

**Rethinking Machine Translation in the Age of AI:
Multimodality, Large Language Models, Neural Networks, and
the Emergence of Human -Machine Synergy.
Repenser la traduction automatique à l'ère de l'IA :
multimodalité, grands modèles linguistiques, réseaux
neuronaux et émergence d'une synergie homme-machine.**

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Abstract:

Translation has not been left behind by the digital revolution; rather, it is among the most affected fields, notably with the emergence of digital tools, smart systems, applications, and platforms, which impact both the translation landscape and the translator's role. This development has posed several challenges and required a set of skills and competencies to improve the quality of machine translation outputs in the digital era. This research paper aims to shed light on the changes brought about by the technological revolution in the field of translation and how it casts a shadow on the role of the translator in the translation process, from creator to post-editor.

keywords:

Machine translation; Large language models; Multimodality, Human -machine synergy; Neural network, Evaluation.

Résumé :

La traduction n'a pas été épargnée par les révolutions numériques ; elle est au contraire l'un des domaines les plus touchés, notamment avec l'émergence d'outils

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numériques, de systèmes intelligents, d'applications et de plateformes numériques qui impactent à la fois le panorama de la traduction et le rôle du traducteur. Ce développement a posé plusieurs défis et a exigé un ensemble de compétences pour améliorer la qualité des résultats de la traduction automatique à l'ère numérique.

Cet article vise à mettre en lumière les changements apportés par la révolution technologique au domaine de la traduction. Il explique également comment elle jette une ombre sur le rôle du traducteur dans le processus de la traduction, d'un créateur à un post-éditeur.

Mots clés:

Traduction automatique ; Grands modèles de langage ; Multimodalité ; Synergie homme-machine ; Réseau de neurones ; évaluation.

1-Introduction:

With information technology and the digital revolution, all domains are being affected. The world is becoming a data -driven ecosystem and a hyper-connected space. Physical and linguistic boundaries now blur, while geographical distances no longer limit human interaction. This shift has redefined how we share knowledge, maintain relationships, ensure data quality and analysis, redefine human tasks, enable quick decision-making, and prioritise information.

Artificial intelligence (AI) is transforming numerous domains of our lives, with a multifaceted impact across multiple fields and disciplines, and translation is no exception. Conventionally, translation has served as a crucial medium of communication between languages and cultures, while playing a significant role in connecting languages, facilitating intercultural exchange, and fostering civilizational relations. However, with the rapid development and the notable change, the role of a translator is transforming. Rather than acting as a linguistic and cultural mediator, he is behaving as a language and culture expert. He undertakes new tasks within a digitally mediated translation environment.

Therefore, in an AI-dominated world, the translator's practice has been reshaped; his role cannot be limited to the transfer of meaning from the source language to the target language. With the considerable change, translators ensure

proofreading of machine-translated content, which means translations are reviewed by human translators to make them easier to understand.

Based on what was said previously, this study addresses the following problematic issues:

-How do large language models reshape the translation process when dealing with multimodal content?

-What new competences are required for translators in mediated multimodal environments based on AI?

-To what extent can translation with artificial intelligence tools be complementary to humans, and how can it impact a translator's creativity?

To address these questions, this paper adopts a qualitative approach. It investigates the impact of artificial intelligence on translation and examines the major transformations enabled by technologies by analyzing illustrative examples.

2-The shift from human translation to machine translation:

The digital revolution represents a decisive and pivotal turning point in human life. It has transformed daily habits, behaviours, and practices, reshaped methods of communication and learning, and provided broad opportunities to access knowledge and exchange information at a very high speed.

Traditionally, the translation process was understood as a cognitive human activity which " has always played a crucial role in interlingual communication by allowing for the sharing of knowledge and culture between different languages (Stephen Doherty,2016, 947), this is indubitable. However, with the rise of neural machine translation, part of this process has been delegated to an automated system. This technological shift has contributed to a wider digital transformation that is redefining both the translation field and the translator's role. Hence, the digital corpus has become enriched through translation activities. Furthermore, translation is no longer merely a traditional linguistic transfer; it is now closely connected to intelligent software, cloud-based platforms, digital applications, neuronal machine

translation systems, and a wide range of computer-assisted tools.

Consequently, a translator is no longer a simple mediator between languages and cultures. Instead, he has become a key contributor to improving translation output quality by actively performing post-editing, revision, and proofreading. In this context, machine translation should not be viewed as a threat or a rival to human translation, but rather as a complementary tool that enhances translators' work. Since the advent of machine translation systems and applications, they aid humans, not replacing their role in the translation process or competing with them; rather, they assist human translation.

