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Does Translation Technology Affect Translators' Performance? A Meta-Analysis

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***Abstract*—Translation technologies, including computer-assisted translation (CAT) tools, translation memory (TM) systems, and machine translation (MT), are increasingly utilized in professional translation workflows and training. However, the effects of these technologies on translators' performance remain inconclusive. This meta-analysis examines the overall impact of translation technologies on translator performance by synthesizing data from 12 experimental studies published between 2000 and 2023. The study investigates the effectiveness of translation technologies compared to traditional translation methods. The findings reveal a significant positive effect size, indicating that translation technologies have the potential to improve translators' performance relative to purely human translation. The integration of advanced interactive CAT systems and post-editing MT demonstrates larger advancements compared to basic TM match retrieval. Moreover, experienced professional translators derive greater benefits from incorporating technologies than student translators, highlighting the importance of leveraging automation capabilities alongside human expertise. However, the study identifies significant heterogeneity among the studies, influenced by factors such as translation direction. Translators translating into their native language exhibit greater advancements, emphasizing the advantages of technologies that strengthen fluency in the target language.**

***Index Terms*—CAT tools, meta-analysis, translator's experience, translation technologies, translators' performance**

I. Introduction

The translation industry has undergone significant technological transformation with the introduction of various computer-assisted tools and automation. Computer-assisted translation (CAT) tools, such as translation memory (TM), terminology management, and project management systems, have been developed to optimize translators' workflows (Melby, 2012). Translation memory systems act as repositories of previously translated content, facilitating efficient retrieval of matches for new similar texts (Lagoudaki, 2006). Machine translation (MT) utilizes artificial intelligence to generate automated translations, which can potentially be post-edited by a human translator (Carl et al., 2011). Additionally, online corpora and parallel texts provide translators with multilingual databases for linguistic reference during translation (Sabzalipour & Rahimy, 2012). As these technologies have become increasingly prevalent in the translation sector, questions arise regarding their real impact on the performance of human translators who rely on these tools in their daily work. Key performance metrics of interest include productivity, quality, errors, and cognitive effort. However, the existing body of research investigating the effects of these technologies on these indicators presents conflicting evidence. Some studies demonstrate improved productivity and quality when translators utilize CAT tools compared to traditional human translation. For instance, Guerberof (2013) reported a 29% increase in productivity with TM tools, while Garcia (2010) found a 50% increase. Post-editing of MT output has also shown potential for enhancing quality compared to human translation alone, as indicated by Lee and Liao (2011). On the contrary, other studies have presented less favorable outcomes. O'Brien et al. (2017) revealed decreased productivity and worsened quality when translators used TM tools, and Kassem (2021) indicated lower productivity and quality when students employed CAT tools compared to traditional teaching methods without technology. Gaspari and Hutchins (2007) even suggested that post-editing MT could lead to increased errors and cognitive effort relative to human translation.

The variability in these existing results underscores the need for an integrated meta-analysis that evaluates overall effect sizes across studies. Meta-analyses leverage the statistical power of aggregating data from multiple studies on a specific topic, enabling more precise calculations of effect sizes compared to individual studies (Cohn & Becker, 2003). The present study aims to conduct a meta-analysis that synthesizes experimental research conducted between 2000 and 2023 on the impacts of translation technology on translators' performance. The aim is to answer the following:

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1) What is the overall effect size of translation technologies on translators' performance? And,

2) How do moderating factors, such as translator's experience, language pair, and technology type, influence the overall effect size of translation technologies?

By evaluating the overall magnitude of the effects of translation technologies and exploring factors that moderate these outcomes, this study is hoped to provide valuable insights for effectively integrating automation capabilities with human skills in professional translation workflows and training.

II. Literature Review

The translation industry has experienced speedy technological transformation through the expansion of computer-assisted translation (CAT) tools and machine translation (MT) systems. CAT tools encompass specialized software programs designed to optimize and automate certain translators' performances. Prominent functions of CAT tools comprise translation memory (TM) databases, terminology management systems, project management platforms, quality assurance checks, and text alignment capabilities (Melby, 2012).

TM systems perform as large repositories which store previously translated content and segment matches, allowing efficient retrieval and leveraging of existing translations for consistent terminology when translating new and similar texts. This can increase translator productivity by reducing duplication (Lagoudaki, 2006; Lagoudaki, 2009). Additionally, MT utilizes artificial intelligence algorithms to generate raw automated draft translations without human intervention. The machine-generated outcome can then potentially be post-edited by a human translator to enhance overall quality (Carl et al., 2011). Online corpora and parallel texts also provide additional multilingual databases that translators can reference as linguistic assets during the translation process (Alotaibi, 2017; Sabzalipour & Rahimy, 2012; Verplaetse & Lambrechts, 2019). Core performance metrics of interest include productivity, translation quality, errors, and cognitive effort during the translation process. Regardless, the existing body of research examining the effects of CAT tools, TM systems, and MT on these key indicators reveals contradicting evidence.

Regarding productivity, certain studies illustrate performance improvements when translators use CAT tools corresponded to purely human translation without technology assistance. Guerberof (2013) noted a 29% increase in translator speed using TM tools. Gaspari et al. (2015) also exhibited productivity increases from post-editing raw MT output into higher quality final translations. Yet, other studies uncover detrimental impacts on productivity. O'Brien et al. (2017) found lower productivity when translators employed TM tools compared to human translation alone without technology. Green et al. (2013) likewise reported less productivity post-editing MT outcome versus purely human translation.

