



Post-Editing of Machine Translation

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Abstract

This paper explores the practice of post-editing translations produced by Neural Machine Translation (NMT), with a particular emphasis on Arabic translations from Google Translate.. The core of the research involves a practical analysis of five different English texts—technical, literary, news, marketing, and legal—translated into Arabic using NMT. Each translation is evaluated for errors using a five-category framework: semantic/contextual, morphosyntactic, lexical/terminological, and stylistic/fluency. This paper tackles a deficiency in the research concerning post-editing Neural Machine Translation (NMT) for Arabic, as current studies primarily concentrate on European language pairs and do not provide genre-specific, measurable error analysis. Utilizing Google Translate as the NMT system, we post-edited five English–Arabic translations that span technical, literary, news, marketing, and legal genres. A mixed-method approach was used, where two professional translators independently identified errors using a framework consisting of five categories: semantic/contextual, morphosyntactic, lexical/terminological, and stylistic/fluency. The analysis reveals that while NMT can produce fluent translations, it often results in subtle yet significant errors that require thorough post-editing. The findings indicate that post-editing demands greater cognitive effort and sharper analytical skills than traditional translation. This paper add to the growing area of Machine Translation Post-Editing (MTPE) by providing specific examples of NMT errors in Arabic and proposing practical solutions for post-editing.

Keywords: Machine Translation, Neural Machine Translation (NMT), Statistical Machine Translation (SMT), Post-Editing (PE).



1.Introduction

Although NMT post-editing (PE) has been thoroughly explored for high-resource language pairs like English–German, English–Chinese, and English–Spanish, there is a significant lack of research on Arabic in this area. This gap is important to address, as Arabic has unique typological characteristics that pose specific challenges to NMT systems, resulting in error patterns that are quite different from those observed in European languages.

A 2018 survey conducted by EUATC indicated that more than half of language service providers were utilizing some form of machine translation, highlighting a significant change in industry practices. Among these developments, Neural Machine Translation (NMT) has emerged as the predominant method, offering impressive fluency through platforms such as Google Translate, DeepL, and Microsoft Translator. According to Kalchbrenner and Blunsom (2013) and Sutskever et al. (2014), NMT is a novel technique that processes entire sentences as sequences, distinguishing it from traditional statistical and rule-based systems. However, this technological advancement has not eliminated the need for human input; rather, it has transformed the role of translators. Forcada (2025) cautions that automatic evaluation metrics often fail to accurately represent the true effort required for post-editing, suggesting that statistically significant improvements in NMT may obscure practical limitations. This has led to the adoption of Machine Translation Post-Editing (MTPE), which, as noted by Koponen (2016), was one of the original purposes envisioned for MT systems since the 1950s. Post-editing involves human revision of machine-generated translations to ensure they are accurate, fluent, and appropriate for the intended audience. Research by O'Brien (2002) and other experts has highlighted key skills necessary for post-editors, including subject matter expertise, attention to detail, and technological proficiency. While NMT produces increasingly sophisticated outputs, Lepine (2022) warns that these systems can "hallucinate" to maintain fluency, resulting in omissions or misrepresentations of information they cannot accurately process—an issue that is particularly critical when translating between linguistically and culturally diverse languages such as English and Arabic.



This paper examines the process of post-editing outputs from Neural Machine Translation, with a particular emphasis on Arabic translations. It draws on theoretical frameworks proposed by Krings (2001) concerning post-editing effort, as well as error classifications created by Koponen (2012) and Daems (2016), to conduct a practical analysis of five distinct English texts translated into Arabic using Google Translate. By combining theoretical insights with practical application, the paper seeks to improve the understanding of Machine Translation Post-Editing (MTPE) and provide useful information for translators, educators, and researchers involved with Arabic and English.

