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Translation Technologies in the Artificial Intelligence Era: Historical Development and Classification

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Abstract

In a globalized world that is increasingly connected, the translation market has grown significantly. The increase in market demand has led to a growing reliance on translation technologies by human translators, who now feel obliged to use them to keep pace and meet deadlines. The development of these tools has experienced exponential growth in recent years, driven by the introduction of Artificial Intelligence into the field of translation. Mastering the different types of tools and how to handle them is essential for efficient use. In this vein, the current study first aims to examine the historical development of translation technologies. Second, it seeks to provide a new classification of translation technologies that incorporates the latest trends in the field. It employs a qualitative method that involves collecting and analyzing data through a rigorous literature review. The results show that translation technology development began many centuries ago, but the boom occurred around the 1980s. Translation technologies can be classified into two large groups: Computer-Assisted Translation tools and Machine Translation systems. The study suggests that, since Artificial Intelligence-driven tools are used in translation, Artificial Intelligence should be classified as a type of translation technology.

Keywords: Artificial Intelligence, ChatGPT, classification, translation, translation technologies

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Introduction

As the world has increasingly become interconnected, the global language services market has experienced exponential growth. In 2020, for instance, the market size was projected to reach nearly 52 billion US dollars, with a continued growth throughout 2021 and 2022 (Statista Research Department, 2023). Given the increasing demand for fast, cost-effective translation services, human translators alone cannot keep up. Many companies now require rapid translation services to meet market demands and maximize profits. This has led to the growing integration of technology into translation. Translation technologies have become increasingly common in the commercial and public service sectors, including schools, hospitals, and other public services. Human translation, while still valuable, is costly and time-consuming, making it challenging to meet these needs at scale.

The idea of machine translation for natural languages, first imagined in the seventeenth century, became a reality by the late twentieth century (Hutchins, 1996). Since then, numerous researchers and translation educators have studied how to integrate these tools into translators' work environments and have contributed to their improvement. These tools cover several areas, including translation studies, computer science, mathematics, linguistics, and translation theory. Computerized tools are designed to partially or fully translate written or spoken messages, depending on the technology used.

Many studies offer a wide range of classifications of translation technologies. However, the world has recently witnessed significant developments in communication and technology, including the invention of Artificial Intelligence (AI). For this reason, it becomes essential for scholars and researchers to update the categorization of translation tools. Since AI-driven tools are used in translation (even though they are not primarily designed for it), some critical questions arise. This study wants to know whether AI should be considered a type of translation technology and which category it belongs to. The current study primarily aims to provide a historical overview of translation technologies, with details on the different periods of their development. Moreover, it proposes a new classification of translation technologies that includes artificial intelligence-driven tools. It draws on the qualitative research method. The methodology mainly involves a systematic and rigorous literature review. It also analyses the data collected. The data is collected from the perspectives of several authors. The study is based on these perspectives to propose a historical development of translation technologies before providing a new classification. Finally, the study recommends that Artificial Intelligence (AI) tools should henceforth be considered translation technologies and placed in the category of Machine Translation. However, classifying AI tools as translation technologies may oversimplify their broader capabilities. Furthermore, this classification raises ethical and legal concerns, as many AI tools process data on remote servers and sometimes in opaque ways.

Literature Review

According to Chan (2012), the history of translation technology can be divided into four periods. The first period, known as the germination period, went from 1981 to 1988. The growth period followed from 1988 to 1993, and the rapid growth period from 1993 to 2003. The current period, referred to as the global development period (2003 to the present), has witnessed the advent of the internet and further technological advancements, such as artificial intelligence. Instead of merely talking about the development of translation technologies, it is more accurate to describe the last period as a revolution. Research in this field dates back to the 1940s (Hutchins, 1996) or even the 13th century (Stein, 2018). However, the breakthrough occurred in the 1980s with statistical machine translation, which has since evolved into neural machine translation, powered lately by artificial intelligence.

