Error Analysis of Neural Machine Translation in Technical Texts: Google Translate as a Case Study

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Abstract: The reliability of neural machine translation has increased in various fields. However, the accuracy of machine translation is still questionable, even with advancements in neural machine translation, but the situation should be better when dealing with technical texts that are known to be clearer, more precise, and fixed. Therefore, the necessity for human intervention in revising the translation should be to a limited extent. This study aimed to investigate the translation errors faced by neural machine translation, represented by Google Translate when translating technical texts. It adopts an error analysis approach to evaluate the quality of the aforementioned neural machine translation by examining its translation of a technical text from Arabic into English and comparing it with a human-certified translation. It also evaluates the extent of the necessity for human intervention in revising the translation. The results indicate some errors in Google translation, varying from comprehension and linguistic errors to translation errors, highlighting the necessity for human intervention. Google translation has proven to be better than human translation in several respects. The implications of this research indicate the remarkable performance of Google Translate surpassing human translation in several contexts, which can be used in translating technical texts with the need for human intervention.

Keywords: Neural Machine Translation, Error Analysis, Google Translate, Technical Texts, Translation Problems.

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تحليل أخطاء الترجمة الآلية العصبية في التعامل مع النصوص التقنية: ترجمة جوجل كحالة دراسية

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المستخلص: إن الاعتماد على الترجمة الآلية يتزايد في مجالات متعددة، ولكن لازالت الدقة لهذا النوع من الترجمة محل تساؤلات بالرغم من التطورات التي شهدها مجال الترجمة الآلية العصبية، إلا أن الوضع قد يكون مختلفاً عند التعامل مع نصوص الترجمة التقنية والتي تتصف بالوضوح والدقة والثبات. وتهدف هذه الدراسة إلى معرفة المشاكل التي تواجهها الترجمة الآلية - ممثلةً بترجمة جوجل- عند التعامل مع النصوص التقنية. وتستخدم هذه الدراسة منهجية تحليل الأخطاء؛ لتقييم جودة الترجمة من خلال تدقيق ترجمة جوجل للنصوص التقنية من اللغة الإنجليزية إلى اللغة العربية ومقارنتها مع ترجمة بشرية معتمدة. وتشير نتائج الدراسة إلى وجود بعض الأخطاء في ترجمة جوجل تتنوع ما بين أخطاء لها علاقة بالاستيعاب، وأخطاء لغوية، وأخطاء في نقل المعنى والتعابير، والتي تظهر الحاجة للتدخل البشري. كما تشير النتائج إلى تفوق ترجمة جوجل على الترجمة البشرية في عدة مواضع، وتستخلص دلالات هذه الدراسة الأداء الملحوظ لترجمة جوجل والتي بالإمكان استخدامها في التعامل مع النصوص التقنية مع استمرار الحاجة للتدخل البشري نسبيًا.
الكلمات المفتاحية: الترجمة الآلية العصبية – تحليل الأخطاء – ترجمة جوجل – النصوص التقنية – مشاكل الترجمة

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1. Introduction:

Errors are possible in human or machine translation (MT); however, with the advancement of Artificial Intelligence (AI), technology is making significant progress. Machine translation has developed since its emergence in 1949; MT has witnessed significant development, and it has recently become more popular with developments in translation technological tools that help to reduce communication barriers between different languages. This has contributed to the development of several MT models. The first model was a Rule-Based Machine, followed by Corpus-Based Machine Translation, Example-Based Machine Translation, Data-Driven Machine Translation, Statistical Machine Translation and, most recently, Neural Machine Translation (NMT) respectively. The NMT model was proposed by Kalchbrenner and Blunsom (2013) and it is "composed of increasingly complex and interconnected layers of basic feed-forward and recurrent units, or neurons" (Balashov, 2022, p.7). The process of translation in NMT comprises three stages: (1) the encoder, which receives the source text; (2) the attention (transformer), which is a technique to create a close characterisation of the source text that then continuously initialises and informs in a way that can be complex and non-modular; and (3) the decoder, which produces a sequence in the target language (TL) (Pérez-Ortiz et al., 2022; Koehn, 2020; Balashov, 2022). In other words, when translating every sentence in the source text, the sentence in the target text is estimated from several conditional probabilities using the final quantity, which has a size and direction coupled with the chain of probable translations. It is important to note that MT is unlike Computer-Assisted Tools (CAT), which assist translators by enabling them to have easy access to databases of terminologies and online dictionaries to carry out their translations.

Among the different types of machine translation software, including Systran, eTranslation, and Bing, is Google Translate (GT), which is one of the most advanced translation machines. GT operates under NMT and its system functions at the sentential level, where it matches the input language to the output language (Griffith 2020). In other words, it does not translate a word or phrase but rather a whole sentence one time and it takes into consideration contexts to assist in selecting the appropriate equivalent for the target language. This has helped to increase the accuracy of GT translation in comparison with its state before 2016 (see section 2.1).