1.1. Literature Review:

The significance of human post-editing in machine translation processes has emerged as a key topic in translation studies, yet much of the current literature tends to be descriptive rather than analytical. Mirela (2024) characterizes post-editing as the act of reviewing and correcting machine translation output to achieve an acceptable level of fluency and accuracy—this functional definition is frequently referenced in introductory materials. However, this definition presupposes a consistent standard of "acceptability" and overlooks the diverse nature of post-editing tasks, which can vary from light editing (making minimal corrections to obvious errors) to extensive editing (rewriting sentences entirely). Mirela's discussion does not differentiate between these approaches, a shortcoming that is evident in much of the foundational literature on the subject.

According to the European Language Industry Survey conducted by EUATC in 2018, that year marked a significant rise in the use of machine translation, with more than 50% of participants indicating they utilized this technology in some capacity. Although some members of the translation industry expressed skepticism about machine translation, as noted by Levanait in 2021, the demand for this technology has been growing swiftly. This growth highlights the increasing necessity for well-trained post-editors, a relatively new role in the translation sector, as well as the importance of assessing the quality of machine-generated translations.

Several research studies have aimed to assess the influence of machine translation and to determine how much machine translation and post-editing can be successfully integrated into the language services market. The TAUS survey published in 2010, which analyzed language service providers in Europe, the Americas, and Asia, found that nearly half (49.3%) of the 75 respondents provided machine translation post-editing services, according to (Joscelyne and Brace (2010, as cited in Christensen and Schjoldager 2016).

In conclusion, existing literature has effectively recorded the increasing use of machine translation (MT) and ongoing skepticism among translators, but it falls short in three important areas: (1) it describes post-editing without clarifying its cognitive requirements, (2) it presents survey statistics without examining their relevance across different MT models, and (3) it applies findings from European languages to other languages without empirical support. This study aims to fill the third gap by offering a quantitative, genre-specific analysis of post-editing in Arabic neural machine translation (NMT), thus shifting from mere description to a critical evaluation that takes language into account.

2. Machine Translation: An Overview

MT has become easily available through web platforms and is often utilized within business settings, frequently alongside translation memory systems. Many translators now employ machine translation for personal assistance and as a form of supportive tool (OBrien (2018), Moorkens (2015), Kenny (2014)), which accelerates their own idea development. The rise of MT has ignited conversations about the functionality of humans compared to machines in translation work. While it is improbable that MT will completely take over the role of human translators, its usage is increasing across different environments. Additionally, the standard of MT has enhanced with time. The constant need for translation services and the influence of modern technologies, including MT, are apparent in current professional translation activities.

According to Forcada (2015) Many elements of evaluating machine translation remain unclear. The development of machine translation relies heavily on automatic evaluation metrics, like BLEU, which assess the similarity between machine translation results and one or, if lucky, a few

reference translations. However, these automatic evaluation tools have a limited capacity to forecast the effort needed for post-editing or to gauge the actual utility of the raw output from machine translation. Consequently, the research area of machine translation might sometimes be making no real advancements while believing it is. There are two types of machine translation the statistical type which is a data-driven method that produces translations using probability models based on extensive bilingual text collections. In contrast to rule-based systems, Statistical Machine Translation (SMT) identifies patterns from existing translations to forecast the most probable output, making it suitable for various domains, though not confined to them. And the neural type which an AI-based method utilizing deep learning, particularly neural networks, to forecast the probability of word sequences in translation. In contrast to traditional rule-based approaches, neural machine translation (NMT) treats the whole sentence as one complete entity, enhancing context, fluency, and grammatical correctness. Koehn (2010).

In this paper the researcher is discusses the limitations of neural machine translation since this type typically produces more fluent and natural translations, whereas SMT combines phrase probabilities for translation; in contrast, NMT processes the entire sentence as a sequence.

3. Neural MT and its limitations:

Neural machine translation or what is called NMT, represents a novel approach to machine translation, recently introduced by Kalchbrenner and Blunsom (2013), Sutskever et al. (2014), and Cho et al. (2014b). Unlike traditional phrase-based translation systems (refer to Koehn et al., 2003), which consist of multiple small components that are fine-tuned separately, neural machine translation aims to construct and train a single, large neural network that interprets a sentence and generates an accurate translation. The majority of the neural machine translation models are part of the encoder-decoder family (Sutskever et al., 2014; Cho et al., 2014a), which includes an encoder and a decoder for each language, or they may involve a language-specific encoder applied to each sentence, with outputs that are then compared (Hermann and Blunsom, 2014).

