"From Digitalization to Digital Transformation: Rethinking Translation in the Digital Age"

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ABSTRACT

This study explores the evolving relationship between digitalization, digital transformation, and translation practices in the digital age. Framed within the shift "from digitalization to digital transformation," the research examines how technological advancements have redefined the nature of translation as both a linguistic and technologically mediated activity. The study adopts a qualitative analytical approach to investigate the impact of machine translation (MT) and neural machine translation (NMT) on translation quality, with particular attention to contextual accuracy, fluency, and idiomatic expression handling. The findings reveal that digitalization has enabled the conversion of linguistic resources into digital formats, while digital transformation has fundamentally reshaped translation workflows through the integration of artificial intelligence and neural technologies. Although NMT significantly enhances efficiency and linguistic fluency compared to traditional MT systems, limitations persist in handling cultural nuances and context-dependent meanings. The study concludes that translation in the digital age is best understood as a hybrid practice that combines human expertise with machine intelligence, rather than a fully automated process.

Keywords: Digitalization, Digital Transformation, Translation Studies, Machine Translation, Neural Machine Translation, Post-editing, AI Translation

الملخص

تستكشف هذه الدراسة العلاقة المتطورة بين الرقمنة والتحول الرقمي وممارسات الترجمة في العصر الرقمي. وفي إطار التحول «من الرقمنة إلى التحول الرقمي»، تبحث الدراسة في الكيفية التي أعادت بها التطورات التكنولوجية تعريف طبيعة الترجمة بوصفها نشاطًا لغويًا وتقنيًا في آنٍ واحد. تعتمد هذه الدراسة منهجًا تحليليًا نوعيًا لدراسة تأثير الترجمة الآلية والترجمة الآلية العصبية على جودة الترجمة، مع التركيز بشكل خاص على الدقة السياقية، والطلاقة، ومعالجة التعبيرات الاصطلاحية. وتُظهر النتائج أن الرقمنة قد مكّنت من تحويل الموارد اللغوية إلى صيغ رقمية، في حين أعاد التحول الرقمي تشكيل سير عمل الترجمة بشكل جذري من خلال دمج تقنيات الذكاء الاصطناعي والشبكات العصبية. وعلى الرغم من أن الترجمة الآلية العصبية تُحسّن الكفاءة والطلاقة اللغوية بشكل ملحوظ مقارنةً بأنظمة الترجمة الآلية التقليدية، فإن هناك قيودًا لا تزال قائمة في التعامل مع الفروق الثقافية الدقيقة والمعاني المرتبطة بالسياق. وتخلص الدراسة إلى أن الترجمة في العصر الرقمي

تُفهم على أفضل وجه بوصفها ممارسة هجينة تجمع بين الخبرة البشرية والذكاء الاصطناعي، بدلًا من كونها عملية مؤتمتة بالكامل.

الكلمات المفتاحية: الرقمنة، التحول الرقمي، دراسات الترجمة، الترجمة الآلية، الترجمة الآلية العصبية، التحرير اللاحق، الترجمة بالذكاء الاصطناعي.

Introduction

The rapid development of digital technologies has profoundly reshaped communication practices across disciplines, and translation is no exception. In recent years, the field of translation has undergone a significant shift, moving from traditional human-centered practices toward technology-assisted and increasingly AI-driven workflows. This transformation is best understood through the conceptual progression from digitalization to digital transformation.

Digitalization refers to the process of converting linguistic and textual materials into digital formats that can be stored, processed, and transmitted electronically (Brennen & Kreiss, 2022). In contrast, digital transformation extends beyond simple digitization, representing a deeper structural change in workflows, professional practices, and institutional frameworks (Vial, 2021). Within translation studies, this shift has led to the emergence of advanced tools such as computer-assisted translation (CAT) systems, machine translation (MT), and more recently neural machine translation (NMT).

