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TRANSLATION

IN THE DIGITAL ERA: A COMPARATIVE STUDY OF AI AND HUMAN APPROACHES

TRADUCCIÓN EN LA ERA DIGITAL: UN ESTUDIO COMPARATIVO DE LOS ENFOQUES DE IA Y HUMANOS

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ABSTRACT

The goal of this research is to compare human translators with AI-powered machine translation systems. The study contrasts the two translation approaches with regard to their linguistic accuracy, semantic depth, and adaptability to different contexts. By using the frameworks of dynamic and formal equivalence theories, the study delves into the topic of translation quality. It brings to light fundamental differences between computer and human comprehension of meaning, cultural nuance, and colloquial expressions. It was found that while deep learning models and neural networks have greatly improved machine translation, human translators continue to excel in areas such as pragmatic context, ambiguity resolution, and polysemic management. The research uncovers ongoing problems with grammatical structure, lexical equivalence, and discourse coherence in machine-generated outputs. The research also emphasizes the importance of human cognition in preserving emotional tone and semantic intent. Results show that machine translation is more useful when used in conjunction with human translators than on its own, even though machine translation is fast and scalable. However, hybrid models, which include both human and AI-driven components, hold promise for the future as a means to improve precision and cultural awareness.

Keywords: AI, Translation, Comparative analysis, Machine translation, Linguistic problems.

RESUMEN

El objetivo de esta investigación es comparar traductores humanos con sistemas de traducción automática basados en IA. El estudio contrasta ambos enfoques de traducción en cuanto a su precisión lingüística, profundidad semántica y adaptabilidad a diferentes contextos. Utilizando los marcos de las teorías de equivalencia dinámica y formal, el estudio profundiza en el tema de la calidad de la traducción. Pone de manifiesto diferencias fundamentales entre la

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comprensión del significado, los matices culturales y las expresiones coloquiales, tanto por parte de las computadoras como de los humanos. Se descubrió que, si bien los modelos de aprendizaje profundo y las redes neuronales han mejorado considerablemente la traducción automática, los traductores humanos siguen destacando en áreas como el contexto pragmático, la resolución de ambigüedades y la gestión de la polisemia. La investigación revela problemas persistentes con la estructura gramatical, la equivalencia léxica y la coherencia discursiva en los resultados generados por las máquinas. La investigación también enfatiza la importancia de la cognición humana para preservar el tono emocional y la intención semántica. Los resultados muestran que la traducción automática es más útil cuando se utiliza en conjunto con traductores humanos que por sí sola, a pesar de ser rápida y escalable. Sin embargo, los modelos híbridos, que incluyen componentes tanto humanos como controlados por IA, son prometedores para el futuro como medio para mejorar la precisión y la comprensión cultural.

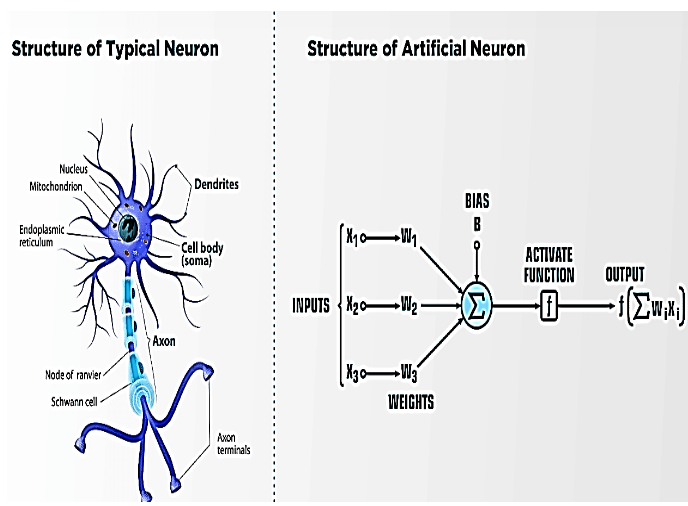
Palabras clave: IA, Traducción, Análisis comparativo, Traducción automática, Problemas lingüísticos.