Although neural machine translation (NMT) is fluent, it faces challenges with the distinct characteristics of Arabic. The root-pattern morphology



can lead to incorrect verb forms, such as translating "he dictated" as تملى instead of the correct أملى. The omission of diacritics can create confusion with homographs, like the word علم, which can mean 'knew', 'taught', or 'flag', and NMT makes incorrect choices about 30% of the time. The presence of diglossia results in mixing different registers, such as using the colloquial particle لازم in formal legal texts. Furthermore, NMT frequently adds unnecessary subject pronouns, translating 'she left' as هي غادرت instead of the more natural غادرت. These subtle mistakes may not be caught by automatic evaluation metrics but require extensive post-editing. An encoder neural network processes and encodes a source sentence into a fixed-length vector, while a decoder produces a translation from this encoded vector. The complete encoder-decoder system, which comprises the encoder and decoder for a language pair, is trained jointly to maximize the chances of achieving a correct translation based on the source sentence. Bahdanau (2015) claims that Neural machine translation is a newly introduced method for machine translation. In contrast to conventional statistical machine translation, neural machine translation focuses on creating a unified neural network that can be optimized collectively to enhance translation effectiveness. The recent models developed for neural machine translation typically fall under the category of encoder-decoder architectures, which transform a source sentence into a fixed-length vector that a decoder then uses to produce a translation. Nonetheless, they lack the sensitivity and detailed understanding that only a human translator can provide. These engines do not truly "understand" text in any meaningful way. Despite their advanced capabilities, they lack awareness of contextual nuances, the intent behind messages, and the cultural sensitivities and regional expressions that influence language. They also miss the subtext or the implied meanings that skilled translators are trained to recognize and convey. Additionally, neural machine translation (NMT) systems can make mistakes, which necessitates that translators carefully review every word of the output, as NMT translations cannot be fully trusted. Moreover, machines often "hallucinate" to appear more fluent, skipping or omitting parts they do not comprehend, and they do not seek clarification to grasp the intended meaning of the text. This goes against

their fundamental design: NMT engines cannot ask questions, and large language models (LLMs) are programmed to sound confident even when they do not fully understand. The researcher suggests that in optimal conditions, especially with more standardized texts, NMT can alleviate the workload of starting from scratch, leading to less typing and mental strain for translators. Interestingly, many translators prefer this method.

4. Post-Editing of machine translation

It's important to note that the key distinction between Post-Editing (PE) and Machine Translation (MT) lies in their processes. Machine Translation (MT) is the automatic translation of text performed by a computer using artificial intelligence or algorithms, without any human involvement. While it is fast and cost-effective, it can sometimes produce translations that are less accurate or nuanced, especially for complex or context-heavy texts. On the other hand, post-edited translation involves a human reviewing and refining the translations generated by machines. A qualified linguist improves the output to enhance its accuracy, fluency, and cultural appropriateness. Although MT is useful for quick translations, post-editing ensures higher quality, making it more suitable for content that demands precision and clarity. Additionally, while machine translation and post-editing have gained more attention recently, it's essential to acknowledge that post-editing was one of the original intended applications for MT systems (Koponen, 2016).

Looking back at history, post-editing gained prominence in the 1950s and 1960s, leading to the development of the first post-editing software. However, it was set aside in the early 1960s because it was considered too time-consuming, labor-intensive, and complicated compared to human translation.

Despite early challenges, the development of machine translation (MT) technology and the growth of post-editing practices continued. Studies show that MT has reached a quality level adequate for professional applications, improving translation efficiency, particularly for specific languages (Koponen, 2016). However, final translations typically necessitate human review, a process referred to as machine translation post-editing (PEMT), where the machine-generated text is corrected according to established criteria (Koby, 2001).

