ADVANCING AI TRANSLATION RESEARCH: TRENDS IN TOP-TIER INTERNATIONAL APPLIED LINGUISTICS JOURNALS

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ABSTRACT The complexities surrounding AI translation in applied linguistics represent a critical challenge in the advancement of language technologies in the 21st century. This research applied content analysis to several articles published in top-tier international applied linguistics journals from 2015 to 2024, focusing on AI translation as the central theme. The study reveals a substantial growth in publications on this subject, particularly over the last four years. Research and development (R&D) has been identified as the central theme, with translation methodologies and assessment frameworks serving as the primary areas of inquiry. The studies exhibit a wide thematic scope, with Artificial Intelligence (AI) and machine learning emerging as the most frequently employed technologies. Among the methodologies, machine translation (MT) and natural language processing (NLP) were the most prominent, while coding sheets and narrative analysis were the preferred instruments for data collection and evaluation. Drawing on these findings, several recommendations are proposed to improve the effectiveness of AI translation. Future research should prioritize the development of comprehensive evaluation frameworks that combine quantitative and qualitative methodologies, emphasizing both linguistic precision and the cultural and contextual nuances of language. Additionally, enhancing the quality and diversity of datasets is essential to achieving broader and more inclusive linguistic representation.

Keywords: *Artificial Intelligence; AI Translation; Applied Linguistics Journals.*

INTRODUCTION

Artificial Intelligence (AI) is widely recognized as a critical innovation transforming the technological domain of the 21st century (Malik et al., 2024). AI is not only expected to enhance conceptual understanding across various fields but also to transcend traditional algorithms and processes by developing innovative solutions to complex problems (Alqahtani et al., 2023). As AI technology continues to evolve, its capabilities increasingly drive advancements in creative problem-solving and practical applications across diverse industries (Boussioux et al., 2024). Collaboration and communication skills, particularly in human-AI interactions, are becoming essential competencies to cultivate (Momose et al., 2024). Furthermore, understanding and applying scientific methods in AI development is critical to achieving success in today's rapidly advancing technological and scientific domains (Krenn et al., 2022). Additionally, skills such as metacognitive thinking (Maor et al., 2023), creative innovation (Cady et al., 2024), and critical analysis (Dumitru & Halpern, 2023) are emphasized as pivotal for ensuring that AI professionals remain competitive in a workforce increasingly influenced by rapid technological advancements.

As AI technology progresses, AI-based translation has emerged as one of its most significant applications (Q. Xu, 2024). AI-driven machine translation technologies, such as neural machine translation (NMT), have revolutionized cross-linguistic communication (Sánchez-Gijón, 2022), offering swift and efficient solutions for translating texts into various languages (Eriguchi et al., 2022). AI translation enables automation in the translation process (Gao, 2024), reduces human errors (Y. Wu & Liang, 2024), and enhances productivity, which is crucial in the context of globalization and intensifying international interactions (X. Li, 2024). Nevertheless, significant challenges remain, particularly in maintaining accuracy and cultural appropriateness (Naveen & Trojovský, 2024), which are often difficult for current translation algorithms to achieve.

In applied linguistics, a deep understanding of linguistic structures, social contexts, and cultural nuances is essential for producing translations that are not only linguistically accurate but also socially and culturally relevant (C. Li et al., 2024; Jenks, 2024; Kubanyiova & Creese, 2024). Although AI translation excels in speed and scalability, it frequently encounters challenges in capturing such complexities, particularly regarding idiomatic expressions (Baziotis et al., 2022), cultural connotations (Al Sawi & Allam, 2024), and dialectal variations that algorithmic systems struggle to interpret (Kunst & Bierwiaczonek, 2023). Applied linguistics can significantly contribute to the development of AI translation by providing a theoretical framework for understanding how language functions in social and cultural contexts. For instance, pragmatic and sociolinguistic studies in applied linguistics can guide the design of translation systems that are more sensitive to the linguistic variations emerging in specific social situations (Mohebbi, 2023; Hovy, 2021). Additionally, corpus linguistics, leveraging large-scale linguistic data analysis, can enrich datasets used to train AI translation systems, enabling them to account for broader and more accurate language variations (Laurençon et al., 2022; Chen, 2021; Fei et al., 2020).

Moreover, integrating insights from applied linguistics allows AI-based translation systems to better address contextual aspects, such as selecting appropriate words for a given conversational or textual situation (Brandt & Hazel, 2024). This is particularly critical for translating literary, political, or scientific texts, where implied meanings and cultural appropriateness significantly impact translation quality (Hui et al., 2024). Therefore, collaboration between applied linguists and computer scientists is crucial to developing AI-based translation systems that not only rely on technology but also preserve the social and cultural dimensions of the languages being translated.

Previous research has extensively focused on algorithmic development and improving translation efficiency. For instance, neural machine translation (NMT) models have significantly enhanced translation accuracy (Costa-jussà et al., 2024). Ling Jin (2023) highlighted how advancements in machine learning enable translations to adapt more effectively to cultural contexts. Wensen Xian (2024) observed that AI-based translation addresses multilingual challenges but often fails to capture emotional nuances in texts. Naveen & Trojovský (2024) found that automated translations are often limited by rigid language use, overlooking critical social nuances. Similarly, Moneus & Sahari (2024) noted that while technical accuracy in translations has improved, many AI-based translation tools are not yet capable of fully replacing human translators, particularly in complex and semantically rich contexts. Despite the breadth of existing research, there remains a lack of comprehensive reviews or synthesis of findings on the development of AI-based translation.

