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A systematic literature review of translation memory mechanisms in technology-based translation processes

Lidhya Zulyani[1], Adika Salsabila[2], Silvia Ramanda Putri[3], Jiehan Ashara Halim[4], Refika Andriani[5]

Lancang Kuning University, Pekanbaru, Indonesia[1,2,3,4,5]
Lidhyazulyani@gmail.com[1]
adikasalsabila24@gmail.com[2]
ramandasilvia5@gmail.com[3]
jiehanaha@gmail.com[4]
refika@unilak.ac.id[5]

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Abstract. This study presents a systematic literature review (SLR) of Translation Memory (TM) mechanisms in technology-based translation processes, explicitly following the PRISMA framework for identification, screening, eligibility, and inclusion of studies. A total of 26 journal articles and conference papers published between 2020 and 2025 were analyzed. Findings reveal that TM operates through core mechanisms, including segmentation, storage of translation units, matching, retrieval, exact matches, fuzzy matches, and similarity measurement, which improve translation consistency, efficiency, and productivity, especially in repetitive and specialized tasks. The study also identifies limitations of TM, including dependence on database quality, reduced contextual flexibility, and challenges in capturing semantic variation with conventional matching methods. Furthermore, recent studies show that TM has evolved beyond traditional CAT tools and is increasingly integrated into neural machine translation and retrieval-augmented systems. This review contributes to the field by synthesizing current research trends, highlighting gaps in the literature, and providing recommendations for future studies to advance the integration and application of TM in modern translation workflows.

Keywords*:* CAT tools; fuzzy matching; retrieval mechanism; translation memory; translation processes

Abstrak. *Penelitian ini menyajikan systematic literature review (SLR) mengenai mekanisme Translation Memory (TM) dalam proses penerjemahan berbasis teknologi, secara eksplisit mengikuti framework PRISMA untuk identifikasi, penyaringan, kelayakan, dan inklusi studi. Sebanyak 26 artikel jurnal dan makalah konferensi yang diterbitkan antara tahun 2020 hingga 2025 dianalisis. Hasil penelitian menunjukkan bahwa TM beroperasi melalui mekanisme inti seperti segmentasi, penyimpanan unit terjemahan, pencocokan, penelusuran kembali, exact match, fuzzy match, dan pengukuran kesamaan, yang meningkatkan konsistensi, efisiensi, dan produktivitas penerjemahan, terutama pada tugas yang repetitif dan bersifat khusus. Penelitian ini juga mengidentifikasi keterbatasan TM, termasuk ketergantungan pada kualitas basis data, fleksibilitas kontekstual yang terbatas, dan tantangan dalam menangkap variasi semantik menggunakan metode pencocokan konvensional. Selain itu, studi-studi terbaru menunjukkan bahwa TM telah berkembang melampaui CAT tools tradisional dan semakin terintegrasi ke dalam sistem neural machine translation serta retrieval-augmented translation. Kajian ini memberikan kontribusi terhadap bidang penerjemahan dengan menyintesis tren penelitian terkini, menyoroti gap penelitian, dan memberikan rekomendasi untuk penelitian berikutnya agar integrasi dan penerapan TM dalam alur kerja penerjemahan modern dapat ditingkatkan.*

Kata kunci: *alat CAT; fuzzy matching; mekanisme penelusuran; penerjemahan berbasis teknologi; proses penerjemahan*

INTRODUCTION

Translation has no longer been restricted to a manual process due to technological advancements. Among the technologies used to support this development, computer-assisted translation (CAT) is one of the most widely used tools. Translation Memory (TM) has become an essential component in this process because it enables translators to store previously translated segments and reuse them whenever needed in new translation tasks (Gamal, 2020; Ranasinghe & Or, 2020)

Previous studies on translation technology show that TM plays an important role in professional translation practice, especially in technical and specialized domains. Translation Memory is generally understood as a search-oriented technology that identifies similarities between a new source segment and previously stored translation units to retrieve potential matches. These matches may appear as exact matches or fuzzy matches, depending on the degree of similarity between the new segment and the stored data. In this context, similarity measurement becomes a crucial factor because it determines the usefulness of the retrieved translation unit for the translator (Ben Milad, 2021; Djabri et al., 2021; Ranasinghe & Or, 2020)