The integration of these technologies has significantly influenced translation production, efficiency, and accessibility. However, it has also raised critical questions regarding accuracy, cultural adaptation, and the evolving role of the human translator. As Cronin (2023) argues, translation in the digital age is no longer solely a linguistic operation but is embedded within complex digital infrastructures.

Against this background, this study investigates how the transition from digitalization to digital transformation has reshaped translation practices, with a particular focus on the comparative role of MT and NMT systems. It seeks to explore not only technological improvements but also their implications for the professional identity of translators and the future of translation as a discipline.

Theoretical Background

Digitalization

Digitalization refers to the process of converting information from analog, physical, or traditional formats into digital forms that can be stored, processed, and transmitted electronically, as noted by Brennen and Kreiss (2022). This process is characterized by the conversion of data into digital formats, which allows for easier storage and retrieval, as well as more efficient information management. In the field of language and translation, digitalization is reflected in resources such as digital dictionaries, linguistic corpora, and digitized translation archives, all of which enhance accessibility and streamline research and professional practices.

Digital Transformation

Digital transformation refers to the strategic integration of digital technologies to fundamentally reshape organizational processes, structures, and service delivery models. It goes beyond simple digitization by enabling systemic change and innovation across institutions. As defined by Vial (2021), digital transformation is "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies." This transformation is typically characterized by the automation of workflows, the integration of artificial intelligence (AI), and the enhancement of productivity and operational efficiency.

In the field of translation, digital transformation has led to the widespread adoption of advanced tools and platforms such as Google Translate, DeepL Translator, SDL Trados Studio, and Memo Q. These technologies have significantly redefined translation practices by increasing speed, consistency, and accessibility, while also introducing new challenges related to quality and cultural nuance (Munday, 2022; O'Hagan, 2023).

Machine Translation (MT)

Machine Translation (MT) refers to the use of computational systems to automatically translate text or speech from one language into another without direct human intervention. According to Koehn (2020), MT encompasses a range of approaches, including rule-based and statistical methods, which rely on linguistic rules or probabilistic models derived from bilingual corpora. Despite its efficiency and scalability, traditional

MT systems are often limited in handling context, idiomatic expressions, and pragmatic meaning, which can result in rigid and literal translations (Kenny, 2022).

Neural Machine Translation (NMT)

Neural Machine Translation (NMT) represents a significant advancement in the evolution of translation technologies. It utilizes artificial neural networks and deep learning architectures to model the entire translation process as a unified system. The introduction of attention mechanisms by Dzmitry, Kyunghyun, and Bengio (2015), followed by the Transformer model proposed by Vaswani et al. (2017), has dramatically improved translation quality by enabling better contextual understanding and long-range dependency modeling.

As a result, NMT systems produce more fluent, coherent, and contextually appropriate translations compared to earlier MT models. Recent studies confirm that NMT significantly enhances idiomatic translation and semantic accuracy, although challenges related to cultural adaptation and domain-specific terminology persist (Zhang & Toral, 2019; O'Brien, 2023).

Machine Translation (MT) vs. Neural Machine Translation (NMT)

Machine Translation (MT) and Neural Machine Translation (NMT) differ fundamentally in their underlying methodologies and the quality of their outputs. Traditional MT systems rely on rule-based or statistical approaches that process language in segmented units, which often results in rigid and literal translations. In contrast, NMT is based on artificial intelligence and deep learning, enabling it to process entire sentences or texts holistically and capture contextual relationships more effectively. As a result, while MT systems are generally efficient and require fewer computational resources, NMT systems tend to produce translations that are more fluent, coherent, and contextually appropriate. Despite these advancements, both approaches still depend on human post-editing to ensure accuracy, cultural sensitivity, and communicative effectiveness, particularly in specialized or sensitive domains (Castilho et al., 2020 ; Vieira et al., 2021). Furthermore, the evolution of translation technologies is characterized by increased automation, the integration of artificial intelligence, and enhanced productivity and efficiency. Prominent

examples of such technologies in practice include Google Translate, DeepL Translator, SDL Trados Studio, and MemoQ.

