ARTIFICIAL INTELLIGENCE TO AUTOMATE: TRANSLATION OF TECHNICAL TERMS IN PROJECT MANAGEMENT

Oleksandr Lysychenko
Postgraduate Student, Kyiv National Linguistic University, Ukraine
e-mail: oleksandr.lysychenko@knlu.edu.ua, orcid.org/0009-0005-6791-6667

Summary

This article highlights the influence of artificial intelligence (AI) on automating the translation of technical terminology in project management. In particular, the article focuses on the use of machine translation (MT), which, thanks to their ability to process large amounts of data, cloud computing, and advanced algorithms, increase the accuracy and speed of translation of technical documentation. It is noted that AI helps to reduce translation costs and improves the consistency of terminology, which is critical for the successful completion of projects with tight deadlines. Nevertheless, challenges in this field are also identified, including the high error rate in translating highly specialized terms and the ongoing need to enhance systems to meet the varied demands of users. Different translation approaches are discussed, including neural machine translation (NMT), statistical machine translation (SMT) and rule-based machine translation (RBMT), which ensure high accuracy and smoothness of translation. Integrating AI into project management systems can also optimise communication in multilingual teams. The article highlights the growing role of AI in the translation of technical terms, which has great potential to improve efficiency in project management.

Key words: artificial intelligence, machine translation, technical terms, project management, translation automation.

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1. Introduction

Artificial intelligence (AI) has greatly improved the translation automation of technical terms in project management. AI-powered machine translation (MT) systems use big data, cloud computing, and advanced algorithms to improve translation accuracy and efficiency *(Li et al, 2023)*. First of all, it significantly increases the speed and efficiency of translation, which is especially important for projects with tight deadlines or a large amount of technical documentation.

2. Advantages and challenges of using AI in automated translation

AI can process large amounts of text much faster than humans. In addition, this approach ensures consistency of terminology across all project documents, which is critical for technical projects as it reduces the risk of misunderstandings and errors due to inconsistent use of terms *(Martins, 2023)*. An equally important aspect is the reduction in translation costs, which is especially noticeable for large projects or companies that regularly need to translate technical documentation (Figure 1). For project management, AI can simplify communication, reduce misunderstandings, and increase the efficiency of multilingual teams by providing accurate translations of technical terms.

However, challenges persist, including error rates and the necessity for ongoing improvements to accommodate varying user needs. *(Li et al, 2023)*. One of the most difficult challenges in the context of project management is to ensure accurate translation of highly specialised terms, which often do not have direct equivalents in other languages or may have different meanings in different contexts. AI must be able to recognise and translate such terms correctly, taking into account the context of their use. In addition, technical terminology is evolving rapidly, especially in innovative industries, which requires constant updating of AI systems' terminology databases. Moreover, AI requires large amounts of high-quality data to function effectively. Insufficient or poor quality information can lead to translation errors *(Raj et al, 2024)*. Another challenge may be integration and adaptation. Integrating AI into existing project management systems can be difficult due to the need to adapt to the specific requirements and processes of each project *(Karamthulla et al, 2024)*. The use of AI raises issues of ethics, data privacy, and possible biases in models that may affect the accuracy and fairness of translations *(Amini et al, 2024)*. Implementing AI also requires staff training, which can be a complex and costly process, especially for large organisations *(Raj et al, 2024)*. Despite these challenges, the role of AI in translation is expanding, and systems are demonstrating capabilities that can rival or surpass specialised translation tools *(Lee, 2023)*.