INTRODUCTION

Over the past few decades, translation has evolved from a specialized human endeavor to a discipline structured by both humanistic criteria and technological solutions. In an increasingly globalized world, the act of translation not only facilitates intercultural communication but also boosts international trade, diplomacy, scientific cooperation, and equitable access to knowledge (Brashi, 2024). The expansion of digital platforms and interconnected information networks has intensified the demand for rapid and massive translations, forcing a rethinking of traditional processes. In this context, the emergence of artificial intelligence tools—from the first statistical translation systems to deep neural networks, exemplified by Google Translate, DeepL, or models based on Transformer and GPT architectures—has radically transformed the landscape: it is no longer enough to reproduce terms and structures; machines are now expected to capture cultural nuances, registers, and discursive coherence (Moneus & Sahari, 2024). This initial shift in the landscape raises essential questions about the true scope of automation and the role that human translator will have to play in the future.

On the technological front, artificial intelligence has revolutionized translation practice through the application of concepts and tools from natural language processing (NLP). NLP combines linguistic and statistical algorithms to automatically interpret and produce text, addressing tasks such as morphological analysis, semantic disambiguation, and sentence segmentation. Neural networks, modeled after the architecture of the human brain (Figure 1), form the basis of contemporary machine translation systems: multiple layers of interconnected artificial "neurons" process sequences of linguistic data, learning hierarchical representations of words and their contexts. Deep learning expands this paradigm by superimposing additional layers (deep neural networks) that capture high-level syntactic and semantic patterns, enabling advances such as transformer models, where autoregressive attention mechanisms achieve translations with remarkable fluency and discursive coherence (Shahin & Ismail, 2024). According to Kembaren et al. (2023), the development of neural machine translation (NMT) systems has been the primary factor in the transformation of the translation environment brought about by the progression of artificial intelligence (AI). However, these systems often fail to preserve contextual meaning and cultural subtlety, which are aspects in which human translation excels. Although these systems promise quick and scalable language processing, they frequently struggle to achieve this goal effectively. Through the use of language intuition and cultural knowledge, human translation (HT) continues to be superior in terms of conveying idiomatic phrases, maintaining discourse cohesiveness, and preserving stylistic consistency. Machine translation (MT), on the other hand, tends to generate outputs that are more literal and potentially semantically erroneous (Lu, 2024).

Fig 1. The current state of AI language translation.



Source. Temelkova (2023).

It is important to highlight that theoretical framework of translation provide crucial conceptual foundations for understanding the goals and achievements of various translation methods. This distinction becomes more apparent when viewed through the lens of translation theories, namely Eugene Nida's dynamic and formal equivalence models. According to Nida (1964), formal equivalence emphasizes structural correctness, while dynamic equivalence focuses on meaning and receptor response. Formal equivalence is often associated with MT systems, consequently neglecting pragmatic and emotional purposes (Marshall, 2024). The German functionalist model of Skopos expands this perspective by positioning the purpose or function (skopos) of the translated text in its new cultural setting as the central axis, guiding translation decisions toward communicative effectiveness rather than formal correspondence (An & Sun, 2022). Postcolonial currents, for their part, challenge dominant paradigms in translation that perpetuate power relations and cultural hierarchies; they propose a practice that is aware of colonial and imperial dynamics, one that makes marginalized voices visible, destabilizes prejudices, and promotes equity between languages and cultures (Akkaliyeva et al., 2021; Schritt & Voß, 2025).

As stated before, research has brought to light the limits of machine-generated outputs in scenarios with complicated semantic settings, as well as the continued need for human supervision, therefore integration of artificial intelligence with human knowledge may prove to be the most efficient way ahead as translation technologies continue to progress. This would combine the effectiveness of machine translation with the nuanced interpretation of human translation. In this scenario interdisciplinarity arise as a fundamental requirement for addressing the complexity of AI-mediated translation from a holistic perspective. Linguistics provides the knowledge of formal, pragmatic, and sociolinguistic structures necessary to design algorithms that respect the variability of language. Computer science supplies the modeling methods, computational architectures, and performance evaluation criteria. Ethics, in turn, raises questions about social responsibility, algorithmic biases, and copyright, demanding standards that guarantee fairness and transparency in automated processes. Finally, sociology contextualizes translation within its community and institutional framework, analyzing how technologies impact intercultural communication, power dynamics, and access to knowledge. Only through the confluence of these disciplines is it possible to design translation solutions that integrate technical efficiency and cultural respect.

