

CHAPTER 5

**Bibliometric Insights into Translation Technology:
A CiteSpace Analysis of Web of Science Core
Collection Publications (2000-2024)**

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Abstract

In the dawn of the 21st century, the advent of innovative translation models has significantly advanced the capabilities of machine translation. This paper aims to conduct a comprehensive bibliometric analysis and visualization of the current landscape of translation technology research. Utilizing the Web of Science (WoS) core collection and employing CiteSpace 6.3.R1 as the analytical tool, this study delves into document citations, authorship patterns, institutional collaborations, and keyword co-occurrence. The findings present a detailed overview of the research from 2000 to 2024, highlighting prominent scholars and institutions, foundational literature, thematic areas, developmental trajectories, and prospective directions in the realm of translation technology.

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innovation in translation technology.

The study also recognizes the challenges and future directions in translation technology, such as the need for data augmentation, addressing gender bias, and the development of robust speech recognition systems for real-time translation applications. The integration of deep learning and attention mechanisms has been identified as a key driver for progress, with applications extending to multimodal representations and neural architecture search.

In conclusion, the field of translation technology is vibrant and continuously evolving, with deep learning and neural networks at its core. The research has become more interdisciplinary, integrating insights from computer science, linguistics, and artificial intelligence. As the field moves forward, it is expected that ongoing advancements will further improve the accuracy, efficiency, and accessibility of translation technologies, potentially transforming the way we communicate and understand languages across the globe.

References

- Bahdanau, D., Brakel, P., Xu, K., Goyal, A., Lowe, R., Pineau, J., ... & Bengio, Y. (2016). An actor-critic algorithm for sequence prediction. *arXiv preprint arXiv:1607.07086*.
- Barrachina, S., Bender, O., Casacuberta, F., Civera, J., Cubel, E., Khadivi, S., ... & Vilar, J. M. (2009). Statistical approaches to computer-assisted translation. *Computational Linguistics*, 35(1), 3-28.
- BL, M. (2021). Analysis of Machine Translation Tools for Translating Sentences from English to Malayalam and Vice Versa. *International Journal of Next-Generation Computing*, 12(4).
- Casacuberta, F., & Vidal, E. (2004). Machine translation with

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- inferred stochastic finite-state transducers. *Computational Linguistics*, 30(2), 205-225.
- Chen, C., & Chen, Y. (2005). Searching for clinical evidence in CiteSpace. In *AMIA Annual Symposium Proceedings* (Vol. 2005, p. 121). American Medical Informatics Association.
- Chen, C. (2016). *CiteSpace: a practical guide for mapping scientific literature*. Hauppauge, NY, USA: Nova Science Publishers.
- Chen, K., Wang, R., Utiyama, M., Sumita, E., Zhao, T., Yang, M., & Zhao, H. (2020). Towards more diverse input representation for neural machine translation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 28, 1586-1597.
- Dabre, R., Chu, C., & Kunchukuttan, A. (2020). A survey of multilingual neural machine translation. *ACM Computing Surveys (CSUR)*, 53(5), 1-38.
- Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)* (Vol. 1, pp. 4171-4186). Stroudsburg, PA: Association for Computational Linguistics.
- Dogru, G., & Moorkens, J. (2024). Data Augmentation with Translation Memories for Desktop Machine Translation Fine-tuning in 3 Language Pairs. *The Journal of Specialised Translation*, (41), 149-178.
- Doherty, S., & Kenny, D. (2014). The design and evaluation of a statistical machine translation syllabus for translation students. *The Interpreter and Translator Trainer*, 8(2), 295-315.
- Federico, M., & Bertoldi, N. (2005). A word-to-phrase statistical translation model. *ACM Transactions on Speech and Language*

- Processing (TSLP)*, 2(2), 1-24.
- Gaspari, F., Almaghout, H., & Doherty, S. (2015). A survey of machine translation competences: Insights for translation technology educators and practitioners. *Perspectives*, 23(3), 333-358.
- Gehring, J., Auli, M., Grangier, D., Yarats, D., & Dauphin, Y. N. (2017, July). Convolutional sequence to sequence learning. In *International conference on machine learning* (pp. 1243-1252). PMLR.
- Gong, Z., Zhong, P., & Hu, W. (2019). Diversity in machine learning. *IEEE Access*, 7, 64323-64350.
- Hutchins, B. (2004). Castells, regional news media and the information age. *Continuum*, 18(4), 577-590.
- Jiang, K., & Lu, X. (2020, November). Natural language processing and its applications in machine translation: A diachronic review. In *2020 IEEE 3rd International Conference of Safe Production and Informatization (IICSPI)* (pp. 210-214). IEEE.
- Jiang, S., & Chen, Z. (2023). Application of dynamic time warping optimization algorithm in speech recognition of machine translation. *Heliyon*, 9(11).
- Juan, A., & Vidal, E. (2002). On the use of Bernoulli mixture models for text classification. *Pattern Recognition*, 35(12), 2705-2710.
- Karyukin, V., Rakhimova, D., Karibayeva, A., Turganbayeva, A., & Turarbek, A. (2023). The neural machine translation models for the low-resource Kazakh-English language pair. *PeerJ Computer Science*, 9, e1224.
- Kenny, D., & Doherty, S. (2014). Statistical machine translation in the translation curriculum: overcoming obstacles and empowering translators. *The Interpreter and translator trainer*, 8(2), 276-294.