This research utilized content analysis on various applied linguistics articles published in reputable international journals from 2015 to 2024, with the goal of gathering insights into studies that examined AI translation. Specifically, the study sought to address the following questions: (1) What was the trend in the number of studies on AI translation over the years? (2) What types of research designs were employed to explore AI translation? (3) Which topics were most frequently explored in relation to AI translation? (4) What interventions did researchers apply to enhance AI translation? (5) What instruments were utilized by researchers to assess AI translation? (6) What data analysis techniques were used in the examination of AI translation? (7) How were the studies on AI translation collectively characterized?

This research presents several distinctions from earlier studies on AI translation. First, it examined a complete set of articles published from 2015 to 2024, all of which were recognized by the Directory of Open Access Journals (DOAJ). Second, the study specifically aimed at analyzing articles with a primary emphasis on AI translation. Finally, various criteria were employed as the basis for conducting the content analysis.

METHOD

Research Design

This research followed the content analysis approach, concentrating on the results from a variety of studies that have been featured in Top-Tier International Applied Linguistics

Journals. The methodology employed was consistent with the techniques applied by Fauzi & Pradipta (2018).

Data Source

The data for this research were gathered through a content analysis of articles within the domain of Applied Linguistics. The articles were extracted from Applied Linguistic journals that are indexed in the Directory of Open Access Journals (DOAJ) as of December 2024. DOAJ is a unique and extensive index of diverse open-access journals from around the world, driven by a growing community, and is committed to ensuring quality content is freely available online for everyone. The DOAJ database includes 181 applied linguistics journals, 30 of which are high-impact publications ranked Q1 and Q2 in Scopus and Web of Science. Accordingly, articles that specifically addressed the AI translation were collected from each of these journals. The articles included in this study were published online before December 2024. Of the hundreds of articles reviewed, 50 focused on the investigation of AI translation. All of these articles were analyzed for this study.

Research Instrument

The current research utilized a content analysis guideline as its primary instrument, encompassing various relevant aspects for observation, as detailed in Table 1. This study focused on seven key dimensions for content analysis, which included: (1) annual publication counts, (2) research types, (3) research subjects, (4) research topics addressed in the studies, (5) treatments implemented, (6) instruments for data collection, and (7) methods of data analysis. Notably, the categories for aspects (1), (4), and (5) were not predetermined due to a lack of prior studies that could inform the categorization process, which raised concerns about the potential for overly generalized classifications during the content analysis of certain articles. In contrast, the categories for aspects (2), (3), (6), and (7) were established prior to data collection. These categories, which have been adapted from the work of Fauzi & Pradipta (2018), are presented in Table 1. Furthermore, aspect (2) was further segmented into three subcategories: (2a) general types of research, (2b) quantitative research design, and (2c) qualitative research design.

Table 1. The Aspects and Categories used for Content Analysis in the Study

Aspects	Categories	
Type of research (2a)	A.1-R and D A.2-CAR	A.3-Qualitative Research A.4-Quantitative Research
Types of Quantitative Research (2b)	B.1-Observation Studies (OS) B.2-Correlational Research (CR) B.3-Survey Research (SR)	B.5-True Experimental Designs (TED) B.6-Quasi-Experimental Design (QED)

	B.4-Pre-Experimental Designs (PED)	B.7-Ex Post Facto Designs (EPFD)
Types of Qualitative Research (2c)	C.1-Biographical Research (BR) C.2-Case Study (CS) C.3-Content Analysis (CA) C.4-Critical Discourse Analysis (CDA) C.5-Ethnography (E) C.6-Grounded Theory (GT)	C.7-Historical Research (HR) C.8-Narrative Research (NR) C.9-Participatory Research (PR) C.10-Phenomenology (P) C.11-Systematic Literature Review (SLR)
Research Subject	D.1-Text Data with Errors D.2-Literary Text Analysis D.3-Political Texts and Speeches D.4-Datasets and Data Collections	D.5-Translation Methods and Evaluation D.6-Teaching Methods and Technology D.7-Undisclosed Data
Data Collection Instruments	E.1-Questionanaire Sheet E.2-Observation Sheet E.3-Test Sheet	E.4-Interview Sheet E.5-Coding Sheet E.6-Unidentified
Data Analysis Methods	F.1-Comparative Analysis F.2-Percentage F.3-N-gain F.4-T-test F.5-ANOVA F.6-ANCOVA	F.7-Correlation F.8-Thematic Analysis F.9-Narrative Analysis F.10-Mean F.11-Others

Data Analysis

Each article was categorized into a specific group based on criteria that aligned with the defined parameters. The categorization decision was made using information provided by the authors in the abstract, method, and discussion sections. Additionally, the collected data were presented in the form of a bar chart.

RESULTS AND DISCUSSION

Number of Publications

The data indicates a significant increase in the number of published articles since 2015, with a remarkable surge occurring in 2024. This trend reflects a growing interest among researchers in exploring and understanding the dynamics of AI translation.