In terms of translation quality, some studies denote potential advancements with CAT tool use. Garcia (2010) exhibited enhanced quality when translators utilized TM tools. Further, Lee and Liao (2011) found better overall quality when translators post-edited MT outcomes compared to purely human translation. Nevertheless, other studies demonstrate lessened quality outcomes. O'Brien et al. (2017) showed decreased quality when translators used TM tools. Moreover, Kassem (2021) observed lower overall translation quality when students post-edited MT output compared to traditional teaching methods without CAT tools. It is analytically evidenced that the use of translation technologies and software programs play on improving the professional standards of translation and EFL students' translation productivity; they are still far from being applied as institutionally authorized parts of translation pedagogy. Without the use of translation technologies, translators cease to operate adequately to offer high-quality translation services (Omar et al., 2020).

Regarding translation errors, Gaspari and Hutchins (2007) suggested that post-editing raw MT output could diminish errors in the final translations. Yet Green et al. (2013) contrarily identified increased errors when translators post-edited MT output compared to purely human translation. The researchers used individual student performance without a specific translation tool as the standard score, individual scores were then compared. Although the use of dedicated translation tools did not seem to affect the quality delivered by the students accomplishing the highest and lowest benchmark scores, performance was far less consistent for those between the two extremes. Some students executed especially well or poorly with one of the three translation tools while acquiring good or average quality scores with the others (Morin et al., 2017). For cognitive effort, Moorkens et al. (2015) reported a lower mental workload for translators employing TM tools. However, O'Brien (2017) demonstrated increased cognitive load inflicted by TM tools relative to human translation alone without technology.

A. Factors Influencing the Impact of Translation Technology

The impact of translation technology on translators' performance is influenced by various factors, including the tools used, translation direction, and translator's level. These variables play a crucial role in shaping the outcomes and are discussed in more detail below.

(a). Translation Tools

One significant factor is the choice of translation tools. Different types of tools, such as Machine Translation (MT), Computer-Assisted Translation (CAT) tools, Translation Memory (TM) systems, and corpora, can have a moderating effect on the outcomes. For example, studies conducted by Guerberof (2013), Garcia (2017) have shown that using advanced interactive CAT tools with integrated TM functions leads to productivity and quality gains compared to relying solely on basic TM match retrieval. This indicates that the level of tool sophistication can significantly impact performance. Additionally, Lee and Liao (2011) found that combining MT with human post-editing resulted in improved translation quality compared to using uncontrolled MT output alone. However, it is essential to consider that the impact of translation tools is not uniformly positive. O'Brien et al. (2017) demonstrated that basic TM systems had detrimental effects on both productivity and translation quality when compared to human translation. This highlights the importance of selecting the appropriate tool for a given task.

Moreover, the variety of available tools also influences the balance between automation and human input, which, in turn, can affect performance outcomes. Translators must strike a balance between leveraging the advantages of automation provided by translation technology and utilizing their linguistic expertise and creativity to ensure high-quality translations.

(b). Translation Direction

The choice of language direction in translation, whether from a foreign language to the native language or vice versa, can significantly impact the results obtained when using translation technology. Several studies have demonstrated that working in one's native language using technology can yield greater improvements compared to translating from a foreign language into the native language (Kassem, 2021; Lee & Liao, 2011).

When translators work in their native language and utilize translation technologies, such as CAT tools or MT followed by human post-editing, they may experience enhanced fluency and leverage their linguistic expertise more effectively. The familiarity with the distinctions, idiomatic expressions, and cultural references of their native language allows them to make more informed decisions during the translation process, resulting in higher-quality translations.

On the other hand, when translating from a foreign language into their native language, technological advantages may be somewhat restricted. In such cases, human judgment and expertise play a more significant role in ensuring accurate and culturally appropriate translations. Translators need to rely on their interpretive skills and cultural knowledge to bridge any gaps or challenges posed by the source language, which may limit the extent to which translation technology can facilitate the process.

It is important to acknowledge that the impact of language direction on the effectiveness of translation technology is not absolute. Factors such as the complexity of the texts, the availability of linguistic resources and tools tailored to specific language pairs, and the individual translator's proficiency in both the source and target languages can also influence the outcomes.

(c). Translator’s Experience

The translator's level of experience plays a crucial role in moderating the impact of translation technology. Numerous studies have consistently shown that professional translators tend to derive significant advantages from using CAT tools, TM systems, and MT compared to students or less experienced translators (Carl et al., 2011; Guerberof, 2013).

Professional translators, who have accumulated extensive practical experience in the field, often possess a range of strategies and techniques that allow them to seamlessly incorporate translation technologies into their workflow. Through years of practice, they have developed specialized aptitudes and refined their skills to effectively leverage these tools. As a result, professional translators can capitalize on the benefits offered by CAT tools, TM systems, and MT to enhance their productivity, improve the consistency of their translations, and streamline their overall workflow (Green et al., 2013; Guerberof, 2013).