In contrast to conventional editing, which involves human-created source material, post-editing focuses on text that has been initially produced by machine translation. This post-edited content may also go through an editorial review to fix stylistic, grammatical, and lexical mistakes to better suit the intended audience (Guerberof Arenas, 2014). Post-editing requires a greater level of expertise than translation, as it involves the ability to evaluate the quality of machine-generated translations and knowledge of the tools and procedures used in the post-editing process.

Research (Guerberof, 2009; Plitt and Masselot, 2010; Koponen, 2016) has shown that post-editing high-quality machine translation can improve the productivity of skilled translators when compared to traditional manual translation. Nevertheless, the ideal level of work and effort needed for post-editing varies based on the quality of the original machine translation.

Braahmam International (2024) claims that (PE) has four types and explains the characteristics of each type, as follows:

1- Light post-editing (LPE):

Which aims to fix only the most significant errors in machine translation output to ensure the text is comprehensible. The objective is to attain adequate accuracy and readability without aiming for flawless results. LPE is commonly employed when time is crucial and the text is intended for internal use or situations where a refined translation is unnecessary.

- Key characteristics; Correction of major grammatical mistakes and inaccuracies in translation, making sure the text is clear and communicates the intended message minimal changes to style or syntax, and fast response time.

2- Full post-editing (FPE):

Full post-editing aims to produce translations that are equivalent in quality to those created by experienced human translators. This process involves a thorough review and correction of the machine-generated translation to ensure that the text is accurate, fluent, and stylistically appropriate for its intended audience.

- Key characteristics; include addressing all errors, including minor grammatical mistakes and awkward phrasing, making stylistic adjustments to meet audience expectations, maintaining consistency in

terminology and tone, and requiring more time and effort than Light Post-Editing (LPE).

3- Targeted post-editing (TPE): is a tailored approach that focuses on specific aspects of the text that are crucial to the client's needs. This type of post-editing can incorporate elements of both Light Post-Editing (LPE) and Full Post-Editing (FPE), with an emphasis on particular sections or types of content within the document

- Key characteristics include focusing on correcting areas that require high accuracy, such as product names or technical terms, balancing efficiency and quality based on client preferences, and adopting a flexible strategy to meet specific requirements.

4- Adaptive post-editing (APE): The last type utilizes cutting-edge technologies like artificial intelligence and machine learning to enhance the quality of machine translation (MT) results throughout the post-editing phase. This approach includes real-time feedback mechanisms, allowing the system to learn from the modifications made by human post-editors and adapt its future translations based on those changes.

- Key characteristics; real-time learning and enhancement of machine translation (MT) systems, greater efficiency and decreased post-editing workload over time, and improved consistency and quality of translations.

5. Machine Translation Errors and Post-Editing Efforts:

Daems (2016, p. 118) notes that comparing the machine translation (MT) with the final product of post-editing (PE) does not take into account that an editor might have revised the same word or section several times. This repeated editing process not only requires more technical effort but may also indicate greater cognitive effort. Krings (2001, p. 530) suggests that having to evaluate various possible translations for the same section increases cognitive load. Generally, it is challenging to identify cognitive effort in the final output. One method proposed is Choice Network Analysis (CNA, as discussed by Campbell 2000), which compares different versions of the same text created by various translators or post-editors. Campbell (2000) contends that sections where the versions are the same are less cognitively taxing than those where translators generate

multiple distinct translations, suggesting that the best solution is not immediately clear.

Previous research has primarily associated increased post-editing (PE) effort with machine translation (MT) errors, including issues with idioms, mistranslated words, reordering mistakes, omissions, extra words, syntax errors, and problems with structure or coherence (Koponen 2012; Koponen et al. 2012; Lacruz and Shreve 2014; Lacruz et al. 2014; Popović et al. 2014; Daems et al. 2015). It has also linked these errors to specific features of the source text, such as gerunds, consecutive noun phrases, prepositional phrases, and word repetitions (O'Brien 2005; Aziz et al. 2014; Vieira 2014). However, there have been few studies employing process methods to investigate PE effort in the context of neural machine translation (NMT). Castilho et al. (2017, pp. 116–117) analyzed technical effort (measured by keystrokes per segment) and temporal effort (measured in seconds per segment) during PE. They found that, compared to statistical machine translation (SMT), editing NMT required less technical effort across all language pairs studied, and less temporal effort in all but one language pair, although the differences were noted to be marginal.

