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A Bibliometric Analysis of Large Language Models in Machine Translation: Trends and Advancements (2020-2024)

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Abstract: This bibliometric analysis of 460 peer-reviewed articles (2020–2024) maps the rapid evolution of Large Language Models (LLMs) in machine translation. The study reveals a significant surge in research, driven by advances in transformer architectures and characterized by robust international collaboration. Key themes identified include pre-trained models, neural machine translation, and specialized applications in domains like healthcare, highlighting the field's interdisciplinary nature. The findings offer valuable insights into current trends and future trajectories for LLM-driven translation.

Keywords: Machine Translation; Large Language Models; Neural Machine Translation; Bibliometric Analysis; Artificial Intelligence

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1. Introduction

Machine translation (MT), a pivotal subfield of artificial intelligence, serves as a critical technology for overcoming language barriers and a key benchmark for assessing progress in natural language understanding. Over the past five years, Large Language Models (LLMs) have introduced a transformative paradigm in machine translation research and development, significantly enhancing translation quality and efficiency while expanding its academic and industrial potential [1]. The performance of machine translation systems has consistently improved with increasing model scale and sophistication [2]. LLMs, capable of producing human-like language, have demonstrated remarkable advances across diverse NLP tasks and are increasingly recognized as transformative for science and technology [3,4]. Since 2020, landmark models such as GPT-3, GPT-4, Llama 3, Claude 3, and Mistral have revolutionized NLP, demonstrating exceptional capabilities in text generation, conversational AI, and cross-lingual understanding, thereby directly impacting the evolution of machine translation [5].

Recent literature reviews have shed light on LLM applications but predominantly employ the Systematic Literature Review (SLR) methodology, often within a broader context of translation studies or NLP [1,6,7,8]. While SLR offers valuable qualitative synthesis, bibliometric analysis provides a powerful quantitative alternative, capable of objectively mapping the scientific landscape, identifying emerging research hotspots, and revealing intellectual structures within a defined field [9-12]. This method is particularly well-suited to capturing the rapid growth and shifting trends characteristic of LLM-driven machine translation research.

Despite these advantages, dedicated bibliometric studies focusing specifically on LLMs within the machine translation domain remain scarce. Fan et al. provide a broad, cross-domain bibliometric survey of LLM research, and Wang et al. concentrate specifically on interactive machine translation, yet neither conducts a full bibliometric review specifically on LLM-driven machine translation [13,14]. While existing reviews, such as Chan & Tang, explore LLMs in broader translation contexts, a clear gap exists for a focused bibliometric analysis that maps the intellectual structure and research trends specifically within the LLM-driven machine translation field [7]. To fill this gap, the present study analyzes 460 peer-reviewed articles from the Web of Science (2020–2024) with a specific focus on LLM applications in machine translation. It aims to address the following three research questions (RQs):

RQ 1: How have publication trends in LLM-driven machine translation evolved from 2020 to 2024? RQ 2: What are the leading institutional and national contributions, and how do their collaboration networks shape the field of machine translation?

RQ 3: What thematic areas and emerging trajectories will define the future of LLM applications in machine translation?

This study is significant in two primary respects. First, it provides a timely, comprehensive bibliometric mapping of recent advancements in transformer-based LLMs specifically within the machine translation domain, highlighting key publication trends, institutional drivers, and emerging research themes that illustrate how LLMs are reshaping the MT landscape. Second, it offers strategic guidance for scholars, industry experts, and decision-makers by uncovering knowledge gaps, identifying new research directions, and supporting innovation for the continued advancement of machine translation technology.