However, debates on the quality of GT for different types of texts such as literary, legal, and administrative texts have arisen whereby some errors were detected. These errors are usually related to connotative pragmatic messages, cultural messages, beliefs, norms, and social values, and the machine may not be capable of realising all of them in different contexts. In addition, GT translation between European languages (French, Italian, German, etc.) including English seems to reach a higher level of accuracy which also leads to a higher degree of data extraction while the accuracy was lower in oriental languages, which includes Arabic language (Gunawan & Khairunnisa 2023; Griffith 2020; and Aiken & Balan 2011). The possibility behind this is due to the low-resource languages in GT in comparison with high-resource languages inserted into the GT database. This indicates the importance of investigating. However, technical texts are characterised as clear, precise, and fixed, and do not always contain connotative or cultural messages and they may share similarities across different languages. Therefore, it is necessary to validate the quality of GT translation when dealing with technical texts. Given this context, this study aims to investigate the quality of GT, which is one of the most prominent types of NMT, and to answer the following questions:

- What types of common errors does GT commit when translating technical texts from Arabic to English?

- To what extent is human intervention necessary in executing technical translation by GT?
- Can GT surpass human translation in the accuracy and quality of translation?

2. Theoretical Framework:

2.1 Google Translate:

GT began to provide translation services in 2006 using Statistical Machine Translation (SMT), which was founded in the 1990s and was dominant in the field of MT for more than two decades. In SMT, translations were 'generated on the basis of statistical models whose parameters are derived from the analysis of bilingual text named as parallel corpora' (Ebrahim, et al. 2017, p.10). However, SMT has several deficiencies related to building models using short co-occurring words in the same sentence, but these co-occurring words are translated independently, disregarding their relationship to one another (Kenny, 2022, p. 37). Other problems involve word drop (when a system fails to find a translation for a word if the source language [SL] word has two distinct ways of translating the same sentence). However, it is important to mention the role of SMT in paving the way for more advanced technology in machine translation and, in particular, making it clear that machine translation systems that are data-learned function better than other types of systems.

Since 2016, with the large-scale revolution of NMT, this technology has managed to make an enormous leap in quality (Kenny, 2022; Balashov, 2022); thus, Google shifted to using NMT. NMT, including GT, is considered revolutionary in MT.

Referring to GT, Benkova et al. argue that 'the ability of the so-called "zero-range translation", i.e., direct translation from the source language to the target language without the need for an intermediate step-translation into English, is an improvement over the previous version of GT (statistical machine translation or rule-based machine translation)' (2021, p.2).

NMT is used by many online translation services such as GT, Bing, Systran, and eTranslation. It works on the basis of predicting the possibility of a word sequence and "it uses a deep neural network to process huge amounts of data, and is primarily dependent on training data, from which it learns. If there is a substantial dataset for training the model, then NMT can process any language pair, including languages that are difficult to understand" (Benkova et. al, 2021, p.1) Using sequence-to-sequence models, NMT progressed enormously with regard to translation accuracy.

However, NMT in general, and GT in particular, may not always be very accurate and human interventions are sometimes needed. This leads to the necessity of Human-Aided Machine Translation (HAMT) which is defined as "the style of translation in which a computer system does most of the translation, appealing in case of difficulty to a (mono- or bilingual) human for help" (Maegaard 1999, p.67). In other words, it is the process of revising and editing of MT translation by a human translator for any type of errors to ensure the quality of the translation.

It is normal for GT to make errors in some deep explanatory texts that could have connotative meanings, such as literary translations, political translations, social sciences, and humanities works, but this may not be the case for technical texts, which are considered to be precise, fixed, and clear.

2.2 Error Analysis in Translation:

In translation, there is no universal categorisation of errors owing to the different theories of translation and definitions of translation errors. Neubert and Shreve (1995) note that defining and identifying translation errors is a complex and difficult process, and Pym (1992, p.281) considers translation errors an illustration of deficiencies in translation skills. In addition, Hatim and Mason (1997, p.203) describe translation errors as a significant discrepancy in the meaning between the SL and TL, and they also describe them as violations of the system in the TL.

The above definitions of translation errors differ because, according to Hansen (2010), they are based on different translation theories and norms, which presumably lead to different categorisations of translation errors. As far as the current study is concerned, the concept of error examined by the current study can be defined, according to the American Translators Association (2016), as having negative impacts on the use or understanding of the TL. This general definition can accumulate the most possibilities for errors when translating from SL to TL.

In addition, these definitions lead to different categorisations of translation errors, in some language pairs, for instance, Arabic–English and Vietnamese–English, as the type of translation errors can be different due to the unique nature and complexities of each language. According to Benhaddou (1991), there are two types of errors, covertly erroneous errors, errors that resulted due to differences in situational dimensions, and overtly erroneous errors, errors that resulted from the level of denotative meaning or any violation of the TL system. Pym (1992) believes that there are two types of errors: binary and non-binary. Binary errors refer to incorrect translations, while non-binary errors refer to translations that are not fully incorrect but need improvement. However, Nord (1997) argues that there are four classifications of translation errors: pragmatic, cultural, linguistic, and text-specific. Pragmatic errors emanate from a lack of knowledge of hidden connotative meanings in the source text, and cultural errors result from a lack of competence in adapting cultural expressions in the source text to the target text. Linguistic errors occur when failing to use the correct structures of the TL to deliver meaning, and text-specific translation errors represent a lack of suitability of the translation to the target readers.

