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Comparative Study of Translation Effects in Low-Resource Languages Based on Pivot Language Method

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Abstract: ***This study aims to compare and analyze the translation effects of low-resource languages in Asia based on the Pivot Language method. By selecting five different low-resource languages in Asia (Urdu, Burmese, Kyrgyz, Kazakh, and Tajik), this study explores the translation effect of using a pivot language (usually English) to build a bridge between the source language and the target language, and compares it with direct translation. The study uses two translation modes, Pivot Translation Technique and Pivot Prompting, to compare the quality differences between translation through a pivot language and translation directly from the source language to the target language. By calculating translation quality evaluation indicators such as Comet and BLEU, this study evaluates the performance of the two translation modes in different languagesand analyzes whether adding a pivot language can effectively improve translation quality, especially in terms of grammatical accuracy, semantic transmission, and fluency of expression. The results show that the pivot language method significantly improves the accuracy and fluency of translation in low-resource language translation, especially in the translation of long and difficult sentences, and the pivot language translation has higher quality than direct translation. This discovery provides a new direction for machine translation research in low-resource languages and is of great significance to the country's cross-language communication and cultural cooperation.***

Keywords: Low-resource languages, Pivot Translation Technique, Pivot Prompting, Automatic translation evaluation.

1. Introduction

This study investigates machine translation between low-resource languages and Chinese, conducting a comparative analysis of the translation quality enhancement achieved via the Pivot Language Method in contrast to direct translation. In this study, the official languages of five countries along the Belt and Road Initiative—Pakistan, Myanmar, Kyrgyzstan, Kazakhstan, and Tajikistan—are selected as representative low-resource languages, specifically Urdu, Burmese, Kyrgyz, Kazakh, and Tajik. Parallel corpora for the five selected languages are extracted from the FLORES-200 multilingual dataset. A purposive sampling strategy is employed, whereby 500 syntactically complex sentences (approximately 10,000 words) are selected per language for automatic evaluation, with a subset of 10% (50 sentences) from each language subsequently used for manual assessment.

2. Research Content

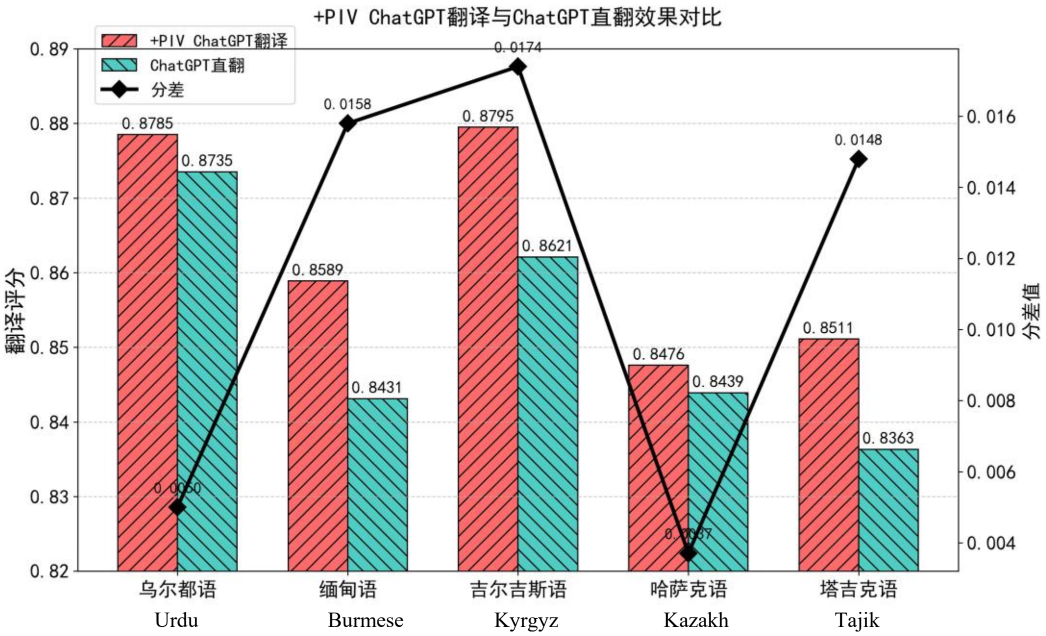
This study explores two approaches to improving translation quality: the Pivot Translation Technique and Pivot Prompting. Both methods share the common principle of introducing an intermediate pivot or mediating step within the generation model. However, Pivot Prompting is more applicable to neural machine translation technologies, as it enables simultaneous recognition of both the [PIV] (pivot) and [TGT] (target) languages, translating the source sentence sequentially into both. In contrast, the Pivot Translation Technique is better suited to traditional machine translation engines, utilizing a third language—typically English—as a pivot to construct a bridge between the source and target languages, thereby enhancing the overall translation quality between the two. Two automatic evaluation metrics, COMET and BLEU, are employed in this study, each with a distinct evaluative focus. COMET prioritizes holistic translation quality, encompassing both accuracy and contextual coherence, while BLEU emphasizes lexical correspondence between the candidate translation and the reference.