In contrast, student translators or those with less experience may require additional training and support to effectively harness the potential of translation technology. While they may possess foundational knowledge and skills, they may still be in the process of developing the necessary expertise to fully utilize these tools. Student translators may need guidance to navigate the complexities of the technology, understand its functionalities, and integrate it seamlessly into their translation process. Furthermore, inexperienced translators may face challenges related to cognitive load, as they need to allocate mental resources to both the translation task and the utilization of technology, which can be overwhelming without proper training.

It is important to note that the impact of experience on the effectiveness of translation technology is not absolute, and individual differences among translators should also be considered. Factors such as the level of technological proficiency, adaptability to new tools, and openness to learning can influence how effectively translators at different experience levels can leverage translation technology.

To sum up, the translator's level of experience significantly influences the outcomes achieved using translation technology. Professional translators, with their accumulated experience and specialized skills, tend to derive substantial benefits from these tools. On the other hand, student translators or those with less experience may require additional training and support to effectively utilize translation technology, ensuring that they can fully leverage its potential and avoid unnecessary cognitive load to sum up, the tools used by the translators, the language pair they work with, and the translator’s experience, may significantly moderate the impact of translation technologies on productivity, quality, errors, and cognitive effort. Carefully assessing their impact through moderator analyses can provide a clear understanding of blending automation capabilities and human judgment during translation. This knowledge can disclose evidence-based implementation of technologies for optimal complementarity with human expertise. Ultimately, the variability in existing findings stresses the need for an integrated meta-analysis to determine the overall effect sizes of CAT tools, TM systems, and MT on critical translator performance indicators. Synthesizing data across empirical studies allows more robust findings compared to individual studies (Cohen, 1988; Cohn & Becker, 2003). Moreover, exploring moderator variables helps explain heterogeneous results, while evaluating publication bias ensures precise interpretation. This meta-analysis aims to guide the informed implementation of technologies to augment rather than replace specialized human translation expertise.

In the next section, a detailed description of the methodology used in this meta-analysis is presented.

III. Methodology

A. Research Design

A comprehensive meta-analysis was conducted to evaluate the influence of technology on translators' performance. This study employed a robust meta-analysis design, which involved synthesizing results from multiple experimental studies. This approach allowed for a thorough summary of findings, with effect sizes calculated to provide a quantitative estimate of the differences observed in post-test scores between experimental and control groups. The analysis followed a sequential procedure, incorporating various stages: (1) an extensive literature search, (2) the establishment of strict inclusion criteria, (3) coding selected studies, and (4) calculating effect sizes. By adopting a multi-methodological approach, this analysis ensured a rigorous and systematic evaluation of the impact of technology on translation.

B. Searching the Literature

To identify relevant studies for the analysis, an exhaustive search across prominent databases was performed, including the Educational Resources Information Centre (ERIC), Web of Science, and SCOPUS. The search, based on key terms like "translation," AND "technology," OR "computer-assisted translation tools," OR "machine translation," OR "artificial intelligence," resulted in 1500 articles between 2000-2023, all studies published until December 31, 2023, were considered eligible. Exclusions were made based on predefined criteria, ultimately resulting in the inclusion of 12 studies. These studies are listed in Appendix A.

C. Study Inclusion Criteria

The formulation of inclusion criteria played a pivotal role in selecting studies for the analysis. Each study that met the following conditions was considered: (1) an experimental or quasi-experimental design was employed, (2) translation technology was used as the primary instrument in the experiment, (3) participants in the experimental group utilized technology for translation, and (4) means, standard deviations and participant counts were reported for each group. The inclusion process is illustrated in Figure 1. Exclusion criteria consisted of the following: (a) qualitative designs, surveys, or interviews, (b) research on fully automated systems without human subjects, and (c) studies lacking adequate statistical information for analysis. The meta-analysis followed the PRISMA model (Figure 1) for literature compilation, screening, and coding, as outlined by Page et al. (2021).