To achieve the objectives of the current study, it is first important to note that the text we are dealing with is technical and second, we are dealing with neural machine translation tools in which cultural aspects may not be the appropriate context for discussion. Pham (2005) classifies translation errors into nine categories: pragmatic errors, addition, omission, inaccurate rendition of lexical items, too-free translation, distorted meaning of the source text, too-literal translation, wrong focus of attention, and wrong lexical choice. Pham’s taxonomy of errors is not limited to translation errors but also includes comprehension and linguistic errors. Comprehension errors occur when the syntax in the source text is misunderstood, or a lexical item is misread and translated accordingly. Linguistic errors include grammatical, morphological, collocational, syntactic, and inappropriate words. The translation error analysis model by Pham (2005) was used in her Ph.D. thesis, whereby she analysed the errors that occur when Vietnamese translation students translated between English and Vietnamese. A more detailed discussion of this model is provided in section 2.

2.3 Nature of Technical Texts:

Technical discourse is a unique discourse in language that is distinct from other types of discourse owing to its characteristics. According to Laplante (2019), two main characteristics of technical discourse among other types of discourse are precision and intent. Because most ideas expressed in technical discourse are fixed, technical texts are precise and do not leave room for different interpretations. In addition, technical discourse does not attempt to elicit emotions from the reader; rather, it seeks to convey messages as concisely and correctly as possible. This is unlike poetry, in which it is preferable to stimulate readers’ emotions. In addition, Race et al. (2021) provided further characteristics of technical discourse: it is accurate, clear, complete, and professional. All these assertions on the concision, clarity, and accuracy of the nature of technical writings are further supported by Tavares et al., who affirms that “it is always important to make sure that technical writing is straightforward, exact, detailed, and accurate to manage its specialised language and deliver its content effectively" (2023, p.3).

This type of text having the aforementioned characteristics of accuracy, precision, and clarity may be more easily handled by machine translation, unlike other types of texts that challenge MT, especially those with pragmatic connotative meanings and cultural elements. Olohan compared technical texts and literary texts, considering that technology is under the umbrella of scientific areas, stating "the translation of science will lack the richness of features that fascinate in literary texts and will provide little scope for translators to make decisions, exercise agency, etc." (2016, p.428). According to Derdi (2023, p.44), scientific texts are known to be abstract and technical texts are more specific, although both are normally written in a simple language.

Technical texts also include different types of information depending on the nature of each context in which the information is presented, as well as the degree of specialisation for each text. According to Pringle and O'Keefe (2009), the information in technical texts can be categorised into four types: interface, reference, conceptual, and procedural. The first category provides visual identification of a piece of information, while the reference information identifies the function. Conceptual information illustrates situations in which function (X) is better than function (Y), and procedural information refers to the way a particular function is used. Travers et al (2023, p.2) asserts that "technical texts are found in a wide range of contexts and include different text types that, though perhaps not identified as technical straightaway, may be technical in nature. A descriptive text may be technical, as may a narrative or even an argumentative text." However, writing technical texts is complex and they may contain multiple types of information.

2.4 Previous Studies:

Many studies have investigated the use of GT in translating from English to Arabic in different fields, but few have analysed errors in translation from Arabic to English with a particular focus on technical texts. Due to the peculiarity of technical texts being normally fixed and not involving sociocultural components, machine translation (GT in this case) should be more accurate than when translating in other fields.

Al-Jarf (2016) conducted an error analysis of the translation of a random sample consisting of 200 technical terms from English to Arabic using GT, which were analysed by the researcher individually and in isolation from context. A further review by three translation and linguistic specialists was conducted to ensure the accuracy of error analysis. GT was found to provide equivalents to technical terminologies that are in full form, but its translation was inconsistent when translating words containing a variety of prefixes, compounds, blends, and roots with the same suffix. The findings revealed several deficiencies in the translation of GT from English to Arabic, including syntactic, morphological, semantic, contextual, and orthographic errors. Al-Jarf attributes these errors to a possible explanation: GT uses Statistical Machine Translation (SMT), whereby translations are conducted based on statistical models derived from bilingual text corpora. Al-Jarf examined the translation of individual technical terminologies, whereby GT was used merely as a dictionary to look up the equivalents of these technical terms in Arabic. Moreover, this study was conducted when GT was using SMT, which was terminated in 2016 when GT started using a more advanced way of translating, namely NMT[1].

[1] Article on Google Shift from SMT to NMT can be accessed through this link: https://blog.google/products/translate/found-translation-more-accurate-fluent-sentences-google-translate/

Al-Timen and Abbas (2021) conducted an error analysis on a selected medical translation text about COVID-19 using GT from English into Arabic, where they analysed the translation at four levels: syntactic, lexical, morphological, and semantic. The results of the study indicated that GT translation contained errors at all four levels; the most common errors were semantic and syntactic errors, followed by morphological errors, and the least common errors were lexical errors. Although the text was relatively short (141 words), the errors detected were relatively frequent, especially when the GT shifted from using SMT to NMT, which relies on deep neural networks to process enormous amounts of data, depending on the training data from which it learns.