There are several types of translation technologies. DePalma (2013, pp. 44–45) categorizes translation software into four main groups: "translation tools, translation management systems, authoring tools, and engineering tools". Translation tools include terminology management systems, machine translation systems, and translation memory systems. Examples of translation management systems include tools like Trados and Systran. Authoring tools comprise dictionaries, editing environments, and controlled language verification tools, while engineering tools support the translator by testing the quality of the translated product. This classification encompasses all the tools designed to support the translator in their work.

Today, the most commonly used translation technologies are Translation Memories (TMs) and Machine Translation (MT). TMs are defined as "databases consisting of previously human-translated segments" (He, 2011, p. 1). TMs emerged as a response to the limitations of machine translation, after professional translators began seeking ways to reuse previously translated material to reduce their workload. Kay (1980, as cited in He, 2011) proposed a human-centric model in which a computer assists the translator at the lexical level, while the translator completes the task through post-editing. Since their inception, TMs have become an essential tool in the translation industry and are widely used by professionals, particularly in the field of localization. He (2011) describes the function of TMs as follows:

> TMs provide a fuzzy match facility, where the closest match in the TM given some input is retrieved, and the translation associated with the closest match is presented to the professional human translator to be post-edited (i.e., adapted to a translation of the input), again with the potential for considerable savings over a manual translation from scratch. (p. 2)

TMs work by searching for segments in a new text that match previously stored human translations, which are then reused in the localization industry when new source texts need translation. The reused data comes from internal databases or shared and exchanged data sources.

In contrast to TMs, MT does not require human intervention before translating texts. Common Sense Advisory (2016) submits that "Machine translation -or MT- refers to software (an engine) that takes input in one language (the source) and automatically renders it in another (the target) without the need for human intervention" (p. 2). However, the output from the process is not always accurate and reliable. To ensure quality in the output, human intervention is often needed.

In the past, MT was accessible only to large translation companies due to its high cost and labour-intensive nature. However, in recent years, it has become more affordable, widely available online, and even open-source. Continuous advancements in MT have been driven by the development of TMs, contributed to by both professional translators and scientists. Doherty (2016) acknowledges the significant improvements in MT in these terms:

> Fueled by the availability of human translation data in TMs, which became widespread in the late 1990s, MT research experienced a further paradigm shift from prescriptive, top-down, rule-based approaches to descriptive, bottom-up, data-driven approaches, chiefly in the form of statistical MT. This paradigm shift has led to the second major technological shift in contemporary translation. (p. 952)

MT systems seek to provide translation solutions without human intervention. With MT, a translator inputs text segments, and the translation is completed within seconds. Several paradigms of MT exist. This includes Rule-Based Machine Translation (RBMT), Statistical Machine Translation (SMT), and, more recently, Neural Machine Translation (NMT). There is an ongoing debate over whether artificial intelligence (AI) represents an extension of NMT or a new paradigm altogether, as AI-driven technologies are also designed to translate texts. Meanwhile, many companies and organizations are funding research to develop AI-driven translation technologies that facilitate global communication and break down language barriers across sectors.

Methodology

Translation technologies have dramatically altered the translation industry, offering numerous advantages and opportunities. Mastering their typology is essential to navigate the landscape of these technologies. To classify them, the study employs a qualitative research method. The methodology primarily involves a systematic, rigorous literature review and the analysis of collected data. It is made possible thanks to the collection of data from scientific books, articles, and relevant sources. This review cross-references various authors' perspectives on translation, the introduction of translation technologies, and their classification.

Historical Development and Evolution of Translation Technologies

The idea of developing translation technologies dates back several decades, when researchers thought about supportive tools that could speed up the translation process. Its evolution can be displayed in three main periods.