2. Data and methods

2.1. Research data

This literature review relies on data sourced from the Web of Science Core Collection. The search strategy included the following terms: (ALL=("Large Language Model" OR "LLM" OR "Neural Language Model" OR "Pre-trained Language Model" OR "Transformer-based Model" OR "Generative AI" OR "Foundation Model") AND ALL=("Machine Translation" OR "Neural Machine Translation" OR "Cross-lingual NLP" OR "Multilingual NLP" OR "AI-assisted Translation" OR "Text Generation" OR "Cross-lingual Transfer Learning" OR translate*)) AND PY=(2020-2024) AND DT=("Article"). These keywords were selected to comprehensively cover the domains of large language models and their applications in machine translation research. This approach was essential for capturing the full scope of advancements in these fields. The period from 2020 to 2024 was chosen to focus on recent developments, particularly following the surge in interest related to large language models after 2020. The search was conducted in January 2025, resulting in a total of 460 articles. The retrieved data were analyzed and visualized using tools like the "Analyze Results" feature in Web of Science and CiteSpace Software. These tools facilitated the categorization and clustering of data, allowing for the identification of publication trends, thematic focus, keyword analysis, and national collaboration networks, as detailed in **Table 1**.

Table 1. Outline structure of the search formula

Item	Details
Keywords	"Large Language Model", "LLM", "Neural Language Model", "Pre-trained Language Model", "Transformer-based Model", "Generative AI", "Foundation Model", "Machine Translation", "Neural Machine Translation", "Cross-lingual NLP", "Multilingual NLP", "AI-assisted Translation", "Text Generation", "Cross-lingual Transfer Learning", translate*
Operators	“OR”, “AND”
Period	2020-2024
Language	English
Data source	Web of Science Core Collection
Document type (included)	Journal papers indexed in WOS, “Article”
Search date	January 2025

Key: LLM=Large Language Model, NLP= Natural Language Processing, WOS = Web of Science.

2.2 Research methods

The methodology of this study is structured into three main stages: data collection, bibliometric analysis and information visualization, and result discussion, as shown in **Figure 1**.

During the Data Collection phase, literature is retrieved using the advanced search function in the Web of Science Core Collection, as detailed in Section 2.1. After an initial screening process, which includes filtering by language (English) and document type (excluding conference papers, non-peer-reviewed sources, books, reports, etc.), a total of 460 relevant articles were selected. These criteria ensure the inclusion of high-quality, peer-reviewed sources for subsequent analysis.

In the bibliometric analysis and information visualization phase, CiteSpace software is employed to create visual maps based on bibliometric data extracted from the selected papers. This stage involves a comprehensive analysis of publication trends, the identification of key research themes, and the exploration of keyword hotspots. Furthermore, the national collaboration network is analyzed to explore the international dynamics of research in the field of large language models and machine translation. By focusing on these aspects, the study aims to uncover the evolution of research priorities and collaborative patterns within this domain.