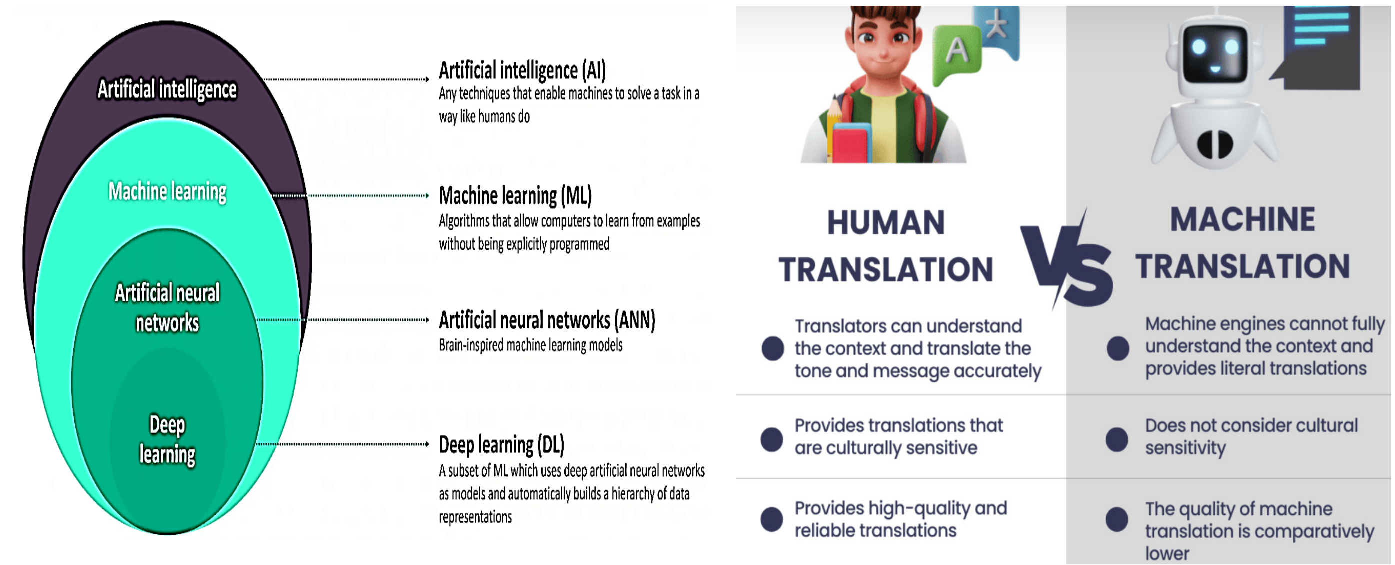
Thus, the core of this study's problematic issue arises from the conflict between speed and accuracy. On the one hand, machine translation offers compelling advantages: the ability to process large volumes of text in fractions of a second, reduced operating costs, and immediate scalability across multiple languages. On the other hand, AI suffers from notable limitations: its difficulty in capturing implicit cultural references, adapting discourse to the target audience, resolving lexical ambiguities, and maintaining coherence at the paragraph or long-form text level. Faced with these shortcomings, the human translator retains irreplaceable attributes: creativity in recreating metaphors, sensitivity in respecting tone and original intent, specialized knowledge in literary, legal, or medical fields, and an ethical commitment to fidelity and social responsibility. However, the academic debate lacks a holistic vision that articulates the technical, cultural, ethical, and socioeconomic dimensions of translation in the digital age within a single framework. Thus, this study aims to evaluate the comparative performance of human translators versus AI-powered machine translation systems by analyzing their effectiveness in linguistic accuracy, semantic interpretation, and contextual adaptation.

DEVELOPMENT

With the introduction of machine translation (MT) systems that are both quick and cost-effective, artificial intelligence (AI) has brought about a radical transformation in the landscape of language translation. Despite these benefits, there are ongoing discussions regarding the language quality, cultural appropriateness, and comparability of these translations to human translation (HT). The purpose of this literature review is to investigate the ever-changing role that artificial intelligence plays in translation, compare it to human efforts, and emphasize the ongoing challenges associated with language processing. Early developments in machine translation (MT), particularly rule-based and statistical techniques, were crucial in laying the foundation for the subsequent development of neural machine translation (NMT). Google and other platforms have implemented neural machine translation (NMT), which utilizes deep learning to improve fluency and context management (Bahdanau et al., 2016). Studies have shown that neural machine translation (NMT) performs substantially better than previous systems, especially in common language pairings; however, it still faces difficulties with idioms, polysemy, and contextually sensitive meanings (Lu, 2024).

