

Chapter 9

The Quality and Accuracy of AI-Generated Translation in Translating Communication- Based Topics: Bringing Translation Quality Assessments Into Practices

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ABSTRACT

This chapter presents the efficacy and obstacles associated with the quality of AI-generated translation, concentrating on instruments such as ChatGPT and Neural Machine Translation (NMT) technology. It emphasizes the superiority of NMT systems over traditional rule-based and statistical methodologies by employing deep learning techniques to understand language contextually, thereby yielding translations that are both more accurate, acceptable, and readable. Nonetheless, considerable challenges persist, particularly in navigating cultural subtleties, idiomatic phrases, and intricate linguistic frameworks. By using a Translation Quality Assessment (TQA), this chapter appraises ChatGPT's translation capabilities based on three criteria:

DOI: 10.4018/979-8-3373-0060-3.ch009

accuracy, acceptability, and readability. Although ChatGPT exhibits commendable performance in terms of general linguistic accuracy and readability, it encounters difficulties regarding acceptability when confronted with culturally rich or highly contextualized texts, especially within specialized domains such as political communication discourses.

INTRODUCTION

AI-generated translation is an automatic rapid message translation processed from a source language into a target language using Artificial Intelligence technology, such as Google Translate, DeepL, ChatGpt, Microsoft Translator, Amazon Translate, IBM Watson Language Translator, SYSTRAN, Reverso, Papago, iTranslate, Amazon Translate, Microsoft Translator, and Translate.com. These applications are the best in their field, with the ability to translate various languages and fields with a level of accuracy that is getting closer to human translation (Gupta, 2020). The translation process differs significantly from Rule-Based Machine Translation (RBM) and Statistical Machine Translation (SMT). The former is processing the message while considering the naturalness of language norms. Costa-Jussà and Fonollosa (2015) stated that the first step of machine translation development bases the transfer system on the linguistic rules such as semantics, morphology, and syntaxes of the language pairs. In line with this, Tao (2023) pointed out that it minimises grammatical errors in the translation process. These two approaches (RBM and SMT) are then commonly known as traditional approaches. Meanwhile, the latter transfers the message by considering idiomatic expressions and language ambiguity (Bojar et al., 2016). It is more dynamic than the former because the corpus system has been developed inside. It is successfully used in language pairs with similar linguistic rules. It was initially used by Google Translate prior to developing Google Neural Machine Translation technology.

The AI-generated translation process makes use of Neural Machine Translation (NMT), which allows the system to be organised from the bottom up as the algorithm has deep learning capabilities. It processes human language and learns language patterns for better contextual understanding. In comparison to SMT, NMT has three main advantages. First, NMT understands how words co-occur. Second, the NMT system takes the whole sentence into account in its translation process. Third, NMT systems can learn complex linguistic relations (Agarwal et al., 2024). NMTs are typically 60% better at translating than SMTs (Ernst et al., 2019). The system can also reduce word order errors by 50%, grammatical mistakes by 19%, and lexical errors by 17% compared to SMT systems (Pestov, 2018). To clarify the ways the

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