Translation and Digital Transformation

The field of translation has undergone a profound transformation as a result of rapid advancements in digital technologies. The integration of artificial intelligence (AI) into translation practices has reshaped both the processes and the roles involved in translation. Contemporary translation is no longer confined to manual linguistic transfer; rather, it is increasingly mediated by intelligent systems that enhance efficiency, consistency, and scalability.

One of the most significant developments is the widespread use of AI-based translation tools, particularly Neural Machine Translation (NMT) systems, which rely on deep learning algorithms to generate contextually informed translations. In parallel, Computer-Assisted Translation (CAT) tools have become essential in professional environments, offering features such as translation memory, terminology management, and alignment tools that support human translators in maintaining consistency and accuracy across large corpora.

Furthermore, cloud-based collaborative translation platforms have enabled real-time cooperation among translators, editors, and project managers across geographical boundaries. These platforms facilitate workflow integration, version control, and shared access to linguistic resources, thereby enhancing productivity and coordination in large-scale translation projects.

In addition, the relationship between translation and digital technologies is reinforced through the use of digital corpora and linguistic databases, which provide translators with authentic language data for improved decision-making. The convergence of CAT tools, AI systems, and cloud computing has thus created a dynamic ecosystem in which human and machine capabilities are increasingly interdependent.

The integration of digital technologies into translation practices has fundamentally reshaped the nature of the profession. The increasing eliance on AI-based translation tools, Computer-Assisted Translation (CAT) tools, and cloud-based collaborative platforms reflects a broader digital transformation that has redefined both the processes and outcomes of translation (Munday, 2022; O'Hagan, 2023).

The Impact onTranslators

The incorporation of digital technologies into translation workflows has significantly altered the traditional role of the translator. Historically perceived as a linguistic expert responsible for producing translations from scratch, the contemporary translator increasingly functions as à post-editor, tasked with revising and refining machine-generated outputs. This shift represents a transition from primarily creative production to evaluative and corrective practices within technology-mediated environments (Toral, 2019 ; Castilho, 2020).

As a result, translators are now required to possess not only advanced linguistic competence but also a high level of digital and technical literacy. Proficiency in CAT tools, familiarity with AI-driven translation systems, and the ability to operate within cloud-based platforms have become essential competencies in the modern translation industry (Koehn & Knowles, 2022 ; O'Brien, 2023).

Moreover, the adoption of technological tools has led to a substantial increase in productivity. Translators are able to process larger volumes of text within shorter timeframes while maintaining consistency through the use of translation memory systems and automated terminology management (Vieira et al., 2023). However, this enhanced efficiency is accompanied by several challenges, including concerns about quality control, over-reliance on machine-generated output, and the potential marginalization of human expertise (Cronin, 2023).

Statement of the Problem

Despite significant advancements in Neural Machine Translation (NMT), substantial challenges persist in achieving fully accurate and culturally appropriate translations. Earlier Machine Translation (MT) systems are often characterized by their literal and structurally rigid output, lacking sensitivity to contextual and pragmatic nuances. While NMT systems have demonstrated notable improvements in fluency and contextual awareness, they continue to struggle with complex linguistic phenomena such as ambiguity, idiomatic expressions, and domain-specific terminology.

This situation gives rise to a critical research problem: the extent to which neural machine translation systems can effectively replace or reliably support human translators without compromising semantic precision, pragmatic meaning, and cultural appropriateness remains uncertain.

Moreover, the rapid adoption of AI-based translation tools in professional contexts has outpaced rigorous linguistic and theoretical evaluation. As a result, important questions remain unresolved regarding the reliability, limitations, and theoretical implications of these technologies within the broader framework of translation studies. Addressing this gap is essential for understanding the evolving relationship between human translators and intelligent systems in the digital age.