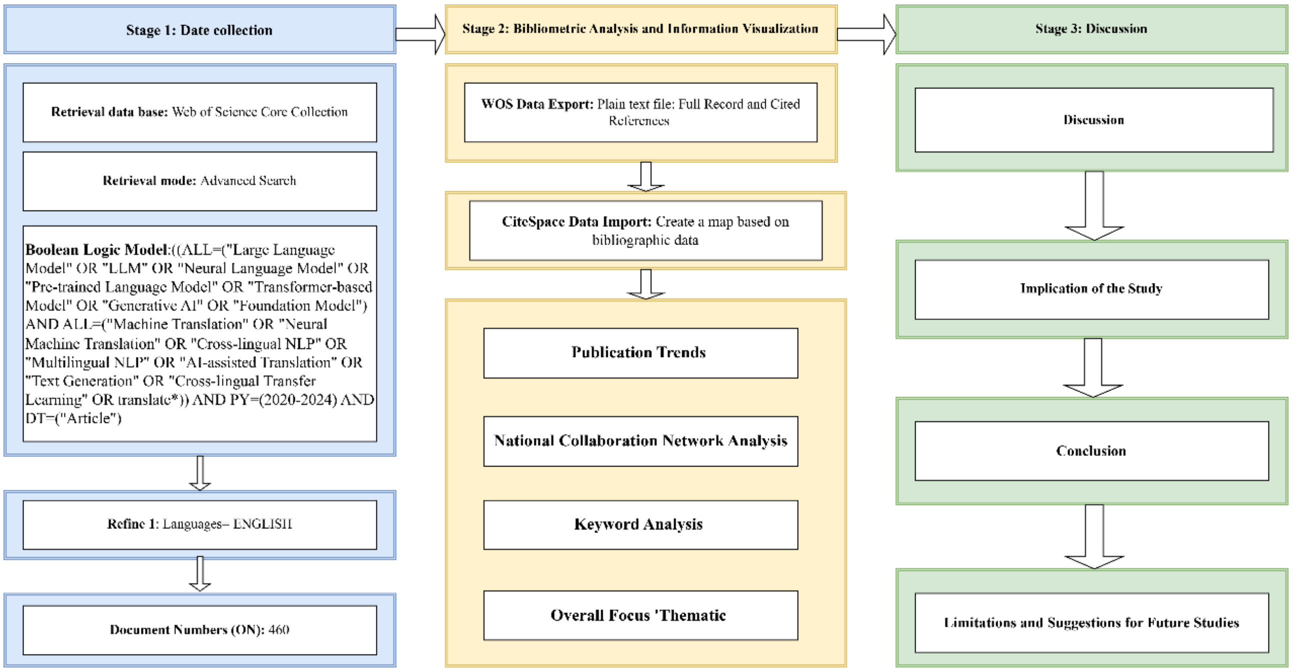

Figure 1. Research methodology steps

3. Bibliometric analysis

3.1. Publication trends

To address the research question 1, "How have publication trends regarding the application of large language models (LLMs) in machine translation evolved from 2020 to 2024?", this analysis examines two key visual representations: a line graph (**Figure 1**) titled "Annual Publication Output (2020–2024)" and a table (**Table 1**) titled "The top ten most fruitful journals." These figures collectively illuminate the temporal dynamics of research productivity and the distribution of scholarly output across major publishing entities within the field of large language models (LLMs) applied to machine translation.

Figure 2 delineates the annual publication output of scholarly works concerning LLMs in machine translation over the five-year span from 2020 to 2024. The line graph employs a horizontal x-axis, marked with the years 2020 through 2024, and a vertical y-axis, scaled in increments of 50 from 0 to 350, representing the number of publications. A single blue line charts the progression of publication counts, commencing at 15 publications in 2020 and rising marginally to 19 in 2021. The output remains relatively stable in 2022 with 28 publications. A notable escalation emerges in 2023, with the number of publications increasing sharply to 75, followed by a dramatic surge to 307 in 2024. This trajectory reveals a pronounced upward trend, particularly evident from 2022 onward, with the exponential growth between 2023 and 2024 signaling a burgeoning interest and intensified research activity in this domain.

Table 2 enumerates the top ten most prolific journals contributing to the research on LLMs in machine translation, ranked according to the number of published papers. Elsevier secures the foremost position with 96 publications, substantially surpassing its counterparts. MDPI follows with 53 publications, while Springer Nature and IEEE register 48 and 45 publications, respectively. Both Nature Portfolio and Oxford Univ Press contribute 32 publications each, succeeded by Wiley with 20, Taylor & Francis with 14, Jmir Publications, Inc. with 13, and Frontiers Media Sa with 11 publications. Presented in a straightforward grid layout, the table facilitates direct comparison, underscoring Elsevier's preeminent role in disseminating research within this field, complemented by significant contributions from MDPI, Springer Nature, and other established publishers. This concentration among reputable academic outlets highlights their pivotal influence in amplifying the visibility and impact of LLM-related machine translation research globally.