The Germination Era

Translation technology is an interdisciplinary field encompassing translation studies, computer science, mathematics, and linguistics. Some researchers (Doherty, 2016; Hutchins, 1997) argue that the development of translation technologies can be traced back to the 1940s when early MT systems emerged shortly after World War II. But Stein (2018) contends that the history of MT extends back several centuries. According to Stein (2018), translation technologies like MT, designed to assist translators, have their origins in the sixteenth century. The author explains that:

Most likely, the first thoughts on MT emerged from two philosophical schools that addressed the nature of language and yielded similar insights, though from different directions. The first was to create secret languages and codes to communicate in secret. The second evolved from the ideal of a universal language which would allow communication without borders in the times after the Babylonian language confusion (Stein, 2018, P. 5)

For Stein, the initial concept of translation technology was proposed by the Catalan philosopher Ramon Llull. Llull's theory of logic "allowed objectifying reasoning about God and the world using a formal language" (Stein, 2018, p. 6). Over three centuries later, the German philosopher Gottfried Wilhelm Leibniz expanded on Llull's ideas to develop a set of "smallest units of meaning" (Stein, 2018, p. 6) intended to compose "all thinkable thought" (Stein, 2018, p. 6). Concurrently, the German physician Johann Joachim Becher developed a system that aligned closely with early MT approaches. Becher's system is similar to what was later known as mechanical translation, relying on dictionaries and terminologies linked by codes. However, as time progressed, scientists discovered that rule-based approaches were inadequate for complex translation tasks. While these methods were practical in cryptology, they struggled to translate challenging texts, such as fiction and cultural texts. Apart from their original wartime applications, these tools could not keep pace with evolving needs.

Stein further attributes the foundation of practical MT to the British mathematician Alan Turing and his team. At the British government's prompting, Turing's team aimed to overcome the limitations of rule-based MT through statistical methods. The constant global threat of conflict and the desire to decode enemy communications led governments and military agencies to invest heavily in machine translation research (Stein, 2018). However, the publication of the Automatic Language Processing Advisory Committee (ALPAC) report in 1966, commissioned by the US administration, resulted in an immediate reduction in funding (Hutchins, 1996). Consequently, only a few researchers in the US and Europe continued to advance MT research.

The Development Era

The integration of large-scale linguistic patterns by research teams with limited funding led to promising results. These advancements, coupled with rapid technological growth, secured additional financing for MT development, which gained popularity in the 1980s. This period marked a resurgence of statistical methods, as suggested by Peter Brown and his team (Stein, 2018). Technological innovations largely drove the evolution of MT during this time.

In the 1990s, Statistical Machine Translation represented a significant leap forward in translation technologies. This data-driven approach enabled systems to learn patterns and probabilistic relationships between source and target languages. The advancement of new technologies in translation significantly altered translators' working conditions, particularly by increasing the availability of language resources such as Machine-Readable Parallel corpora. As noted by He (2011, p. 13), "statistical models used in SMT are language-neutral". This means that as long as corpora for a pair of languages are available, scientists can easily build SMT approaches. These insights enabled the development of similar MT systems quickly, often without the need for linguists. Consequently, the majority of research in the following decade focused on SMT systems.

Over time, researchers recognized that SMT systems had several shortcomings similar to those found in RBMT systems. They discovered that these issues could not be resolved by simply using word groups. As a result, researchers began exploring hybrid machine translation systems in the 2000s. These hybrid systems combine SMT with linguistic knowledge to address the limitations of previous systems. According to Stein (2018, p. 8), "since the mid-2000s, hybrid approaches that combine SMT with linguistic knowledge ('context-based' or 'knowledge-based' MT) have become more common, and a new trend is to use corpora that are not parallel but at least comparable". Alongside MT systems, other translation technologies have also advanced. One notable development is Translation Memory (TM) systems, which store and retrieve previously translated segments for reuse (Doherty, 2016). Unlike MT, which is computer-centred and has been developed over several centuries, TM systems are human-centred. TMs are particularly useful for translating texts or portions of texts from previous translation projects. They save everything typed or uploaded into an editor and support various formats, allowing translators to select sentences that best fit the new text, unlike MT systems, which suggest direct possible translations.

Terminology management tools have also been crucial in the evolution of translation technologies. These tools enable translators to build and maintain domain-specific terminology databases, ensuring consistency and accuracy. Localization technologies, which adapt content to the cultural and linguistic conventions of specific locales, have also evolved alongside translation technologies.