Research Objectives

This study aims to achieve the following objectives:

To compare Machine Translation (MT) and Neural Machine Translation (NMT) in terms of linguistic accuracy and translation quality.

To analyze the ability of MT and NMT systems to handle idiomatic expressions, ambiguity, and polysemy.

To evaluate translation performance through the application of relevant theoretical frameworks within translation studies.

Research Questions

The study is guided by the following research questions:

1. How does Neural Machine Translation differ from traditional Machine Translation in handling contextual meaning and linguistic ambiguity?
2. To what extent do MT and NMT systems effectively translate idiomatic and culturally embedded expressions?
3. What role does digital transformation play in reshaping contemporary translation practices and the role of the translator?

Significance of the Research

This study contributes to the field of translation studies by critically examining the role of Machine Translation (MT) and Neural Machine Translation (NMT) within the broader context of digital transformation. It highlights the potential of these technologies as supportive tools that can enhance translation efficiency and accessibility in the age of artificial intelligence.

At the same time, the research emphasizes the continued importance of human expertise in ensuring semantic accuracy, cultural sensitivity, and communicative effectiveness. By bridging the gap between technological advancement and theoretical inquiry, the study provides valuable insights

for translators, researchers, and educators seeking to understand and navigate the evolving landscape of translation in the digital era.

Previous Studies

A growing body of research has explored the development and limitations of machine translation systems, particularly in relation to Neural Machine Translation (NMT). For instance, Kohen and Knowles (2022) identified several persistent challenges in NMT, including difficulties in handling rare words, long sentences, and domain adaptation.

Similarly, Toral and Cartagena (2017) examined the extent to which NMT systems improve translation quality compared to earlier statistical approaches, concluding that while fluency has significantly improved, issues related to adequacy and accuracy remain.

Furthermore, Vanmassenhove et al. (2021) investigated the presence of bias in neural machine translation systems, highlighting how gender and cultural biases can be reproduced and amplified by AI-driven models. These findings underscore the importance of critically evaluating NMT systems not only from a technical perspective but also from linguistic and ethical standpoints.

Collectively, these studies demonstrate that although NMT represents a major advancement in translation technology, it is not without limitations, thereby reinforcing the need for continued research into its capabilities and implications.

Research Methodology

Research Design

This study adopts a qualitative descriptive-analytical approach to investigate the relationship between digitalization, digital transformation, and translation. The research focuses on analyzing linguistic data and interpreting the impact of technological tools on translation practices.

Data Collection

The data for this study consist of carefully selected translation samples that illustrate the performance differences between Machine Translation (MT) and Neural Machine Translation (NMT) systems. These samples were purposively chosen to represent a range of linguistic phenomena, including idiomatic expressions, culturally bound terms, syntactic complexity, and context-dependent meanings. The selection process follows a criterion-

based sampling strategy, ensuring that each example provides meaningful insight into the strengths and limitations of both translation paradigms.
In addition to primary data (i.e., the translation outputs), the study draws on secondary data sources, including peer-reviewed academic literature, previously published case studies, and empirical findings in the field of translation studies and computational linguistics. This triangulation of data enhances the validity and reliability of the analysis by situating the selected examples within a broader scholarly context (Creswell, 2014 ; Munday, 2022).
Furthermore, the data collection process is informed by the principles of qualitative research, where depth of analysis is prioritized over quantity. Rather than relying on large-scale corpora, the study emphasizes analytical richness, allowing for a detailed examination of how meaning is constructed, distorted, or improved across different translation systems.

Data Analysis

The study adopts a comparative analytical method to evaluate the outputs of MT and NMT systems. Each selected example is systematically analyzed by juxtaposing the translations produced by both approaches, followed by a critical evaluation based on three key criteria:
Accuracy, which refers to the degree to which the translated text faithfully conveys the meaning of the source text without omission, addition, or distortion.
Fluency, which concerns the naturalness and readability of the translated output in the target language, including grammatical correctness and stylistic appropriateness.