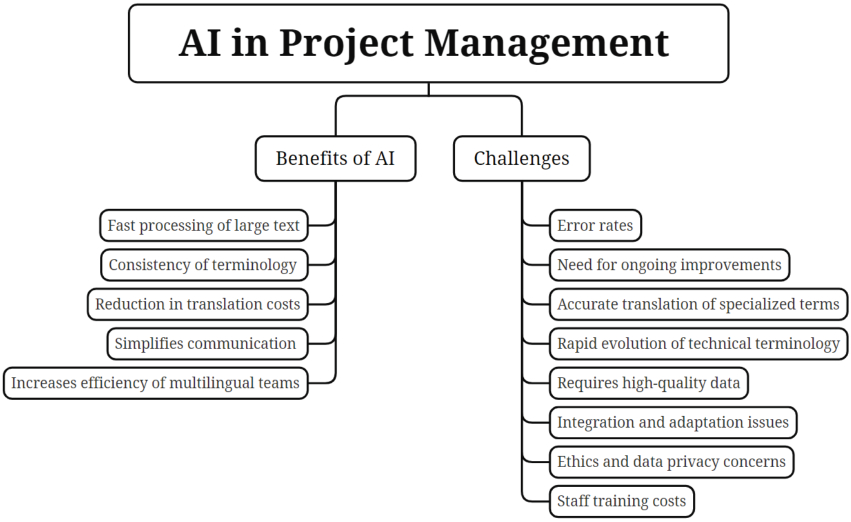

Figure 1. Benefits and Challenges of AI in Project Management

3. Methods of translation quality improvements

There are various approaches to solve these problems *(Xu et al, 2020)*. Modern machine translation systems based on neural networks can be trained on specialised corpora of technical texts to improve translation quality. The use of neural machine translation (NMT) has significantly improved the accuracy and fluency of translations due to its ability to handle complex semantic structures and contexts *(Um et al, 2022)*. The creation and integration of project-specific glossaries can also significantly improve translation accuracy *(Vo et al, 2024)*.

A hybrid approach is often used, where AI does the bulk of the translation work and a human expert checks and corrects the result, striking the right balance between speed and quality. Combining AI with traditional translation methods, such as autoregressive models and neural network-based methods, has resulted in high levels of accuracy and fluency, particularly for English-Chinese translations *(Sumita, 2001)*. The use of deep learning algorithms and neural networks, such as Transformer, to automatically identify and correct errors in translations has significantly improved the quality of translations *(Ju and Salvosa, 2024)*. The use of cloud computing and data aggregation algorithms to process large amounts of language data, allowing translation systems to be more efficient and reliable *(Yang et al, 2024)*. These advances are contributing to the accuracy and fluency of translations, making them more suitable for use in a variety of contexts, including project management.

Hybrid translation systems using artificial intelligence (AI) combine different approaches to achieve high accuracy and fluency. Let's take a look at some of the main approaches. Statistical Machine Translation (SMT) treats natural language translation as a machine learning task. SMT uses parallel corpora to automatically learn a translation by analysing numerous samples of human translations *(Hassan and Darwish, 2014)*. Another achievement of this approach is the translation of cognates. It exploits similarities between related languages to improve translation quality, reduce resource requirements, and improve generalisation *(Bhattacharyya et al, 2016)*. Research shows that SMT can outperform neural translation techniques (NMT) in some cases, especially for resource-constrained languages *(Das et al, 2023)*.

Rule-based machine translation (RBMT) is a traditional AI-based translation approach that relies on linguistic rules and dictionaries to translate text from one language to another *(Macketanz et al, 2017)*. RBMT systems use large sets of linguistic rules and bilingual dictionaries to perform translations. These rules are manually developed by experts and cover syntax, morphology, and semantics *(Tang, 2024)*. Modern RBMT systems incorporate machine learning techniques to eliminate ambiguity in word meanings by taking into account contextual information such as part-of-speech tags, semantic concepts, and cases. This approach improves translation accuracy through a better understanding of the context *(Charoenpornsawat et al, 2002)*. RBMT can be combined with statistical or neural machine translation methods to leverage the strengths of both approaches. For example, integrating RBMT with neural networks can improve translation quality *(Schwenk, 2012)*. RBMT is particularly useful for translation between languages with significant structural differences or for languages with limited digital resources. For example, RBMT has been used effectively for translation between English and Sanskrit, and between Tunisian dialect and modern standard Arabic *(Mishra et al, 2023)*. RBMT is also being developed for low-resource languages to democratise access to machine translation services and create parallel corpora for these languages *(Torregrosa et al, 2020)*.

