The Evaluation and Comparison of Translation Technologies on the Learning Outcomes of Legal Text Translation Studies

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ABSTRACT

This paper analyses the relationship between translational technology and learning outcomes and investigates the type of translational technology most beneficial towards students' translations of legal texts. This study tests whether differences were found in the learning outcomes of legal text translation for students with high and low placement test scores using Machine Learning. Translations were conducted from Indonesian to English and vice versa, encompassing students from leading Indonesian universities enrolled in a professional legal translation certification programme. This research was designed with a treatment by level 3x2, quantitatively analysing the impacts of Machine Learning, Google Translate, and Online Dictionaries. The study revealed statistically significant interactive effects among the variables of translational technology in relation to the outcomes of legal translation

learning. The data indicated variances in the students' learning with Machine Learning demonstrating the most substantial influence. We also found that low-scoring students on the placement test who used Machine Learning in translating legal texts revealed better learning outcomes than high-scoring students. This insight is useful for educators and scholars designing legal translation courses. This could also serve as a foundational element in the field of English for Specific Purposes particularly concerning the integration of technology in legal translation education.

Keywords: Machine Learning, Google Translate, placement test, legal translation, differentiated learning

Introduction

Legal text translations between languages are by nature complex practices within the legal system it is established. Despite its challenges, legal text translation is crucial towards national and industry interests, as well as educational purposes (Salmani-Nodoushan, 2020). For instance, foreign investors looking to invest would find it necessary to understand and make decisions according to national laws, the basis of which is allowed by the work of legal translators. A misunderstanding could put contracts into jeopardy. Bilingual contracts with high quality of translation offer clarity and legal security, preventing contract annulments by the National or Supreme Court due to language and different interpretation issues.

The enactment of Indonesia Law number 6 of 2023, alongside regulations like Presidential Regulation number 63 of 2019, mandates that legal documents for foreign entities be provided in both Indonesian and English. This ensures investors comprehend local laws, a practice reinforced under President Jokowi's administration to facilitate foreign investment. If compared with the total number of legal documents available at this moment, it could be said that the number of translated legal texts from Indonesian (INA) to English (ENG) is extremely minimal; as evident in publicly available government records, only 295 out of 55,385 legislations have been translated from Indonesian to another language. Furthermore, a majority of local regulations currently remain untranslated, despite Indonesia being a regionally autonomous system: the latest local regulation uploaded in both Indonesian and English was in the year 2020 (data taken May 2024).

Creating legal documents in two languages demands skilled human resources. This challenging task requires precision in translation to comply with existing regulations. English for Specific Purposes (ESP) addresses this

need by providing specialised language training. ESP is more complex than English for General Purpose (EGP), or everyday English, and caters to specific fields like law, medicine, and finance. ESP availability is driven by market demands and the evolution of English.

Salmani-Nodoushan (2020) recognizes ESP as an evolving independent field, particularly in translation learning. However, Jabu et al. (2021) observe that the progression of English-Indonesian translation learning is sluggish, attributing this to the traditional focus of English courses in Indonesia on basic skills, with speaking being notably challenging. The curriculum has remained largely unchanged, lacking integration and student-centric approaches, underscoring the necessity for this research. It also remains that at this moment, the educational field does not quantitatively match up to industry and student demands in legal text translation despite the development of legal translation training globally. Research on translations from English to Indonesian, or vice versa, is also very limited — especially if narrowed down to legal text translations.

To meet these current challenges, as well as to support government programmes in increasing foreign investors to Indonesia, educational institutions are expected to produce a larger number of graduates with state-of-the-art legal text translational competencies. In pursuit of this, the use of technology may provide the answer. Literature has previously noted a positive relationship between learning outcomes and technological assistance (see, e.g., Chang & Hung, 2019). In the field of language learning, technologies such as Computer Assisted Language Learning (CALL) has become critical to improvements in listening (see, e.g., Barani, 2011) and reading (see, e.g., Aghajani & Amanzadeh, 2017) in students. Considering that the majority of research in this area encompasses EGP, a question is thus raised: exactly what kind of technology is needed by educational institutions to support professional legal text translators?