The Revolution Era

Neural Machine Translation, Natural Language Processing, and Deep Learning primarily define the era of translation technology. NMT has emerged as a transformative force in translation technology. Wu et al. (2016, p.1) describe NMT as "an end-to-end learning approach for automated translation, with the potential to overcome many of the weaknesses of conventional phrase-based translation systems". Using deep learning techniques and neural network models, Neural Machine Translation generates translations with notable improvements in quality by addressing limitations of earlier methods. Unlike traditional MT systems, NMT learns directly from input and output corpora. Additionally, NMT can handle long and complex texts more effectively.

Initially, NMT systems were less accurate compared with previous MT methods. Wu et al. (2016, p. 2) identify three main weaknesses: slower training and inference speeds, difficulties with rare words, and occasional failures to translate all words in a source sentence. These issues arose because NMT systems required extensive time and computational resources for training due to their complex parameters. However, the shortcomings have been addressed primarily through ongoing research. Today, NMT systems have become reliable tools used globally by both professional and non-professional translators. For instance, Google Translate now relies on NMT technology. As the quality of NMT translations continues to improve, it has gained recognition from both translators and scholars. Human evaluations by Wu et al reveal that "GNMT has reduced translation errors by 60% compared to the previous phrase-based system on many language pairs: English ↔ French, English ↔ Spanish, and English ↔ Chinese" (2016, p. 2). NMT translations are now nearly as accurate and high-quality as human translations.

Types of Translation Technology

Translation technologies encompass a diverse range of tools and software applications designed to enhance the translation process. Various types of translation technology play a vital role in supporting translators and language professionals. They are of two kinds: CAT tools and MT.

Computer-Assisted Translation (CAT) Tools

Computer-Assisted Translation (CAT) tools are among the most widely used technologies in the translation field. These tools are designed to assist translators by providing a range of features that enhance their workflow. The development of CAT tools began in the 1960s, when researchers realized that achieving near-perfect MT would be challenging (Bowker& Fisher, 2010). "The first CAT tools were term banks, which used computers to store large volumes of structured information" (Bowker & Fisher, 2010, p. 60). With the advent of the internet and the integration of various programs, translators can now access both offline and online dictionaries.

Unlike MT systems, which aim to replace human translators, CAT tools support translators by allowing them to select appropriate words and expressions based on the text type and context. These tools improve translators' efficiency and speed, giving them more time to focus on other tasks.

CAT tools store previously completed translations in their memory, including both source and target texts. When a new source text is input, the tool retrieves similar matches from its memory, allowing the translator to correct any inconsistencies or adapt the translation as needed. This functionality is especially beneficial for specialized translators who frequently handle similar texts or texts with significant repetition. CAT tools help them save time and achieve greater accuracy, making them popular among freelance translators and translation companies.

Some of the most well-known and widely used CAT tools include Trados, MemoQ, OmegaT, and Wordfast (Lagoudaki, 2018). These tools enable translators to quickly build large translation memory databases by consolidating individual memories. Even two translators can collaborate by importing one translator's database into another's. Translation Memory (TM) is a key component of CAT tools, along with other features such as terminology management, localization tools, quality assurance, and calculators.

Translation Memory (TM) Systems

In the history of translation technologies, Translation Memory Systems (TMS) hold a prominent place. Their significance emerged as translators recognized the limitations of Rule-Based Machine Translation (RBMT) and Statistical Machine Translation (SMT). Faced with the need to streamline their work, translators sought solutions to reuse previously translated segments and reduce their workload (He, 2011). Translation Memory Systems address this need by storing translated segments for reuse in future projects. According to Bowker& Fisher (2010), TMS can recognize six types of matches: Exact match, Full match, Fuzzy match, Sub-segment match, Term match, and No match.

Exact Match

In Translation Memory Systems (TMS), an Exact Match occurs when a segment of the new source text exactly matches a previously translated segment stored in the database. This match represents an ideal scenario in which the phrases or segments are identical to those previously translated. Such matches can be reused without modification, as they are ideally suited to the current context.