Nevertheless, as always, the domain of machine translation continues to achieve significant progress by exploring more computational techniques and introducing new linguistic models.

3-Neural networks in machine translation in the digital era:

The introduction of neural networks in machine translation marked a turning point in the digital translation process and research. Initially, machine translation relied heavily on manually crafted linguistic rules and dictionaries, requiring extensive human intervention for each language pair and struggling with linguistic nuances, idiomatic expressions, and contextual understanding (Baban Gain, 2020). But the transition from machine translation to neural machine translation has brought about a radical change in how texts are handled, how natural language has evolved into neural language, and how pre-trained models have become large language models.

In more detail, the pre-trained models depend on the transformer architecture, which allows the comprehension of the relation between words through the attention mechanism, and the most famous training methods are:

- Masked language modeling:** some words are hidden from sentences, and the computational model is asked to predict them based on the context.

- Next sentence prediction:** the relationship between the successive sentences is asked to be understood by the computational model.

As for moving from the pre-trained models to the large language models, the process depends on the amount of text data (websites, books, articles...) that the machine learning system has trained on to learn linguistic patterns through repeated operations until the reduction of errors and the generation of texts in the target language based on the big data recognized through previous training.

Neural machine translation has replaced statistical machine translation. It is a system implemented as an encoder-decoder architecture based on recurrent neural networks. The encoder is a bidirectional neural network with gated recurrent units that reads an input sequence, while the decoder is a recurrent neural network that predicts a target sequence word by word using a recurrent hidden state (Rico Sennrich, Barry Haddow, and Alexandra Birch, 2015). In parallel, neural networks have demonstrated the ability to learn relationships between different data modalities, leading to significant evolution in understanding complex information. In this context, "the concept of "attention" has gained popularity recently in training neural networks, allowing models to learn alignments between different modalities, between image objects and agent actions in the dynamic control problem, between speech frames and text in the speech recognition task, or between visual features of a picture and its text description in the image caption generation task " (Minh-Thang Luong Hieu Pham, Christopher D. Manning, 2015).

Neuronal machine translation goes through many steps to generate an accurate translation:

1-First, the text must be preprocessed to help algorithms digest it effectively. This operation has many steps, which are carried out in sequence :

-Noise removal: this step concerns the quality of the dataset, removing non-meaningful data (data that does not contribute to analysis) and filtering out noise (irrelevant or random information that can obscure results) .

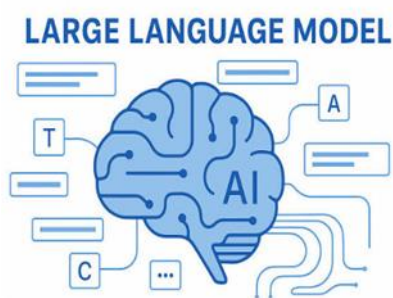
-**Tokenisation** (segmentation) is the process of splitting up text into smaller fragments called tokens. These tokens are associated with a numeric representation, such as an ID, that enables their use in machine translation mode.

For example: « porte-fenêtre » is segmented as « porte »+ « fenêtre.»

2 -After preprocessing, the model should be trained using a bilingual corpus. Training requires substantial computational capacity and a large amount of data, since neural machine translation operates on a fixed vocabulary. Translation, however, is an open vocabulary process that should encode unknown words as a sequence of subword units to align the new sentences correctly, which means each sentence with its translation is not provided to the machine previously (Rico Sennrich, Barry Haddow, and Alexandra Birch, 2015) .

As a result, the integration of neural networks has initiated a significant transformation that required adaptation to the progressive shift from human translation to machine translation, and subsequently to neural machine translation.

4-Large language models in reshaping translational practices:



Large language models are advanced generative systems that use deep learning algorithms to understand and generate human texts.

Humza Naveeda and his colleagues have shown that Language Models (LLMs) have emerged as cutting-edge artificial intelligence systems capable of processing and generating text with coherent communication and generalising to multiple tasks (Humza Naveed and others, 2015). This reveals that LLMs can't be limited to simple tools; they are advanced systems with versatile and articulate capabilities (Humza Naveed and others, 2015).

Language models have witnessed significant advances aimed at simulating the human mind and approximating human performance tasks. This revolutionary transformation, embodied in attributed to transformers, increased computational capabilities and the availability of large-scale training data (Humza Naveed and others, 2015).

These models are trained on large amounts of text data using deep learning, especially the transformer, which helps improve and refine the neural machine translation result. So, their remarkable effectiveness and performance are largely due to progress in deep learning architectures (coder/encoder), massive training datasets, expanded computational capacity, and others.