Moreover, numerous studies have shown that the effectiveness of translation memory (TM) is largely dependent upon the quality of its alignment and acquisition process. The alignment of traditional machine translation typically relies on long-edit techniques, which are effective at identifying surface-level similarities but are often limited when it comes to finding semantic equivalences amid linguistic variations . Changes in word order, tense, synonym selection, and morphology can significantly reduce alignment scores, even when two segments express a nearly identical meaning. Therefore, incorporating advanced techniques for linguistic variation, ambiguity, and equivalence, a refined approach to machine translation retrieval has been proposed in recent research (Ben Milad, 2021; Djabri et al., 2021; Ranasinghe & Or, 2020; Tezcan et al., 2021)

Advances in translation technology also indicate that translation memories are no longer limited to traditional CAT tools. Recent research shows that TM is increasingly being integrated into neural network-based machine translation systems and into translation models with enhanced search capabilities. In these systems, while segments retrieved from the database assist the translation process, even partial matches can improve translation quality if interactions with the source text are managed effectively. These developments demonstrate that TM has evolved from simple storage systems into dynamic mechanisms within broader, technology-driven translation workflows (Cai et al., 2021; Hoang et al., 2023; Xu et al., 2023)

In recent years, the evolution of Translation Memory (TM) has shown that TM is no longer viewed merely as a conventional feature of computer-assisted translation (CAT) tools, but rather as part of a broader translation technology ecosystem. In their early days, TM systems focused primarily on the storage and retrieval of bilingual segments. At the same time, recent advances have integrated TM with neural network-based machine translation, retrieval-augmented systems, and even support for translation based on large language models. TM is increasingly viewed not only as a productivity tool for repetitive translation tasks but also as a knowledge resource capable of improving translation quality, semantic relevance, and contextual support. Therefore, analyzing the mechanisms of TM is important not only for understanding the conventional CAT environment but also for explaining its increasingly significant role in contemporary translation technology.

Although previous studies have examined TM in the context of search, fuzzy matching, and system integration, a few of them clearly and systematically explain how the TM mechanism works in

Zulyani, Lidhya, et al. (2026). A systematic literature review of translation memory mechanisms in technology-based translation processes. *E-Structural (English Studies on Translation, Culture, Literature, and Linguistics).* 9 (01), 15–31.

translation practice. Most existing studies focus on improving efficiency and solving technical problems rather than providing a comprehensive explanation of TM as a mechanism in technology-assisted translation. This gap is significant because a clearer understanding of TM can demonstrate that TM is not merely a technical feature of computer-assisted translation (CAT) tools, but also a central mechanism in modern translation practice. (Ben Milad, 2021; Cai et al., 2021; Djabri et al., 2021; Hoang et al., 2023; Tezcan et al., 2021; Xu et al., 2023)

Therefore, this study aims to examine how Translation Memory functions in technology-based translation processes. This study seeks to investigate the basic principles associated with the use of TM, including segmentation, storage, matching, searching, exact matching, fuzzy matching, and similarity measurement. Additionally, this study explores the advantages and disadvantages of using TM for translation purposes, to better understand the role of translation memory in modern translation technology. This study is important for the field of translation studies in general, and specifically for the study of translation technology.

The research questions posed are as follows:

1. How do the findings across studies published between 2020 and 2025 compare in terms of Translation Memory (TM) mechanisms, including segmentation, storage, matching, and retrieval?
2. What patterns emerge regarding the application of TM in different contexts (e.g., technical, legal, medical) and its integration with various translation technologies (e.g., CAT tools, neural machine translation, retrieval-augmented systems)?
3. What gaps exist in the current literature on TM, and how can future research address these gaps to improve translation quality, efficiency, and consistency in technology-based translation processes?

METHOD

Research Design

This study employed a Systematic Literature Review (SLR) design to examine the mechanisms of Translation Memory (TM) in technology-based translation processes. The review adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure methodological transparency, rigor, and replicability throughout the review process. PRISMA was used to guide the stages of identification, screening, eligibility assessment, and final inclusion of relevant studies. The use of SLR was considered appropriate because this study focused on synthesizing findings from previously published academic studies rather than collecting primary empirical data.