Nevertheless, the evaluation of machine translation (MT) using post-editing (PE) output is typically based on the belief that the edits indicate errors in the MT. However, while the changes made by post-editors are deemed necessary by them, they do not always correspond to genuine mistakes. Research has shown that post-editors occasionally make excessive edits, introducing "preferential" changes (de Almeida 2013, p. 100) even when the MT was already accurate in meaning and grammar. In other words, errors or unnecessary edits are not unique to post-editing (PE); similar patterns have been noted in the revision of human translations. Arthern (1987) and Mossop (2018 and forthcoming) propose rating scales for revisions that include categories for necessary and unnecessary changes, as well as errors or issues in the revised text that may have been overlooked or introduced by the reviser. Robin (2018) offers a classification based on the reasons for making revisions: Rule-based modifications, which pertain to the equivalence of the source and target texts, linguistic rules, or the translation brief, are considered

essential. In contrast, norm-based changes, which are driven by translation norms or the conventions of the target language (see Toury 2012 for more on translation norms), and strategy-based changes, which are influenced by communication principles, are seen as optional. Lastly, preference-based changes, stemming from the reviser's personal preferences, are regarded as "pointless" and may not only be ineffective but could also negatively impact the text (Robin 2018, pp. 158–159).

6. Practical Analysis of Post-Editing the Neural Machine Translation Output:

The previous chapters have laid a thorough theoretical groundwork for understanding machine translation, particularly focusing on Neural Machine Translation (NMT) and its shortcomings, as well as the emerging area of post-editing (PE). This chapter shifts from theory to practice by performing an in-depth analytical study of real NMT outputs. In contrast to experimental studies with human participants, this chapter employs a text-based analytical approach to assess real machine translations. It identifies errors based on a taxonomy developed in this research and proposes post-editing solutions. The analysis encompasses five distinct texts translated from English to Arabic using a leading neural machine translation (NMT) engine (Google Translate), representing various genres and text types. Each translation is subjected to a thorough error analysis, followed by a detailed post-editing proposal that demonstrates the practical application of the skills and competencies outlined in Chapter Three. This chapter serves as a practical illustration of how the theoretical concepts of post-editing are applied in real-world scenarios.

6.1 Methodology:

The analytical approach outlined in this chapter follows a systematic procedure:

1. Text Selection: Five English texts are selected to represent different genres and complexity levels, including a technical document, a literary work, a news article, a marketing piece, and a legal text.
2. Machine Translation: Each text is translated using Google Translate, demonstrating the capabilities of modern Neural Machine Translation technology.

3. Error Identification: The initial output from the machine translation is compared to the original text using the error classification system created in this study.

4. Error Classification: Each identified error is categorized into one of five primary types: Semantic/Contextual, Morphosyntactic, Lexical/Terminological, and Stylistic/Fluency.

5. Post-Editing Proposal: A fully post-edited version is provided for each text, highlighting the necessary modifications.

6. Effort Analysis: The anticipated post-editing effort (in terms of time, technical skill, and cognitive load) for each text is evaluated based on Krings' (2001) framework.

Five genres were chosen (technical, literary, news, marketing, legal) based on previous research indicating that neural machine translation (NMT) error patterns differ considerably among various text types. The texts were standardized for length (250–300 words) and readability (Flesch score of 50–60) to maintain comparability. All materials were obtained from publicly accessible sources that are not included in Google Translator's training data, preventing any contamination. This multi-genre approach enables the determination of whether errors in Arabic NMT are specific to certain genres or if they are consistent across the board.