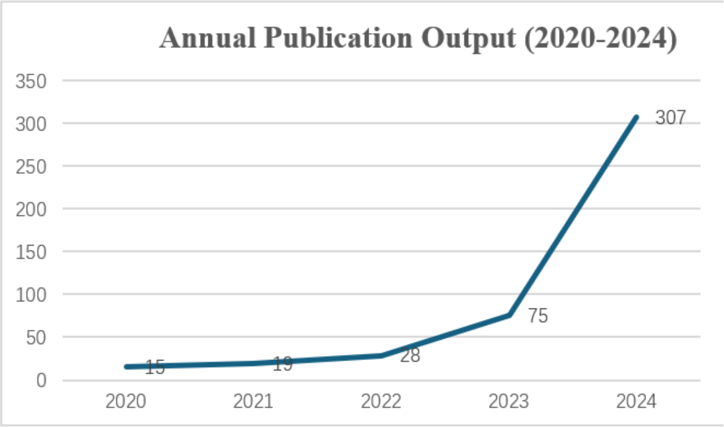

Figure 2. Publication years (2020-2024). Source: Web of Science

Table 2. the top ten most prolific journals

Number	The name of journals	The number of published papers
1	Elsevier	96
2	Mdpi	53
3	Springer Nature	48
4	IEEE	45
5	NATURE PORTFOLIO	32
6	Oxford Univ Press	32
7	Wiley	20
8	Taylor & Francis	14
9	Jmir Publications, Inc	13
10	Frontiers Media Sa	11

3.2. Country Co-occurrence map

To answer the second part of the second research question, "how do their collaboration networks between countries shape the field?", **Figure 3** provides a clear visualization of the collaboration networks between countries in the field of large language models (LLMs) applied to machine translation. In **Figure 3**, each node represents a country, with the node size proportional to the country's level of research activity in this domain. The edges connecting the nodes vary in thickness and color, reflecting the strength and frequency of collaborations between different nations.

The map clearly identifies the USA, China, and England as the central nodes in the global LLM research network. These countries are represented by large circles, indicating a high volume of co-authored papers, and are surrounded by a dense network of collaborations with other nations. The USA emerges as the leading country, with institutions such as Harvard University and Stanford University contributing significantly to foundational LLM research and application in machine translation. The USA's dominant position highlights its leadership in advancing LLM technologies and fostering international research collaborations. China, with institutions like Chinese Academy of Sciences and Shanghai Jiao Tong University, holds a central position as well, reflecting its rapid advancement in LLM research. China's collaborations with other nations are particularly strong, reflecting its growing influence in global LLM research. England, with institutions such as University of Cambridge and Oxford University, is a key player in the development of multilingual machine translation systems. Its involvement in high-impact research and global collaborations highlights its ongoing contribution to LLM-based machine translation.

The map also highlights the increasing contributions from Turkey, Saudi Arabia, Singapore, and Sweden, indicating the growing global interest in LLMs and machine translation across different regions. Turkey and Saudi Arabia are emerging players in the Middle East, collaborating with leading institutions to enhance their capabilities in machine translation and LLM research. Singapore has become an important research hub in Southeast Asia, contributing to the development of LLMs tailored for the region's multilingual and multicultural context.