Javier García Gilabert and his colleagues, in their article titled “Investigating the translation capabilities of Large Language Models trained on parallel data only,” examined the role of large language models in translation. Their focus is based on three fundamental factors:

-Vocabulary size:

Vocabulary size plays a significant role in neural machine translation, particularly when the tokeniser is trained on larger vocabularies (128K, 256K), which can improve translation quality and downstream performance in multilingual settings.

-The different elements of the prompt:

The prompt is composed of the Begin of Sentence <s>, source tag (indicating the source language), source sentence, target tag (indicating the target language), target sentence, and End of Sentence </s>, which encode the translation direction and structure the training examples for the model.

-Number of attention heads:

The importance of each attention head is assessed by calculating coverage, which was initially introduced in encoder-decoder attention mechanisms and refers to the total amount of attention a source token receives from target tokens. (Javier García Gilabert and others, 2024)

5- Multimodality and the changing landscape of translation:

In response to the growing demand for interaction, texts in the digital landscape have changed their form, incorporating various ways to express themselves, such as images, videos, audios, metadata, and so on. This multimodal translation has undergone various shifts. This change stems from the integration of artificial tools in multimodal translation. On the one hand, multimodal translation concerns the transfer of linguistic symbols and the restoration of the message from language A to language B, taking into account the target culture; on the other hand, it involves non-linguistic elements that can provide supplementary explanations of the source text and clarify its meaning. For example, **the boy is running fast**. The context of this sentence seems ambiguous because the translator can interpret the meaning in different ways, such as:

He is an athlete

He is escaping

He is playing

The presence of a visual cue can lead to the correct translation, so an image of a boy running helps the translator understand that the context is a sporting competition.

Thus, the combination of linguistic and non-linguistic symbols can help clarify context, reduce ambiguity, and produce a sound translation.

6-The paradigm of human-AI collaborative translation: relationship between competition and integration:

The integration of technological tools into translation has brought about multiple changes in the translation process, the evaluation of translations, and the role of the translator.

Since then, the translator function has been changed from a transmitter of linguistic signs from language A(source) to language B (target) to a post editor, which can be defined as “to edit, modify and/or correct pre-translated text that has been processed by an MT system from a source language into (a) target language(s)” (Ana Guerberof Arenas, 2020). In other words, it means reviewing a pre-translated text generated by a machine, comparing it with the source text, and correcting errors.

Neural networks, digitalization, and artificial intelligence have changed the translator’s work; this development does not delete the translator from the translation process, but it has only shifted its location. Rather than being at the first step, he moved to the final one.

As mentioned above, the development influences both the translation process and the translator’s role, but more voices argue that translators are at the center of the translation process, surrounded by different technologies that support their work. The augmented translators work in a technology-rich environment that automatically processes many of the low-value tasks that consume an inordinate amount of their time and energy. It brings relevant information to their attention when needed. This computing power will help them be more consistent, more responsive, and more productive (Jean Nitzke, Silvia Hansen-Schirra, 2021); hence, the translators should be aware of the rules of the neural translation machine and the post-editing tasks to assess the output product and make informed decisions.

In the example below, the role of a post-editing translator can be observed in improving translation quality by correcting grammar mistakes and selecting the appropriate equivalent.

Source text	Target text
Les chercheurs en traduction ont développé un modèle capable d'améliorer la traduction automatique neuronale	Translation researchers developed a model that can improve neural machine translation
Human post Editing	
Translation researchers have developed a model capable of improving neural machine translation.	

This example demonstrates the collaborative relationship between human expertise and machine, where the machine ensures productivity and the human establishes linguistic and contextual accuracy.

We can say that translation in the digital era has brought the human and the machine into a complementary relationship; hence, the neural translation machine does not have a competitive relationship with the translator; on the contrary, they collaborate.

7-Challenges of neural machine translation:

Despite the advancement, neural translation faced different challenges:

7-1-Understanding cultural contexts:

Neural machine translation is based on a neural network, and cultures can't be reduced to the geographical or linguistic borders of their countries; rather, they go beyond these borders through translation.

Human translation and neural machine translation can't convey cultural context in the same way. The cultural context can be varied; the model can't understand all

input contexts because it relies on the data and information that algorithms receive recurrently and train on; therefore, the computational capacity can fail to accommodate cultural contexts it does not know. For example:

ما يجي الصياد غير ما يطير في رأسه الطير، وما يجي البحار غير ما يلمع في رأسه
"الصخر"

This proverb is taken from the novel "ريح الجنوب." By Abelhamid Ben Haddouga. The translation given by ChatGpt 5 was: « Le chasseur n'apparaît que lorsque l'oiseau vole au-dessus de sa tête, et le marin n'arrive que lorsque le rocher brille au-dessus de sa tête ».