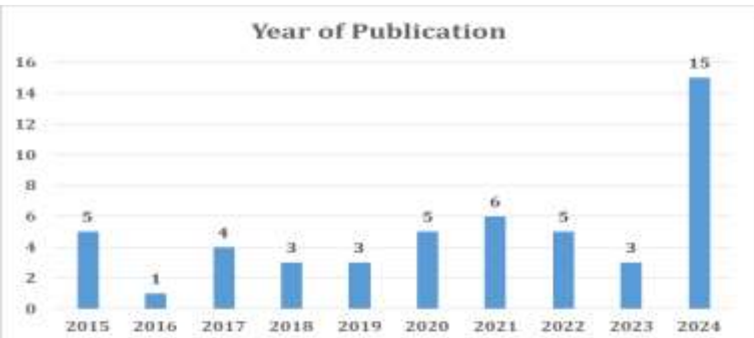

Figure 1. The Increasing Trend in Research Focused on AI Translation over the Past Decade

As illustrated in Figure 1, the number of publications concerning AI translation has experienced fluctuations; however, there is an overall consistent upward trend. In 2024, the number of publications peaked at 15 articles, marking the highest figure in the past decade. This increase not only signifies a growth in academic interest but also indicates that AI translation is increasingly recognized as a relevant and important field within applied linguistics research.

The observed rise in publication aligns with previous findings that suggest technology, particularly AI in the context of translation, has become a focal point in linguistic research. According to Lu Yang (2024), advancements in machine learning algorithms and natural language processing have opened new avenues for more accurate and efficient translation. This observation is consistent with the results of this study, which indicate that researchers are increasingly interested in exploring the practical applications of these technologies in translation contexts. However, despite the significant increase in publications, some earlier researchers, such as Hui et al. (2024), argue that machine translation cannot fully replace human translators. They emphasize the importance of cultural context and linguistic nuances that are often beyond the grasp of algorithms. This argument remains pertinent, especially when considering that, despite rapid advancements in AI technology, challenges in understanding context and meaning persist.

Thus, while the publication trend indicates a growing interest in AI translation, it is crucial to consider the existing critiques. This research contributes to a broader discourse regarding the role of AI in translation, highlighting that while this technology offers substantial potential, a deep understanding of linguistic context and nuances remains a challenge that researchers and practitioners must address. Overall, the findings of this study suggest that AI translation is not only an evolving field but also requires a more holistic approach that integrates technology with a profound understanding of linguistics. The increase in publications in 2024 can be viewed as an indication that the academic community is increasingly recognizing the importance of interdisciplinary research in tackling the challenges present in the field of translation.

Types of Research

Through a comprehensive analysis of the data, the researcher identified three primary types of research: research and development (R&D), qualitative research, and quantitative research. As illustrated in Figure 2, R&D dominates the landscape with 25 publications, followed by qualitative research with 19 publications, and quantitative research with 6 publications. Notably, research categorized as Classroom Action Research (CAR) was not found within the analyzed articles.

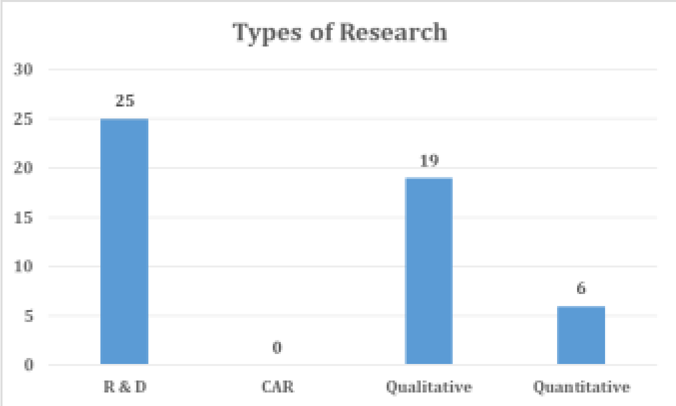

Figure 2. The Classification of Research on AI Translation According to Research Types

The prominence of R&D in the context of AI translation underscores a robust commitment to innovation and the development of new technologies. This type of research encompasses the creation of novel algorithms, enhancements to translation models, and the exploration of practical applications for translation technologies. For instance, the work of Y. Li et al. (2021) on the Transformer model has revolutionized the field of machine translation, demonstrating that neural network-based approaches can yield more accurate and contextually relevant translations. However, some scholars, such as Angermeyer (2023), caution against an overemphasis on technology, which may overlook critical aspects of traditional translation practices. This highlights the necessity for a balanced approach that integrates technological innovation with a profound understanding of the social and cultural contexts in which translation occurs.

Conversely, qualitative research provides valuable insights into user experiences and the social contexts in which AI translation is applied. Research by Mohebbi (2023) illustrates that translation is not merely a linguistic process but also involves cultural and social considerations. The findings indicate that while qualitative research has a smaller publication count compared to R&D, its contributions to understanding the contextual use of translation technology are invaluable. Nonetheless, previous studies, such as those conducted by Drisko (2024), argue that qualitative research may often lack generalizability and may not reflect broader trends in AI translation usage. This underscores the need for an integrated approach that combines qualitative and quantitative methodologies to achieve a more comprehensive understanding.