Sulaiman and Mohammed (2019) conducted another study that investigated error analysis in an administrative translation, which is the field that the current research examines, but not by GT, by students in the third year of their translation BA program. The authors distributed six texts in the administrative field to be translated by 58 students, and these translations were error-analysed using Liao's (2010) taxonomy of errors, namely rendition errors, language errors, and miscellaneous errors. The results indicate that semantic errors were most common among all errors detected in students' translations of administrative text, and most of these errors were related to students' difficulties in finding appropriate equivalents in the TL. The second most common errors were syntactic errors relevant to selecting appropriate tenses, and translation errors were at the bottom of the list of errors in students' translations of administrative texts. These types of errors are most commonly committed by human translators when translating administrative texts.

Another study in which the quality of GT was assessed, by analysing its errors when translating legal texts from Arabic into English, was conducted by Alkatheery (2023). Five legislative texts were translated using GT and then manually error-analysed by the researcher according to four error classifications: lexical errors, syntactic errors, omissions, and legal-register–related errors. To ensure the reliability of the translation quality assessment, official human translations of the five legislative documents were used to ensure inter-rater reliability. The results of the study revealed that the highest percentage of errors made by GT was lexical, accounting for nearly half of all detected errors, followed by syntactic and legally registered errors. Omission errors were the least frequently committed by GT when translating legal texts from Arabic into English. Legal texts require a high level of accuracy, and errors can be disastrous. It can be seen that GT may include errors at different levels, but this tool can be accurate in omitting nothing from the ST.

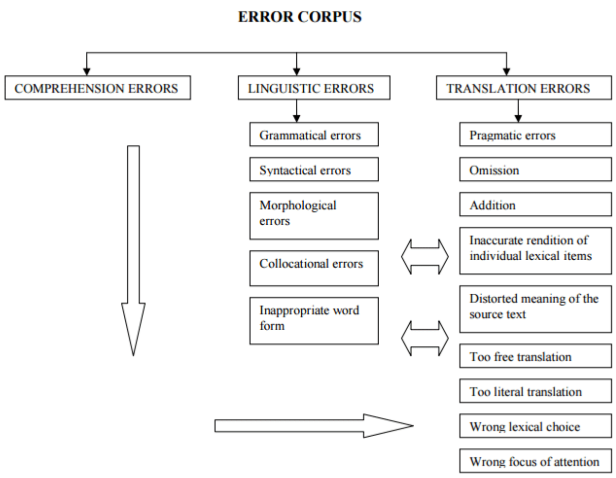
A study on the assessment of GT was carried out by Jabak (2019) in which he used samples of eight random Arabic texts from the book entitled *Thinking Arabic Translation: A Course in Translation Method: Arabic to English*. The eight texts were translated from Arabic into English by GT, and the researcher analysed the errors in the translations using the model translation of these texts given by Dickins et al. (2017). The findings revealed that the lexical and syntactic errors made by GT led to ambiguous meanings in the output translation. It can be seen that lexical and syntactic errors are present in the GT translations of these different texts in different areas.

From the above studies, it can be seen that the quality of GT translation varies from field to field, and it is important to explore the common errors committed in each field when translated. However, an examination of the literature shows few studies that examine the quality of GT in translating technical texts from Arabic into English, which is the target of the current study.

3. Methodology:

This study compares one type of neural machine translation, namely GT, and an official translation of a government document. The tool used in this research consists of translating a technical text entitled "Annual Report 2022" issued by the Ministry of Communication and Information Technology (MCIT)[2] in Saudi Arabia with a word count of 21,430. The text is mostly technical and includes the objectives of the MCIT, efforts to build an innovative digital economy and digital society, and achievements in 2022. To ensure the reliability of the translation quality assessment, GT was used to translate the entire document from Arabic into English, and the translation was evaluated and compared with the English version of the MCIT report, which was translated by certified human translators and is available on the MCIT website[3]. The MCIT translation was also used as an evaluation tool for GT quality. To ensure the accuracy of the error analysis, the detected errors in the GT translation and the official certified translation of the MCIT were reviewed by two researchers holding PhDs to appropriately classify these errors.

Figure 1. Pham's (2005) Error Analysis Model



Corder (1974), one of the key figures in error analysis, lists five phases in analysing errors: 1) selecting a text, 2) identifying errors in the text, 3) classifying errors in the text, 4) disclosing errors, and 5) evaluating errors. The first phase was carried out as explained in Section 2. In the second stage, several errors were identified in the GT translation. In the third phase, the study used Pham's model (Figure 1) to analyse translation errors. This model groups errors into three main categories: comprehension errors, linguistic errors, and translation errors. Translation errors commonly happen due to the interference of the SL into the TL, insufficient comprehension of the ST and lack of linguistic competence in the TL and this is the reason behind these three error categories. Most of these errors are interrelated, as shown in Figure 1, where comprehension errors can lead to translation

[2] MCIT website: https://www.mcit.gov.sa/sites/default/files/2023-05/MCIT_Annual%20Report_2022_Media_Web_1.pdf

[3] MCIT Annual Report in English can be accessed through this link: https://www.mcit.gov.sa/sites/default/files/2023-07/MCIT_Annual%20Report_2022_En-Web_0.pdf

errors, linguistic errors can lead to translation errors, and vice versa. These categories help to validate the quality of the translation and determine the types of errors found in the translation.

