AI in Political Translation: Revolutionising Communication or Risking Manipulation?

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Abstract: The increasing production of diverse political texts due to rapid developments in international politics and social changes necessitates accurate and timely translation. Translation technology combined with AI is emerging as a powerful tool for translations, increasing productivity and ensuring consistency. This research focuses on the use of AI in translating political texts and explores the challenges it poses, particularly in the realm of political translation. The aim is to identify these challenges and develop effective strategies to address them. The research methodology involves analysing translations of German politicians' speeches into Greek using AI and evaluating their cultural adaptation, emotional impact, and persuasiveness. The study utilises machine translation evaluation tools and questionnaires to assess the benefits and risks of using AI in translation, with a specific focus on the democratisation of information and its potential impact on public opinion. The research aims to provide valuable insights for both trainees and professional translators.

Keywords: artificial intelligence, political translation, bias.

1 Introduction

The integration of technology and AI in translation enhances productivity and ensures consistency in terminology (Mohamed et al., 2024). However, translating political texts with AI presents unique challenges, requiring future translators to develop appropriate strategies. AI's primary challenge is to encompass all stages of political text translation and convey their cultural, ideological, and political complexity. Political texts are intricate, containing legal and economic terms, and their analysis is difficult due to language diversity. Translators need a multidimensional knowledge base to handle explicit or implicit cultural references and persuasive strategies. In the initial translation stages, a comprehensive analysis of the original text, an emotional charge assessment, and an understanding of the text's purpose are required. Research questions arise about AI's accuracy, performance in cultural elements, and objectivity in political text translation (Liu et al. 2023). A comparative study was conducted, comparing human translations of selected political texts from German to Greek with AI-produced translations.

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2 Methodology

Twenty-six German political speeches were selected based on emotional charge, cultural references, colloquialisms, and idioms. The corpora span different periods of German political rhetoric and various political ideologies to evaluate AI systems' impartiality and information. Specifically, the speeches were selected from the Nazi period (Goebbels), post-war period (Adenauer, Brandt), and Reunification of Germany (Kohl, Brandt), as well as modern politics (Merkel, Steinmeier, Scholz, Lindner, and Gauland). In 2022–2024, third- and fourth-year students in the Department of Foreign Languages, Translation, and Interpreting (Ionian University) performed the human translations. Along with translation theory classes, the students have taken courses in political translation, political analysis, European culture, and European institutions. Three models—Open AI GPT-3.5, Microsoft Copilot GPT4 and GPT4o, and Julius—were used for machine translation. Using machine tools (Bleu, BLEURT, COMET, and TER) and questionnaires filled out by language experts, political scientists, and students, translations were assessed for lexical, cultural, and stylistic accuracy. Two AI translation techniques were applied: a grid of prompts for a five-stage translation process (text analysis, problem identification and resolution, translation, and evaluation) and prompts for direct translation.

3 Merits and Demerits of Artificial Intelligence

The three models yielded different results during the text analysis and emotional charge assessment stage. Experiments were required to determine the appropriate prompts for Open AI and Copilot, which also required precise prompts and additional information (such as CDA, PDA, etc.). When no particular cue was provided, they consistently employed different emotional charge scales (0–10, 0-5, -1 to +1). On the other hand, even in the absence of explicit prompts, Julius offered comprehensive, multilevel text analysis and context. A scale ranging from -1 to 1 was also employed for evaluating emotional charge.

During the second stage of the translation process (resolution of translation problems), the three AI models also showed various approaches. While Copilot used a practical approach with a grid of prompts to suggest specific solutions, Open AI used Skopos Theory to provide theoretical answers. Using multilevel data from the texts, Julius provided: (a) meanings of proverbs, linguistic expressions, and cultural allusions; (b) definitions of linguistic, cultural, and pragmatic requirements for each problem; and (c) a maximum of three translation options for every task, giving the translator the freedom to select the best fit. Every solution was accompanied by a rationale and a list of its shortcomings regarding semantic correspondence with the original.