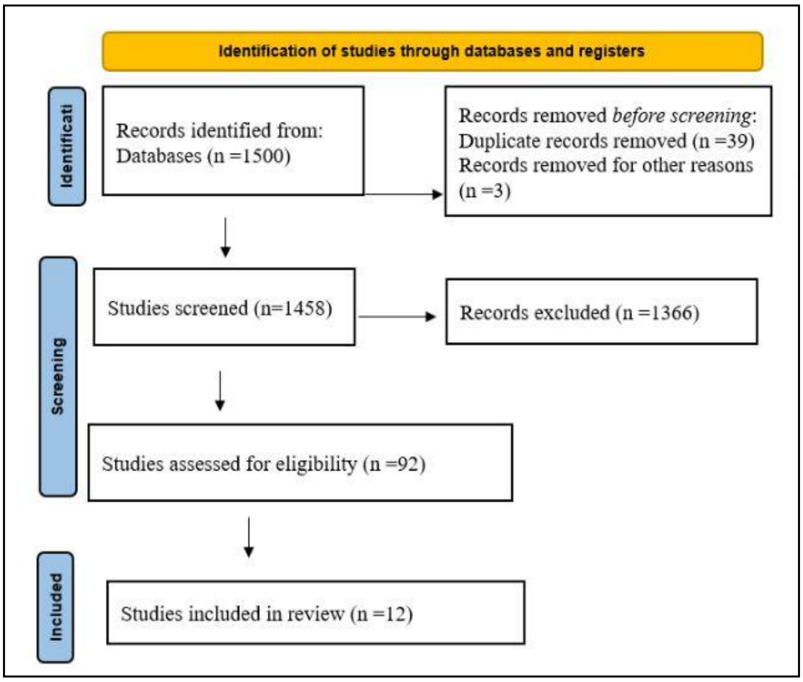

Figure 1. PRISMA Flowchart

Comprehensive searches were performed using Google Scholar, Web of Science, Scopus, and Semantic Scholar databases to identify experimental studies conducted between 2000 and 2023 that examined the performance of human translators with and without translation technologies. Reference harvesting and hand-searches were also undertaken. After screening, moderator variables were coded, including language pair, translator's experience level, and technology type. Effect sizes were calculated using reported statistics to quantify the performance differences between human and technology-assisted translation groups. A random-effects meta-analysis was conducted using Comprehensive Meta-Analysis software to assess overall effect sizes. Heterogeneity was assessed using Q and I2 values, and publication bias was also evaluated.

D. Coding of Study Characteristics

Investigating the impact of technology on translators' performance within the present meta-analysis required considering three significant factors: translation tool used in the study, translation direction, and translators' levels. These factors were systematically coded as variables for analysis. The first variable encompassed machine translation (MT), Computer-Assisted Translation (CAT) tools, online corpora, and a combination of MT and CAT tools, which were divided into four categories. The second variable focused on the translation direction and was categorized as English to target language (TL) and TL to English. The third variable, related to translators' levels, was classified into three categories: undergraduates, postgraduates, and professional translators. Detailed definitions of these variables can be found in Appendix B.

E. Effect Size Calculation

In determining the effect size of technology on translators' performance, the present meta-analysis utilized Hedge's g to calculate effect sizes. Hedge's g divides the observed mean difference in a study by the combined standard deviation, represented by the formula: Hedge's g: g = (M1 – M2) / SDpooled. Here, M1 represents the mean of Group 1, M2 represents the mean of Group 2, and SDpooled is the combined estimate of the population standard deviation (Borenstein et al., 2009). Following Plonsky and Oswald's (2014) scale, effect sizes are classified based on the benchmarks: 0.40 (small), 0.70 (medium), and 1.0 (large). Unlike traditional classifications by Cohen (1988) where effect sizes are categorized as large (0.80 or above), medium (0.51–0.79), small (0.20–0.49), or negligible (less than 0.20), this study assumes the random-effects model to account for variability in effect sizes across studies (Borenstein, 2012; Borenstein & Rothstein, 1999). Oswald and Plonsky (Oswald & Plonsky, 2010; Plonsky & Oswald, 2011, 2014) differentiated between the fixed effects and random effects models, the latter is preferred due to its explicit testing for heterogeneity, providing a more robust conceptual foundation.

As a result, any observed distinction in effects across studies is attributed to variations in sampling error variance or other statistical artefacts, such as disparities in measurement reliability. Contrarily, the random effects model suggests a direct assessment of heterogeneity by quantifying it as a variance estimate, accounting for sampling error variance. If the confidence interval of the variance estimate excludes zero and is deemed practically significant, it indicates heterogeneity in the effects within the study population, demonstrating a lack of uniformity in fixed values. When determining between the fixed effects and random effects models, the random effects model holds stronger conceptual justification as it explicitly tests for heterogeneity rather than presuming homogeneity.

The I^2 statistic, as recommended by Huedo-Medina et al. (2006), serves as a valuable indicator of heterogeneity. In this study, I^2 values are interpreted as follows: approximately 25% suggesting low heterogeneity, 50% indicating medium heterogeneity, and 75% signifying high heterogeneity. This understanding of heterogeneity is important for drawing meaningful conclusions from the diverse range of studies contained in the meta-analysis.

To conduct this comprehensive analysis, the Comprehensive Meta-Analysis (CMA) software designed by Borenstein (2012) was employed. CMA serves as a specialized statistical tool particularly tailored for meta-analyses, providing necessary features like effect size calculations, forest plots, subgroup analyses, and assessments for publication bias. This software ensures a rigorous and systematic approach to synthesizing results from multiple studies related to the impact of technology on translation within the scope of this research.

F. Publication Bias

The evaluation of publication bias is an essential aspect of any meta-analysis, and in this study, it was performed using a funnel plot, the graphical representation of the distribution of effect sizes across primary studies. Figure 2 demonstrates the nuances of this analysis, which unfolds into two distinctive components. Firstly, upon examining most black patches and data points on the funnel plot, a notable pattern emerged, a symmetrical spread around the mean effect size along the 95% CI line. This symmetry is denoting of a balanced distribution, suggesting that the population of primary studies did not reveal any noticeable publication bias. The funnel plot's depiction of the study outcomes symmetrically aligned on both sides of the mean effect size proposes confidence in the unbiased representation of the research landscape. Secondly, a closer investigation of the funnel plot's lower section disclosed a few black areas, implying potential areas of concern. These areas hinted at studies with smaller sample sizes that may have understated their results, a phenomenon often associated with asymmetry in funnel plots. Nonetheless, it's critical to note that these localized irregularities do not necessarily translate to a systemic issue of publication bias or outliers across the entire meta-analysis. The intriguing aspect of studies showing both positive and negative impacts points up the balanced distribution of effect sizes on either side of the average. This balance is crucial because the absence of solely positive impact sizes alleviates worries commonly associated with the detection of publication bias. In essence, the diversity in study outcomes, containing both favourable and unfavourable impacts, contributes to the robustness of the meta-analysis.