Based on this translation generated by ChatGPT 5. We can notice that the model/system didn't understand what the proverb meant, running after interest or opportunity only. So, it shows the difficulty in conveying the cultural context and how the translator should resort to simplification, explanation, or fulfill the meaning in the target language

The equivalent that preserves its meaning is: "les amis de beau temps."

7-2-Understanding the subtle linguistic differences between languages:

-Existing reference-free metrics struggle to align with human judgment, resulting in inaccuracies being propagated

-The integration of neural quality estimation modules and the sequential execution by large language models leads to increased decoding time, which poses concerns for efficient translation in practical applications (Jiali Zeng, Fandong Meng, and al, 2023).

7-3-Difficulties in translating unknown words:

Because neural machine translation operates on words that the machine has been trained on, new contexts or linguistic differences can prevent a sound, accurate, and somewhat successful translation.

7-4-Monolingual data and bilingual data:

Generating monolingual translation data poses challenges for a model trained only on monolingual input, since translation requires pairs of source and target languages. To address this, Sennrich has proposed an approach that uses monolingual data to generate artificial synthetic parallel data via backward translation and lets the training procedure run as usual (Franck Burlet, Francois Yvon, 2018) .

7-5-Domain mismatch:

One known challenge in neural machine translation is that, across domains, words have different translations, and meaning is expressed in different styles. Hence, domain adaptation for a specific use case is a crucial step in developing machine translation systems to ensure good translation quality.

7-6-Amount of translation data:

Better translation quality generally results from an increased amount of training.

7-7-Rare words:

Neural machine translation models perform particularly poorly on rare words. This is due, on the one hand, to the smaller vocabularies used by neural machine translation systems, and, on the other hand, to their belonging to highly inflected categories.

7-8-Long sentences:

A well-known flaw of early encoder-decoder neural machine translation was the inability to translate long sentences, which is why the attention model was designed to address this issue.

7-9-Word alignment:

The contribution of the attention model in neural machine translation was the imposition of an alignment between output words and input words, represented in bidirectional gated recurrent neural networks that leverage the entire sentence

context. Nevertheless, the alignment challenge of neural machine translation appears in the mismatch between this attention model and the alignment of the words, or in the alignment position errors (Philipp Koehn and Rebecca Knowles, 2017) .

8-Skills and competences required:

In contrast to human translation, neural translation requires more skills and competencies to produce sound and accurate translations. After the computational processes, the translator should revise the translation and post-edit it to correct the potential errors and improve the neural machine translation output. Thus, this complex task needs specific skills and competencies. Whether the machine handles the majority of the translation process, the question is: which skills and competencies must be owned in the digital translation workflow?

Translation requires bilingual and extra-lingual competencies, knowledge of text types, and awareness of linguistic contrastive and cultural differences, while machine translation and neural machine translation demand the possession of other skills, because the translator's role here will be later than the machine translation.

Jean Nitzke and Silvia Hansen-Schirra note that translators in the digital era need further skills, such as (Jean Nitzke, Silvia Hansen, 71) :

-Research competence: the translator should know where and how to find information they lack.

-Error-spotting competence: In recent years, neural machine translation has become the state-of-the-art, making errors generated by neural machine translation systems more difficult to identify; therefore, translators must have the competence to spot mistakes.

-Awareness of machine translation engineering: As a post editor, the translator should understand how the machine translation system operates and recognize potential pitfalls.

-Service competence: (in translation agencies): post-editors should have at least a little knowledge about potential risks associated with using machine translation or neural machine translation systems in the post-editing process to support clients and raise doubts if certain decisions seem risky or implausible.

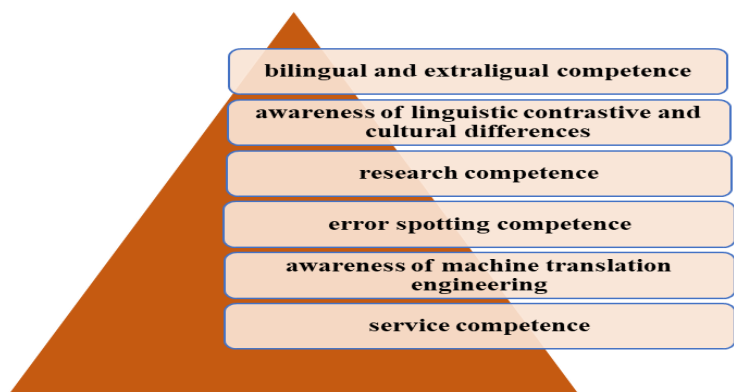


Figure: skills and competences required.