Meanwhile, quantitative research, despite having the fewest publications at only 6, remains crucial for evaluating the effectiveness of translation algorithms. This research focuses on measuring and analyzing numerical data to assess the performance of translation systems. For example, the study by Sosnin et al. (2022) demonstrates that automatic evaluation metrics can provide clear insights into system performance, although there are critiques suggesting that these metrics may not fully capture translation quality in broader contexts. Criticism of quantitative approaches, as highlighted by Piattoeva (2021), emphasizes the importance of considering linguistic nuances and cultural contexts that are often overlooked in numerical analyses. Therefore, it is essential to integrate quantitative approaches with qualitative research to gain a more holistic understanding of AI translation.

The findings of this study reveal that trends in AI translation research encompass a diverse array of complementary approaches. R&D provides a solid foundation for innovation, while qualitative research adds critical contextual dimensions. Although less represented, quantitative research still significantly contributes to performance evaluation. By synthesizing these three approaches, we can develop a more comprehensive understanding of the application of AI in translation, as well as the challenges and opportunities that lie ahead.

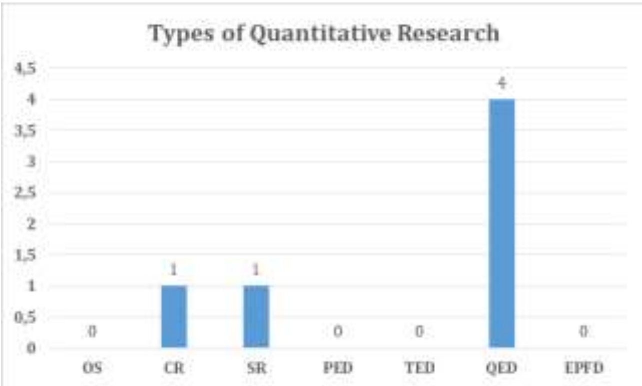

Figure 3. The Spread of Quantitative Research on AI Translation

This study also aimed to explore the distribution of quantitative research methodologies chosen by researchers. The data shows considerable diversity in the research designs used, as shown in Figure 3. The quantitative research designs identified include Observational Studies (OS), Correlational Research (CR), Survey Research (SR), Pre-Experimental Designs (PED), True Experimental Designs (TED), Quasi-Experimental Designs (QED), and Ex Post Facto Designs (EPFD).

According to the data, no Observational Studies (OS) were found; however, one Correlational Research (CR), one Survey Research (SR), and four Quasi-Experimental Designs (QED) were identified. Moreover, no studies employed Pre-Experimental Designs (PED), True Experimental Designs (TED), or Ex Post Facto Designs (EPFD). These findings indicate that research in the field of AI translation tends to rely more heavily on quasi-experimental designs, which offer deeper insights into the relationships between variables without the need for the strict control typical of true experimental designs.

The prevalence of QED in this research aligns with the findings of Remler & Van Ryzin (2024), who noted that quasi-experimental designs are frequently used in educational and technological contexts, where achieving full control over variables is challenging. This view is also supported by E. Wu et al. (2022), highlighted that QED allows researchers to explore the effects of interventions in real-world settings, which is particularly relevant in the AI translation context, often applied in complex and dynamic environments. However, despite the flexibility that QED offers, some researchers, such as Ballance (2024), criticize this approach due to the potential biases arising from the lack of randomization. They argue that the results derived from quasi-experimental designs may not be fully generalizable, thus reducing the external validity of the findings. Therefore, it is crucial to consider using more rigorous research designs in the future, such as True Experimental Designs (TED), although none of the studies in this review employed this design.

Meanwhile, Observational Studies (OS) and Pre-Experimental Designs (PED) were absent from the data, suggesting that these approaches may be less common in current research. Survey Research (SR), while providing rich data on user experiences, is often criticized for the potential bias in responses and limitations in the generalizability of results (Moniz et al., 2024). Therefore, while this approach can offer preliminary insights, its findings need to be followed up with more in-depth studies using stronger designs. The results of this study demonstrate that, despite the dominance of quasi-experimental designs, there is an urgent need for methodological diversification in AI translation research.

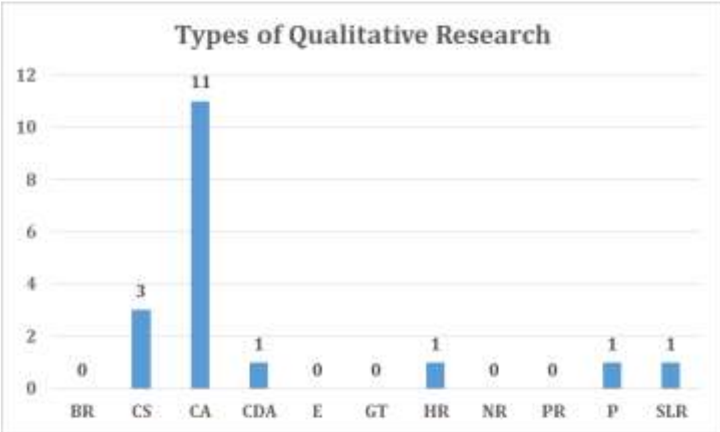

Figure 4. The Spread of Qualitative Research Focused on AI Translation

Furthermore, based on the data collected, the researchers identified various types of qualitative research conducted within this context, as illustrated in Figure 4. The analysis reveals significant variation in the research types employed, with a primary focus on content analysis (CA) and case studies (CS). The data indicates that content analysis (CA) is the most prevalent method, with a total of 11 publications. This dominance suggests that researchers are inclined to utilize this approach to explore and analyze data related to AI translation. Content analysis allows for the identification of patterns, themes, and trends in the use of translation technology, as well as its impact on translation practices. This finding aligns with the work of Lee et al. (2020), who emphasizes that content analysis can provide profound insights into how AI translation technologies are adopted and implemented in professional contexts.