3. Research Technical Scheme

The study adopts two methods—Pivot Translation Technique and Pivot Prompting—utilizing a traditional machine translation engine and ChatGPT, respectively, for multilingual translation. The final translation outputs are evaluated using two metrics: COMET and BLEU. The following analysis integrates the results from both evaluations to explore in depth the performance of different methods and translation systems across five languages: Urdu, Burmese, Kyrgyz, Kazakh, and Tajik.

4. Data Analysis

COMET serves as an automated evaluation metric designed to assess translation quality with a primary focus on accuracy and fluency. The scoring outcomes provided by COMET allow for a clear comparison between translations generated through pivot-based translation using English as the pivot language (PIV) and those produced via direct neural machine translation from the source to the target language:



Evaluation outcomes reveal that translations into Urdu exhibit relatively high quality, with those utilizing English as a pivot language performing marginally better than direct source-to-target translations. The COMET score of 0.8785 indicates a noticeable improvement resulting from the inclusion of a pivot language, underscoring the potential of the pivot translation technique to enhance translation quality.

For Burmese, the performance gap is relatively small; however, the translation score obtained through the pivot translation technique (0.8589) remains slightly higher than that of direct translation (0.8431). Although the difference is modest, this marginal improvement suggests that using English as an intermediary language may better handle certain linguistic structures or grammatical patterns in Burmese, thereby contributing to more accurate and natural translation outputs.

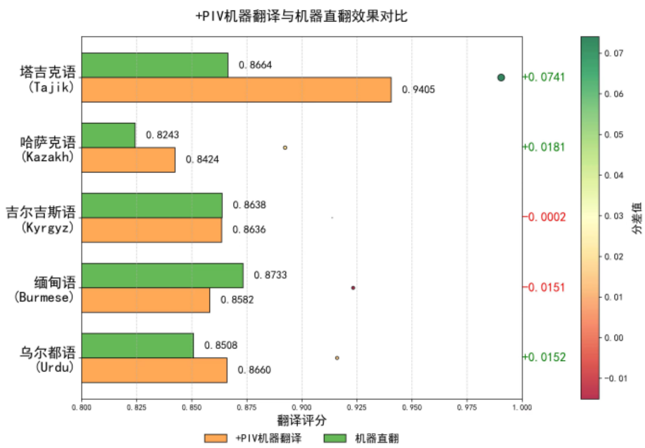
For Kyrgyz, the improvement in translation quality is more pronounced, with the pivot translation technique achieving a score of 0.8795, compared to 0.8621 for direct translation. This indicates a stronger advantage of using a pivot language in the translation of Kyrgyz, which may be attributed to substantial differences in grammar, vocabulary, or sentence structure between Kyrgyz and the target language (Chinese). In this context, English as a pivot language appears to function effectively as a linguistic bridge, enhancing the accuracy of the translation.

The difference between the two translation methods for Kazakh is relatively small, with the pivot translation scoring 0.8476 and the direct translation scoring 0.8439. Although the pivot translation performs slightly better, the minimal gap may indicate that the structural and grammatical differences between Kazakh and Chinese are relatively limited, or that the machine translation engine is already capable of effectively handling direct translation from Kazakh to Chinese.