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- Khurana, D., Koli, A., Khatter, K., & Singh, S. (2023). Natural language processing: State of the art, current trends and challenges. *Multimedia tools and applications*, 82(3), 3713-3744.
- Klein, G., Kim, Y., Deng, Y., Senellart, J., & Rush, A. M. (2017). Opennmt: Open-source toolkit for neural machine translation. *arXiv preprint arXiv:1701.02810*.
- Koehn, P., & Knowles, R. (2017). Six challenges for neural machine translation. In *Proceedings of the 1st Workshop on Neural Machine Translation* (pp. 28-39). Association for Computational Linguistics.
- Lalrempuii, C., Soni, B., & Pakray, P. (2021). An improved English-to-Mizo neural machine translation. *Transactions on Asian and Low-Resource Language Information Processing*, 20(4), 1-21.
- Läubli, S., Castilho, S., Neubig, G., Sennrich, R., Shen, Q., & Toral, A. (2020). A set of recommendations for assessing human-machine parity in language translation. *Journal of artificial intelligence research*, 67, 653-672.
- Lin, Y., Guo, D., Zhang, J., Chen, Z., & Yang, B. (2020). A unified framework for multilingual speech recognition in air traffic control systems. *IEEE Transactions on Neural Networks and Learning Systems*, 32(8), 3608-3620.
- Liu, X., Zeng, J., Wang, X., Wang, Z., & Su, J. (2024). Exploring iterative dual domain adaptation for neural machine translation. *Knowledge-Based Systems*, 283, 111-182.
- Liu, Y., Gu, J., Goyal, N., Li, X., Edunov, S., Ghazvininejad, M., ... & Zettlemoyer, L. (2020). Multilingual denoising pre-training for neural machine translation. *Transactions of the Association for Computational Linguistics*, 8, 726-742.
- Mai, Y., & Yuan, X. (2024). Deep learning based optical network transmission application in Chinese English translation system in cloud computing environment. *Optical and*

- Quantum Electronics*, 56(4), 598.
- Maimaiti, M., Liu, Y., Luan, H., & Sun, M. (2022). Data augmentation for low-resource languages NMT guided by constrained sampling. *International Journal of Intelligent Systems*, 37(1), 30-51.
- Moorkens, J. (2017). Under pressure: translation in times of austerity. *Perspectives*, 25(3), 464-477.
- Moorkens, J. (2018). What to expect from Neural Machine Translation: a practical in-class translation evaluation exercise. *The Interpreter and Translator Trainer*, 12(4), 375-387.
- Nath, B., Sarkar, S., Das, S., & Mukhopadhyay, S. (2022). Neural machine translation for Indian language pair using hybrid attention mechanism. *Innovations in Systems and Software Engineering*, 1-9.
- Ott, M., Edunov, S., Baevski, A., Fan, A., Gross, S., Ng, N., ... & Auli, M. (2019). fairseq: A fast, extensible toolkit for sequence modeling. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Demonstrations* (pp. 48-53). Stroudsburg, PA: Association for Computational Linguistics.
- Pathak, A., Pakray, P., & Bentham, J. (2019). English–Mizo machine translation using neural and statistical approaches. *Neural Computing and Applications*, 31(11), 7615-7631.
- Pellicer, L. F. A. O., Ferreira, T. M., & Costa, A. H. R. (2023). Data augmentation techniques in natural language processing. *Applied Soft Computing*, 132, 109-803.
- Peris, Á., Domingo, M., & Casacuberta, F. (2017). Interactive neural machine translation. *Computer Speech & Language*, 45, 201-220.
- Post, M. (2018). A call for clarity in reporting BLEU scores. In