Full Match

A Full Match occurs when a segment from the source text is identical to a segment in the Translation Memory (TM) database, except for certain elements such as proper nouns, dates, numbers, and other specific details. In this case, the segment's core content is a perfect match, and only the variable elements need to be adjusted to fit the new context. This allows for efficient reuse of previously translated material with minimal modifications.

Fuzzy Match

A Fuzzy Match identifies segments that closely resemble, but do not precisely match, the source text in the Translation Memory (TM) database. The degree of similarity can vary, with matches ranging from 50% to 90% depending on the richness and coverage of the TM database. These partial matches suggest segments that share similar wording or structure but may not be an exact fit. In such cases, the translator must decide whether to use the suggested segment as is or modify it to better align with the new translation's context and specific requirements.

Sub-Segment Match

As the name suggests, a Sub-Segment Match refers to a situation where a small part of a segment from the source text aligns with a corresponding fragment in the target text. This type of match involves identifying and reusing smaller, partial segments rather than entire sentences or phrases.

Term Match

A Term Match occurs when specific terms or phrases in the source text correspond to previously translated terms stored in the Translation Memory (TM) database. Unlike a full or partial segment match, which applies to entire sentences or larger segments, a Term Match focuses on individual words or terminology.

No match

A "No Match" occurs when none of the segments from the source text align with any entries in the Translation Memory (TM) database. In this case, the translator must translate the entire segment from scratch. This situation provides an opportunity for the translator to introduce new terminology or phrases into the TM database, enriching it for future use. By manually translating the "No Match" segments, the translator helps expand and update the database, thereby enhancing the efficiency and accuracy of subsequent translations.

Terminology Management Tools

"The science of terminology is the study of the composition, evolution, application, and control of terminologies in translation" (Zayyanu, 2024, p. 182). For Bowker and Fisher (2010), a Terminology Management System is "a tool used to store and retrieve terminological information from a term base" (p. 61). These systems play a crucial role in maintaining consistent, accurate use of domain-specific terminology. They enable translators to create and manage specialized terminology databases, ensuring consistent use of terminology throughout translations.

Localization Tools

Localization tools help adapt content to specific cultural and linguistic contexts. They are essential for adjusting software, websites, and multimedia content to meet the needs of different regions and languages. These tools include Computer-Aided Software localization, Internationalization Management Systems (IMS), and multimedia localization platforms.

Quality Assurance

CAT tools also incorporate quality assurance features to ensure that translations meet high standards and satisfy client expectations. This quality assurance process guides the translator throughout the entire translation workflow, from start to finish, to ensure that the target text is error-free.

Calculator

In addition to the features previously mentioned, CAT tools often include a built-in calculator. This tool allows translators to determine the exact word count of the text to be translated, estimate the time required to complete it, and calculate the potential cost of the job. Since translation work is typically billed per word, this feature helps translators accurately assess the project's scope and manage their pricing.

Machine Translation (MT) Systems

Machine Translation (MT) systems automatically translate text from one language to another. As noted by AL-Hemyari, "the goal of machine translation is to develop a system that can translate a text from one language into another while preserving the original meaning of the text" (2023, p.160). Notable MT systems include Google Translate, DeepL, Yandex Translate, Bing, and the newer one, ChatGPT. Although ChatGPT was not explicitly designed for translation, it should be classified as an MT system because it employs Natural Language Processing (NLP) to translate text.

MT systems are typically online and open source, making them accessible to everyone and easy to use. This accessibility allows both professional translators and non-translators to use these tools. MT systems streamline the translation process by quickly translating entire texts—often in a matter of seconds—allowing translators to save time. Unlike Computer-Assisted Translation (CAT) tools, which translate only parts of a text that match existing database entries, MT systems provide complete translations with minimal user input. Translators need to copy and paste the text into the MT system and receive an instant translation. Sometimes they post-edit the output.

MT systems use various approaches, including rule-based, statistical, neural machine translation, and NLP, each with its own strengths and limitations.