4. Results and Discussion:

Table 1. Error Analysis of GT Translation

Error Category	Frequencies	Percentage
Comprehension Errors/Misunderstanding of Socio-Cultural Nuance	**4**	**7.69%**
Linguistic Errors/Syntactical Errors	**9**	**17.31%**
Linguistic Errors/Wrong Use of Prepositions	**2**	**3.85%**
Linguistic Errors/Grammatical Errors	**1**	**1.92%**
Linguistic Errors/Wrong Word Order	**1**	**1.92%**
Translation Errors/Cohesion Errors	**6**	**11.54%**
Translation Errors/Wrong Transliteration	**3**	**5.77%**
Translation Errors/Too literal Translation	**5**	**9.62%**
Translation Errors/Addition	**2**	**3.85%**
Translation Errors/Inaccurate Rendition of Individual Lexical Items	**9**	**17.31%**
Translation Errors/Wrong Lexical Choice	**9**	**17.31%**
Translation Errors/Distorted Meaning of the Source Text	**1**	**1.92%**
Total	**52**	

It can be seen from Table 1 that the total number of errors detected in the GT translation of the technical report from Arabic into English is 52, ranging from comprehension errors (four in total) and linguistic errors (13 in total) to translation errors (35 in total). The total number of errors was relatively low considering the volume of the report, which has a length of 21,430 words. To gain a more in-depth understanding of these errors, each error category is discussed separately.

First, only four comprehension errors were made by GT. All of these errors fall under "Misunderstanding of socio-cultural nuance". For example, the sentence تستخدم لإثبات هوية الموقع وموافقته على التعامل الإلكتروني "*tstkhdm lithbāt hwyt l-mūqʿ ūmwāfqth ʿl t-tʿāml l-ilktrūnī*" is supposed to be translated neutrally with no gender specification. Unlike English, Arabic uses masculine pronouns to refer to non-gender specifications. Gender specification exists in most Arabic verbs and nouns, as no sentence can be written without it. Due to this lack of cultural nuance, GT mistranslated the verb موافقته "*mwāfqth*" into "his approval" and the translation was "to prove the identity of the signatory and his approval of the electronic transaction". In comparison, the translation of the MCIT maintained gender neutralism in English and provided the translation "to prove the identity of the signatory and their approval of the electronic transaction". Nevertheless, this error did not distort the meaning of the sentence; rather, it affected the translation quality.

Another example of comprehension errors is the GT translation of the phrase جميع زملائي وزميلاتي "*jmīʿ zmlā'ī ūzmīlātī*", which is translated as "all my colleagues and male colleagues". It is unnecessary to indicate the gender of "colleagues" in the TL (English), as "colleagues" has the characteristic of being genderless, which can give the intended meaning of the source text, unlike Arabic, where both genders should be indicated. In contrast, in the MCIT translation, the phrase was simply translated as "all my colleagues" with no reference to gender.

Second, linguistic errors comprised 13 errors, accounting for 25% of all errors found in the GT translation. These errors vary from syntactical errors, grammatical errors, wrong use of prepositions, and wrong word order, and syntactical errors were the most common among them. For example, the sentence وبالدعم المباشر من سمو سيدي ولي العهد-رعاه الله- حافظ سوق التقنية في المملكة على مكانته كأكبر سوق في منطقة الشرق الأوسط وشمال أفريقيا حيث وصل إلى أكثر من 154 مليار ريال "*ūbāldʿm l-mbāshr mn smū sīdī ūli l-ʿhd-rʿāh Llāh- ḥāfẓ sūq t-tqnīt fi l-mmlkt ʿl mkānth k'akbr sūq fī mnṭqt sh-shrq l-awsṭ ūshmāl afrīqīā ḥīth ūṣl il akthr mn 154 mlīār rīāl*" is one sentence, but in the GT translation, it is divided into two sentences: "...and with the direct support of His Highness the Crown Prince - may God protect him - the technology market in the Kingdom maintained its position as the largest sector. In the Middle East and North Africa region, it reached more than 154 billion riyals..". As a result, the meaning in the target text was changed and did not deliver the idea that the "technology market is the largest in the Middle East and North Africa". This syntactic error in the GT translation leads to a loss of meaning. Syntactic errors are not considered to be frequent in GT translation, which is further seen in Alkatheery (2023), where syntactic errors were not the most common type of error. In addition, syntactic errors were found in the GT translation by Al-Jarf (2016), Jabak (2019), and Al-Timen and Abbas (2021).