Contextual Appropriateness, which assesses the system's ability to interpret and render meaning in relation to the broader linguistic and cultural context.
The analysis is interpretative in nature and guided by established frameworks in translation studies, particularly functionalist approaches such as Skopos Theory, which emphasize the communicative purpose of translation (Vermeer, 1984). Through this lens, translation quality is not judged solely on literal equivalence but on the extent to which the target text fulfills its intended function.

Additionally, elements of error analysis are incorporated to identify recurring patterns of mistranslation, especially in MT outputs, such as literalism, ambiguity, and failure to process idiomatic language. In contrast, NMT outputs are examined for improvements in semantic coherence and contextual sensitivity, while also acknowledging their residual limitations.

Research Approach

This study employs a qualitative research approach grounded in an analytical and interpretive framework. The primary objective is to explore how different translation technologies process language, rather than to measure their performance quantitatively. As such, the research prioritizes depth, nuance, and contextual understanding over statistical generalization.

The approach integrates aspects of contrastive analysis, comparing traditional rule-based or statistical MT systems with contemporary NMT models. This comparison highlights the evolution of translation technologies and their respective impacts on linguistic output. By examining differences in structure, semantics, and pragmatics, the study provides a comprehensive understanding of how translation quality has developed over time.

Moreover, the research is informed by interdisciplinary perspectives, drawing from translation studies, artificial intelligence, and applied linguistics. This allows for a more holistic interpretation of findings, particularly in relation to how computational models simulate human-like language processing.

Limitations of the Study

Despite its contributions, this study is subject to several limitations that should be acknowledged. First, the analysis is based on a limited number of illustrative examples, which, while allowing for in-depth examination, may not fully capture the wide variability of translation performance across different text types and domains. Consequently, the findings cannot be generalized to all MT and NMT applications.

Second, the study focuses primarily on English–Arabic translation, a language pair characterized by significant linguistic and cultural differences. While this focus provides valuable insights, it also limits the

applicability of the results to other language pairs, particularly those with closer structural similarities.

Third, the research does not incorporate large-scale quantitative evaluation methods, such as BLEU scores or corpus-based statistical analysis. Although this is consistent with the qualitative nature of the study, it restricts the ability to provide measurable performance comparisons.
Finally, the study does not account for all variables influencing translation quality, such as domain specificity, training data variability, and system updates, which may affect the consistency of MT and NMT outputs over time.
In light of these limitations, future research is encouraged to adopt a mixed-methods approach combining qualitative and quantitative analysis, expand the corpus size, and include multiple language pairs and domains to enhance the generalizability and validity of findings.

Data Analysis and Discussion

This section presents a systematic analysis of the data used in the study, followed by a critical discussion of the findings in relation to existing literature in translation studies and computational linguistics.
This section presents a systematic analysis of the data used in the study, followed by a critical discussion of the findings in relation to existing literature in translation studies and computational linguistics. The present study is based on qualitative data derived from two primary sources: (1) applied translation examples comparing Machine Translation (MT) and Neural Machine Translation (NMT), and (2) relevant findings from previous scholarly studies in the field.
The first category of data consists of carefully selected translation examples that illustrate specific linguistic phenomena, such as idiomatic expressions, syntactic ambiguity, lexical choice, and cultural references. These examples serve as practical evidence to evaluate the performance differences between traditional rule-based or statistical MT systems and more advanced NMT models. Qualitative analysis of such examples enables a deeper understanding of how meaning is constructed and transferred across languages, which aligns with the interpretive nature of translation studies (Munday, 2022).
The second category of data is drawn from existing literature on MT and NMT. Incorporating findings from previous research enhances the analytical framework of the study and allows for triangulation of results.

Studies such as those by Bahdanau et al. (2015) and Vaswani et al. (2017) have demonstrated that NMT systems, particularly those based on attention mechanisms and transformer architectures, significantly improve fluency and contextual accuracy. However, other scholars (Kenny, 2020 ; Toral & Way, 2018) argue that challenges related to cultural nuance, idiomaticity, and semantic precision persist.