Data Sources and Search Strategy

Data were collected from several academic databases, namely Scopus, Google Scholar, Directory of Open Access Journals (DOAJ), and ERIC. These databases were selected for their broad coverage of translation studies, computational linguistics, and technology-assisted translation research. The search focused on studies published between 2020 and 2025 to identify recent developments in Translation Memory and related translation technologies.

Several search strings and keywords were used during the search process, including "translation memory," "translation memory mechanism," "translation memory retrieval," "fuzzy matching in translation memory," "translation memory in CAT tools," "translation memory and neural machine translation," and "retrieval-augmented translation systems." The search process combined these keywords using Boolean operators such as AND and OR to obtain more relevant studies. In addition, reference lists from selected studies were examined to identify other relevant publications on Translation Memory research.

Inclusion and Exclusion Criteria

The inclusion criteria of this study were: (1) studies discussing Translation Memory mechanisms, retrieval systems, matching processes, or integration into translation technologies; (2) studies published between 2020 and 2025; (3) peer-reviewed journal articles or conference proceedings; and (4) studies written in English. Meanwhile, studies were excluded if they: (1) focused solely on general machine translation without discussing Translation Memory; (2) lacked conceptual relevance to translation technology; (3) were duplicate publications; or (4) did not provide sufficient academic information for analysis.

Screening and Study Selection Process

The screening process was conducted in several stages. First, studies were identified through database searching using the selected keywords. Second, duplicate and unrelated studies were removed. Third, titles and abstracts were screened to determine their relevance to the research topic and research questions. Finally, a full-text assessment was conducted to evaluate the eligibility of the studies for qualitative synthesis. After the screening and eligibility process, 26 studies were selected as the final sources for analysis.

The study selection process was summarized using a PRISMA flow diagram to illustrate the stages of identification, screening, eligibility assessment, and final inclusion of studies (Figure 1).

Data Analysis

The selected studies were analyzed qualitatively through thematic analysis. The analysis focused on identifying recurring themes and mechanisms related to Translation Memory operation, including segmentation, storage of translation units, matching, retrieval, exact matching, fuzzy matching, similarity measurement, and integration into neural machine translation and retrieval-augmented translation systems. The findings were then categorized and synthesized according to the research questions to provide a systematic understanding of Translation Memory mechanisms in technology-based translation processes.

To increase analytical clarity, the reviewed studies were grouped into several thematic categories, namely: (1) Translation Memory retrieval and matching mechanisms, (2) similarity measurement and fuzzy matching, (3) integration of Translation Memory into neural machine translation systems, and (4) advantages and limitations of Translation Memory in translation practice. These thematic categories helped identify dominant trends, recurring issues, and research gaps across the reviewed literature.

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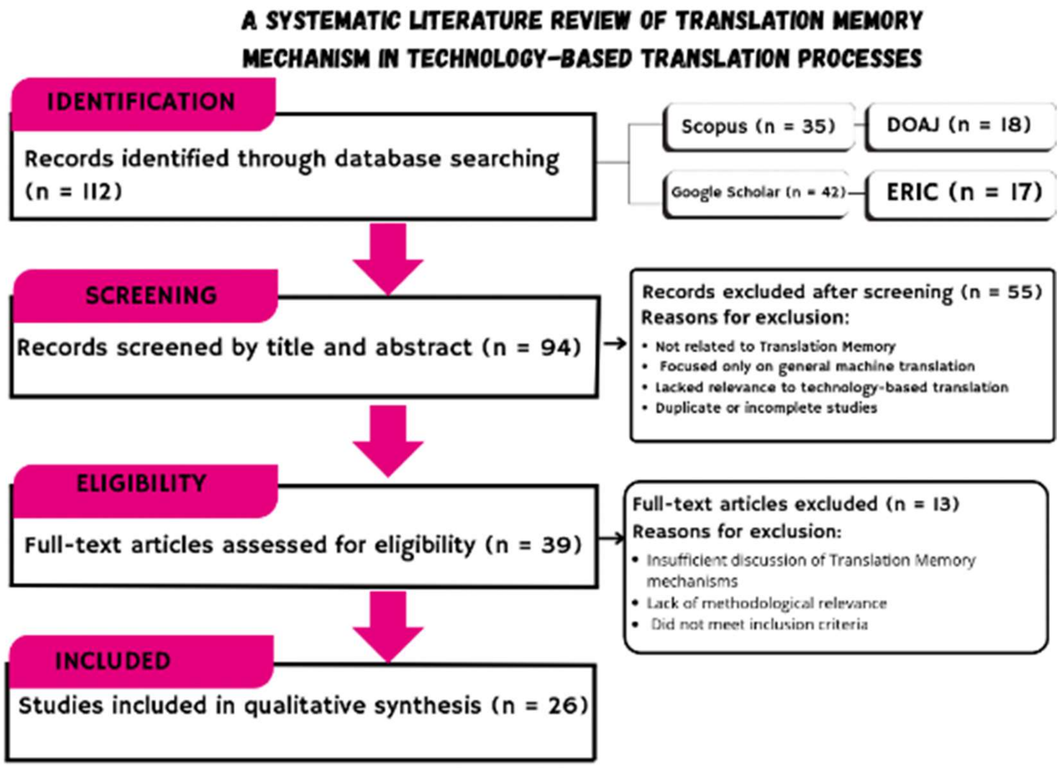