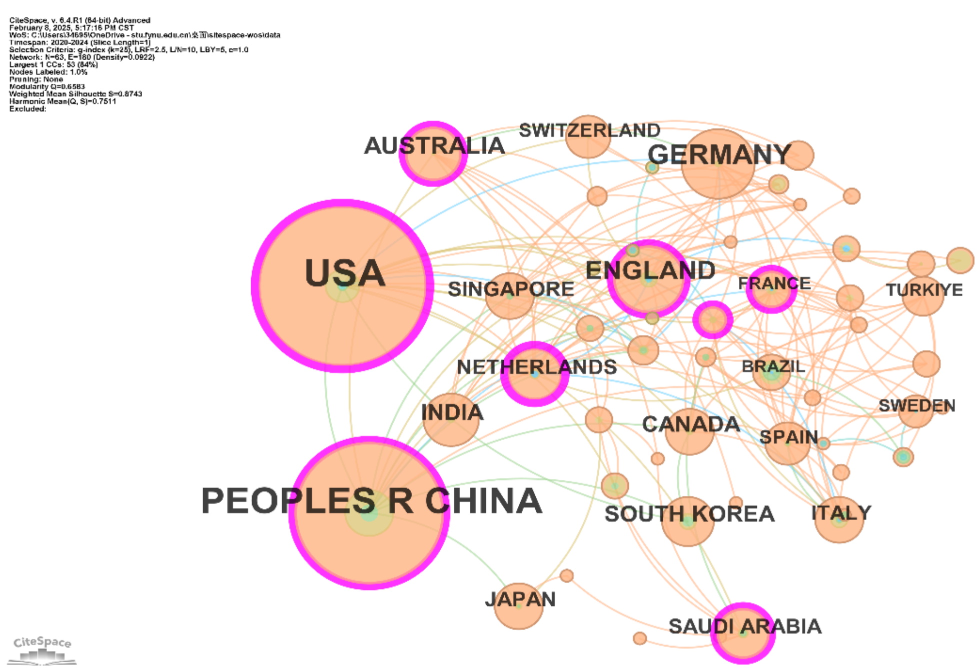

Figure 3. Country Collaboration Network (2020–2024)

3.3. Keyword analysis

To address the first two parts of the final question of this research, "What are the key thematic areas and emerging research trajectories that will shape the future of LLM applications in machine translation, based on recent developments and trends?", this study systematically identifies the top 10 high-frequency keywords through bibliometric screening of LLM-driven machine translation research (2020–2024), conducts co-occurrence network analysis, and constructs a comprehensive thematic focus matrix to delineate the intellectual architecture of this emerging field. The keyword analysis aims to conduct an in-depth exploration of the keywords in LLM-driven machine translation research, understanding the frequency, distribution, and relationships among different keywords. This analysis will reveal how the research topics and areas within LLM-driven machine translation are interconnected.

Table 4 highlights the most prominent keywords and their frequency of occurrence in the research related to LLM applications in machine translation. "Artificial intelligence", "large language model", and "natural language processing" are the most central and frequently occurring terms, indicating their crucial role in the ongoing development of LLMs for machine translation. The rising interest in "large language models" and "deep learning" reflects a shift toward more sophisticated and powerful models for translating across languages. Additionally, the presence of terms like "pre-trained language model" and "text generation" underscores the increasing emphasis on improving LLM capabilities, specifically in producing coherent and contextually relevant machine translations. **Figure 3** presents the keyword co-occurrence network in LLM-based machine translation research. This analysis organizes the keywords into eight clusters in **Figure 4**, each representing a distinct theme within the field.

Figure 4 showcases the co-occurrence of key terms, provides a network visualization where the centrality of terms like "artificial intelligence", "large language model", and "natural language processing" stands out. The relationships between these terms suggest that there is a significant body of work focusing on the application of these technologies to machine translation. The presence of "task analysis", "pre-trained language model", and "generative AI" further emphasizes the growing intersection of different AI approaches in advancing machine translation technologies. The connections between keywords illustrate an integrated, cross-disciplinary approach to LLM-driven machine translation, where developments in AI, machine learning, and NLP converge to enhance machine translation accuracy and efficiency.

Figure 5 shows clusters of emerging research trends, highlighting various domains where LLMs are being applied beyond traditional machine translation, such as "neural machine translation", "synthetic clinical notes", and "sequence modeling". The dominant "pre-trained language model" cluster (#0) ties closely with neural machine translation (#1), which suggests that recent research is moving toward the application of pre-trained models in machine translation tasks. Additionally, there is an increasing focus on specialized areas such as "synthetic clinical notes", indicating the potential application of LLMs in specific domains like healthcare machine translation. These clusters point to an interdisciplinary approach where LLMs are being tailored to meet specific needs in fields like medical machine translation and other niche areas.

In conclusion, the figures and tables in this section collectively reflect a growing interest in applying LLMs to machine translation, with a focus on improving the performance of these models through deep learning, pre-trained models, and generative AI. They also highlight the increasing complexity and specialization in LLM applications, with emerging research addressing both general machine translation tasks and specific domain-focused challenges, such as in healthcare.