The funnel plot not only determines whether publication bias exists but also shows how close the observed mean is to the actual population mean. The standard error is predicted to decrease with sample size, eliciting a more precise measurement of the treatment effect (Plonsky & Oswald, 2011). Yet, the complexity of funnel plot anomalies urges a comprehensive approach to validate findings. In this context, the Fail-safe N test and Egger's regression test are used as instrumental tools. Egger's test, designed to identify asymmetry in the funnel plot, a graphical representation of the relationship between the effect size (typically the standardized effect size) and a measure of study precision (usually the inverse of the standard error). In a balanced set of studies, the points on the funnel plot should be approximately symmetrical around the estimated effect size. The p-value associated with the regression intercept is employed to evaluate the statistical significance of any funnel plot asymmetry. A low p-value (typically below a chosen significance level, such as 0.05) implies the presence of publication bias. In this meta-analysis, the intercept was 11.79 and a corresponding p-value of 0.00. The p-value associated with the regression intercept is used to assess the statistical significance of any funnel plot asymmetry. A low p-value (typically below a chosen significance level, such as 0.05) denotes the presence of publication bias. The intercept significantly deviating from zero suggests the presence of funnel plot asymmetry, a potential indicator of publication bias.

The Fail-safe N test, another dimension of scrutiny, endeavours to estimate the number of additional non-significant or null studies necessary to nullify the observed statistically significant effect. If the calculated fail-safe N is large, it indicates that a substantial number of unpublished or missing studies with null results would be required to contradict the observed effect. The calculated z-value of observed studies, standing at 21.26, coupled with a p-value of 0.000, reflects the rigour applied in affirming the existence of publication bias. Nevertheless, it's essential to approach the Fail-safe N results with caution, recognizing that it provides an estimate under the assumption that all missing studies are non-significant.

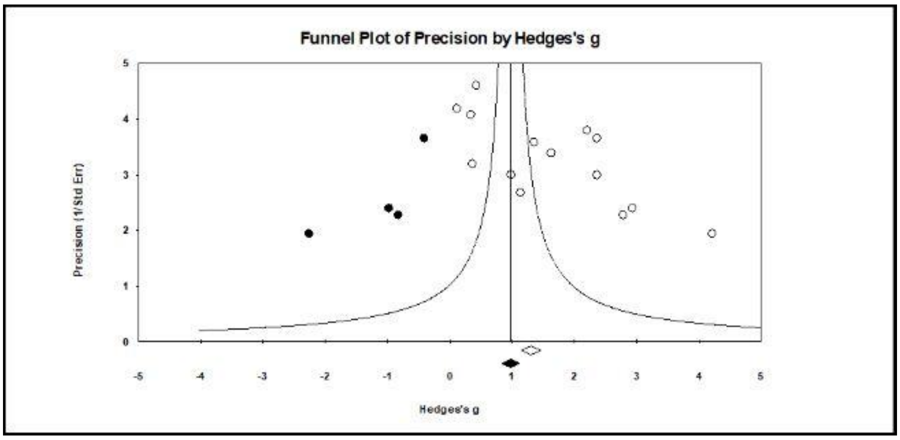

Figure 2. Funnel Plot of Publication Bias

IV. Results

The focus of this meta-analysis is to answer the following research questions: what is the overall effect size of translation technologies on translators' performance? and, how do moderating factors, such as translator's experience, translation direction, and technology used, influence the overall effect size of translation technology? The analysis of the 12 studies was made across diverse categories. The overall impact of translation technology on translators' performance is discussed. Then, variables that may affect the use of technology on translators' performance are analyzed.

A. The Overall Effect Size

The current meta-analysis included 12 studies and produced 14 effect sizes. The overall result of these studies is shown in Table 1 below.

Table 1
Overall Effect Size

k*	G	SE	Confidence intervals		p-value	Q-value	df	I-squared
14		0.28	Lower limit	Upper limit				
	1.61		1.052	2.17	.000	163.42	13	92.04

*k= number of effect sizes calculated

The analysis was carried out using the standardized mean difference as the outcome measure, which is represented in Table 1 with (g). A random-effects model was fitted to the data. Table 1 shows that the overall effect size of translation technology had a large effect size (g=1.61). In addition, the Q-test for heterogeneity and the I^2 statistic were reported. The confidence intervals ranged from 1.05 to 2.17. Therefore, the average outcome differed significantly from zero. According to the Q-test, the true outcomes appear to be heterogeneous (Q =163.42, p= .000). This indicates that translation technologies are more effective than traditional methods of translating. The forest plot, as shown in Figure 3, provides context for the analysis.