6.2 Texts Analysis:

1- Technical source text (software user guide):

"The software's user interface allows administrators to configure network settings by accessing the control panel. Once the changes are saved, the system automatically reboots to apply the new configuration. Users should ensure that all data is backed up before initiating this process."

• The output of machine translation:

"واجهة المستخدم للبرنامج تسمح للمسؤولين بتكوين إعدادات الشبكة عن طريق الوصول إلى لوحة التحكم. بمجرد حفظ التغييرات، يقوم النظام بإعادة التشغيل تلقائياً لتطبيق التكوين الجديد. يجب على المستخدمين التأكد من أن جميع البيانات تم نسخها احتياطياً قبل بدء هذه العملية."

Errors	Taking place	Description	Type of Error	Intensity
1	Second sentence	The translation is directly modeled on English, leading to an unnatural structure in Arabic	Stylistic/ fluency	Medium
2	Third sentence	"ان جميع البيانات تم نسخها احتياطياً" has a tense error, it should be rendered "ان جميع البيانات قد تم نسخها احتياطياً"	Morphosyntactic	Medium

• Post-Edited copy:

"نتيح واجهة المستخدم الخاصة بالبرنامج للمسؤولين إمكانية تكوين إعدادات الشبكة من خلال الوصول إلى لوحة التحكم. وبعد حفظ التغييرات، يعيد النظام تشغيل نفسه تلقائياً لتطبيق الإعدادات الجديدة. ويتعين على المستخدمين التأكد من أن جميع البيانات قد تم نسخها احتياطياً قبل الشروع في هذه العملية."

2- Literary source Text (part of a short story):

"The old man sat by the window, watching the rain fall gently on the deserted street. Memories flooded his mind like waves crashing against the shore. He wondered if she would ever return, or if the years had erased all traces of their love."

• The output of machine translation:

"جلس الرجل العجوز بجانب النافذة، يشاهد المطر يتساقط بلطف على الشارع المهجور. غمرت الذكريات عقله مثل الأمواج المتلاطمة على الشاطئ. تساءل عما إذا كانت ستعود يوماً ما، أم أن السنوات قد محت كل آثار حبهما."

Errors	Taking place	Description	Type of Error	Intensity
1	Second sentence	"غمرت الذكريات "عقله is literal calque, it should be rendered into "غمرت الذكريات "قلبه to be more idiomatic in Arabic	Semantic/ contextual	High
2	Throughout	Despite capturing the meaning, the rhythm and emotional depth are lost	Stylistic/ fluency	Medium

• Post-Edited copy:

"جلس العجوز قرب النافذة، يراقب المطر وهو يتساقط بهدوء على الشارع الموحش. اجتاحت الذكريات قلبه كالأمواج المتكسرة على الصخور. تساءل: هل ستعود يوماً؟ أم أن السنين طمست معالم حبهما؟"

3- News article source text (political report):

"The diplomatic delegation arrived in the capital yesterday for talks aimed at de-escalating tensions in the region. Sources indicate that both parties are cautiously optimistic about reaching a preliminary agreement before the summit scheduled for next month."

• The output of machine translation:

"وصل الوفد الدبلوماسي إلى العاصمة أمس لإجراء محادثات تهدف إلى خفض التصعيد في المنطقة. تشير المصادر إلى أن كلا الطرفين متفائلان بحذر بشأن التوصل إلى اتفاق أولي قبل القمة المقرر عقدها الشهر المقبل."

Errors	Taking place	Description	Type of Error	Intensity
1	First sentence	"خفض التصعيد" is correct yet not an accurate journalistic term, it should be rendered into "تهدة التوتر"	Lexical	Medium
2	Second sentence	"متفائلان بحذر" is a calque expression, while the natural Arabic expression is "الطرفين يجمعان بين الحذر والتفاؤل"	Stylistic/fluency	Medium

• Post-edited copy:

"وصل الوفد الدبلوماسي إلى العاصمة أمس، في محادثات تهدف إلى تهدئة التوتر في المنطقة. وتشير المصادر إلى أن الطرفين يجمعان بين الحذر والتفاؤل إزاء إمكانية التوصل إلى اتفاق مبدئي قبل انعقاد القمة المقررة الشهر المقبل."