Literature Review

Translation Technologies

There exists a gap in empirical studies on technology's role in legal text translation, specifically the use of translating technologies like Machine Learning, Google Translate, and Online Dictionaries. Prior research has focused on technology's general educational applications, such as the use of digital tools in English classroom (Huong & Hung, 2021), the use of multimedia for English learning (Godwin-Jones, 2019) and Google Docs (Abrams, 2019). Additionally, studies have explored the use of various applications and technologies in English language learning, including the

development of custom EGP learning apps (Bond et al., 2020; Yang et al., 2020), mobile English learning apps (Elliott & Chen, 2019), and factors influencing technology's effectiveness in language education (Müller & Wulf, 2020).

Recent advancements in technology have spurred research into utilising various translation technologies like Machine Learning, Google Translate, and Online Dictionaries for language learning. Notable examples include the Customised Online Dictionary's improvement over Collins and Oxford platforms for scripture translation (Almarwaey & Ahmad, 2021), its role in easing cognitive load and translation time for EGP translators (Gayed et al., 2022), the development of a Customised Digital Translation Tool based on Google Translate for quicker EGP text translation (Shadiev & Huang, 2022), and how Artificial Intelligence (AI) is considered beneficial to support learning English as the second language (Sumakul et al., 2022). More specifically, Hidalgo-Ternero (2020) and Kamaluddin et al. (2024) found how Machine Translation tool DeepL outperformed Machine Translator tool Google Translate when findings appropriate equivalents whereas Google Translate outperformed another Machine Translation tool namely SYSTRAN (Aldawsari, 2023) and Microsoft Bing (Ahmed & Lenchuk, 2024).

Furthermore, AI's contribution to English language learning has been recognized for improving writing skills and student engagement (Gayed et al., 2022; Khoiriah et al., 2024; Zhai & Wibowo, 2023). However, these studies often lack comparative analysis of their effectiveness in enhancing language learning outcomes especially in the context of legal translation. In addition, while prior studies' findings are applicable, they must be used cautiously due to varying environments and variables.

Lack of Comprehensive Research of Legal Text Studies

It is a fact that quantitative research on the learning outcomes of legal text translation especially when new technologies involved is still lacking. Prior studies have focused on English writing skills, including business document composition (Abrams, 2019; Chun, 2019), student engagement both in and out of the classroom (Yang et al., 2020), and disengagement in non-translation settings (Bond et al., 2020). Additionally, research has examined the quality of EGP translation (Jabu et al., 2021), and factors influencing positive learning outcomes (Jabu et al., 2021; Wang et al., 2020).

Existing research in the ESP world is mostly on the topics of: (i) how technology can be used to maximise learning in the field of scriptural translation (see, e.g., Almarwaey & Ahmad, 2021) or in the field of financial economics (see, e.g., Wang et al., 2020), and (ii) what skills a translator should

have when doing his/her job of translating legal language in front of legal officials or in front of the court (see, e.g., Loiacono, 2022).

From an industry perspective, one of the key requirements for a successful translator of legal texts, and all ESP in general, is for the translator to possess and apply both diligence and commitment to meticulous work and consistent practice. This is often expressed in training sessions held by the Indonesian Translators Association. Commonly, successful professional ESP translators will build a personal glossary (dictionary) containing a collection of words, phrases, sentences, or idiomatic expressions in one language and their equivalents in other languages. Routinely, a well-archived personal glossary (dictionary) is of great professional benefit and will be used provide speed and consistency to the translator's tasks.

Potential of Translation Technologies in Legal Text Translations

Chang & Hung (2019) found that technology enhances language learning outcomes. This view is supported by Chun (2019) who also noted improvements in English writing skills. Enayati & Gilakjani (2020) observed that Computer-Assisted Language Learning (CALL) not only makes learning more engaging but also improves vocabulary acquisition and teacher-student interaction. However, Lerma-Noriega et al. (2020) reminds us that the effectiveness of technology varies, and each has unique impacts on education. Ubhayawardhana & Hansani (2023) support this opinion and qualitatively show how the translation of legal texts in the Birth, Marriage, and Death registration forms utilizing technology are considered less acceptable. Similarly, Cahyaningrum (2022) was able to provide additional qualitative evidence by recording the number of mistakes that Google Translate made when translating several legal texts from Bahasa Indonesia to English.