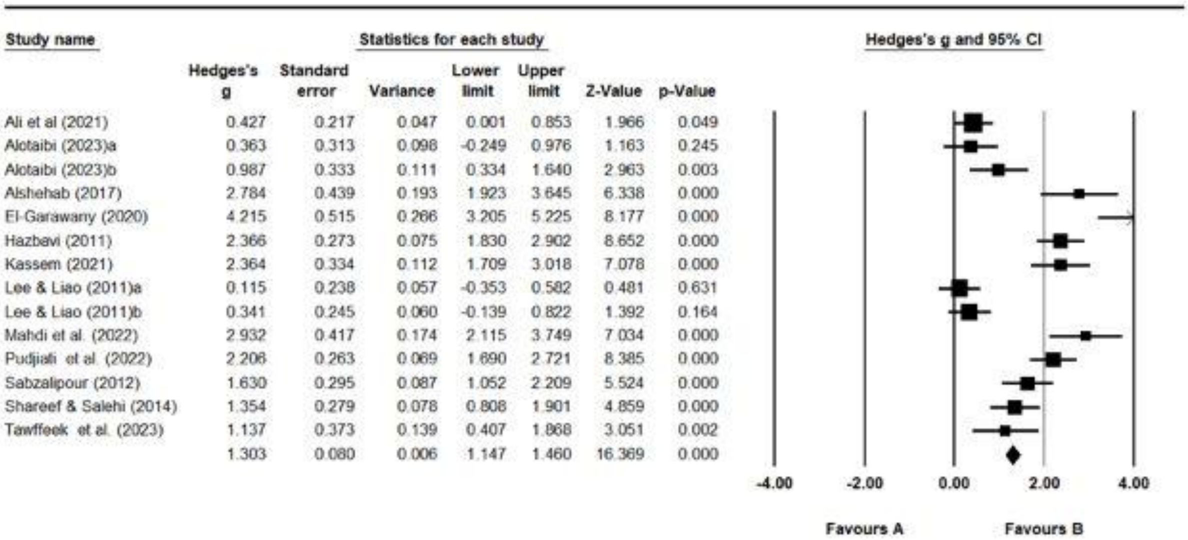

Figure 3. Forest Plot of Overall Effect Size

The forest plot graphs illustrate the effect sizes and accuracy of the individual studies, providing a visual display of the heterogeneity. The diamond represents the overall effect size, with the width indicating the 95% confidence interval. The squares depict the effect sizes for each study, with sizes directly proportional to their precision based on sample sizes. The varied locations of the squares visually demonstrate the heterogeneity in effects between studies, centred around the overall effect. As studies range from negative effects on the left to strongly positive effects on the right, this reinforces that translation technology appears to have large positive effects on average, but true impacts likely differ depending on other factors in each study context. The forest plot complements the overall analysis by illustrating the distribution of heterogeneous study effects contributing to the overall estimate.

B. Translation Tool

The selection of the translation tool used in the study stands as a prominent factor with potential moderating effects on outcomes. The tools moderator analysis, outlined in Table 2, systematically explores the impact of various translation tools. In the initial analysis, TM systems indicated a medium effect size. The other tools revealed a large effect size. Notably, CAT tools alone exhibited a large effect size of 1.64, emphasizing their significant impact. Online corpora demonstrated a large effect size of 1.95, conveying its notable influence and emphasizing the key role these supplementary linguistic databases play in improving terminology and phrasing. Contrariwise, standalone MT exhibited a medium effect size of 0.59, suggesting that solely relying on fully automated MT, without human post-editing, may fall short of achieving quality translation.

TABLE 2
THE OVERALL EFFECT SIZE

	k*	d	Confidence intervals		P-value	Q-value	df
			Lower limit	Upper limit			
MT	5	0.59	0.336	0.848	0.000	163.423	13
CAT	7	1.64	1.415	1.874			
Online corpora	2	1.95	1.566	2.336			

*k= number of effect sizes calculated

C. Translation Direction

Table 3 presents findings from the moderator analysis examining the impact of translation direction on the effects of technology on translators' performance. Translation direction refers to whether translators were working from their native language into a foreign language or vice versa when employing the technologies. The results reveal translation from English into the native language showed a larger effect size (g=1.91) compared to translation from the native language into English (g=0.83) which was deemed a medium effect size. This suggests technologies present greater performance benefits when translators are working in their native tongue rather than from a foreign language. The enhanced effects for native language translation could be attributed to higher fluency and proficiency in the target language. In contrast, translating from a foreign language into the native language appears to derive less advantage from technologies.

TABLE 3
TRANSLATION DIRECTION

	k*	g	Confidence intervals		P-value	Q-value	df
			Lower limit	Upper limit			
English to native language	8	1.91	1.675	2.14	0.00	163.423	13
Native language to English	6	0.83	0.625	1.041			

*k= number of effect sizes calculated

D. *Translator's Experience*

Table 4 presents the moderator findings for the translators' experience level. The initial variables analysis illustrated professionals derive more advantages from technologies than students. Here, professional translators had the highest effect size of 2.93, affirming that experienced subjects maximize technologies' benefits. Both Postgraduates and undergraduates revealed a large effect size of 1.20 and 1.26 respectively.

TABLE 4
TRANSLATOR'S EXPERIENCE

	k*	g	Confidence intervals		P-value	Q-value	df
			Lower limit	Upper limit			
Undergraduates	10	1.26	1.067	1.453	0.00	163.423	13
postgraduates	3	1.20	0.921	1.484			
Professional translators	1	2.93	2.115	3.749			

*k= number of effect sizes calculated

V. DISCUSSION

This meta-analysis aimed to investigate the overall impact of translation technologies, including computer-assisted translation (CAT) tools, translation memory (TM) systems, machine translation (MT), and corpora, on translators' performance. By synthesizing data from 12 experimental studies, the quantitative analysis provided insights into the effectiveness of technology-assisted translation compared to traditional translation methods.