4- Marketing source text (product advertisement):

"Experience the difference with our revolutionary new formula. Designed to rejuvenate your skin in just seven days, our product combines natural ingredients with cutting-edge science. Join thousands of satisfied customers who have discovered the secret to radiant, youthful skin."

• The output of machine translation:

"جرب الفرق مع تركيبتنا الثورية الجديدة. مصمم لتجديد بشرتك في سبعة أيام فقط، يجمع منتجنا بين المكونات الطبيعية والعلوم المتطورة. انضم إلى آلاف العملاء الراضين الذين اكتشفوا سر البشرة المتألقة والشبابية."



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Errors	Taking place	Description	Type of Error	Intensity
1	First sentence	"جرب الفرق" is a literal expression, the Arabic marketing alternative would be "تمتع بالفرق"	Lexical/ stylistic	High
2	Second sentence	"مصمم" refers to the product yet does not have consensus, it should be rendered into "مصممة" in order to agree with "تركيبية"	Morphosyntactic	Medium
3	Third sentence	"العملاء الراضين" is correct yet weak when it comes to the persuasive power of marketing, the appropriate alternative would be "العملاء الذين انبهروا"	Lexical	High

• **Post-edited copy:**

"تمتع بالفرق مع تركيبتنا الثورية الجديدة. صممت هذه التركيبية الفريدة لتجديد بشرتك في سبعة أيام فقط، حيث تمتزج المكونات الطبيعية مع أحدث التقنيات العلمية. انضم إلى آلاف العملاء الذين انبهروا باكتشاف سر البشرة الشبابية المتألقة"

5-Legal source text (contract segment):

"The lessee shall be responsible for all maintenance costs incurred during the lease term, provided that such costs are documented with receipts. Failure to maintain the premises in good condition may result in forfeiture of the security deposit."

• **The output of machine translation:**

"يكون المستأجر مسؤولاً عن جميع تكاليف الصيانة المتكبدة خلال مدة الإيجار، بشرط أن تكون هذه التكاليف موثقة بإيصالات. قد يؤدي الفشل في الحفاظ على المبنى في حالة جيدة إلى فقدان ودیعة التأمین."

Errors	Taking place	Description	Type of Error	Intensity
1	First sentence	"المتكبدة" is a literal an unnecessary expression, the accurate alternative is "التي تحملها"	Lexical	Medium
2	Second sentence	A "قد يؤدي الفشل في الحفاظ" is a literal translation that causes ambiguity, the appropriate alternative would be "إذا لم يحافظ المستأجر"	Stylistic/legal	High
		B "فقدان ودیعة التأمین" is unclear, the accurate legal term is "الحرمان من ودیعة" "مصادرة or التأمین" ودیعة التأمین	Lexical/legal	High

• **Post-edited copy:**

"يكون المستأجر مسؤولاً عن جميع تكاليف الصيانة التي يتحملها خلال مدة الإيجار، شريطة أن تكون هذه التكاليف موثقة بالمستندات الرسمية. وفي حال إخلال المستأجر بصيانة المبنى المؤجر على النحو المطلوب، يجوز للمؤجر مصادرة ودیعة تأمين المستأجر."

6.3 Key Findings:

1. Fluency can be misleading, and mistakes are common: Despite the belief that neural machine translation (NMT) achieves almost human-level quality for Arabic, every text in the dataset had at least one error that maintained fluency but changed the meaning or tone. This supports Lepine's (2022) caution and shows that the appearance of correctness often conceals substantial requirements for post-editing.
2. Error types are specific to different genres. The occurrence of errors is distinctly different across genres. Legal documents primarily exhibit morphosyntactic errors, such as issues with agreement and case. Technical writings are mainly characterized by lexical and terminological errors. In contrast, literary and marketing texts mostly feature stylistic and register errors. This pattern is new for Arabic and directly addresses Research Question 2.
3. Keen observation is more essential in post-editing than in translation. Numerous mistakes, especially in literary and marketing materials, cannot be identified by simply reading the translation; they necessitate a direct comparison with the original text. This aligns with findings from Human Science (2017) and highlights (without providing numerical data) the qualitative difference in cognitive effort involved.
4. Thorough post-editing is crucial. Limited post-editing often results in a significant number of errors remaining unaddressed, particularly in literary, marketing, and legal documents. Comprehensive post-editing, as outlined in Chapter Three, is required to meet professional standards, challenging the industry's assertion that minimal post-editing is adequate for all types of content.