The translation results for Tajik similarly demonstrate the advantage of the pivot translation method, with a score of 0.8511 significantly higher than the direct translation score of 0.8363. This may be attributed to the substantial structural differences between Tajik and Chinese, where the pivot language (English) serves as a crucial intermediary, contributing to improved translation quality.

Overall, the findings demonstrate that employing neural machine translation in combination with the pivot translation method—using English as the intermediary—yields consistent improvements in translation quality over direct translation. This advantage becomes especially pronounced when translating between linguistically distant language pairs, such as Kyrgyz–Chinese and Tajik–Chinese.

COMET-based automatic evaluation of translations using English as a pivot language versus direct translation from the source to the target language via traditional machine translation:



The translation results for Urdu show only a minor difference between the two methods, with the pivot translation scoring slightly higher at 0.8660 compared to 0.8508 for direct translation. Although the gap is small, the use of a pivot language may still lead to a modest improvement in translation quality, indicating that pivot translation remains beneficial for handling Urdu—particularly in terms of syntactic structuring and linguistic transfer.

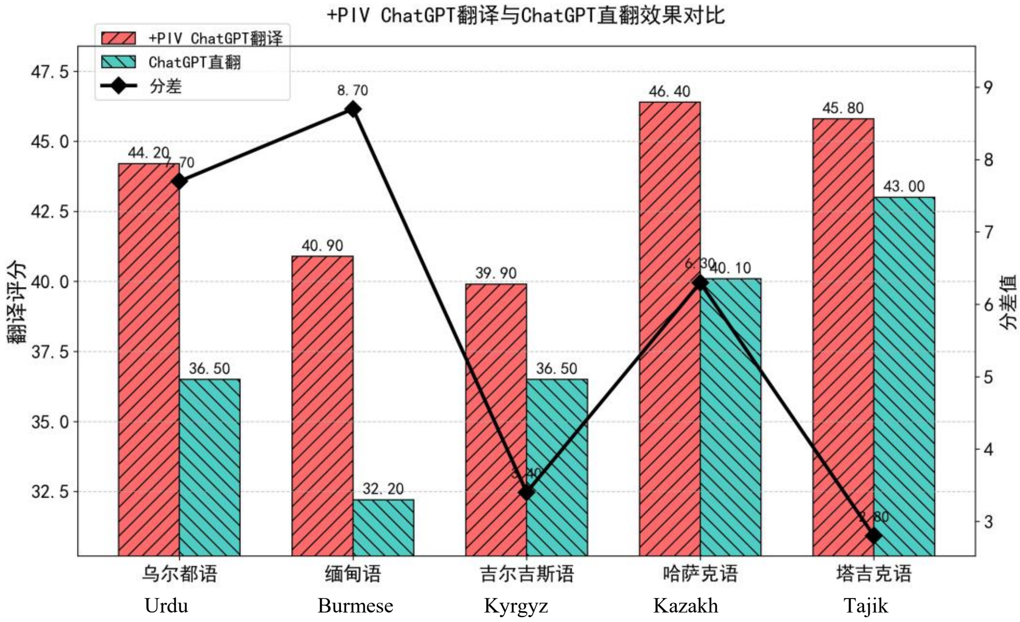
The case of Burmese presents a notable exception, as direct translation achieves a significantly higher COMET score (0.8733) compared to pivot translation (0.8582). This suggests that in the Burmese-to-Chinese translation task, the machine translation system is already capable of effectively handling linguistic differences between the source and target languages. Introducing English as a pivot language may, in fact, lead to information loss or misinterpretation, thereby diminishing overall translation quality.

The scores for the two translation methods in Kyrgyz are nearly identical—0.8636 for pivot translation and 0.8638 for direct translation—indicating that, in this language pair, the difference in translation quality between pivot and direct approaches is minimal.