Figure 1 PRISMA Flow Diagram of Study Selection Process

[Source: Developed by the researchers based on the PRISMA framework]

RESULTS AND DISCUSSION

Overview of Reviewed Studies

The reviewed studies consisted of journal articles and conference proceedings indexed in databases such as Scopus, DOAJ, ERIC, and Google Scholar. Most of the selected studies published between 2020 and 2025 focused on Translation Memory retrieval mechanisms, fuzzy matching, similarity measurement, and the integration of Translation Memory into neural machine translation systems. Although this review covered the period 2020–2025, studies published in 2024 and 2025 specifically discussing Translation Memory mechanisms were relatively limited. Most recent publications during this period focused more broadly on artificial intelligence, large language models, and machine translation systems rather than specifically examining Translation Memory mechanisms. Therefore, the majority of reviewed studies were concentrated between 2020 and 2023.

The selected studies were categorized into several major themes, namely: (1) Translation Memory retrieval and matching mechanisms, (2) fuzzy matching and similarity measurement, (3) integration of Translation Memory into neural machine translation systems, and (4) advantages and limitations of Translation Memory in translation practice. This categorization was intended to improve analytical clarity and provide a more systematic synthesis of the reviewed literature. Table 1 summarizes the reviewed studies, including publication year, database source, research focus, and major findings related to Translation Memory mechanisms.

Zulyani, Lidhya, et al. (2026). A systematic literature review of translation memory mechanisms in technology-based translation processes. *E-Structural (English Studies on Translation, Culture, Literature, and Linguistics)*. 9 (01), 15–31.

Table 1 Summary of Reviewed Studies on Translation Memory Mechanisms (2020–2025)

Author(s)	Year	Database source	Research Focus	Main Findings
Ranasinghe & Or	2020	Scopus	TM retrieval and sentence encoders	Sentence encoders improve semantic retrieval beyond traditional edit-distance methods.
Djabri et al.	2021	Scopus	Linguistic transformation in TM retrieval	Semantic and syntactic variation reduce retrieval effectiveness in TM systems.
Ben Milad	2021	Google Scholar	Similarity measurement in TM	Similarity scoring strongly affects retrieval quality and matching usefulness.
Tezcan et al.	2021	Scopus	Fuzzy matching integration	Fuzzy matches improve translation quality when integrated effectively into translation systems.
Cai et al.	2021	Scopus	TM in neural machine translation	Retrieved memory supports neural machine translation as contextual information.
Xu et al.	2023	Scopus	TM in non-autoregressive machine translation	Retrieved memory supports neural machine translation as contextual information.
Hoang et al.	2023	Scopus	Retrieval-augmented translation	Controlled fuzzy-match interaction improves translation quality.
Hao et al.	2023	Scopus	TM-augmented neural translation	TM contributes to improving retrieval and translation relevance.
Mu et al.	2023	Scopus	TM and large language models	Translation memories can support LLM-assisted translation systems.
Zhang et al.	2024	Google Scholar	TM and CAT tool integration	TM integration improves intelligent support in human translation processes.

[Source: developed by the researcher based on reviewed studies]

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How Translation Memory Works in Technology-Based Translation Processes

The reviewed studies indicate that the operation of Translation Memory (TM) generally begins with segmentation. Before retrieval, source texts are divided into smaller translation units, usually sentence-based segments, which are then aligned with their target-language equivalents and stored in the TM database. Once a new source segment is introduced, the system compares it with previously stored translation units and retrieves possible matches. This mechanism enables translators to reuse previously translated segments in new translation tasks.

