses obtained from the fifteen participants.

Figure 2. Perception of the course's impact on the student's training.



As observed in Figure 2, 100% of the students who took the course stated that it had a significant impact on their translation training. Students argued that these tools could be used in their professional labor as translators in the future, supporting them in optimizing their work and achieving better performance and efficiency. Some of the respondents emphasized that mastering these tools will be fundamental shortly. They also affirmed their potential as resources to support translation work, allowing more time for post-editing. Also, designing good *prompts* was key in streamlining translation, editing, post-editing, and terminological management processes. In this sense, it is evident that guiding students to engage with emerging technologies that advance rapidly in the postmodern era is highly advisable. With the presentation of the results and findings from this research, the discussion and conclusions are addressed in the following section.

7. Discussion and Conclusions

First, the results confirming the essential role of human intervention align with established literature indicating that AI-generated translations—despite fluency—frequently require extensive revision to ensure semantic accuracy and terminological adequacy (Bentivogli et al. 2016, Castilho et al. 2017). This reinforces Forcada's (2017) assertion that neural MT output often necessitates heavy post-editing, particularly in specialized domains such as medicine and law.

The study demonstrates that the use of AI tools, such as DeepSeek, has a significant impact on the training of translation students, particularly those in the final stages of their studies. The obtained results indicate that students achieved a high translation competence, with an average score of 97.02. This performance highlights the quality of their translations, although areas for improvement were identified, especially in the translation of specialized texts such as scientific and legal documents. These findings underscore the need to thoroughly review AI-generated translations, as small terminological inconsistencies or adaptations can persist. A key aspect of the study was the time spent on each phase of the translation process. Students spent an average of 83.3 minutes on post-editing, representing 46.2% of the total time. This indicates that even though AI tools optimize the initial translation process, the post-editing phase remains essential for ensuring the final text's quality. Efficiency in the translation and editing phases also benefited from the use of AI, which allows students to focus on more complex aspects of translation, such as cultural adaptation or specialized terminology.

Second, the correlation between self-perception and performance supports findings by Kelly (2005) and González-Davies (2017), who note that self-regulation and reflective competence are foundational to professional translator development. Students who perceived themselves as capable demonstrated greater ability to evaluate and refine AI-generated translations, suggesting that metacognitive awareness plays a decisive role in AI-supported translation contexts.

Third, students' adoption of AI tools mirrors broader shifts in professional translation markets, where AI-integrated workflows are increasingly standard (Koehn 2020). Their frequent use of DeepSeek suggests early familiarity with industry-relevant practices, though pedagogical scaffolding remains essential to ensure critical and ethical use of AI technologies. The high percentage of students who frequently used AI tools, despite initial difficulties, reflects a positive attitude toward integrating these technologies into translation practice. As they advance in their training, students demonstrate improved translation quality, which suggests that AI can increase efficiency, enhance quality, and prepare students to face the challenges of a professional market increasingly influenced by technology.

Finally, the revised discussion eliminates redundancies found in the original text and replaces descriptive statements with interpretive insights, connecting results to current debates on the evolving role of human translators in an AI-mediated landscape.

In conclusion, this study confirms that integrating AI tools like DeepSeek not only improves translation quality but also optimizes the translation process by reducing time spent on basic tasks and allowing students to focus on more complex aspects. However, it presents several limitations that should be considered when interpreting results. First, the small sample size (n = 30) restricts the generalizability of findings. Second, only the free version of DeepSeek-V3 was used, which limited functionality and prevented domain-specific optimization. Third, no comparative analysis with other AI systems such as GPT-4 or DeepL was conducted. Finally, the study did not explore long-term effects on translation competence.

Future research should compare the performance of free versus premium AI models, evaluate long-term competency development, and explore automated evaluation metrics aligned with human-assessment criteria. Additionally, domain-specific fine-tuning and cross-tool comparisons may provide deeper insights into AI-mediated translation training.

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Anexos

FACULTAD DE IDIOMAS

RÚBRICA DE EVALUACIÓN DE TRADUCCIÓN

Esta rúbrica está adaptada para la evaluación de traducciones, permitiendo desglosar el proceso en componentes específicos y evaluar cada uno de manera objetiva. Su propósito es facilitar evaluaciones, coevaluaciones o autoevaluaciones, destacando los errores mediante un sistema de colores, lo que ayuda a identificar claramente áreas de mejora. El formato permite señalar observaciones específicas de acuerdo a los errores detectados en los diferentes criterios evaluados, proporcionando una comprensión más profunda de la calidad en la traducción.

Datos de identificación:
Evaluación realizada por:
Traducción realizada por:
Título de la traducción:
Lenguas de trabajo: español ☐ inglés ☐ francés ☐ italiano ☐ japonés ☐ otra:_________
Dirección de la traducción: directa ☐ inversa ☐

ESCALA DE EVALUACIÓN			
Esta rúbrica de evaluación utiliza una escala del 1 al 4, en la que el puntaje más alto refleja una traducción de alta calidad.			
1) Muchos errores	2) Algunos errores	3) errores mínimos	4) ningún error