Example-based machine translation (EBMT) is a method that relies on a database of previously translated examples to create translations for new input sentences. EBMT retrieves similar examples (pairs of source phrases, sentences or texts and their translations) from a database and adapts these examples to translate the new input. This method is easily updated by adding new examples to the database and assigning a reliability factor to the translation result *(Alkhatib & Haider, 2024)*. EBMT systems can process structural translation examples that are highly usable, but require advanced technology to create such examples. These systems compare favourably with other approaches in terms of performance *(Aramaki & Kurohashi, 2004)*.

Neural machine translation (NMT) has revolutionised the field of machine translation by using deep learning techniques to improve translation accuracy and fluency. Attentional mechanisms allow the model to focus on different parts of the input sentence while generating each word of the output sentence. This approach helps to cope with long sentences and improves translation quality by providing contextual information *(Luong, 2016)*. Variational NMT models introduce continuous latent variables to explicitly model the underlying semantics of the source sentences, guiding the creation of target translations. This approach improves the model's ability to capture complex semantic relations *(Zhang et al, 2016)*. Multimodal NMT integrates different forms of information, such as images, video, and audio, into the translation process. Methods such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used to process different modalities, significantly improving translation accuracy and fluency *(Mohamed et al, 2024)*.

Table 1

Comparison of the Benefits and Challenges of AI methods in Project Management

Method	Key Features	Advantages	Disadvantages
Neural Machine Translation (NMT)	Uses deep learning and attention mechanisms to contextualize long sentences and complex structures	High accuracy, context consideration	Requires large amounts of data for training
Statistical Machine Translation (SMT)	Utilizes parallel corpora for machine learning based on statistical analysis of human translation samples	Effective for languages with similar structures, especially among related languages	May be less effective for resource-intensive languages
Rule-Based Machine Translation (RBMT)	Based on linguistic rules and dictionaries for translating between languages	Useful for languages with different structures, does not rely on the availability of parallel corpora	Requires significant human resources to develop linguistic rules
Example-Based Machine Translation (EBMT)	Uses a database of previously translated examples, adapting them for new input sentences	Easily updated with new examples, ability to assign reliability factors	Requires a substantial number of relevant examples for effectiveness

4. Integrating AI into project management

Integrating AI translation into project management processes can take place in a number of ways. For example, automated translation can be built into document management systems to create multilingual versions of project plans, reports, and other documents. Multilingual task management systems can use AI to automatically translate tasks, comments, and status updates for international teams.

AI can also be integrated into messaging and video conferencing systems to provide real-time translation during meetings and chats. Future prospects for this technology include further improvements in translation quality through the development of deep learning and natural language processing technologies, expanded support for languages and technical fields, and tighter integration of AI translation systems with other project management tools, version control systems, and collaboration platforms *(Aldawsar, 2024)*. These improvements will allow for more specialised and efficient translation systems for different technical fields, which will greatly facilitate the work of international project teams and increase the efficiency of multilingual project management.

5. Conclusions

There are several approaches to using artificial intelligence (AI) to automate the translation of technical terms in project management. Neural Machine Translation (NMT) has shown promise in handling large vocabularies of technical terms using a method that replaces these terms with tokens, allowing for more accurate translation when combined with Statistical Machine Translation (SMT) *(Amini et al, 2024)*.

Machine learning techniques are transforming project management by improving decision-making, resource allocation and risk assessment, which can indirectly support the translation process by simplifying project workflows *(Nair et al, 2023)*.

These advances highlight the potential of AI to improve the accuracy and efficiency of technical translation in the context of project management.

The use of artificial intelligence to automate the translation of technical terms in project management has become a practical tool in various industries. For example, large international companies such as Siemens or General Electric use AI to translate technical documentation when implementing large engineering projects where teams from different countries need to understand the same technical standards *(Kononova, 2024)*. Automated translation systems help to quickly adapt manuals or engineering reports, which reduces the cost of manual translation and reduces the risk of errors.

AI-powered translation platforms have shown improved engagement and understanding in educational environments, suggesting their potential usefulness in project management, where accurate understanding of technical terms is critical *(Kolhar & Alameen, 2021)*. In this case, AI helps to adapt educational content, including technical terminology, to regional language standards, which allows students to learn the material more easily.

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