Gaspari et al. (2015) conducted comparative research that demonstrates that although machine translation (MT) excels in speed and scalability, human translation (HT) delivers superior outcomes in terms of nuanced interpretation, domain-specific terminology, and maintaining cultural and emotional intonation. Due to their pragmatic and cultural competence, human translators are able to provide translations that are more accurate and comprehensible in context-sensitive situations. Human translation also accommodates stylistic diversity, emotional undertones, and creative adaptability—capabilities that AI often lacks. In contrast, artificial intelligence remains susceptible to errors in literal interpretation, semantic disambiguation deficits, and overgeneralization, particularly in resource-limited languages or complex sentence patterns (Koponen, 2021). A comparative picture of these processes is shown in Figure 2.

Fig 2. Machine and AI translation.



Source: Temelkova (2023).

Problems with language continue to be a fundamental constraint of MT. Syntactic ambiguity, morphological inconsistencies, and discourse-level coherence all present challenges that artificial intelligence is unable to address consistently. It is common for artificial intelligence to incorrectly perceive the meaning of sentences in languages that allow for arbitrary word order, such as Turkish or Finnish (Sreelakshmi et al., 2024). In addition, semantic drift, which is also known as the deviation of AI translation from the intended meaning, may occur, particularly in situations when the context is ambiguous or inferential. Examples of pragmatic mistakes include the failure to understand humor, irony, or etiquette rules. Pragmatic errors are also known to occur.

An increasing body of research shows that hybrid techniques, in which machine learning is used as a preliminary tool and humans post-edit the output, have the potential to improve efficiency while maintaining quality (Toral & Way, 2018). Such models are compatible with computer-assisted translation (CAT) systems, which integrate artificial intelligence into the translator's workflow. This allows for increased efficiency without compromising the interpretive depth of translation. Artificial intelligence can also help with terminology extraction, glossary creation, and predictive typing, which can speed up human translation processes and reduce the amount of human error. However, ethical issues continue to exist, particularly in relation to the de-skilling of translators, job displacement, and excessive reliance on AI-generated content without sufficient validation.

Translation is more than just the process of language equivalency; it also entails the transmission of cultural values. Artificial intelligence systems often provide outputs that are uniform and decontextualized, lacking understanding of socio-cultural registers. In contrast to machine translators, human translators adapt information for localization by taking into consideration the norms and expectations of the target audience. There is also the possibility of algorithmic bias, which occurs primarily when the training data is biased or lacks diversity. This results in representational imbalances and stereotyped outputs, particularly in linguistic situations that require consideration of gender or ethnicity (Bender et al., 2021).

The literature shows a growing consensus that artificial intelligence has transformed the field of translation with speed and efficiency; nevertheless, it is not yet capable of replicating the depth, context-sensitivity, and cultural intuition that human translation possesses. Collaborative systems that combine the effectiveness of machines with human intelligence represent the most promising path forward. Future research should concentrate on enhancing the verbal cognition of artificial intelligence, minimizing bias, and establishing ethical boundaries in the context of human-AI cooperation.

In terms of language correctness, idiomatic expression, and contextual appropriateness, the comparative study of Machine Translation (MT) and Human Translation (HT) reveals a significant performance disparity between the two types of translation. Neural Machine Translation (NMT) systems, such as Google Translate and DeepL, exhibit impressive fluency when translating phrases that are syntactically straightforward and commonly used. However, when tested on texts that are literary, culturally embedded, or complex, they often provide outputs that are either extremely literal or distorted in terms of their semantic content. Toral and Way (2018), for example, pointed out that while Neural Machine Translation (NMT) is capable of producing remarkably fluent literary translations, it is unable to comprehend metaphorical language, emotional tone, and authorial style—aspects that human translators naturally preserve.