Rule-Based Machine Translation

Rule-Based Machine Translation (RBMT) uses linguistic rules and dictionaries to translate meaning from a source text to a target text. As one of the earliest approaches to machine translation, RBMT, often regarded as the classical method, is still in use today (Stein, 2018). However, RBMT faces challenges with semantic and pragmatic issues in translation, particularly when dealing with specialized terminology or complex language patterns. Despite these limitations, it remains helpful in translating texts with simpler language structures. According to Stein (2018), RBMT systems are categorized into three levels of complexity: direct translation, Transfer, and Interlingua.

Direct Translation

As the name suggests, direct translation involves replacing each word in the source text with its equivalent in the target language, essentially performing a word-for-word translation. At this level of complexity, the machine translation (MT) system does not analyse, interpret, or generate new content; it simply uses a dictionary to substitute source words with their target-language counterparts. This approach is straightforward but limited, as it does not account for context, syntax, or nuances that may affect the meaning of the translated text.

Transfer

This level of complexity considers a comprehensive set of morphological, syntactic, semantic, and pragmatic rules to convey meaning accurately. As Stein (2018, p. 9) notes, "Regarding the complexity of these rules, there are no limits; tens of thousands of rules, combinations, and exceptions may be coded". Despite the extensive range of rules applied, this approach is not immune to errors and may still produce inaccuracies in the translation output.

Interlingua

This level of complexity envisions "the utopia of a neutral language that could represent all meaningful information from every utterance in every language" (Stein, 2018, p. 10). The goal is to establish a universal metalanguage that bridges the source and target languages, eliminating the need for Transfer or direct translation.

Statistical Machine Translation

Statistical Machine Translation (SMT) represents the second generation of machine translation, offering improved performance over Rule-Based Machine Translation (RBMT) and Translation Memories (TMs). Peter Brown proposed revisiting SMT in 1988 as a solution to the limitations observed in RBMT (Stein, 2018). SMT relies on probabilistic models and is freely available online, helping translators reduce costs. According to He (2011), SMT systems generally provide translations with sufficient quality that often do not require post-editing, unless high precision is required for specialized texts. SMT systems use large datasets of parallel corpora derived from human translations. When a source text is entered, the system searches the database for the most likely correspondences. There are two main types of SMT: word-based SMT and phrase-based SMT (Stein, 2018).

Word-Based SMT

The word-based approach forms the foundation of Statistical Machine Translation (SMT). It "analyses data at the level of individual lexical units" (Stein, 2018, p. 12). The first step in this process is word alignment, where the system identifies which words in the source language correspond to those in the target language. For example, in a parallel sentence pair like "the house" (English) and "la maison" (French), the model learns that "the" typically aligns with "la" and "house" with "maison."

After aligning the words, the model estimates the probability that each source-language word maps to a corresponding target-language word. These probabilities are derived from the frequency of word pairs found in the training data.

Phrase-Based SMT

Phrase-based Statistical Machine Translation (SMT) builds on and improves the earlier word-based approach. It marks a significant advancement in machine translation by shifting from translating individual words to translating sequences of words or "phrases" (Koehn, 2010). However, as Stein (2018) notes, the system still struggles to accurately identify and process complex phrases, such as those involving intricate combinations of determiners and nouns.

Neural Machine Translation

While Statistical Machine Translation (SMT) relies on statistical models trained on parallel corpora, Neural Machine Translation (NMT) employs neural network models. It has made significant advancements in recent years (Wu et al., 2016). It "applies Neural Network (NN) techniques to estimate the possibility of a sequence of words, placing this translation tool at the height of its development" (Zayyanu, 2024, p. 181). Wu et al. (2024, p. 1) note that "the strength of NMT lies in its ability to learn directly, in an end-to-end fashion, the mapping from input text to associated output text". Key features of NMT include end-to-end learning, which enables the system to translate entire texts using a single neural network, and sequence-to-sequence models. In these models, an encoder network first encodes the source sentence into a fixed-length vector, and a decoder network, typically another Recurrent Neural Network (RNN), then generates the translated sentence from this vector.