The reviewed studies also demonstrate that matching and retrieval constitute the core mechanisms of Translation Memory systems. Exact matching occurs when a new source segment is identical to a stored segment, allowing direct reuse of the previous translation. In contrast, fuzzy matching occurs when segments are only partially similar, requiring further revision by the translator. Similarity measurement, therefore, becomes a crucial factor because it determines the quality and usefulness of retrieved translation units.

Recent studies further reveal that Translation Memory has evolved beyond conventional CAT environments. Several reviewed studies show that TM is increasingly integrated into neural machine translation, retrieval-augmented translation systems, and machine learning-based translation technologies. In these systems, retrieved segments function not only as stored references but also as contextual support to improve translation quality and semantic relevance.

Main Mechanisms Involved in Translation Memory Operation

The findings demonstrate that several interconnected mechanisms support the operation of Translation Memory systems, namely segmentation, storage of translation units, matching, retrieval, exact matching, fuzzy matching, and similarity measurement. These mechanisms work collectively to support translation consistency, efficiency, and reuse of previous translations.

Segmentation is the initial stage in which source texts are divided into manageable translation units before storage and retrieval. Storage mechanisms then preserve bilingual translation units for reuse in future tasks. Matching and retrieval processes subsequently compare new source segments with previously stored units to identify relevant suggestions for translators.

Another important mechanism identified in the reviewed studies is similarity measurement. Traditional retrieval approaches commonly rely on edit-distance calculations; however, recent studies suggest that these approaches often fail to capture deeper semantic similarity when linguistic variation occurs. Consequently, newer approaches increasingly utilize sentence encoders, neural retrieval systems, and semantic-based matching models to improve retrieval quality and contextual relevance.

The reviewed studies also indicate that retrieval quality strongly influences the effectiveness of Translation Memory systems. Studies focusing on semantic retrieval suggest that linguistic transformations such as changes in word order, synonym selection, and morphological variation may reduce retrieval performance when conventional matching approaches are applied. As a result, recent developments increasingly emphasize semantic-sensitive retrieval approaches rather than purely surface-level similarity comparison.

Zulyani, Lidhya, et al. (2026). A systematic literature review of translation memory mechanisms in technology-based translation processes. *E-Structural (English Studies on Translation, Culture, Literature, and Linguistics).* 9 (01), 15—31.

Advantages and Limitations of Translation Memory in Translation Practice

The reviewed studies indicate that Translation Memory provides several significant advantages in professional translation practice (Table 2). One of the most frequently discussed benefits is consistency. Through the reuse of previously translated segments, TM enables translators to maintain stable terminology and phrasing across multiple documents. This benefit is especially important in technical, legal, and specialized translation contexts where terminological consistency is essential.

In addition, Translation Memory improves efficiency and productivity by reducing repetitive translation tasks. Translators can reuse existing translations rather than retranslating similar segments repeatedly. The reviewed studies also suggest that TM contributes to the long-term development of bilingual translation resources that can support future translation projects. Despite these advantages, the reviewed literature also identifies several limitations of Translation Memory systems. One major limitation is the dependence on database quality and retrieval accuracy. If stored translation units contain inaccuracies or irrelevant information, these issues may be reproduced in future translations. Another limitation concerns semantic and contextual flexibility. High similarity scores do not always guarantee contextual appropriateness, especially when linguistic variation, semantic shifts, or communicative differences occur between source segments.

Furthermore, the reviewed studies suggest that Translation Memory should not be viewed as a replacement for human translators. Rather, TM functions most effectively as a support mechanism that assists translators in decision-making processes. Human evaluation remains essential to ensure contextual suitability, semantic accuracy, and communicative effectiveness in translation output.

Discussion of Translation Memory Evolution

The reviewed studies demonstrate that Translation Memory has evolved significantly from a conventional storage-and-retrieval feature in CAT tools into a more dynamic mechanism integrated into advanced translation technologies. Earlier studies primarily emphasized exact matching and edit-distance retrieval, whereas more recent studies increasingly focus on semantic retrieval, neural integration, and retrieval-augmented translation systems. This shift indicates that contemporary Translation Memory research is moving toward context-sensitive and machine learning-based approaches.