Another example of linguistic errors is the grammatical error in which the sentence تلا ذلك الموافقة على نظام الاتصالات وإنشاء هيئة الاتصالات وتقنية المعلومات لتتولى تنظيم "*tlā dhlk l-mwāfqt ʿl nẓām l-ātṣālāt winshā' hī'it l-ātṣālāt ūtqnīt l-mʿlūmāt t-tūl tnẓīm*" is translated as "Approval of the communications system and the establishment of the Communications and Information Technology Authority to regulate…" which lacks a verb in the first part of the sentence to indicate that there was approval and then the establishment of Communication and Information Technology. This grammatical error conveyed a message different from the ST. However, the translation of the MCIT was more accurate: "This was followed by the approval of the Telecommunications Act and the establishment of the Communications and Information Technology Commission". Additionally, another linguistic error was detected in the GT translation, but this time with word order, whereby the phrase رأس المال البشري "*r'as l-māl l-bshrī*" was rendered as "capital human resources", which is normally referred to as "human capital"; this is how the MCIT translation delivered it, where the word "human" functions as an adjective for capital.

The third category of errors, namely translation errors, constituted more than half (67.23%) of the errors made by GT translation, and it includes cohesion errors, incorrect transliteration, too-literal translation, addition, inaccurate rendition, wrong lexical choice, and distorted meaning of the ST. This result is in line with the results found by Al-Timen and Abbas (2021) and Alkatheery (2023); translation errors were the most common errors made by GT. First, cohesion is essential in any translation text, as it ensures the logical connection of sentences through appropriate lexical items. One example of GT translation where the sentences were not connected appropriately that affected the delivery of meaning is the translation of رأى الحاجة إلى هذه المخترعات الحديثة بوصفها ضرورة من ضرورات التنمية ووسيلة من وسائل الأمن الداخلي والخارجي، "*r'a l-ḥāj.t il. h.dh l-mkhtrʿ.āt l-ḥdīth.t būṣfh.ā ḍ.rūrt m.n ḍ.rūrāt t-tnmī.t wus.īlt mn ūs.ā'il l-amn d-dākhl.ī wālkhārj.ī*", which was transferred into English in two separate sentences that led to a change in the meaning: "He saw the need for these modern inventions as a necessity. Development vehicles and a means of internal and external security..." In addition, there is no mention of vehicles in the target text, which also causes a distortion in meaning. There should have been no division of the sentence so that the sentence would mean "He realized the urgent need for modern inventions and systems being expedient to the development and maintenance of our nation's security, internal and external alike", as rendered by the MCIT.

Another translation error detected in the GT neural translation is the inaccurate rendering of transliteration. For example, the proper name in the sentence أطلقت الوزارة خدمة "موثوق" لإصدار التراخيص الإعلانية "*'aṭlqt l-ūzārt khdmt "mūthūq" liṣdār t-trākhīṣ l-iʿlānīt*" should have been transliterated from Arabic into English. However, when GT translated the sentence, it neglected the proper name, as "The Ministry launched the "Trustworthy" service for issuing advertising licenses", where it should have been rendered as the MCIT translated it: "MUTHUQ".

Furthermore, in translation errors, the translation of GT sometimes becomes very literal and imitates the source text to a large extent, even in sentence structures where there could instead have been easier lexical expressions in English. For example, the phrase المنهجية المتبعة في التقارير "*ālmnhjīt l-mtbʿt fī t-tqārīr*" is translated as "the methodology used in preparing the report…" where GT could have simply rendered it into "report methodology". This example shows the literalness of GT when translating some expressions, not only in the meanings of lexical items but also at the structural level; this can be problematic because every language has its own structure and style in composing language expressions. However, this error was avoided in the MCIT translation, which translated the phrase simply as "report methodology".

Another error in GT is the addition of extra lexical items as in the case of translating the sentence والسعي إلى توفير بيئة جاذبة للإستثمار "*wālsʿī il tūfīr bī'it jādhbt llistthmār*", which is rendered in the TL as "We seek to provide an attractive environment for investment". However, there is no pronoun in the source text, and the correct translation, given in the MCIT translation, is "The Ministry also strives to provide..." (GT mistakenly used the pronoun "we"). Similarly, another addition was found in the translation of the phrase بالتوافق مع استراتيجية الوزارة "*bāltwāfq mʿ astrātījīt l-ūzārt*", which was translated by GT as "in accordance with with the Ministry's strategy". The addition of the preposition with was unnecessary.

In other cases, GT provided inaccurate renditions of specific lexical items; for example, one word was mistranslated in the sentence وفي ظل الدعم والتمكين والثقة التي أولتها قيادتنا الرشيدة-حفظها الله- لقطاع الاتصالات وتقنية المعلومات "*ūfī ẓl d-dʿm wāltmkīn wālthqt t-tī awlthā qīādtnā r-rshīdt-ḥfẓhā Llāh-lqṭāʿ l-ātṣālāt ūtqnīt l-mʿlūmāt*", which is translated as "In light of the support, empowerment and confidence that our wise leadership - may God protect it - has given to the communications and information technology sector". The error here is the selection of the word "confidence" instead of "trust" because confidence is not given but built.