By combining applied examples with theoretical insights, the study adopts a qualitative comparative approach. This approach is particularly suitable for examining translation as a communicative act, rather than merely a technical process. As emphasized by the functionalist perspective, especially Skopos Theory (Reiss & Vermeer, 1984), the success of translation depends on its purpose and communicative effectiveness, which cannot always be captured through quantitative metrics alone.

Corpus Analysis :

Ambiguity

Example :

As I walked through the park, I suddenly noticed something strange near the pond. I saw her duck just as the ball flew toward me.

ST :

"I saw her duck."

MT :

I saw her duck

NMT :

I saw her bend down

Analysis :

This example illustrates lexical ambiguity, where the word "duck" can function either as a noun (a bird) or a verb (to lower one's head or body quickly). Traditional rule-based or phrase-based machine translation (MT) systems tend to process language at a more surface level, often translating words based on their most frequent or direct equivalents without fully disambiguating meaning. As a result, the MT output preserves the ambiguity of the source sentence.

In contrast, Neural Machine Translation (NMT) systems rely on contextualized representations of language. By processing the sentence as a whole rather than as isolated segments, NMT models can infer that

"duck" is more likely being used as a verb in this context. Thus, it produces the disambiguated and semantically explicit translation : "I saw her bend down."

English Idiom

Example :

It was raining cats and dogs that evening, the streets quickly filling with water as people hurried home under umbrellas.

ST :

"It's raining cats and dogs."

MT :

It is raining cats and dogs

NMT:

It is raining heavily

Analysis :

This example highlights the challenge of idiomatic expressions, where the meaning of a phrase cannot be derived from the literal meanings of its individual components. In phrase-based MT, translation is often performed word-for-word or through memorized phrase correspondences. If the idiom is not stored as a fixed unit in the system's database, the output remains literal, resulting in a translation that may be grammatically correct but semantically misleading.

NMT systems, however, are trained on large corpora of naturally occurring language data, enabling them to recognize idioms as multi-word semantic units. In this case, NMT correctly interprets "kicked the bucket" as an idiomatic expression meaning "died." It then produces a translation that captures the intended meaning rather than the literal wording.

English Idiom

Example :

She was nervous before the school play, but her teacher smiled and said, "Break a leg!" to encourage her, which made her feel more confident and ready to perform.

ST :

"Break a leg!"

MT:
Break your leg
NMT:
Good luck

Analysis :

In this example the Neural Machine Translation (NMT) output "Good luck" demonstrates a clear sensitivity to idiomatic meaning, rather than relying on a literal, word-for-word rendering as seen in the Machine Translation (MT) output "Break your leg." Idioms are inherently non-compositional, meaning their overall sense cannot be deduced from the individual words. In this case, the phrase "Break a leg !" is conventionally used to wish someone success, especially in performance contexts.
In contrast, the MT output reflects a form-based or literal translation strategy, which fails to account for cultural and pragmatic nuances, resulting in a semantically inaccurate and potentially confusing translation.

Polysemy

Example :
He is cold. He sits quietly by the window, wrapped in his coat, shivering as the winter wind blows outside. His words are few, and his face shows no emotion, making it hard for others to know what he is thinking.

ST :
"He is cold."
MT :
He is cold
NMT:
He feels cold

Analysis :

This example illustrates how polysemy—the presence of multiple related meanings for a single word—can create ambiguity in translation. The adjective "cold" may refer either to a physical state (low temperature) or an emotional condition (lack of warmth or empathy).

In the MT output ("He is cold"), the translation remains ambiguous and context-neutral, reflecting a word-for-word rendering that does not attempt to disambiguate meaning.
By contrast, the NMT output ("He feels cold") demonstrates contextual interpretation, where the system selects the physical sensation meaning of "cold." This suggests that NMT models rely on probabilistic context modeling and learned language patterns to infer the most likely sense in a given situation.
more explicit and communicatively functional, even when the source text itself is underspecified.