In addition, case studies (CS) accounted for 3 publications, indicating that while less frequent than content analysis, this approach remains crucial for understanding the specific contexts in which AI translation technologies are applied. Research by Pardo-Ballester (2022) illustrates that case studies can offer clearer insights into the challenges and successes faced by translation practitioners when utilizing AI tools, as well as how they adapt to the changes brought about by this technology. Moreover, there is one publication each for critical discourse analysis (CDA), historical research (HR), phenomenology (P), and a systematic literature review (SLR). Although these numbers are limited, the presence of these research types indicates an effort to explore broader dimensions of AI translation. For instance, critical discourse analysis can help uncover biases that may exist within translation algorithms, as highlighted by Mahgoub & Mohamad (2024), who stresses the importance of considering social and cultural aspects in the development of translation technologies.

However, it is noteworthy that several research types, such as biographical research (BR), ethnography (E), grounded theory (GT), narrative research (NR), participatory research (PR), and phenomenology (P) did not yield any identified publications. This gap suggests a deficiency in the exploration of more diverse approaches within AI translation research. Silvester (2019) argues that a more holistic and varied approach could provide deeper insights into the interactions between technology and translation practices. Overall, the findings of this study indicate that while significant progress has been made in AI translation research, there remains ample opportunity for further exploration, particularly concerning diverse qualitative approaches. By adopting a more inclusive and holistic methodology, future research can contribute more meaningfully to our understanding of the interplay between technology and translation practices.

Research Subjects

The analysis reveals six primary research subjects: *Text Data with Errors*, *Literary Text Analysis*, *Political Texts and Speeches*, *Datasets and Data Collections*, *Translation Methods and Evaluation*, and *Teaching Methods and Technology*. In addition to the six research subjects identified, there are three instances of undisclosed data. The following graph illustrates the results of the data analysis related to the research subjects in this study.

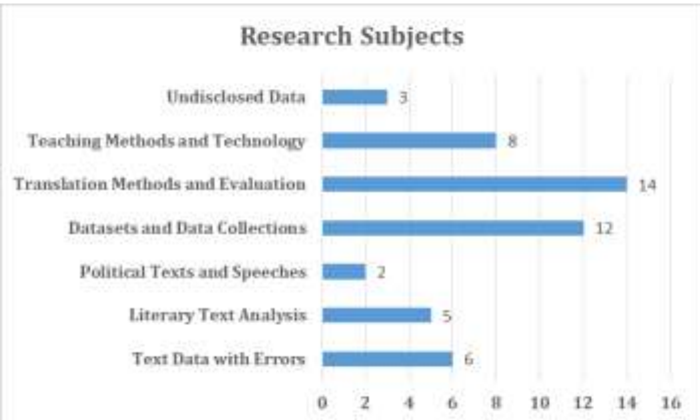

Figure 5. The Allocation of Research Subjects on AI Translation in Applied Linguistics Studies

The findings indicate that the category *Translation Methods and Evaluation* is the most prominent, with 14 publications, underscoring the significant focus on developing and assessing translation methodologies. This aligns with the work of Egdom & Declercq (2023), who emphasize the necessity for more accurate evaluation methods to assess the quality of translations produced by AI systems. Additionally, the category *Datasets and Data Collections* also shows a substantial presence with 12 publications, reflecting an urgent need for high-quality datasets to train translation models. Research by Vieira et al. (2024) supports this observation, demonstrating that the quality of datasets directly impacts the performance of translation models.

Conversely, the category *Teaching Methods and Technology*, comprising 8 publications, indicates a growing interest in the integration of technology within translation education. S. Xu et al. (2024) highlight that the use of AI-based translation tools in educational settings can enhance students' understanding of the translation process. However, there are critiques suggesting that reliance on technology may diminish students' analytical skills (Gorjón & Osés, 2022).

The results of this study illustrate that while significant advancements have been made in the application of AI in translation, challenges persist, particularly concerning the quality and reliability of translation outputs. Previous research by Naveen & Trojovský (2024) indicates that although AI systems can produce rapid translations, they often contain significant errors in context and nuance that cannot be resolved solely through algorithmic improvements. Moreover, critiques regarding the use of AI in translation have emerged from studies such as Kunst & Bierwiaczonek (2023), which argue that translations generated by AI frequently overlook essential cultural and emotional elements. This highlights the ongoing necessity for human translators to ensure the quality and accuracy of translations, especially in the context of literary texts and political speeches that are rich in meaning.

In this context, it is crucial to develop a balanced approach that integrates technology with human expertise in the translation process. This study contributes to a deeper understanding of the current trends in AI translation research and paves the way for further investigations that can explore the synergy between technology and human skills in this field. This research underscores the importance of developing quality methods and datasets in AI-based translation research, as well as the need to consider educational aspects and human involvement in the translation process.

Research Topics

The researchers identified five main themes based on the data collected that are the topics of research: AI and Machine Learning, Translation Quality and Evaluation, Contextual and Comparative Studies, Educational Impact, and Technical Challenges. The graph presented in the following provides a clear overview of the distribution of research attention across these themes.