In GT translation, the inaccurate selection of appropriate words for certain contexts can also be found; for example, the sentence باعتماد نظام الاتصالات وتقنية المعلومات "*bāʿtmād nẓām l-ātṣālāt ūtqnīt l-mʿlūmāt*" was translated as "Telecommunications and Information Technology system". However, the sentence came in a legal context in which the word نظام refers to "acts", not the technical concept "system". This depicts the deficiency of the GT in distinguishing between the contexts surrounding the word to realise the appropriate equivalent. Similarly, another inaccurate selection of words is seen in the translation of the phrase التقنيات التقليدية "*āltqnīāt t-tqlīdīt*", which is translated by GT as "traditional technologies". The intended meaning in the ST refers to "basic technologies", as shown in the MCIT translation, but GT did not manage to select the suitable word. Moreover, these contextual errors were also found in the GT translation of technical terms in the Al-Jarf study (2016); although GT has shifted from SMT to NMT, contextual errors seem to be problematic for GT in some cases.

Some translation errors by GT distorted the meaning of the ST, as shown in the following example: The phrase من قبل القيادة الرشيدة "*mn qbl l-qīādt r-rshīdt*" was rendered into English as "we accept wise leadership", which is significantly different from the intended meaning by the source text. However, in the MCIT translation, it was translated accurately as "by the wise leadership".

It is important to note that the translation was carried out in GT by inputting several paragraphs in GT and then translating them automatically without having the entire source text altogether, owing to the large number of words in it. These paragraphs were taken from the same topic, ensuring that no overlap occurred between subtopics.

No omission errors were found in the GT translation of this technical text, which is consistent with the results of previous studies surveyed in the literature (Al-Jarf, 2016; Sulaiman & Mohammed, 2019; Jabak, 2019). In fact, although Alkatheery (2023) found some omission errors, they represented the least-frequent type of errors in her study, which shows that NMT, represented by GT in this regard, rarely commits omission errors.

3.1 Errors in the MCIT translation:

When comparing the translation of GT with the translation of the MCIT, which was conducted by certified official translators, several instances were observed where the GT proved to be more accurate than the certified translators.

Table 2. Error Analysis of the MCIT Translation

Error Category	Frequencies	Percentage
Linguistic Errors/Wrong Use of Prepositions	**1**	**5%**
Linguistic Errors/Grammatical Errors	**2**	**10%**
Translation Errors/Omission	**6**	**30%**
Translation Errors/Addition	**4**	**20%**
Translation Errors/Inaccurate Rendition of Individual Lexical Items	**6**	**30%**
Translation Errors/Distorted Meaning of the Source Text	**1**	**5%**
Total	**20**	

Although several errors were made by GT when translating this technical document, GT delivered more accurate translations than the MCIT on several occasions. As shown in Table 2, these errors are mainly linguistic and translation-related. There are 19 such errors, more than half of which are divided between omissions in the translation and inaccurate renditions of some lexical items in the source text. The remaining errors are linguistic, including incorrect use of prepositions; grammatical errors; and translation errors, including additions and distortion of the meaning of the source text.

First, regarding linguistic errors, the sentence وتغطية بنسبة 100% من المناطق النائية في المملكة "*ūtghṭīt bnsbt 100% mn l-mnāṭq n-nā'īt fi l-mmlkt*" was translated in the MCIT translation as "with a coverage rate of (100%) of the remote areas of the Kingdom"; in this translation, there is an unnecessary repetition of the preposition "of", resulting in a poor linguistic strcutre. However, GT managed to translate this phrase accurately as "with 100% coverage of remote areas in the Kingdom". Another example of a linguistic error in the MCIT translation is the mistranslation of the phrase الاقتصاد الرقمي "*ālāqtṣād r-rqmī*" as "economic digital", which is grammatically incorrect; the correct translation given by GT is "digital economy". In total, the linguistic errors are not considered significant, as they make up only 15% of all errors in the MCIT translation, which is relatively small. This result is in line with the results found by Sulaiman and Mohammed (2019), where translation was conducted by human translators, as linguistic errors represented the least common type of errors in translation.

Second, translation errors were found in the MCIT translation. These made up the majority of errors at 85%, but they were avoided in the GT translation, which indicates the accuracy of GT, especially in these contexts. For example, in translating the sentence تعزيز كفاءة سوق الاتصالات "*tʿzīz kfā't sūq l-ātṣālāt*", the MCIT translated it as "enhancing communication market", in which the word "efficiency" was omitted; in contrast, GT did not omit this word and provided the full lexical items given in the source text: "enhancing the efficiency of the communication market". Although it can be argued that the meaning is delivered by both the MCIT and GT, the latter was more accurate. This could be one of the advantages of literalness in neural machine translation, where almost no lexical items are neglected. Similarly, an omission occurred when the sentence يحتوي على معمل متنقل يقدم ورش عمل تفاعلية "*īḥtwy ʿl mʿml mtnql īqdm ūrsh ʿml tfāʿlīt*" was translated by the MCIT as "The festival includes interactive workshop", omitting an essential word in the sentence ("mobile laboratory") that was retrieved in GT translation: "It contains a mobile laboratory that provides interactive workshops".