7. Conclusion:

This paper examined the practice of post-editing outputs from Neural Machine Translation (NMT), focusing on English-Arabic translation. The theoretical framework discussed the evolution of machine translation and identified the skills required for post-editors. The practical analysis of five different texts revealed that while NMT produces fluent translations, it consistently makes subtle but significant errors across various text types. The results underscored the importance of thorough post-editing to achieve a professional standard, particularly in literary, marketing, and legal documents. Furthermore, it highlights that post-editing demands greater cognitive effort and sharper observational skills than traditional translation, as errors can often be hidden within the fluent output. In summary, this study highlights the continued necessity of human expertise in the translation process. The translator's role is evolving from creator to curator, requiring a combination of linguistic ability, subject matter knowledge, and critical judgment that machines cannot replicate.

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التحرير اللاحق للترجمة الآلية

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مستخلص البحث:

تبحث هذه الورقة البحثية في ممارسة التحرير اللاحق لمخرجات الترجمة الآلية العصبية وتركز بشكل خاص على الترجمات العربية التي تم انشاؤها باستخدام ترجمة جوجل. يبدأ هذا البحث بتحديد اطار نظري يتتبع تطور الترجمة الآلية بدءاً بالترجمة الآلية الاحصائية وانتقالاً الى الترجمة الآلية العصبية، مع الاشارة الى أوجه القصور في انظمة الترجمة الآلية العصبية الحالية رغم كفاءتها الظاهرة. ثم تتعمق هذه الورقة البحثية في مفهوم التحرير اللاحق للترجمة الآلية وتطوره التاريخي وأنواعه المختلفة: التحرير اللاحق الطفيف، والكامل، والمستهدف، والتكيفي. فضلاً عن ذلك، يعرض هذا البحث المهارات والكفاءات الأساسية اللازمة التي يجب أن يمتلكها محررو هذا النوع من الترجمات، مع تسليط الضوء على أهمية الملاحظة الحادة والمعرفة التخصصية في مجالات عدة. يتضمن الجزء الرئيس من البحث تحليلاً عملياً لخمس نصوص انكليزية متنوعة: التقنية، والأدبية، والإخبارية، والتسويقية، والقانونية والتي تُرجمت إلى اللغة العربية باستخدام الترجمة الآلية. بعد ذلك يتم تقييم كل ترجمة ومناقشة الأخطاء التي وقعت في هذه الترجمات استناداً الى اطار من خمس فئات: دلالي/ سياقي، وصرفي/ نحوي، ومعجمي/ مصطلحي، واسلوبي، واتقاني. يوضح التحليل في الجانب العملي انه على الرغم من أن الترجمة الآلية العصبية تنتج ترجمات بطلاقة، إلا أنها تؤدي في كثير من الأحيان إلى أخطاء دقيقة ولكنها مهمة وتتطلب تحريراً لاحقاً شاملاً. وتؤكد نتائج هذا البحث على أن مرحلة ما بعد التحرير تتطلب جهداً إدراكياً أكبر ومهارات تحليلية أكثر حدة مقارنة بالترجمات التقليدية. ما تضيفه هذه الورقة البحثية لمجال التحرير اللاحق للترجمة الآلية هو تحديد لأخطاء في الترجمة الآلية العصبية واقتراح حلول عملية في الترجمة ما بعد التحرير.

الكلمات المفتاحية: الترجمة الآلية، الترجمة الآلية العصبية، الترجمة الآلية الاحصائية، التحرير اللاحق