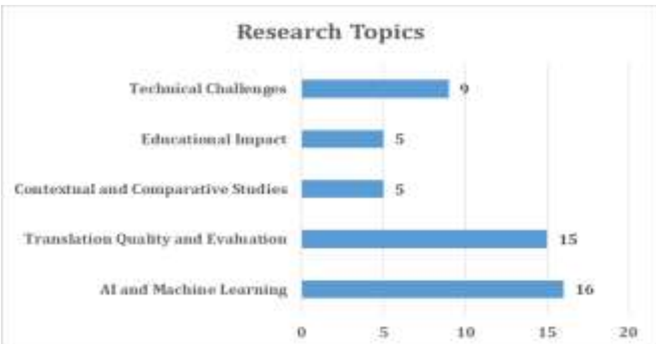

Figure 6. Topics in Applied Linguistics Centered on AI Translation

The first prominent theme is AI and Machine Learning, which dominates research attention with a total of 16 publications. This reflects a high interest in the application of machine learning algorithms in translation. Research by Zhang & Shafiq (2024) on the Transformer model has become a significant milestone in the development of more accurate machine translation systems. However, some researchers, such as Bruera et al. (2023), argue that despite these technological advancements, challenges in understanding cultural context and language nuances remain obstacles. These findings indicate that while AI can enhance efficiency, a deep linguistic understanding is still necessary to achieve optimal results.

Next, the theme of Translation Quality and Evaluation, with 15 publications, underscores the importance of developing more comprehensive evaluation metrics. Research by Afrouz (2023) emphasizes that quality evaluation of translations should involve feedback from end-users to gain a more holistic perspective. However, previous studies, such as those conducted by Martins et al. (2022), argue that user-based evaluations can be influenced by subjectivity, potentially leading to inconsistent results. This highlights the need for a more systematic approach to evaluating the quality of translations produced by AI-based systems. The third theme, Technical Challenges, with 9 publications, indicates that despite significant technological advancements, there are still issues related to natural language processing (NLP) that need to be addressed. Research by Vu et al. (2024) shows that errors in contextual understanding can lead to significant translation mistakes. Faheem et al. (2024) long argued that machine translation cannot fully replace human translation, especially in contexts requiring a deep understanding of culture and language nuances. This suggests that while technology can assist, the role of human translators remains crucial in ensuring translation quality.

The educational impact of AI application in translation, reflected in 5 publications, indicates that the integration of technology into linguistic education curricula can enhance students' translation skills. Research by Karataş et al. (2024) supports this finding by demonstrating that the use of AI-based translation tools in teaching can increase student motivation and engagement. However, Shen & Teng (2024) cautions that reliance on technology may diminish students' analytical and critical skills. Therefore, it is essential to find a balance between technology use and the development of foundational skills in translation.

The final theme, Contextual and Comparative Studies, also has 5 publications and indicates that contextual and comparative research is becoming increasingly important in understanding the application of AI across various linguistic contexts. Research by Sell et al. (2024) shows that translation outcomes can vary significantly depending on the source and target languages as well as cultural context. However, J. Shen et al. (2021) argue that comparative approaches often overlook local nuances that can affect translation outcomes. These findings highlight the need for more in-depth research to understand how context influences the effectiveness of AI-based translation. The results of this study indicate that while the application of AI in translation offers great potential, existing challenges must be addressed through further research and the development of better methodologies. The integration of technology with a deep linguistic understanding will be key to achieving higher-quality translations in the future.

Treatments & Interventions

The analysis identified several key categories reflecting diverse treatments & interventions within AI-driven translation research in applied linguistics. The following graph illustrates the results of the data analysis related to the treatments and interventions in this study.

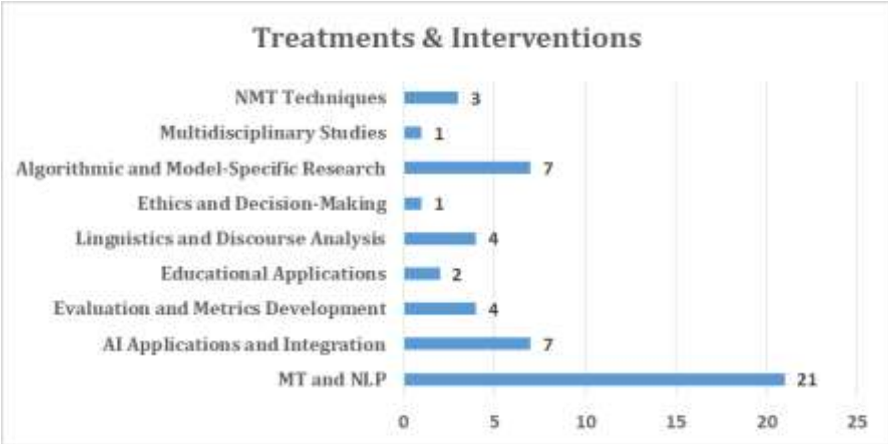

Figure 7. Variations of Treatment & Intervention in Applied Linguistics Research Centered on AI Translation

Among these treatments and interventions categories in the graph above, Machine Translation (MT) and Natural Language Processing (NLP) emerged as the most prominent category, encompassing 21 publications. This body of work highlights significant advancements in MT techniques and NLP, with foundational studies such as Weng et al. (2020) demonstrating how transformer models have revolutionized translation processes, greatly enhancing both accuracy and efficiency. The second major category, AI Applications and Integration, is represented by 7 publications. This area underscores the growing importance of embedding AI into linguistic applications. Supporting this, research by Mittal et al. (2024) illustrates how AI-driven tools can enrich language learning experiences, providing innovative solutions to traditional educational challenges.