English expression

Example :

After many years of struggling with illness, he finally kicked the bucket, leaving behind memories and a grieving family.

ST :

"He kicked the bucket."

MT:

ركل الدلو

NMT :

توفي / مات

Analysis :

This example highlights the difficulty of translating idiomatic expressions across languages, particularly between English and Arabic. The phrase "He kicked the bucket" is a well-known English idiom meaning "he died," and its meaning cannot be derived from the literal meanings of its individual words.

The MT output (ركل الدلو)demonstrates a literal, word-for-word translation, which fails to convey the intended meaning. This reflects a limitation of traditional rule-based or statistical MT systems, which often prioritize lexical equivalence over contextual or cultural meaning. As a result, the translation is semantically incorrect and pragmatically inappropriate.

In contrast, the NMT output (مات / توفي)shows a successful idiomatic translation, where the system correctly interprets the figurative meaning and renders it into a natural and culturally appropriate Arabic equivalent. This illustrates how NMT systems leverage contextual embeddings and large-scale training data to recognize idiomatic usage and map it to functionally equivalent expressions.

English Expression

Example :

He is running out of time, and the pressure is increasing as each passing moment brings him closer to the deadline. He realizes that he must act quickly if he wants to finish everything on time.

ST :

“He is running out of time.”

MT:

هو يركض خارج الوقت

NMT :

يوشك الوقت على النفاد

Analysis :

The MT output " هو يركض خارج الوقت"is a literal, word-for-word translation that misinterprets the figurative meaning of the English expression. It treats “running” as a physical action and “time” as a spatial entity, resulting in an unnatural and semantically incorrect sentence in Arabic.

In contrast, the NMT output " يوشك الوقت على النفاد"accurately captures the intended meaning—that time is almost finished. Instead of translating the individual words, it interprets the expression as a whole unit (a fixed phrase), producing a natural and idiomatic equivalent in Arabic.

English Text :

Example :

She broke the record_by achieving a performance that exceeded the previously established highest benchmark, thereby setting a new standard within the evaluated category.

ST :
"She broke the record"
MT :
She broke the record
NMT :
She set a new record.

Analysis :

The MT output ("She broke the record") is a literal word-for-word translation that preserves the original structure but may introduce ambiguity in Arabic or other target languages, as "broke" can be interpreted physically rather than figuratively in some contexts.
In contrast, the NMT output ("She set a new record") reflects a meaning-based translation that prioritizes semantic and pragmatic equivalence. Instead of translating the verb "broke" literally, the system interprets the idiomatic meaning ("achieved a higher performance than before") and renders it in a culturally and linguistically natural form.

English Text

Example :
ST :
"After finishing the project, he submitted it to the manager for review."
MT :
After finishing the project, he submitted it to the manager for review
NMT :
After completing the project, he submitted it to the manager for review.

Analysis :

This example shows a clear improvement in lexical choice and stylistic naturalness in Neural Machine Translation (NMT) compared to Machine Translation (MT).

The MT output reproduces the source text almost word-for-word, maintaining the structure "After finishing the project…". While grammatically correct, it is somewhat literal and less idiomatic in formal English. The phrase "finishing the project" is acceptable but slightly informal in academic or professional contexts.

In contrast, the NMT output replaces "finishing" with "completing," which is a more precise and formal collocation in project-related discourse ("completing a project" is more commonly used in professional and academic registers). This demonstrates NMT's ability to draw on broader contextual patterns and preferred collocations rather than relying on direct lexical substitution.

Research Findings and Discussion.

The analysis of the selected examples reveals a clear distinction between traditional Machine Translation (MT) systems and Neural Machine Translation (NMT) models in terms of performance and translation quality. The findings indicate that MT tends to produce translations that are largely literal and structurally rigid, often adhering closely to the source text at the expense of naturalness and communicative effectiveness. In contrast, NMT demonstrates a noticeable improvement in fluency and contextual interpretation, as it is better equipped to process linguistic patterns within broader textual and semantic contexts.