Table 4. Top 10 Keywords in LLM-Driven Machine Translation Research (2020–2024)

Label	Frequency	Centrality	Year	Keywords
1	84	0.14	2022	artificial intelligence
2	75	0.01	2023	large language model
3	53	0.03	2023	large language models
4	50	0.16	2021	natural language processing
5	40	0.07	2023	generative ai
6	38	0.16	2021	deep learning
7	28	0.05	2022	machine learning
8	22	0.16	2021	pre-trained language model
9	15	0.03	2021	task analysis
10	14	0.24	2021	text generation

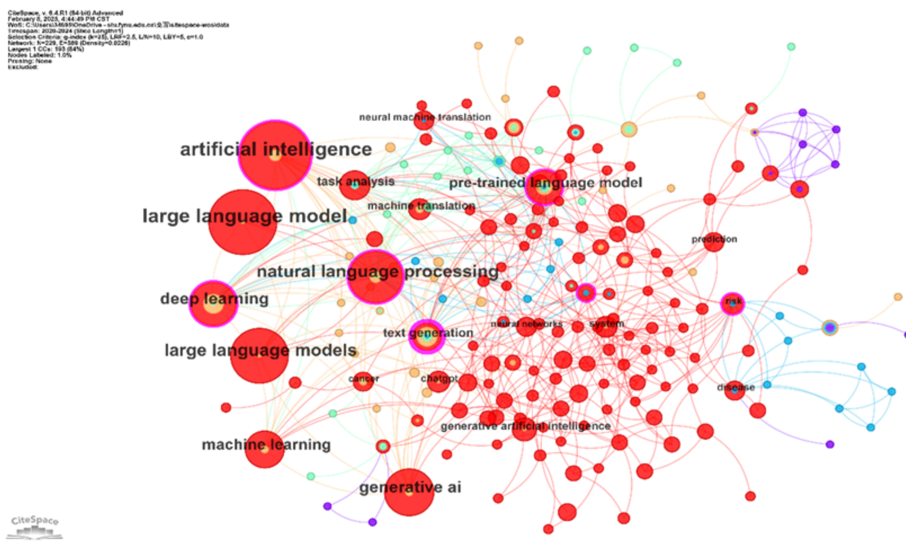

Figure 4. Keywords analysis (2020–2024)

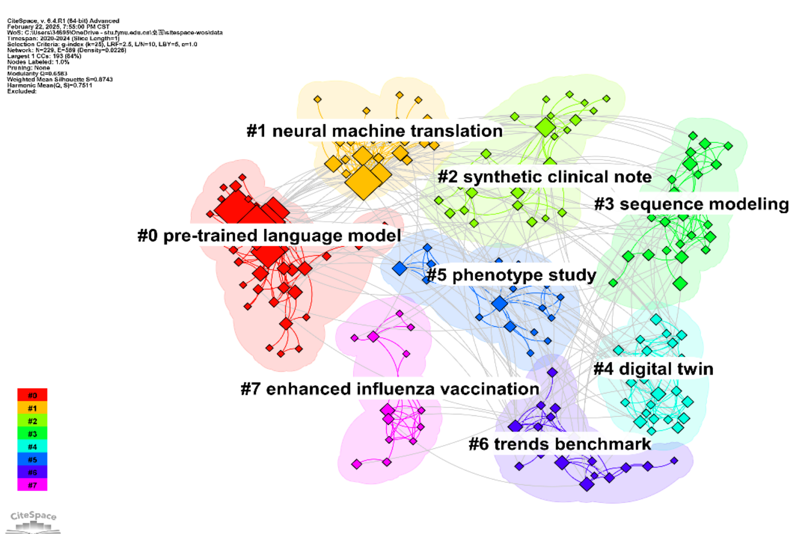

Figure 5. Keyword Clusters (2020–2024)

3.4. Overall focus thematic

To address the final part of the last research question, “What is the distribution of research articles?”, this study identifies the top ten disciplines based on bibliometric data related to LLM-driven machine translation across various Web of Science categories from 2020 to 2024. As shown in **Table 5**, the majority of research falls under “Computer Science Information Systems” (17.39%) and “Computer Science Artificial Intelligence” (13.48%), emphasizing the pivotal role of AI and computer science in LLM development for machine translation. Additionally, fields like “Engineering Electrical Electronic” (12.17%) and “Medical Informatics” (11.96%) highlight LLM applications beyond traditional computing, notably in engineering and medical machine translation.