Nowadays, Machine Learning technology is at the forefront of translation tools, surpassing the capabilities of Google Translate and Online Dictionaries. In this article, Machine Learning refers to tools and techniques which are specifically used for supervised learning and recommendation systems. POEdit is based on a pre-developed corpus and is used as the Machine Learning tool in this study. This translation tool allows users to develop, share, and modify their own translation databases based on the open environment. As a result, it enables POEdit's algorithms to learn and recommend the most accurate translation of words based on user inputs and shared corpora. On the other hand, Google Translate (one of the most used Machine Translation tools) operates within a closed environment where users are not able to directly interact with or modify the underlying corpus. While Google Translate also uses Machine Learning (primarily neural machine translation), its system is not designed to allow user intervention or corpus

sharing. As a result, it limits user control over the translation data and recommendations.

In addition, notably, Machine Learning technology has advance features (e.g., contextual understanding, adaptive learning, and collaborative translation platform) to elevate the quality of the translation outputs (Reballiwar et al., 2023; Vázquez-Cano et al., 2021). In contrast, Google Translate and Online Dictionaries lack these advanced features, leading to a disparity in translation quality. Consequently, students using Machine Learning technology for translation are likely to achieve better learning outcomes than those using traditional methods. Comparatively, Google Translate has the advantage of translating full sentences, a task challenging for Online Dictionaries. Abidin et al. (2020) confirm that Google Translate generally delivers superior Arabic to Malay translations than Online Dictionaries, indicating a clear difference in performance between the two technologies.

Despite the publication of previous literature on this field and the implications of established national laws, it is a fact that the number of translated Indonesian legal documents and English legal documents (applicable in Indonesia context) has yet to meet industry and national demands. Thus, this paper seeks to examine the effects of translational technologies on the outcomes of legal translation learning. Specifically, this investigation focuses on the translation of both Indonesian and English legal documents, such as but not limited to, agreements, memorandums of understanding, and constitutional court laws, between Indonesian and English and vice versa.

Research Design and Research Questions

This research was designed with a treatment by level 3x2, quantitatively analysing translational technology usage (i.e., Machine Learning, Google Translate, and Online Dictionaries) as three independent variables, high/low placement test scores as two moderator variables, and learning outcomes of legal text translation as a dependent variable. This setup leads to six different treatment combinations (3x2), as each technology usage as the independent variable is combined with each level of the moderator variables. Such treatment allows researchers to observe both the main effects and interaction effects on the outcome variable being measured.

Google Translate was selected because of its accessibility and wide availability. In this research, only Google Translate with manual word input is utilized as the Machine Translator tool for translation. Both Google Translate and Online Dictionary are currently the default translation tools in the legal translation classes in Indonesia which still emphasize human

translations. Unfortunately, these courses have not yet fully integrated Machine Learning nor machine translation technologies (i.e., DeepL or ChatGPT) into their curricula even though the Indonesian Translators Association always recommends exploring Machine Learning tools. Currently only University of Indonesia includes Machine Learning tools in its legal translation courses and this action is appreciated by the industry. Hence the selection of Machine Learning, Google Translate, and Online Dictionary was performed to create an environment that closely mirrors actual conditions.

This research was conducted on participants in the Legal Text Translation Class for English literature students at Jakarta State University (*Universitas Negeri Jakarta*) and engineering students at the University of Indonesia (*Universitas Indonesia*). This study delved into various key variables, focusing on the outcomes of legal text translations, referred to as Y. These outcomes were examined for students utilising a range of translation technologies: Machine Learning (A_1), Google Translate (A_2), and Online Dictionaries (A_3). Additionally, the performance of students using Machine Learning was analysed based on their placement test scores, distinguishing between high achievers (B_1) and those with lower scores (B_2).