The quantitative findings revealed a large effect size (g=1.61), indicating that translation technology can greatly enhance translators' performance. This result aligns with previous research that has reported performance benefits associated with the use of translation technologies. For instance, Alotaibi and Salamah (2023) demonstrated that translation apps can improve productivity and quality, suggesting that mobile translation apps are valuable resources that can be successfully integrated into translator training environments. Similarly, Hazbavi (2011) found that Translation Memory Systems had a positive effect on English into Persian translation, highlighting the potential of carefully integrating technologies to enhance the capabilities of human translators.

However, it is important to note that significant heterogeneity was observed among the included studies. To gain further insights into the factors contributing to this variability, moderator analyses were conducted. These analyses provided crucial information on the elements that influence the outcomes of technology-assisted translation. Factors such as the specific technology used, the experience level of translators, and the direction of translation were identified as potential moderators affecting the successful integration of translation technology.

The findings of this study highlight the significant impact that different translation tools have on translators' performance. It was observed that advanced interactive computer-assisted translation (CAT) tools yielded the most substantial improvements in productivity and quality (Guerberof, 2013; Garcia, 2010). These tools, which incorporate features such as TM match retrieval, terminology management, and quality checks, optimize workflows and enhance translators' capabilities. This finding is consistent with previous research of Moorkens et al. (2015), which suggests that well-designed interfaces can reduce extraneous cognitive load and facilitate translators' efficiency.

In contrast, the study found that basic TM match retrieval alone had inadequate effects, supporting the findings of O'Brien [8], who demonstrated that relying solely on this feature could have detrimental impacts on productivity and quality. Furthermore, the use of corpus-based translation tools was found to enhance performance, aligning with the findings of Sabzalipour and Rahimy (2012). The incorporation of corpus tools improved the quality of translation by providing translators with valuable resources and references.

However, the study also revealed that raw, uncontrolled machine translation (MT) output exhibited weaker effects, consistent with the findings of Lee and Liao (2011) and this highlights the importance of human intervention, such as post-editing, in ensuring translation quality. Fully automated systems that rely solely on MT without human involvement demonstrated limitations in achieving high-quality translations. These findings support the notion that advanced translation tools, which reinforce human expertise and involve human intervention, tend to yield the most significant benefits.

Additionally, the study found that the combination of MT and human intervention at the back-end of the automated process can be particularly beneficial for students or individuals with limited language proficiency. This approach allows them to produce more accurate translations compared to starting from scratch with the source text. These findings emphasize the value of leveraging technology to support and enhance the translation process, especially for individuals who may face language proficiency challenges.

The results of this meta-analysis underscore the importance of selecting appropriate translation tools and considering their impact on translators' performance. Advanced interactive CAT tools, incorporating features such as TM match retrieval, terminology management, and quality checks, have the potential to significantly improve productivity and quality. Similarly, the use of corpus-based translation tools can enhance the quality of translation. However, it is crucial to recognize that human intervention, such as post-editing, remains necessary when working with raw machine translation output. By leveraging advanced tools that reinforce human expertise and integrating technology with human intervention, translators can maximize their performance and produce high-quality translations. These findings have significant implications for translator training, highlighting the importance of equipping translators with the necessary tools and skills to effectively utilize technology in their practice.

The direction of translation language emerged as a significant moderator of the outcomes in this study. It was found that technologies had a greater impact on performance when translators were translating from foreign languages into their native language. This finding is consistent with previous research Lee and Liao (2011) Kassem (2021), which suggests that native language fluency plays a crucial role in effectively leveraging translation tools. The use of technologies appears to enhance, rather than replace, the specialized linguistic expertise developed through native language immersion. Translating from the native language to foreign languages, on the other hand, showed reduced effects, indicating that human judgment and the application of target language knowledge remain essential in these translation scenarios.

Furthermore, the findings align with research demonstrating that professional translators derive more significant benefits from technologies compared to students (Carl et al., 2011; Dehbashi & Salehi, 2015). According to the findings of Dehbashi and Salehi (2015), translation technologies had a positive effect on critical thinking and translation performance of Translation Studies students. The accumulated experience of experts allows for the seamless integration of tools with human competencies. In contrast, students may require comprehensive training to effectively utilize technologies without experiencing extraneous cognitive load. These findings emphasize the importance of considering the level of expertise and training when implementing translation technologies, as professionals may have a better understanding of how to strategically utilize these tools compared to students.

The overall findings of this meta-analysis support the notion that thoughtfully implemented translation technologies can enhance translator performance and complement their strengths. However, it is important to note that certain studies have reported contrasting results, highlighting the need for careful consideration and assessment of the specific tools utilized. For example, O'Brien (2017) demonstrated reduced productivity and quality when students used basic TM tools compared to traditional teaching methods without technology. This finding likely reflects the inadequacies of the specific tools used and the students' lack of training. Similarly, Wang et al. (2024) indicated that CAT tools may have negative effects on productivity, naturalness, and fluency for translators. Gaspari and Hutchins (2017) also found increased errors and cognitive effort when post-editing raw MT output compared to human translation alone. These studies align with the current meta-analysis, which suggests that uncontrolled automation has limited performance benefits. These findings underscore the importance of assessing the design and integration of technologies to avoid detrimental consequences.