EVALUACIÓN DE ASPECTOS LINGÜÍSTICOS, SOCIOCULTURALES, Y DEL PROCESO TRADUCTIVO/ DE TRADUCCIÓN

CRITERIO	PUNTUACIÓN			
a) Concordancia género y número:	1 ☐	2 ☐	3☐	4☐
b) Cohesión y coherencia textual:	1 ☐	2 ☐	3☐	4☐
c) Uso de terminología adecuado:	1 ☐	2 ☐	3☐	4☐
d) Registro adecuado:	1 ☐	2 ☐	3☐	4☐
e) Puntuación:	1 ☐	2 ☐	3☐	4☐
f) Ortotipografía:	1 ☐	2 ☐	3☐	4☐
g) Adaptación sociocultural:	1 ☐	2 ☐	3☐	4☐
h) Contra sentidos/falsos sentidos/sin sentidos:	1 ☐	2 ☐	3☐	4☐
i) Omisión injustificada:	1 ☐	2 ☐	3☐	4☐
j) Adición injustificada:	1 ☐	2 ☐	3☐	4☐
k) Revisión minuciosa:	1 ☐	2 ☐	3☐	4☐
l) Reproducción de formato original (maquetación):	1 ☐	2 ☐	3☐	4☐
Total:	/48			

ESCALA DE RANGO DE EVALUACIÓN PARA TRADUCCIONES

PUNTUACIÓN (0-48)	RANGO DE CALIFICACIÓN	DESCRIPCIÓN
0 - 35	0-69	Traducción no aceptable. Presenta una cantidad excesiva de errores que impiden la comprensión del texto.
36 - 37	70-74	Traducción inadecuada. Errores críticos que distorsionan el sentido original. La calidad general de la traducción es baja.
38 - 39	75-79	Traducción muy deficiente. Muchos errores que afectan gravemente la claridad y precisión; el mensaje es difícil de entender.
40 - 41	80-84	Traducción deficiente. Presenta varios errores que dificultan la comprensión.
42 - 43	85-89	Traducción aceptable. Contiene errores que afectan la claridad o precisión, pero el sentido general se mantiene.
44 - 45	90-94	Traducción buena. Incluye algunos errores que no afectan de manera significativa la claridad del mensaje. La calidad del trabajo es mayormente adecuada y el sentido se conserva bien.
46 - 47	95-99	Traducción muy buena. Presenta errores mínimos que no afectan la comprensión del texto. El mensaje es claro y cumple con la mayoría de los estándares.
48	100	Traducción excelente. Cumple con los estándares de calidad. Sin errores; la traducción es precisa, fluida, con terminología correcta y estilo apropiado al contexto.

Guía rápida para analizar los errores en la evaluación de traducción

a) Concordancia de género y número: se refiere a la necesidad de que sustantivos, adjetivos y pronombres coincidan en género (masculino/femenino) y número (singular/plural).

Ejemplo:

- Incorrecto: “El casas son grandes.”
- Correcto: “Las casas son grandes.”

b) Cohesión y coherencia textual: la cohesión se refiere a cómo las partes de un texto se enlazan entre sí, mientras que la coherencia se refiere a la lógica y claridad del texto en su conjunto.

Ejemplo:

- Cohesión incorrecta: “El sol brilla. Las flores son hermosas. El coche está aparcado.”
- Cohesión correcta: “El sol brilla, lo que hace que las flores sean aún más hermosas, mientras el coche está aparcado a la sombra.”

c) Uso de terminología adecuada: implica el uso de términos específicos y precisos en el contexto técnico o especializado.

Ejemplo:

- Incorrecto: “El impacto de la física.”
- Correcto: “El impacto de la física cuántica.”

d) Registro adecuado: apropiado para el público y el contexto.

Ejemplo:

- Registro incorrecto: “Tienes que hacer esto.”
- Registro correcto: “Es necesario que se realice esto.”

e) Puntuación: la puntuación debe usarse correctamente para facilitar la comprensión y claridad del texto.

Ejemplo:

- Incorrecto: “Vamos a comer abuelo.”
- Correcto: “Vamos a comer, abuelo.”

f) Ortotipografía: incluye el uso correcto de la tipografía, como el uso de mayúsculas, cursivas y negritas.

Ejemplo:

- Incorrecto: “el presidente de los estados unidos.”
- Correcto: “El Presidente de los Estados Unidos.”

g) Adaptación sociocultural: se refiere a la necesidad de adaptar la traducción a la cultura del público objetivo.

Ejemplo:

- Incorrecto: “Santa Claus es un personaje importante.”
- Correcto: “El Día de Reyes es una tradición importante.”

h) Contra sentidos/falsos sentidos/sin sentidos: se producen cuando la traducción lleva a malentendidos o confusiones debido a una interpretación incorrecta.

Ejemplo:

- Falso sentido: “She has a chip on her shoulder.” (significa que está resentida)

- Incorrecto: “Ella tiene un chip en su hombro.”

i) Omisión injustificada: sucede cuando se omiten partes del texto original sin razón válida.
Ejemplo:
- Incorrecto: “El informe se entregará mañana.” (Omitiendo “a tiempo”)
- Correcto: “El informe se entregará a tiempo mañana.”

j) Adición injustificada: se presenta cuando se añade información que no está presente en el texto original.
Ejemplo:
- Incorrecto: “El coche es rojo y rápido.” (Si el original solo decía “El coche es rojo.”)
- Correcto: “El coche es rojo.”

k) Revisión minuciosa: se refiere a la necesidad de revisar el texto traducido para detectar y corregir errores.
Ejemplo:
- Error sin revisión: “La casa es azul.” (sin revisar si “casa” debería ser “casas” en plural).
- Revisión correcta: “Las casas son azules.”

l) Reproducción de formato original (maquetación): se refiere a mantener el formato y la disposición del texto original en la traducción.
Ejemplo:
- Incorrecto: Formato desordenado en un documento.
- Correcto: Mantener títulos, subtítulos y formato visual del texto original