The translation results for Kazakh show that the pivot translation score (0.8424) is higher than that of direct translation (0.8243). This indicates that pivot translation still holds a certain advantage in the translation of Kazakh, possibly due to significant linguistic differences between Kazakh and Chinese, with the pivot language effectively contributing to improved accuracy and fluency in translation. The translation results for Tajik reveal a significant difference, with the pivot translation scoring markedly higher at 0.9405 compared to 0.8664 for direct translation. This indicates a substantial improvement in translation quality when English is used as a pivot language, likely due to the considerable grammatical differences between Tajik and Chinese. The pivot language helps facilitate a better understanding of the source language's structure and expressions, thereby enhancing the overall quality of the translation.

These findings suggest that while pivot translation via English tends to enhance translation quality for most low-resource language pairs—especially those with substantial syntactic and structural divergences from Chinese—the superior performance of direct translation in the Burmese case highlights the need for language-specific strategies in machine translation design.

BLEU is another widely used automatic evaluation metric that emphasizes translation precision by measuring lexical alignment between machine outputs and reference translations. A higher BLEU score reflects a greater degree of consistency. The BLEU-based comparison allows for a clear observation of the performance gap between pivot-based translations utilizing English (PIV) and direct neural machine translation from source to target language:



When using a pivot language (English as an intermediary), the BLEU score for Urdu is significantly higher (44.2 vs. 36.5). This indicates that, through pivot translation, ChatGPT is better able to handle grammatical and expressive differences between the source and target languages, thereby improving translation quality. The pivot translation facilitates the system's understanding of complex syntactic structures and lexical usage, resulting in a higher score.

The results for Burmese also show that pivot translation (40.9) significantly outperforms direct translation (32.2). This suggests that the translation quality from Burmese to Chinese improves when English is used as a pivot language. The improvement is likely due to substantial differences in grammatical structure and syntactic order between Burmese and Chinese, where English, as an intermediary, helps better interpret and convey sentence meaning, thereby enhancing translation quality.

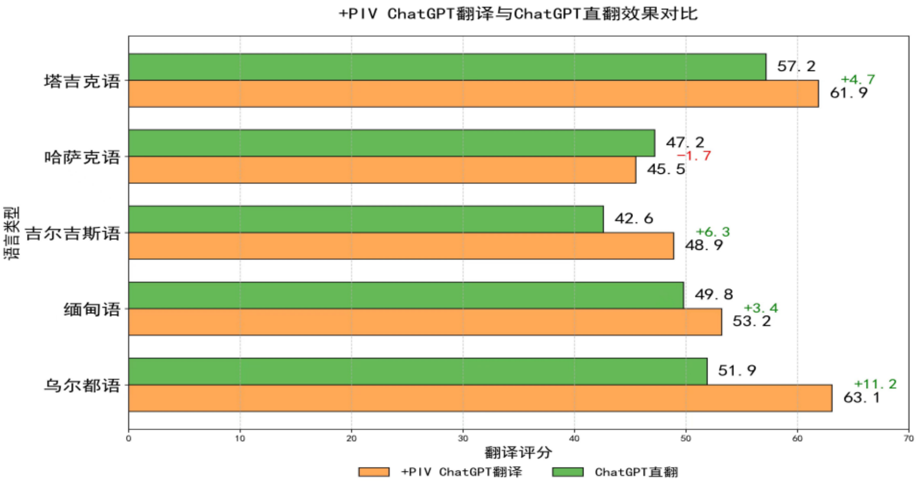
The difference between the two translation methods for Kyrgyz is relatively small (39.9 vs. 36.5). Although the use of a pivot language slightly improves the score, the gap is not significant. This suggests that the machine translation system can handle the transfer between the source and target languages without heavily relying on a pivot language. Therefore, the advantage of pivot translation is not as pronounced as it is for other languages.

The score difference for Kazakh is relatively large (46.4 vs. 40.1), indicating a clear advantage for pivot translation. Given the significant grammatical structural differences between Kazakh and Chinese, the pivot language (English) serves as an intermediary, helping the system better understand and generate expressions in the target language. As a result, the use of pivot translation significantly improves translation quality.

The score difference for Tajik is relatively small (45.8 vs. 43.0), but it still shows a slight advantage for pivot translation. While direct translation already performs quite well, the slight improvement in pivot translation suggests that English, as an intermediary language, still provides some benefit in translating Tajik.