The “Computer Science Interdisciplinary Applications” category (10.43%) shows the growing interdisciplinary nature of LLM-driven translation, with applications spanning various scientific domains. The focus on “Health Care Sciences Services” (8.91%) reflects the increasing use of LLMs in healthcare translation, particularly in medical document machine translation and multilingual clinical communication.

Emerging sectors such as “Physics Applied” (6.52%), “Materials Science Multidisciplinary” (5.87%), and “Telecommunications” (5.43%) indicate that LLMs are expanding into new technological and industrial fields. The “Multidisciplinary Sciences” category (5.22%) underscores the broad, cross-sectoral applications of LLM-driven machine translation.

In summary, LLM-driven machine translation research is highly interdisciplinary, with significant contributions from computer science, engineering, medicine, and emerging fields, demonstrating the broad potential of LLMs in addressing complex, cross-disciplinary challenges.

Table 5. Overall focus thematic

Web of Science Categories	2020-2024
Computer Science Information Systems	**80(17.39%)**
Computer Science Artificial Intelligence	**62(13.48%)**
Engineering Electrical Electronic	**56(12.17%)**
Medical Informatics	**55(11.96%)**
Computer Science Interdisciplinary Applications	**48(10.43%)**
Health Care Sciences Services	**41(8.91%)**
Physics Applied	**30(6.52%)**
Materials Science Multidisciplinary	**27(5.87%)**
Telecommunications	**25(5.43%)**
Multidisciplinary Sciences	**24(5.22%)**

4. Discussion

This study offers a bibliometric analysis of large language model (LLM) applications in machine translation (MT) from 2020 to 2024, revealing rapid growth and shifting research priorities. Publications increased exponentially, especially from 2023 to 2024, reflecting breakthroughs in transformer architectures such as GPT-4 and BERT. This surge empirically validates the findings of scholars like Zeng & Liang, demonstrating that

LLMs are surpassing conventional neural machine translation in key performance indicators such as translation quality, interactivity, and domain adaptation [15]. The data confirms that LLM-driven machine translation has entered a phase of accelerated development, moving from theoretical exploration to large-scale application and optimization.

The publication patterns and influential journals identified (e.g., Elsevier, MDPI) underscore the field's transition towards industrial-scale research and development. The dominance of leading institutions from the U.S., China, and the UK is not merely a reflection of academic excellence but is likely deeply intertwined with the presence of major tech corporations (e.g., OpenAI, Google, Baidu) and substantial R&D funding in these regions, which fuel both foundational research and rapid commercialization. The rise of contributors from Turkey, Saudi Arabia, and Singapore signals the globalization of machine translation research, potentially driven by regional demands for multilingual technologies and strategic national investments in AI.

Keyword and disciplinary analyses reveal a mature core of computer science and AI research, now radiating into highly specialized domains. The strong presence of "Medical Informatics" and the emergence of themes like "synthetic clinical notes" are particularly telling. They indicate that machine translation research is increasingly driven by real-world, high-stakes applications where accuracy is critical, pushing the boundaries of domain adaptation.

However, this very focus on technical performance and domain specialization has led to significant research gaps. The relative neglect of human factors within the machine translation workflow, such as user interaction design and post-editing processes, reveals a technocentric bias. As O'Brien and Wang et al. suggest, the ethical dimensions of deploying these systems—including job displacement and the mitigation of contextually critical errors—remain underexplored [14,16]. Furthermore, while domain-specific challenges in legal and medical machine translation are acknowledged, the solutions proposed are predominantly technical [17,18]. There is a pressing need for research that integrates human-centered design and socio-technical perspectives to develop LLMs that are not only powerful but also trustworthy, usable, and aligned with human needs in professional machine translation contexts.