Another important development identified in the reviewed studies is the growing integration of Translation Memory into neural machine translation systems. In recent approaches, retrieved segments are no longer treated merely as passive references but are increasingly used as contextual information to improve translation quality, semantic relevance, and fluency. This evolution demonstrates that Translation Memory now functions as part of a broader technology-assisted translation ecosystem.

The findings also suggest that Translation Memory is increasingly associated with artificial intelligence-assisted translation environments. Rather than functioning solely as a static archive, TM now contributes to dynamic retrieval processes capable of interacting with neural models and retrieval-augmented translation architectures. This development reflects the broader transformation of translation technology toward more intelligent and context-aware systems.

Zulyani, Lidhya, et al. (2026). A systematic literature review of translation memory mechanisms in technology-based translation processes. *E-Structural (English Studies on Translation, Culture, Literature, and Linguistics)*. 9 (01), 15–31.

Table 2 Advantages and Limitations of Translation Memory in Translation Practice (2020 – 2025)

Researcher(s)	Database Source	Advantages	Limitations
Ranasinghe & Or, (2020)	Scopus	Improves the matching and retrieval of previously translated segments and supports more effective reuse in translation tasks.	Traditional retrieval methods based on edit distance may fail to capture semantic similarity accurately.
Djabri et al. (2021)	Scopus	Helps translators retrieve prior segments and reduce repetitive translation effort.	Retrieval quality decreases when segments undergo syntactic or semantic transformation, such as word order or voice change.
Ben Milad (2021)	Google Scholar	Supports segment reuse through similarity measurement in Translation Memory systems.	Similarity scoring may penalize linguistic variation too heavily, reducing the usefulness of retrieved matches.
Tezcan et al. (2021)	Scopus	Fuzzy matches can improve translation quality when integrated effectively into technology-based translation systems.	The usefulness of fuzzy matches depends on how well the system handles similarity and integration.
Gamal (2020)	DOAJ	Increases consistency, efficiency, and productivity, especially in terminology-based and repetitive text genres.	Its effectiveness varies depending on text genre and is lower in fields requiring more creativity or contextual flexibility.
Cai et al. (2021)	Scopus	Translation memory can support neural machine translation by providing additional memory-based information.	The benefit of memory support still depends on the relevance and quality of the retrieved segments.
Xu et al. (2023)	Scopus	TM can be integrated into non-autoregressive machine translation through edit-based mechanisms such as insertion and deletion.	Effective performance still requires careful control of edit operations and memory use.
Hoang et al. (2023)	Scopus	Retrieved fuzzy matches can improve translation quality in retrieval-augmented translation systems	Translation quality may decrease if the interaction between the source text and fuzzy matches is not well controlled.

[Source: developed by the researcher based on reviewed studies]

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Research Trends and Gaps

The findings reveal several dominant trends in recent Translation Memory research. Most reviewed studies focus heavily on retrieval quality, fuzzy matching, similarity measurement, and integration into neural translation systems. Considerable attention has also been given to improving semantic retrieval through sentence encoders, neural retrieval models, and retrieval-augmented translation approaches.

However, the review also identifies several research gaps. First, relatively few studies investigate translator interaction and human decision-making when using Translation Memory suggestions. Most studies prioritize technical system performance over examining how translators interpret, evaluate, and adapt retrieved segments during real translation practice. Second, studies specifically discussing Translation Memory mechanisms in the context of large language models and generative AI systems remain limited, particularly in publications from 2024 and 2025.

Another research gap concerns the limited number of empirical studies examining the effectiveness of Translation Memory across different translation genres and professional contexts. Most studies focus primarily on technical performance evaluation rather than on investigating practical translator experiences in real working environments. Therefore, future research may further explore the interaction between translators, Translation Memory systems, and AI-assisted translation technologies.

Theoretical and Practical Implications

The findings of this review have both theoretical and practical implications. Theoretically, this study contributes to translation technology research by clarifying the interconnected mechanisms underlying Translation Memory systems, including segmentation, retrieval, matching, and similarity measurement. The study also demonstrates how Translation Memory has evolved from a conventional CAT feature into a more integrated mechanism within modern translation technologies.