Another translation error found in the MCIT translation is in the translation of the sentence الرامية إلى تعزيز دور قطاع الاتصالات وتقنية العلومات لبناء مجتمع رقمي، واقتصاد رقمي مبتكر ومستقبل مزدهر للمملكة "*ālrāmīt il tʿzīz dūr qṭāʿ l-ātṣālāt ūtqnīt l-ʿlūmāt lbnā' mjmʿ rqmī, wāqtṣād rqmī mbtkr ūmstqbl mzdhr llmmlkt*", which is rendered into English as "which aims to enhance the role of ICT sector to build a digital society, a digital government, a thriving digital economy, and an innovative future for the Kingdom". There is no mention of "digital government" in the source text, but the MCIT has added it unnecessarily and has also made a lexical choice for providing the equivalent "thriving digital economy" instead of "innovative digital economy" and selecting "innovative future" instead of the appropriate "prosperous future". However, GT maintained the meaning of the source text, although with a syntactical error, by separating the sentences as follows: "which aims to enhance the role of the communications and information technology sector to build a digital society and an innovative digital economy. And a prosperous future for the Kingdom."

In addition, 30% of translation errors found in the MCIT translation are due to an inaccurate rendition of individual lexical items. For example, the sentence وشهد قطاع الاتصالات بعد ذلك تطورات متلاحقة "*ūshhd qṭāʿ l-ātṣālāt bʿd dhlk tṭūrāt mtlāḥqt*" was translated as "Communication sector went through radical shifts" with an extreme selection of the phrase "radical shifts". The phrase "*tṭūrāt mtlāḥqt*" means "successive developments" and does not entail any negativity or extremism in its meaning, as is found in the expression "radical shifts". However, GT has provided a more accurate rendering: "The communications sector then witnessed successive developments", which conveys the sense of the positivity found in the source text. Another example can be seen in the translation of the sentence ورصد أبرز مؤشرات الإنجازات والتحديات والحلول "*ūrṣd abrz mu'shrāt l-injāzāt wālthḍīāt wālḥlūl*", which was translated by the MCIT as "monitor KPIs of achievements, challenges and solutions"; this is an inaccurate translation. The phrase "mu'shrāt l-injāzāt" refers to "achievement indicators", not the wrong selection "KPIs", which refers to "Key Performance Indicators". However, GT translated this more accurately as "And monitor the most prominent indicators of achievements, challenges and solutions".

Some translation errors distort the meaning in the translation; these errors made up only 10% of the overall translation errors made by the MCIT. For example, the sentence الاستفادة من منظومة البحث والتطوير التقني في حل تحديات القطاع الخاص والعام وتعزيزه في قطاع التقنية "*ālāstfādt mn mnẓūmt l-bḥth wālttwyr t-tqnī fī ḥl tḥdīāt l-qṭāʿ l-khāṣ wālʿām ūtʿzīzh fī qṭāʿ t-tqnīt*" was translated by MCIT as "Leveraging IT research and development ecosystem in solving challenges of private and public sectors and strengthening such aspects across IT sector". There is no mention of the word "ecosystem" in the source text; instead, the intended meaning was "technology development", which shows the distorted meaning when delivering this sentence into the TL. On the other hand, GT rendered this as "Benefiting from the technical research and development system in solving the challenges of the private and public sectors and enhancing them in the technology sector", but it did not deliver the appropriate equivalent "technology development". Instead, it opted for "development system", which is inaccurate.

The above examples affirm the accuracy of GT over the MCIT translation in some contexts at the linguistic and translational levels. Errors related to the incorrect use of prepositions or grammar were spotted in several translation cases, and translation errors represented by omitting lexical items, adding lexical items, the inaccurate rendering of some phrases, and the expression and distortion of the intended meaning in the ST were all found in the MCIT.

However, the number of errors detected in the MCIT translation (19 errors) was less than that in the GT translation (52 errors), which explains the superior quality of the human translation. It is also important to note that, in a very long document (21,430 words), only 52 errors were detected in the GT translation, which can be considered a huge leap of improvement in the quality of Google NMT, considering the arbitrariness and complexity of syntactic and grammatical lexical items in Arabic. This can be seen as a highly reliable intelligent NMT tool, though its translation still requires revision by a human translator to tackle these errors.

5. Conclusion:

The development of machine translation from SMT to NMT has made significant progress in the quality of translation, which can be seen in this study, where error analysis of a large technical text has shown a countable number of errors made by GT. Although the GT translation, even when working with a technical text, is not too complex in nature in comparison to other types of texts, these errors occurred in its translation. Errors of different types, namely comprehension, linguistic, and translation errors, were found, but they were relatively rare considering the size of the translated text. It was also observed that the source text contained some non-technical expressions, where some errors were also found in the translation. This can be seen as a justification for these errors, which is a limitation of this study. At the same time, an error analysis of the MCIT human translation also found several errors, namely linguistic and translation errors. This implies that the GT translation of technical texts has greatly improved, but human intervention is still needed to tackle some issues. GT can be a reliable machine translation method that saves translators time and effort in achieving translation tasks. There is also room for further investigation of the GT translations of other types of texts which do not have cultural features nor connotative meanings such as medical, engineering and purely scientific texts to analyse translation errors and assess the quality of this NMT. Future research may not be also limited to GT but other types of NMT.

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