In controlled experiments on post-editing productivity, Gaspari et al. (2015) discovered that although machine translation (MT) reduces overall translation time, human intervention is still required for post-editing in more than sixty percent of cases due to grammatical errors and context misalignment. This finding suggests that machine output cannot yet match human-level quality, particularly in more nuanced domains. In terms of operational efficiency, machine translation (MT) systems provide greater scalability and cost-effectiveness, particularly when meeting the requirements of bulk translation or real-time multilingual communication. This is of special significance within the realms of international commerce, news distribution, and digital marketing. Bahdanau et al. (2016) pioneered the development of attention-based neural machine translation (NMT) models. These models have significantly enhanced the real-time flexibility of machine translation (MT) systems, thus enabling more coherent translations over longer sequences. Nevertheless, even with such models, output fidelity remains significantly dependent on the language pair, domain specialization, and training corpus size.

Marshall (2024) discovered in her thesis that participants preferred human translations for academic and legal topics, despite the fact that machine translations were generally faster than human translators. Therefore, although MT systems are faster, they may sacrifice semantic clarity and stylistic consistency. Polysemy, word order variations, grammatical ambiguity, and semantic confusion are examples of linguistic issues that continue to be significant hurdles for Machine Translation (MT). Pronoun resolution, irony, cultural idioms, and homonyms are all situations with which AI models often struggle. According to Koponen (2021), while MT output may appear grammatically acceptable at first glance, it typically lacks cohesiveness and coherence at the discourse level. As a result, it is not ideal for texts that require a high degree of cognitive and emotional interpretation.

There are also ethical considerations that arise from overdependence on MT mechanisms. Large-scale language models, frequently trained on biased corpora, may repeat or amplify gender, racial, and geopolitical prejudices, according to Bender et al. (2021), who caution against this possibility. This presents a potentially problematic situation in terms of both translation quality and the social responsibility of language technology. One promising trend is the advent of hybrid systems, which incorporate machine translation (MT) for initial translation and human involvement in subsequent post-editing. This approach combines the efficiency of artificial intelligence with human judgment and subtlety to create a synergistic framework. According to Koponen (2021) and Toral and Way (2018), these technologies can boost overall efficiency while simultaneously ensuring improved translation quality. However, there is concern over the deskilling of translators, which occurs when excessive dependence on post-editing reduces the requirement for entirely manual translation and diminishes language competence over time.

Furthermore, Nida (1964) was the first to propose dynamic equivalence theories, which argue that effective translation must consider meaning equivalency rather than form alone. This is a philosophy that, unfortunately, the current generation of AI models is unable to replicate. Rather than relying on more in-depth semantic interpretation, the majority of NMT systems depend on statistical alignment and frequency-based prediction algorithms. Thus, despite the significant advancements that artificial intelligence has made in the field of translation, the results suggest that it is not a replacement for human translation but rather a complement to it. Furthermore, human oversight continues to be essential, particularly in circumstances that are literary, culturally sensitive, and technical in nature. Finally, the integration of computational linguistics, sociolinguistics, and cognitive science will be essential to developing artificial intelligence translators that are more culturally sophisticated.

CONCLUSIONS

To compare human translation with artificial intelligence techniques it is important to recognize a complex interaction between the efficiency of technology and the depth of language. Although technology has rapidly improved, particularly through neural networks, enabling unprecedented speed and accessibility, the ability of machine translation to handle sophisticated language structures, cultural context, and pragmatic meaning remains limited. Human translation's ability to preserve idiomatic expressions, emotional tone, and cultural significance continues to be superior to that of artificial intelligence, especially in literary and specialized texts. Despite these limitations, artificial intelligence is not a competitor but rather a helpful working partner for human translators. Hybrid models that combine machine efficiency with human supervision indicate a promising future, particularly in industries that require high-volume or time-sensitive translations. However, as artificial intelligence continues to improve, it is imperative that ethical issues, such as bias, overreliance, and the loss of linguistic competence, receive the critical attention they deserve. Ultimately, translation is not merely a mechanical process of converting words; rather, it is an act of interpretation and cultural mediation that enriches the human experience. The incomparable insight of human translators remains essential for capturing the richness of human language and communication, and this will likely continue to be the case for the foreseeable future. We believe that artificial intelligence will complement human translators, but it will not replace them.

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