In summary, for most low-resource languages—such as Urdu, Burmese, and Kazakh—pivot translation using English as an intermediary generally demonstrates a clear advantage in BLEU scores, particularly in language pairs with substantial structural differences. The pivot approach facilitates better comprehension of the source language's grammatical and syntactic structures by the machine translation system, thereby enhancing overall translation quality. For Kyrgyz and Tajik, however, the difference in BLEU scores between pivot and direct translation is relatively minimal.

BLEU-based automatic evaluation of translations using English as a pivot language versus direct translation from the source to the target language via traditional machine translation:



The BLEU score for Urdu shows a significant advantage for pivot translation (using English as an intermediary), with a score of 63.1 compared to 51.9 for direct translation. This indicates that the pivot translation method is better at handling the differences between the source and target languages, particularly in terms of grammatical structure, vocabulary choice, and word order. In this case, English as an intermediary language helps improve the accuracy and fluency of the translation.

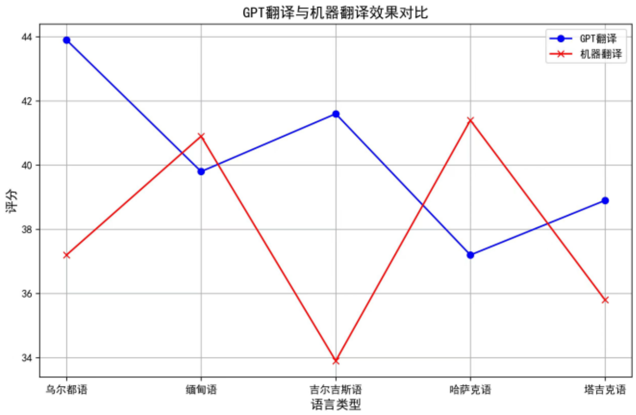
The score difference for Burmese is small, but it still shows that pivot translation (53.2) slightly outperforms direct translation (49.8). This suggests that, in the translation between Burmese and Chinese, English as an intermediary language helps improve translation quality, particularly when handling differences in vocabulary and grammatical structure. Although the gap between the two methods is not as pronounced as it is for Urdu, pivot translation still brings a certain level of improvement.

The score difference for Kyrgyz is quite noticeable, with 48.9 compared to 42.6, highlighting the advantage of pivot translation in improving translation quality. For Kyrgyz, direct translation yields more ordinary results, while pivot translation significantly enhances translation quality. This is likely due to the considerable structural differences between Kyrgyz and Chinese, with the pivot language (English) effectively serving as a bridge for language conversion.

For Kazakh, the scores show a slight reversal, with direct translation achieving a BLEU score of 47.2, surpassing the pivot translation score of 45.5. This outcome suggests that direct translation is already capable of handling the language pair effectively, rendering the advantage of pivot translation less pronounced compared to other language pairs. In such cases, direct translation may prove to be the more effective approach.

The score difference for Tajik is small, but pivot translation (61.9) still outperforms direct translation (57.2). This indicates that in the translation process between Tajik and Chinese, pivot translation helps improve translation quality, especially in terms of complex sentence structures and vocabulary usage. Pivot translation helps overcome the differences between the source and target languages, thereby enhancing translation accuracy and fluency.

In addition, I also employed the MQM (Multidimensional Quality Metrics) manual evaluation method, and the results showed minimal discrepancies compared to the automatic evaluation.



Urdu Burmese Kyrgyz Kazakh Tajik

5. Research conclusion

Based on the above analysis, neural machine translation systems employing the Pivot Prompting approach generally demonstrate superior performance across most language pairs. Notably, the introduction of a pivot language significantly enhances translation quality for languages such as Urdu, Kyrgyz, and Tajik. The pivot language effectively assists neural models in bridging the gap between the source and target languages, resulting in translations that are both more fluent and accurate. Similarly, machine translation utilizing the Pivot Translation Technique outperforms direct translation in several cases, particularly in the translation of Tajik and Urdu, where the use of a pivot language contributes to improved quality. However, for language pairs such as Burmese and Kazakh, direct translation yields better results, indicating that in certain contexts, direct translation may offer a more efficient solution.