Furthermore, the presence of publication bias suggests that studies reporting positive effects of technologies on performance may be overrepresented compared to research showing impartial or negative effects. The asymmetry observed in the funnel plot indicates that smaller studies with results contrary to the overall effects may be under-published. This highlights the need for a balanced research agenda that considers the complexities of translation technologies.

This meta-analysis is hoped to provide evidence that thoughtfully implemented translation technologies have the potential to improve translator performance and complement their expertise. However, it is crucial to recognize that technologies are not a universal remedy. Factors such as the design of the tools, their real-world integration, the specific language pairs involved, and the experience levels of the users critically shape the outcomes. A comprehensive, evidence-based approach that takes into account these complex and interacting factors is essential. By leveraging the advantages of human translators and informed technology implementation, these tools can empower professionals to provide high-value linguistic and cultural expertise. However, relying solely on uncontrolled automation carries the risk of negative consequences. Ultimately, this meta-analysis emphasizes that technologies should remain human-centric tools rather than autonomous solutions. Moreover, there is an ongoing need for the continued development and improvement of translation technologies, with a particular focus on enhancing their usability. As translators increasingly rely on these tools, it is essential to refine their design, user interfaces, and functionalities to ensure they are intuitive, efficient, and seamlessly integrated into the translation process. By addressing usability issues and continually innovating in this field, the potential benefits of translation technologies can be maximized, leading to further advancements in translator performance and productivity (Alotaibi, 2020; Wang et al., 2024).

VI. Conclusion

The objective of this meta-analysis was to examine the overall influence of translation technologies, such as computer-assisted translation (CAT) tools, translation memory (TM) systems, machine translation (MT), and corpora, on the performance of translators. By analyzing data from 12 experimental studies published between 2000 and 2023, this quantitative analysis yielded valuable insights into the effectiveness of technology-assisted translation in comparison to conventional translation approaches. The findings of this study demonstrated a significant positive effect size, suggesting that translation technologies can enhance translator performance compared to solely relying on human translation. This indicates that the strategic integration of translation technology such as CAT and MT has the potential to increase productivity, improve quality and accuracy, and alleviate the cognitive load on translators.

However, it is crucial to acknowledge that there was substantial variability among the studies, influenced by several moderating factors. Specifically, the direction of translation had a significant impact on the results, with more significant improvements observed when translators translated into their native language compared to translating from a foreign language into their native language. This highlights the considerable advantages of utilizing technologies that reinforce the translators' fluency and proficiency in the target language.

Moreover, the specific technology employed also had an impact on the outcomes. Advanced interactive CAT systems and post-editing machine translation (MT) yielded greater improvements compared to basic translation memory (TM) match retrieval, which offers more limited assistance in generating translations.

Furthermore, experienced professional translators derived more significant benefits from integrating technologies compared to student translators. This difference in outcomes is likely attributed to the professionals' adeptness at effectively combining automation capabilities with their own expertise, employing exceptional strategies to complement the use of technology. While this meta-analysis aimed to provide a comprehensive overview of the impacts of translation technologies on performance, it is important to acknowledge certain limitations. Firstly, the limited number of studies available for certain technologies and language pairs may have influenced the findings related to moderating factors. Further research with larger sample sizes and controlled variables is necessary to validate these effects. Secondly, the majority of studies focused on English and major European languages, indicating a need for research on diverse language pairs. Thirdly, there was a lack of studies analyzing interactive CAT tools or exploring the active generation of subtitles, presenting avenues for future investigation. Fourthly, the relatively short duration of many included studies may restrict the generalizability of long-term effects. Lastly, addressing potential publication bias requires the inclusion of unpublished research to ensure representative findings.

To validate the results of this meta-analysis, further experimental studies with robust designs are warranted. Specifically, research focusing on interactive CAT tools, online corpora, and understudied language pairs could enhance our understanding of how technologies can augment human cognitive processes in translation. Additionally, qualitative research that explores translators' perceptions and experiences when incorporating technologies into their practice could complement the quantitative synthesis. By addressing these limitations through multifaceted research approaches, we can gain a deeper understanding of the intricacies of human-computer collaboration in translation.

Appendix A List of Studies Included in the Current Meta-Analysis

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APPENDIX B DEFINITIONS OF VARIABLES

Machine translation (MT)	Machine Translation refers to the automated process of translating text or speech from one language to another using computer algorithms. This involves computational linguistics and artificial intelligence techniques.
Computer-Assisted Translation (CAT)	Computer-Assisted Translation involves the use of computer tools to aid human translators in their work. It includes tools for translation memory, terminology management, and other aids to improve efficiency and consistency.
Online Corpora	Online corpora are large collections of texts or linguistic data that are available on the internet. These corpora serve as valuable resources for linguistic research, language analysis, and development of language technologies.
Professional translators	Professional translators are individuals who engage in translation as a career, providing translation services for various clients or organizations. They typically possess expertise in specific subject matters and linguistic domains.

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