Regarding the translation results, it is significant to mention that the three TN models produced different translations for direct and five-stage translations of documents. The translations were excellent in both instances, however, there were a few minor problems in the first, mostly pragmatic ones. The models were evaluated with the MT tools: Bleu, BLEURT, COMET, and TER. Bleu measures the correspondence of n-grams between a machine translation and a reference human translation (Papineni et al., 2002). BLEURT is trained for reverse translation, consistency, and predicting existing machine translation metrics (Sellam et al., 2020).

Unlike other machine translation algorithms, COMET considers the source text as part of the input (Rei et al., 2020). The Translation Error Rate (TER) is a simple baseline metric that calculates how many edits a machine translation needs to make in order to match a reference translation exactly (Snover et al., 2006). With the highest scores on BLEURT, Bleu, and COMET—on average 50%, 70%, and 95%, respectively—Julius demonstrated strong translation evaluation abilities. TN models generated translations that were comparable to human translations, despite the meanings being complex. Only minor editing is required to align with human translation, with an average of 35% in TER.

Although these percentages demonstrated high quality at the grammatical and lexical levels, a qualitative human evaluation of the translations using questionnaires revealed errors related to pragmatic and stylistic levels as well as idiomatic expressions. According to the frequency with which they are found, the errors have been particularly classified into the following:

- Misinterpretation of idiomatic expressions: Copilot and ChatGPT models often translate idiomatic expressions literally, resulting in contextually inappropriate translations, as confirmed by other researchers (He et al., 2024). For example, Copilot translates the term *bärenstark* (Bär = bear, stark = strong), *δυνατός σαν αρκούδα* (dynatos san arkouda = strong as a bear), whereas the correct Greek expression is *δυνατός σαν ταύρος* (dynatos san tavros = strong as a bull). Perhaps one of the most prominent examples is the term *Hamsterung*, attributed by ChatGPT as *η ιδιότητα του χάμστερ* (i idiotita tou chamster = the attribute of hamster) while referring to Greek phrase *μανιώδης αποθήκευση* (maniodis apothikefsi = hamstering), correctly attributed by Julius.

- Style/emotional charge: AI models struggled to capture cultural and contextual nuances, often producing neutral translations that nullified emotional charge, especially during the first research period with an average of 30-35% as shown by the questionnaires. In the second period, of course, the conviction rate of the translations rose rapidly to 65-67%.

- Nevertheless, there is reason for concern regarding the user's ability to alter the text's political tone in response to a prompt. By using prompts to highlight ideological or emotional components, translators could manipulate the models to produce misinterpreted messages and styles. This could lead to biassed or politically motivated translations that are subsequently disseminated as fake news or propaganda. However, the Julius model's reluctance to translate texts containing particular political quotes or content raises even more serious concerns. Among other texts, the three models received political speeches by Goebbels and members of the modern far-right AfD. Julius effectively refused to translate these texts, indicating that the context and content are dangerous. The refusal of the Julius model to translate certain texts is a significant finding. This implies that AI models can be trained to reject particular ideologies, and by indicating that these are "dangerous" political stances, they can influence users' viewpoints. The importance of the security and ethics of content translated from AI models has been highlighted by a number of researchers (Brown et al., 2020). Fears of a dystopian future in which AI limits knowledge and moulds users' political awareness are aroused by this rejection, which implies politically charged training. Furthermore, this raises concerns about potential bias or censorship as well as the ethics of employing AI for translating.

4 Conclusions

The study demonstrates that prompt tone and clarity affect the quality of AI translation. To increase the effectiveness of using AI in translation, prompt engineering knowledge and application should be incorporated into translator training programs. Analysing real-world instances where prompt engineering has enhanced or degraded political text translation can be very beneficial to comprehending how to apply AI models appropriately. Translators can discern the quality difference by comparing translations produced with and without optimised prompts. AI can effectively translate political texts, but it has limitations and risks in terms of political sensitivity and ideology. Translators must consider the censorship AI imposes on their work, considering both the source text and the target audience.

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