Practically, the review confirms that Translation Memory remains highly valuable for improving translation consistency, efficiency, productivity, and terminology management, especially in repetitive and specialized translation tasks. However, the findings also emphasize the continued importance of human evaluation due to the limitations of contextual flexibility and semantic interpretation in Translation Memory systems.

In professional translation environments, the findings suggest that Translation Memory should be utilized as a collaborative support mechanism rather than as a replacement for human translators. The effectiveness of TM ultimately depends on the interaction between technological retrieval systems and human decision-making processes during translation production and revision.

Study Contribution

This study contributes to translation studies by providing a systematic synthesis of recent developments in Translation Memory mechanisms across both traditional CAT environments and emerging AI-assisted translation systems. Unlike previous studies that discuss technical improvements , this review integrates findings from multiple studies to explain how Translation Memory mechanisms operate within broader technology-based translation processes.

Furthermore, this study identifies current research trends, dominant themes, and existing research gaps related to Translation Memory. The findings may therefore serve as a conceptual reference for future studies investigating Translation Memory, translator interaction, semantic retrieval, and AI-assisted translation technologies.

This study also contributes methodologically by applying a systematic review approach using the PRISMA framework to synthesize recent Translation Memory research. Through this approach, the study provides a more transparent and structured overview of Translation Memory developments in contemporary translation technology research.

CONCLUSION

This paper finds that TM is a critical component in technology-assisted translation procedures. According to the selected research articles, TM functions as a broader mechanism involving several procedures such as segmentation, storage of translation units, matching, retrieval, and measuring similarity. With the help of these mechanisms, TM allows translators to use their translated texts before and helps them become more consistent and productive. In other words, TM acts as a crucial factor not only in making translators' work less monotonous but also more stable. Another thing that the results show is that the efficiency of TM relies heavily on the quality of its match and search processes. Exact matches serve as the best evidence, since they allow for the reuse of previous translations without much alteration. However, fuzzy matches would still need human assessment, especially if variations in language affect the degree of similarity. This shows that similarity measurement remains one of the most important and challenging aspects of TM. Although traditional edit-distance-based approaches are still useful, they are often limited in capturing deeper semantic, syntactic, and morphological variation. As a result, the usefulness of TM is closely related not only to the size of the translation memory database, but also to the quality, relevance, and accuracy of the translation units stored in it.

Moreover, this study reveals that TM is more than just a feature in CAT tools. Recent advancements indicate that TM has increasingly found its way into more sophisticated translation technologies, including neural machine translation, non-autoregressive machine translation, and retrieval-augmented translation systems. Such progress implies that TM cannot be seen merely as a repository of previously translated texts , but rather as a dynamic element involved in modern translation technologies. Hence, TM must be regarded not only as a useful tool for translators but also as a component of modern technological advancements within translation studies. Nonetheless, the reviewed studies indicate that TM has strengths and weaknesses. The major strengths of TM are enhancing consistency, saving time, boosting efficiency, and accumulating resources through repeated translation work. However, some of the limitations of TM are the need for good-quality databases, inability to adapt to changing contexts, and inability to handle semantic variations due to alterations in the wording of segments. Thus, TM cannot be thought of as an alternative to professional translators. Instead, it should be viewed as an additional tool that performs best when humans are involved in the process.

In summary, this paper provides insights for a more systematic understanding of the mechanisms of Translation Memory in technology-assisted translation. First, TM emerges as an important component of both traditional CAT environments and modern machine-aided translation tools. Furthermore, it is necessary to emphasize the importance of TM not only for its technical aspects, but also for its ability to contribute to the quality and efficiency of translations. Future studies should focus on examining TM application in various text types, studying translator-machine interactions related to TM suggestions, and developing TM with greater semantic awareness.

Despite its contributions, this study has several limitations. First, the review was limited to studies published between 2020 and 2025, meaning that earlier foundational studies on Translation Memory may not be fully represented in the analysis. Second, the study relied only on selected databases, namely Scopus, Google Scholar, DOAJ, and ERIC, so relevant studies from other academic databases may have been excluded. Third, although this study adopted a systematic review approach, the final selection of 26 reviewed studies may still involve selection bias due to the limited number of studies specifically addressing Translation Memory mechanisms in technology-based translation . Therefore, future studies are encouraged to expand database coverage, include more diverse sources, and conduct empirical investigations on translator interaction with Translation Memory systems in real translation environments.

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