Chapter 1
From Google Translate to ChatGPT:
The Use of Large Language Models in Translating, Editing, and Revising

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ABSTRACT

This chapter examines the quality of machine translated texts of various genres with a view to finding out to what extent these texts/genres have been accurately translated by neural machine translation systems and LLMs. The chapter also examines the potential use of these technologies in editing and revisions to enhance both quality and productivity. A theoretical and conceptual framework that is based on text-typology linguistic models and Mossop's parameters of revising and editing in translation is used to assess the quality of transactions produced by Google Translate (GT) as a neural-based machine translation system and ChatGPT as a large language model (LLM). In particular, the chapter investigates the GT and ChatGPT translations of argumentation within journalistic texts, exposition within both promotional and philosophical genres, and instrumental texts within the legal genre. This emphasis on diverse text types allows for a comprehensive evaluation of the translation performance of neural-based systems and LLMs across different communicative purposes and stylistic demands.

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INTRODUCTION

Communication across languages and cultures has been one of the priorities of technology. With the advent of the Fourth Industrial Revolution (4IR), digital technologies, such as artificial intelligence (AI), automation, and the Internet of Things have become a reality and they have been integrated into various aspects of society (Alsulaimani & Islam, 2022; Park, 2018), and the field of translation and interpreting was no exception.

Early machine translation (MT) systems were based on rule-based approaches. That is, the generation of translation depends on a set of linguistic rules (Stein, 2018). Phrase-based statistical machine translation (PBSMT) systems have been introduced over the last decades (Lyons, 2020) and they have included more advanced features. While the role of these systems cannot be denied as they laid the foundation for advanced systems of machine translation (MT), the end translation product is poor in terms of fluency and accuracy (Jia et al., 2019). The problem is more complicated in the translation of complex linguistic structures and frozen and idiomatic expressions. In a post which gained immense traction on social media more than a decade ago, the frozen Arabic expressions *ḥill ʿan samāʾī* and *yastur ʿalā ʿirḍik* have been literally translated as "dilute my sky" and "cover your width". Undoubtedly, these translated expressions do not make any sense in the target language.

However, the introduction of neural machine translation (NMT) systems, powered by deep learning algorithms and trained on vast amounts of multilingual data (Bhadauria et al., 2023; Dabre et al., 2020), has made remarkable strides in producing more fluent and natural-sounding translations (Dwivedi et al., 2025). While they still have certain limitations, such as difficulties with low-resource languages or highly specialized domains, present-day machine translation systems have reached a level where they can provide usable translations for a wide range of texts. In addition, the advancements in artificial intelligence (AI) and the use of AI-driven machine translation (MT) systems have undoubtedly improved the accuracy and fluency of translations between various directionalities (Siu, 2024). The poor machine translations of some text types have become a matter of the past today. Google Translate (GT) among other systems have become so advanced that they can produce quality translations (Johnson et al., 2017) that can rival human capabilities. A recent report has revealed that a neural-based translation program similar to Google Translate (GT) can be used in the translation of Akkadian cuneiform into English (Krueger, 2023; Mair, 2023). It has successfully facilitated the decoding and translation of thousands of previously unread digitized tablets. The report has, however acknowledged that the accuracy of the translations remains a subject of debate (Mair, 2023). The fact that remains is that machine translation (MT) systems and large language models

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