Another critical focus is Evaluation Metrics Development, highlighted by 4 publications. These studies address the urgent need for robust frameworks to assess the quality of AI-generated translations. This aligns with critiques from Shin et al. (2023), who advocate for more comprehensive and holistic evaluation methodologies to ensure reliable assessments. In the field of education, the Educational Applications category, with 2 publications, explores the role of AI tools in language teaching and learning. For instance, Rejeb et al. (2024) demonstrated the capacity of AI-based translation tools to enhance students' linguistic abilities, offering practical benefits in educational contexts.

Although no dominant category is represented, Linguistic and Discourse Analysis, with 4 publications, underscores the continued relevance of detailed linguistic and discourse-focused research within translation studies. Next, Ethics and Decision-Making, represented by 1 publication, addresses pressing concerns about the ethical implications of AI applications in translation. Das et al. (2023) highlights challenges related to fairness, transparency, and accountability in algorithmic implementations. Another noteworthy area is Multidisciplinary Research, with 1 publication emphasizing the value of integrating perspectives from various disciplines to provide innovative insights into translation studies. Meanwhile, Neural Machine Translation (NMT) Techniques, with 3 publications, reflect growing interest in this advanced technology. Studies like Jooste et al. (2021) reveal that NMT produces translations that are more natural and contextually accurate than traditional methods.

Last but not least, the Algorithm-Specific and Model-Focused Research category, represented by 7 publications, highlights the importance of exploring specific algorithms to drive technological advancements in AI translation systems. In summary, these categories illustrate the breadth and depth of research in AI-driven translation, revealing significant progress while also pointing to areas that require further exploration, particularly in ethical considerations, educational applications, and the refinement of evaluation metrics.

Data Collection Instruments

One of the key findings revealed in the data is the distribution of data collection instruments used in this research, as illustrated in Figure 8. Based on the analysis, the most frequently utilized instrument is the coding sheet, accounting for 40 publications, followed by the test sheet at 6 publications, and the interview sheet at 1 publication. Meanwhile, the questionnaire and observation sheet were used at rates of 1 publication and 0 publication, respectively, with 2 publications of the data remaining unidentified.

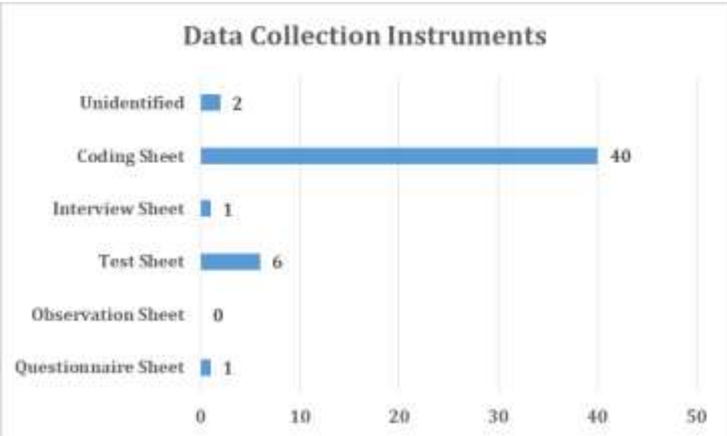

Figure 8. The Distribution of Data Collection Instruments in Applied Linguistics Research Focused on AI Translation

The predominance of coding sheets in this research indicates that researchers tend to rely on more systematic and structured data analysis. This aligns with the findings of Morgan (2023), who emphasize the importance of coding in qualitative data analysis to understand patterns and themes emerging from the use of AI-based translation technology. The use of coding sheets allows researchers to efficiently identify and categorize data, thereby providing deeper insights into the interactions between users and translation systems.

However, the relatively low usage of test sheets (6 publications) suggests that this research may not sufficiently explore the evaluative aspects of translation technology. He et al. (2020) indicates that testing translation systems can yield valuable information regarding the effectiveness and accuracy of such technologies. Therefore, there is a need to enhance the use of evaluative instruments in future research to obtain a more comprehensive picture of AI translation system performance. Additionally, the very low use of interviews (1 publication) indicates that qualitative approaches in this research area are still underutilized. Kelly & Sennott (2024) demonstrate that in-depth interviews can reveal nuances of user experiences that quantitative instruments may not capture. This highlights the importance of integrating qualitative methods to understand the social and cultural contexts influencing the use of translation technology.

The limitations in the use of questionnaires and observation sheets also warrant attention. The mere 1 publication usage of questionnaires suggests that researchers may be underutilizing the potential for data collection from a broader respondent base. Juric et al. (2024) argues that questionnaires can provide valuable insights into user perceptions of AI-based translation systems and should be more frequently employed in research within this field. Overall, the findings of this study indicate that while there is a clear trend towards the use of coding sheets in AI translation research, it is crucial not to overlook the value of qualitative approaches and evaluative instruments. Further research is needed to explore how various data collection instruments can be effectively integrated to provide richer and more in-depth insights into the interactions between humans and technology in the context of translation.