The use of a pivot language has demonstrated notable benefits in many translation tasks involving low-resource languages. By introducing English as an intermediary (pivot) language, structural disparities between the source and target languages can be mitigated, thereby improving overall translation quality. Low-resource languages such as Urdu, Kyrgyz, and Tajik typically exhibit substantial grammatical differences from Chinese. In such cases, the pivot language helps bridge these structural gaps, resulting in more syntactically coherent translations. For instance, English, when used as a pivot, facilitates the handling of complex sentence constructions by aligning divergent syntactic patterns between the source and target languages. As a globally dominant language with a highly developed translation infrastructure, English offers extensive linguistic resources and high-quality translation systems that are often unavailable for low-resource languages. Consequently, using English as a pivot in PIV translation enables access to richer corpora and more precise lexical choices, reducing the likelihood of rigid or unnatural expressions that may occur in direct translations between typologically distant language pairs.

Therefore, from an overall perspective, neural machine translation employing the Pivot Prompting approach and traditional machine translation using the Pivot Translation Technique have demonstrated clear advantages in the majority of low-resource language translation tasks. This is particularly evident in language pairs characterized by complex sentence structures and significant grammatical differences, where the use of a pivot language effectively facilitates cross-linguistic transfer and enhances translation quality.

6. VI. Scientific Significance of Research

6.1 Social Benefits

6.1.1 Promoting Cross-Cultural Communication and Understanding

Translation technologies for low-resource languages—particularly those leveraging advanced natural language processing systems such as ChatGPT—play a significant role in enhancing cross-cultural communication. Traditional machine translation systems often face substantial challenges when handling low-resource languages, especially in rendering content embedded with specific cultural references, technical terminology, or complex syntactic structures. In such contexts, translation inaccuracies or distortions are common, which undermines the effectiveness of intercultural dialogue. By integrating techniques such as the Pivot Translation Technique and Pivot Prompting, ChatGPT demonstrates a stronger capacity to address these challenges, thereby fostering mutual understanding and cooperation among speakers of different languages and cultural backgrounds.

Enhancing Multilingual Communication: These approaches provide more accurate and natural translation tools for multilingual societies, particularly benefiting languages that have historically received limited technological attention. They contribute to overcoming communication barriers among diverse linguistic communities. Facilitating International Collaboration: Improved translation quality supports educational, scientific, and diplomatic exchanges in multilingual contexts, accelerating global academic cooperation and technical knowledge transfer. Supporting Language Preservation: From a global perspective, such technologies offer critical support for the preservation and dissemination of endangered or minority languages, serving as a technological foundation for cultural heritage protection in the context of globalization.

6.1.2 Enhancing Equity in Information Access:

Advancements in translation technologies for low-resource languages contribute significantly to the equitable distribution of information resources on a global scale. Existing translation systems tend to prioritize high-resource languages such as English, Chinese, and French, thereby marginalizing speakers of low-resource languages who often face a pronounced information gap. The application of ChatGPT and other deep learning-based technologies can help bridge this divide, enabling broader access to essential information in domains such as education, healthcare, and legal services for communities in underrepresented linguistic regions. Ultimately, this fosters greater social inclusion and contributes to the improvement of quality of life for speakers of low-resource languages.

6.1.3 Enhancing Interactivity in Multilingual Societies:

In multilingual and multicultural societies, advancements in translation technologies not only improve language communication efficiency but also enhance social cohesion among members. By providing more natural and fluent translations, these technologies can reduce misunderstandings and conflicts, fostering a greater sense of harmony. For instance, in multi-ethnic countries or international organizations, accurate translation technologies facilitate mutual understanding of differing perspectives, thereby promoting equitable dialogue and cooperation. This contributes to social stability and helps cultivate an inclusive environment where diverse voices are effectively heard and respected.