One of the most significant improvements observed in NMT is its ability to handle idiomatic expressions. While MT frequently fails to render idioms accurately due to its reliance on word-for-word translation, NMT shows a higher capacity for producing more natural and contextually appropriate equivalents. Nevertheless, despite these advancements, the issue of cultural adaptation remains only partially resolved, as both MT and NMT systems still struggle with culturally bound expressions and implicit meanings that require deep cultural awareness.

Furthermore, the findings highlight that human intervention continues to play a crucial role in ensuring translation quality. This aligns with post-editing theory, which views translation in the digital age as a hybrid process involving collaboration between human translators and machine systems. Human translators are essential for refining output, resolving ambiguities, and ensuring that translations meet communicative and cultural expectations.

From a theoretical perspective, the results strongly support the principles of Skopos Theory, which emphasizes that the success of a translation depends on its communicative purpose. In this regard, NMT proves to be more effective than MT in approximating the intended function of the target text. Additionally, when examined through the lens of equivalence theory, MT can be seen as operating primarily at the level of formal equivalence, whereas NMT moves closer to dynamic equivalence, albeit not consistently.

Finally, insights from cognitive linguistics help explain the limitations of MT systems, particularly in dealing with idiomatic language and ambiguity. Since MT lacks conceptual and experiential grounding, it is unable to fully interpret meaning beyond surface structures. Consequently, the study concludes that digital transformation has not replaced human translation but has instead redefined it as à collaborative human–machine system, where both technological efficiency and human expertise are necessary to achieve high-quality translation outcomes.

Conclusion

This study has examined the evolution of translation practices through the lens of the transition from digitalization to digital transformation. The findings demonstrate that digitalization initially enabled the conversion of linguistic content into digital formats, facilitating access, storage, and computational processing. However, digital transformation has gone further by fundamentally restructuring translation workflows through the integration of artificial intelligence, particularly machine translation (MT) and neural machine translation (NMT).

The analysis reveals that NMT represents a significant advancement over traditional MT systems in terms of fluency, contextual coherence, and syntactic accuracy. Nevertheless, limitations remain in handling culturally specific meanings, idiomatic expressions, and context-dependent interpretations. These findings confirm that while technology has enhanced translation efficiency, it has not eliminated the need for human intervention.

Ultimately, translation in the digital age is best understood as a hybrid practice in which human expertise and machine intelligence operate in a complementary relationship.

Recommendations

Based on the findings of this study, the following recommendations are proposed:

1. Curriculum Reorientation in Translation Studies

Translation education should be restructured to reflect ongoing digital transformation. This includes integrating training in computer-assisted translation (CAT) tools, neural machine translation (NMT) systems alongside linguistic and cultural competencies.

2.Strengthening Post-Editing Competence

Given the increasing reliance on NMT systems, professional training programs should prioritize the development of post-editing skills. Particular attention should be paid to error correction, stylistic refinement, cultural adaptation.

3.Adoption of Hybrid Translation Models

Translation workflows should move toward a human–machine collaborative model. In this framework, artificial intelligence can support initial drafting, while human translators ensure accuracy, contextual appropriateness, and overall quality.

4.Enhancement of Arabic NLP Resources

There is a pressing need to develop more comprehensive Arabic language datasets and computational resources. Strengthening these resources will significantly improve the performance and reliability of machine translation systems involving Arabic.

5. Promotion of Interdisciplinary Collaboration.

Future advancements in translation technology should be supported through collaboration between linguists, computational scientists, and software engineers.

6.Ethical and Data Governance Frameworks

Institutions should establish clear ethical guidelines governing the use of digital translation tools. These should address issues such as data privacy, confidentiality, and the handling of sensitive or proprietary content.

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