9-Evaluation of neural machine translation output:

Evaluation in translation is a crucial step to ensure quality; however, assessing human translation differs from assessing digital translation in terms of criteria, processes, and objectives.

While the evaluation of human translation focused on linguistic competence, cultural adequacy, and stylistic quality, digital translation concentrated on accuracy, fluency, and the efficiency of the underlying technological systems. Therefore, developing appropriate evaluation frameworks for both types of translation has become essential in the rapid technological advancement.

The evaluation of neural machine translation output has posed a real challenge, since its quality has become high-performing, particularly in producing translations that mimic, or even match, those generated by the human mind.

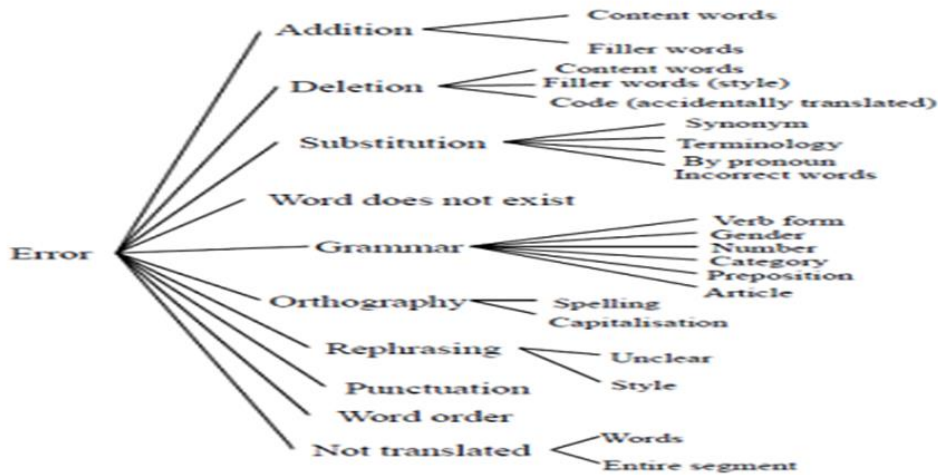


Figure: errors categorization (Marie Escribe, 2019, 40)

Despite the metrics created to evaluate neural machine translation, human judgment is more valuable, on the one hand, only human evaluators can tell whether the type of language used is adequate according to the context (register) or if a change in grammar or lexis at the post-editing stage is considerably affecting the meaning of a sentence(Marie Escribe, 2019, , 37) On the other hand, humans can detect subtle linguistic and cultural differences, despite technical and digital development and the machine’s achievement in the field of translation based on smart systems, humans can choose the most appropriate equivalent depending on the context. In contrast, machines may produce grammatically correct translation but less precise (errors are categorized in the schema above). Also, human cultural awareness helps in conveying cultural nuances, recognizing values and references, and identifying implicit cultural meaning, whereas a machine can fail.

In addition, Marie Escribe stated that digital tools could not provide quality assessment at the semantic or pragmatic levels. That means that machine evaluation is formal; it is unable to comprehend the essential meaning of words and cannot express their deep meaning, much less, reading between the lines, such as: intention, tone, irony

As previously pointed out, human evaluation is more valuable than machine evaluation. Other levels can be cited here, including conceptual interpretation, methodological validation, and terminological consistency.

10-Conclusion:

Our findings reveal that the significant transition from human translation to machine translation to neural machine translation in the digital era is characterized by technological advancement, rapid speed, and more accessible knowledge.

Digital development has produced a wide range of digital tools, such as computer-aided translation tools, electronic language blogs, electronic dictionaries, smart applications, translation assistance platforms, electronic terminological databases, translation smart systems, and large language models. Furthermore, significant linguistic resources have been made available, significantly improving the quality of translation and accelerating its process .

Although this shift, the translator's role can't be deleted, the introduction of technology and artificial intelligence into the translation field can't create a competitive relationship between humans and machines that may enhance human creativity in translation. Contrary to this, it is a complementary relationship .

Furthermore, neural machine translation evaluation can be divided into two types: human and machine evaluation, but human evaluation is more valuable because it assesses performance and efficiency at various levels where the machine can fail.

In conclusion, the technological revolution has become a necessity in the digital era; humans should rationalize their investments to benefit from, rather than delete, the translator's role and creativity .

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