6.2 Economic benefit

6.2.1 Promoting Global Business and Trade Development:

The improvement of translation technologies holds significant economic value, particularly in areas such as cross-border e-commerce and international market expansion. As globalization deepens, businesses are increasingly confronted with the challenges of operating in multilingual and multicultural markets. Enhancing translation quality for low-resource languages not only aids companies in penetrating new markets and increasing global user engagement but also improves the accuracy of advertising, marketing, and customer support processes. This, in turn, strengthens market competitiveness and enables businesses to better cater to diverse consumer needs, fostering sustainable growth in the global economy.

6.2.2 Supporting Technological and Industrial Innovation:

The advancement of translation technologies for low-resource languages can provide more opportunities for collaboration within the technological and industrial sectors. Particularly in areas involving multinational research cooperation, technology transfer, and knowledge sharing, a robust translation system ensures the accurate dissemination of academic achievements, technical documents, and other crucial information across different linguistic communities. This contributes to the rapid development of the technology and innovation industries, driving global scientific progress and fostering innovation on a global scale.

6.2.3 Optimizing Government and Public Service Efficiency:

Governments and public service sectors often need to provide services to multilingual communities, particularly in countries that receive immigrants and refugees. By leveraging advanced translation technologies, governments can offer more efficient services to citizens from diverse linguistic backgrounds, reducing inconveniences caused by language barriers and enhancing service quality. Furthermore, improved communication in international affairs allows governments to engage more effectively in trade and diplomatic relations, promoting better bilateral and multilateral cooperation.

Therefore, the translation technologies provided in this study, particularly the advancements in low-resource language translation, are poised to have a profound impact on both social and economic development. From a social perspective, they can promote equitable access to global information, foster cross-cultural communication and understanding, and enhance interaction in multilingual societies. Economically, they contribute to the advancement of global business and trade, innovation in the tech industry, and the optimization of public services. As translation technologies for low-resource languages continue to mature, they have the potential to trigger broader changes worldwide, facilitating multicultural exchange and economic cooperation in the process of globalization.

References

[1] Artetxe, M., Labaka, G., Agirre, E., & Cho, K. (2018). Unsupervised Neural Machine Translation. In Proceedings of the International Conference on Learning Representations (ICLR)2018. arXiv:1710.11041 [cs.CL].

[2] Bahdanau, D., Cho, K., & Bengio, Y. (2015). Neural Machine Translation by Jointly Learning to Align and Translate. Proceedings of the International Conference on Learning Representations (ICLR).

[3] Currey, A., Miceli-Barone, A. V., & Heafield, K. (2017). Copied monolingual data improves low-resource neural machine translation. In Proceedings of the Second Conference on Machine Translation. Retrieved from aclanthology.org

[4] Dewangan, S., Alva, S., Joshi, N., & Bhattacharyya, P. (2021). Experience of neural machine translation between Indian languages. Machine Translation, 35(3-4), 71–99.

[5] González-Rubio, J., Navarro-Cerdán, J. R., & Casacuberta, F. (2013). Dimensionality reduction methods for machine translation quality estimation. Machine Translation, 27(3-4), 281–301.

[6] Haque, R., Liu, C.-H., & Way, A. (2021). Recent advances of low-resource neural machine translation. Machine Translation, 35, 451–474.

[7] Kumar, S., Anastasopoulos, A., Wintner, S., & Tsvetkov, Y. (2021). Machine Translation into Low-resource Language Varieties. In C. Zong, F. Xia, W. Li, & R. Navigli (Eds.), Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers) (pp. 110–121). Association for Computational Linguistics.

[8] Lavie, A., & Denkowski, M. J. (2009). The METEOR metric for automatic evaluation of machine translation. Machine Translation, 23(3-4), 105–115.

[9] Liu, C.-H., Karakanta, A., Tong, A. N., Aulov, O., Soboroff, I. M., Washington, J., & Zhao, X. (2020). Introduction to the Special Issue on Machine Translation for Low-Resource Languages. Machine Translation, 35(1), 247–249.

[10] Liu, C.-H., Karakanta, A., Tong, A. N., Aulov, O., Soboroff, I. M., Washington, J., & Zhao, X. (2021). Introduction to the second issue on machine translation for low-resource languages. Machine Translation, 35(1), 1–2.