Artificial Intelligence

In the dynamic landscape of language translation, the emergence of artificial intelligence (AI) marks a transformative leap, revolutionizing how we bridge linguistic divides and facilitate global communication. Bellardi and Abidi (2024, p. 19) define AI as "a branch of computer science developed to simulate the behaviour of neural cells in the human brain using neural networks". AI-powered translation technologies represent a fusion of human ingenuity and computational prowess, offering unprecedented capabilities in understanding, processing, and generating natural language. An AI-driven translation technology such as ChatGPT is based on its capacity to excellently understand and interpret linguistic structures, nuances, and contexts. Traditional rule-based and statistical machine translation (SMT) systems paved the way for early advancements in machine translation. This provides raw solutions for converting text from a source language to a target language. However, these approaches often fell short in capturing the richness and complexity of human language, struggling with idiomatic expressions, ambiguity, and cultural subtleties.

Furthermore, AI-driven translation technologies extend beyond mere word-for-word translation to encompass more sophisticated forms of linguistic analysis and understanding. "AI systems use a variety of components, including data, neural networks, and linguistic expertise to comprehend the intricacies inherent in many languages effectively" (Mohamed *et al*, 2024, p. 255). Contextual understanding, sentiment analysis, and natural language generation are just a few examples of AI capabilities that enhance translation technology, allowing for more nuanced, fluent, and culturally sensitive translations. Moreover, AI-powered translation technologies continue to evolve and improve through ongoing research and development. Advancements in Natural Language Processing (NLP), deep learning, reinforcement learning, and transfer learning are pushing the boundaries of what is possible in machine translation, driving improvements in accuracy, fluency, and efficiency.

Natural Language Processing (NLP) is a crucial approach within Machine Translation (MT) that focuses on the interaction between machines and human languages. As a subfield of Artificial Intelligence (AI), NLP equips translation systems to process and understand language beyond simple word substitution. In the context of machine translation, NLP enables more accurate, context-aware translations by combining traditional and modern methods. NLP integrates a variety of approaches, including Rule-Based Machine Translation (RBMT), statistical models, neural networks, and deep learning. RBMT applies linguistic rules, while statistical models focus on the probability of word and phrase pairings based on large corpora of parallel texts. With the advent of neural networks and deep learning, translation systems have gained the ability to understand complex language patterns, context, and even idiomatic expressions, allowing for more nuanced translations.

As for Deep Learning, it involves teaching computers to perform tasks that are not explicitly programmed for each one previously. This technology has been a major factor in the development of fields such as translation. Deep Learning techniques are commonly used to process and understand text to translate it. These techniques also serve to convert speech to text and translate several languages worldwide. By combining these techniques, NLP and Deep Learning systems enable machines to analyse both the structure (syntax) and the meaning (semantics) of the source language, creating a deeper understanding of the content. This allows the system to generate more accurate, contextually appropriate translations in the target language, improving not only word accuracy but also overall fluency and coherence.

Conclusion

Translation technologies have been developed to increase accuracy and enhance productivity. Nowadays, almost every translator uses them to meet the demand of a translation services market that needs much faster translation. It is then important for both scholars and practitioners to master the different types of translation technology available in order to make efficient use of them. The updated classification of translation technologies presented in this study should help educators better design translators' training programs.

As the study shows, the primary translation tools were human-centred with the invention of Computer-Assisted Translation (CAT) tools. However, over the years, computer scientists have focused more on machine translation. This has brought about a paradigm shift, which puts computer software at the core of the translation process. From rule-based machine translation to Neural Machine Translation and AI-driven models, machine translation makes the task of human translators less challenging. However, the issue of input quality from different types of translation tools remains.

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AI Statement

This document has been enhanced through the use of Grammarly which was employed to refine its linguistic style and correct grammar and spelling. While the incorporation of these technologies may introduce some AI-generated linguistic patterns, it is important to note that the core intellectual content, data interpretation, and conclusions presented are entirely the work of the author.

Statement of Absence of Conflict of Interest

The author declares that there are no conflicts of interest related to the research, findings, or recommendations presented in this paper. All conclusions drawn are independent and unbiased.

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