In conclusion, this bibliometric map outlines a field in the midst of a dramatic expansion, defined by technical breakthroughs and global collaboration. The path forward must now involve a deliberate shift to address the identified gaps, forging a new paradigm for machine translation that is both technologically robust and profoundly human-aware.

5. Implication of the Study

This study employs bibliometric analysis to map publication trends and thematic areas of large language model (LLM) applications in translation from 2020 to 2024. By visualizing keyword co-occurrence networks, national collaboration patterns, and co-citation clusters, it outlines the development of LLM-driven translation systems, identifies emerging themes, and highlights research gaps, thus clarifying the evolving role of LLMs in shaping machine translation.

Researchers can build on these findings through targeted systematic reviews and meta-analyses focusing on pre-trained or domain-specific models and multimodal translation. Future studies may examine real-world impacts on machine translation accuracy, multilingual transfer learning, and language inclusivity, providing actionable insights for optimizing LLMs across diverse domains and languages. Methodologically, the use of literature landscape analysis, co-occurrence analysis, and thematic clustering with tools such as CiteSpace demonstrates the value of bibliometrics for tracking research dynamics in LLM-based machine translation and offers a replicable framework for related technology-driven fields.

For educators, policymakers, and industry stakeholders, the findings on domain-specific models and cross-lingual transfer learning inform curriculum design, professional training, and policy development to integrate LLM-driven translation into public services efficiently and equitably. At the societal level, this study highlights the transformative potential of LLMs to enhance global knowledge access and support underrepresented languages, underscoring the importance of ethical AI and inclusive machine translation in promoting multilingual communication.

In conclusion, this study enriches understanding of LLM-based machine translation and provides a roadmap for future research, practical applications, and responsible deployment, supporting the development of more accessible and inclusive global machine translation practices.

6. Conclusion

This study has presented a comprehensive bibliometric analysis of the rapidly evolving landscape of LLM applications in machine translation between 2020 and 2024. The exponential growth in publications, led by transformer-based models, underscores a paradigm shift in the field. Our findings not only quantify this surge but also delineate the intellectual structure, key contributors, and collaborative networks that define it.

We have identified the central role of pre-trained models, neural machine translation architectures, and the critical expansion into domain-specific applications, most notably in healthcare. The mapping of international collaborations highlights a global research effort, while the thematic analysis confirms the field's strong foundation in computer science and its growing interdisciplinary reach.

Looking forward, the future of LLM-driven machine translation will be shaped by how effectively the field addresses its current imbalances. The most promising trajectories lie in bridging the gap between machine capability and human interaction. This entails pioneering research into human-computer interaction and post-editing frameworks tailored to LLMs, developing ethical guidelines for their deployment, and creating robust, domain-adapted models that are accessible to a wider range of languages and cultures. Ultimately, the success of these technologies will be measured not solely by benchmark scores but by their ability to integrate seamlessly into human workflows and to foster genuine, equitable multilingual communication. This study provides a foundational map to guide that necessary and timely evolution.

7. Limitations and research outlook

This study has several limitations that should be addressed in future research. First, the exclusive reliance on Web of Science may have omitted relevant studies from other databases. Second, the 2020–2024 timeframe excludes earlier foundational work and emerging trends beyond 2024, such as DeepSeek's 2025 breakthroughs in cost reduction and Chinese-language optimization, which are likely to influence future publications. Additionally, despite comprehensive keyword strategies, some relevant literature may have been missed due to rapid terminological evolution in the field.

To address these limitations, future research should incorporate multiple databases—such as Scopus, PubMed, and CNKI—and include gray literature for broader coverage. Qualitative methods like content analysis or thematic coding could complement bibliometric findings by offering deeper insight into research themes and gaps. Comparative bibliometric analyses across platforms and regions would also help illuminate global collaboration patterns and regional variations, enriching understanding of LLM-driven machine translation.

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Disclosure statement

The author declares no conflict of interest.

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