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- Proceedings of the Third Conference on Machine Translation: Research Papers* (pp. 186-191).
- Prates, M. O., Avelar, P. H., & Lamb, L. C. (2020). Assessing gender bias in machine translation: a case study with google translate. *Neural Computing and Applications*, 32, 6363-6381.
- Riemland, M. (2022). Translation and technocracy in development: defining the potentials and limitations of translation technology for Maya inclusion in Guatemalan development. *Linguistica Antverpiensia, New Series–Themes in Translation Studies*, 21.
- Riemland, M. (2023). Theorizing sustainable, low-resource MT in development settings: Pivot-based MT between Guatemala's indigenous Mayan languages. *Translation Spaces*, 12(2), 231-254.
- Ruffo, P. (2023). Literary translators and technology: SCOT as a proactive and flexible approach. *Perspectives*, 1-15.
- Sennrich, R., & Haddow, B. (2016). Linguistic input features improve neural machine translation. *arXiv preprint arXiv:1606.02892*.
- Sharma, V. K., Mittal, N., & Vidyarthi, A. (2022). Context-based translation for the out of vocabulary words applied to hindi-english cross-lingual information retrieval. *IETE Technical Review*, 39(2), 276-285.
- Singh, S. M., & Singh, T. D. (2022). An empirical study of low-resource neural machine translation of manipuri in multilingual settings. *Neural Computing and Applications*, 34(17), 14823-14844.
- Thomas, A., & Sangeetha, S. (2019). An innovative hybrid approach for extracting named entities from unstructured text data. *Computational Intelligence*, 35(4), 799-826.
- Touvron, H., Bojanowski, P., Caron, M., Cord, M., El-Nouby, A., Grave, E., ... & Jégou, H. (2022). Resmlp: Feedforward

- networks for image classification with data-efficient training. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(4), 5314-5321.
- Tutek, M., & Šnajder, J. (2022). Toward practical usage of the attention mechanism as a tool for interpretability. *IEEE access*, 10, 47011-47030.
- Waswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, 30.
- Wang, H. (2023). Defending the last bastion: A sociological approach to the challenged literary translation. *Babel*, 69(4), 465-482.
- Wang, H., Wu, H., He, Z., Huang, L., & Church, K. W. (2022). Progress in machine translation. *Engineering*, 18, 143-153.
- Wang, H., Xia, X., Lo, D., He, Q., Wang, X., & Grundy, J. (2021). Context-aware retrieval-based deep commit message generation. *ACM Transactions on Software Engineering and Methodology (TOSEM)*, 30(4), 1-30.
- Wang, R., Utiyama, M., Finch, A., Liu, L., Chen, K., & Sumita, E. (2018). Sentence selection and weighting for neural machine translation domain adaptation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 26(10), 1727-1741.
- Wang, R., Zhao, H., Lu, B. L., Utiyama, M., & Sumita, E. (2015). Bilingual continuous-space language model growing for statistical machine translation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 23(7), 1209-1220.
- Wang, S. (2023). Recognition of English speech—using a deep learning algorithm. *Journal of Intelligent Systems*, 32(1), 20220236.
- Xue, Y., Chen, C., & Słowik, A. (2023). Neural architecture search based on a multi-objective evolutionary algorithm with probability stack. *IEEE Transactions on Evolutionary*

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Computation.

- Yu, J., Li, J., Yu, Z., & Huang, Q. (2019). Multimodal transformer with multi-view visual representation for image captioning. *IEEE transactions on circuits and systems for video technology*, 30(12), 4467-4480.
- Zhang, J., Li, C., Liu, G., Min, M., Wang, C., Li, J., ... & Chen, H. (2022). A CNN-transformer hybrid approach for decoding visual neural activity into text. *Computer Methods and Programs in Biomedicine*, 214, 106-586.
- Zhang, J., Tian, Y., Mao, J., Han, M., Wen, F., Guo, C., ... & Matsumoto, T. (2023). WCC-JC 2.0: A Web-Crawled and Manually Aligned Parallel Corpus for Japanese-Chinese Neural Machine Translation. *Electronics*, 12(5), 1140.
- Zhang, J., Zhou, L., Zhao, Y., & Zong, C. (2020). Synchronous bidirectional inference for neural sequence generation. *Artificial intelligence*, 281, 103-234.
- Zhang, J., & Zong, C. (2015). Deep Neural Networks in Machine Translation: An Overview. *IEEE Intell. Syst.*, 30(5), 16-25.
- Zheng, W., Liu, X., Ni, X., Yin, L., & Yang, B. (2021). Improving visual reasoning through semantic representation. *IEEE access*, 9, 91476-91486.
- Zhou, L., Zhang, J., & Zong, C. (2019). Synchronous bidirectional neural machine translation. *Transactions of the Association for Computational Linguistics*, 7, 91-105.
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