Data Analysis Methods

For the last aspect, this study examines the distribution of data analysis methods employed in applied linguistics research focusing on AI-based translation. According to the data presented in Figure 9, Narrative Analysis emerged as the most frequently used method, appearing in 21 publications. This is followed by Thematic Analysis, applied in 4 publications. Statistical methods, including Correlation and T-test, were each employed in 2 publications, while ANOVA and ANCOVA appeared in 3 and 1 publication, respectively. Score-based methods such as N-gain and Percentage were utilized in 2 publications each. Meanwhile, Comparative Analysis, though not dominant, was employed in 9 publications to assess translation system performance. Interestingly, mean-based analysis (Mean) was not used at all. This distribution highlights a strong preference for qualitative analysis methods, particularly Narrative Analysis, which underscores the focus on narrative and interpretative aspects of AI translation processes.

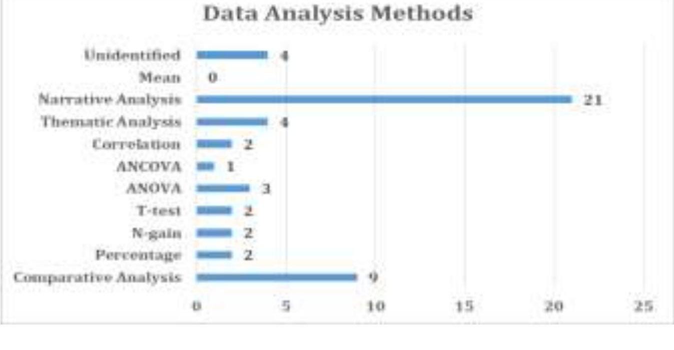

Figure 9. The Allocation of Data Analysis Methods in Applied Linguistics Studies Focused on AI Translation

The findings reveal a significant tendency towards the use of qualitative methods in AI translation research. The dominance of Narrative Analysis (21 publications) indicates a focus on exploring how AI translation technologies address complexities such as contextual meaning, cultural nuances, and narrative representations. This aligns with the findings of Alaa & Al Sawi (2023), who stated that narrative analysis is an effective tool for evaluating translation quality from the user’s perspective, especially in cultural and idiomatic contexts.

Moreover, the application of Thematic Analysis in 4 publications reflects efforts to identify key patterns and themes emerging in the evaluation of AI translation technologies. While these qualitative approaches provide in-depth insights, their predominance may point to limitations in addressing research questions requiring systematic quantitative assessments. Halevi Hochwald et al. (2023) emphasized that combining qualitative and quantitative methods often yields more comprehensive results, thereby reducing the risk of interpretive bias. On the other hand, the use of statistical methods such as Correlation (2 publications), T-test (2 publications), and ANOVA (3 publications) highlights that quantitative approaches remain underutilized in this area of research. This poses a challenge, as statistical methods can offer stronger empirical validation of research findings. Nava-Muñoz et al. (2024) underscored the significance of statistical approaches, particularly ANCOVA and multivariate regression analysis, for conducting deeper evaluations of AI systems' performance.

Meanwhile, the use of Comparative Analysis in 9 publications indicates a notable focus on comparing different AI translation systems. Sekeroglu et al. (2022) observed that this approach is highly beneficial for evaluating AI algorithms based on varying linguistic and cultural parameters. However, reliance on simple comparative analyses risks overlooking complex dimensions such as social and semantic contexts. Interestingly, the absence of mean-based analysis (Mean) suggests a gap in evaluation approaches that could be further optimized. El Sherif et al. (2024) advocated for mixed-method approaches integrating qualitative and quantitative analyses to provide more holistic insights that align with the advancements in AI-based translation technologies.

The results support arguments by Guenduez & Mettler (2023) and Robertson & Maccarone (2023), who found Narrative Analysis to be the dominant approach in AI translation research. However, these findings contrast with (Gong, 2024), who highlighted the importance of advanced statistical methods for systematically evaluating the performance of AI models. Gong’s findings suggest that an overreliance on narrative and descriptive methods may limit the generalizability of research outcomes. Thus, these findings offer a clear picture of current trends in the distribution of data analysis methods in applied linguistics research. The study emphasizes the need for diversification in analytical approaches, particularly through the integration of qualitative and quantitative methods, to generate more comprehensive insights and support further advancements in AI-based translation studies.

CONCLUSION

This study examined articles on AI translation published in reputable international Applied Linguistics journals between 2015 and 2024. The findings indicate a notable increase in publications on this topic, with a significant surge over the past four years. Research and development (R&D) emerged as the dominant focus, with translation methods and evaluation serving as the primary areas of investigation. The studies encompassed a broad range of topics, with AI and machine learning being the most widely applied technologies. Machine translation (MT) and natural language processing (NLP) were the most frequently utilized approaches, while coding sheets and narrative analysis were the preferred tools for data collection and analysis. To enhance the effectiveness of AI translation, future research should focus on developing robust evaluation methods that integrate both quantitative and qualitative approaches, addressing linguistic accuracy as well as cultural and contextual subtleties. Improving dataset quality and diversity is crucial for ensuring broader linguistic representation. Researchers must also ensure transparency in the validity and reliability of their instruments while selecting research designs aligned with their objectives. Collaboration between linguists and computer scientists is vital for driving innovation, and incorporating AI translation tools into educational curricula can equip students with analytical skills, bridging the gap between research and practical application in this evolving domain.

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