This comprehensive analysis led to the formulation of specific research questions:

1. Is there an interaction effect between the Use of Translation Technology (A) on the Learning Outcome of Legal Text Translation (Y)?
2. Is there a difference in Learning Outcomes of Legal Text Translation (Y) between students who translate using Machine Learning (A_1), Google Translate (A_2), and Online Dictionaries (A_3)?
3. Is there a difference in the Learning Outcomes of Legal Text Translation (Y) for High (B_1) and Low (B_2) Scoring Placement Test students who translate using Machine Learning (A_1)?

Methodology

This study was conducted between July and December 2023 at the University of Indonesia Faculty of Engineering, wherein training and certification programmes in legal translation were held. These courses were held online for 40-hours. The 40-hour course here is part of a blended learning model where additional materials like readings and extra practices are provided outside the structured 40-hours to ensure that learners engage more deeply with the content of the course. 40-hours is the standard translation course hours for each level of proficiency (beginners, intermediate, and advanced) in Indonesia, as well as the norm in a majority of other countries (see, e.g., UC Davis Health, 2022).

Participant recruitment was handled through communication between educational programme coordinators, with 50 initial participants. A sample size of 50 students can be considered sufficient for an experimental study that involves detecting correlations (Creswell, 2012; Sittirak & Ranong, 2023). Participants were then required to take the international Test of Legal English Skills (TOLES), wherein their scores were sorted from highest to lowest. There are 21 participants received medium to high scores (61-80), 21 participants received low scores (41-60), and 8 participants achieved Band Four scores (1-40); thus, these eight participants were excluded from the study. The high score is equal to Band Two of TOLES (students have very good legal English skills). The low score is equal to Band Three of TOLES (students have satisfactory legal English skills).

TOLES is a specialized English proficiency exam designed to assess the legal English abilities of non-native English speakers working in or aspiring to work in the legal field (Cambridge Law Studio Limited, 2000; Haigh, 2015). The test focuses on practical legal English skills and evaluates language proficiency of legal professionals including legal translator.

Following Thomas (2018)'s recommendations, the participants are divided based on their scores into three categories: (i) low-scoring participants were assigned to use Machine Learning tools for their translations, (ii) mid-scoring participants were assigned to use Google Translate, and (iii) high-scoring participants used Online Dictionary. In this study, the participants using Machine Learning and Google Translate form the experimental group, while those using Online Dictionary make up the control group.

In this study, researchers built a corpus encompassing over 2,000 vocabulary and sentences in legal texts, as well as their translations, in both the source and target language. This data was obtained from the researchers' own experience in undergoing 'Legal Text Translation Class' from a basic to advanced level at the University of Indonesia, in addition to the researchers' own data post-completion of the certified training programme. This corpus was integrated with a pre-selected Computer Aided Translation (CAT) tool, namely the Pro+ POEdit software. POEdit was selected compared to Lokalise, Unbabel or EasyTranslate because of: (i) its free version, (ii) its offline translation capability, and (iii) recommendation from experts in the Indonesia Translator Association including the trainer. Several Indonesian leading legal translation companies also currently use POEdit compared to other Machine Learning translation tools.

Integration was done to create a more intelligent CAT tool and a base for participants to expand on, as advised by previous literature (see, e.g., Kizil, 2019). Participants and the CAT tool would interact in deciding the most accurate translation of legal texts, as well as any necessary revisions. This data would then be stored by the CAT tool to use as a reference in recommending

later translations towards other participants. The development and testing of this Corpus was conducted in tandem with the participant recruitment process. No such Corpus was necessary for Google Translate and Online Dictionaries, as they are publicly available free-of-access. Online Dictionaries used in this study include the Cambridge Online Dictionary, the Ozdic Collocation Online Dictionary, as well as the Online Black Law's Dictionary.

Following the course, an essay-based assessment was given to measure each participant's learning results and right to certify in basic legal text translation. The essay testing used in this study reflects the common industry accepted parallel translation testing and the provided translation practice tests. During the test, students must create a side-by-side layout. The source text in its original language is typically on the left side whereas the target text is on the right side. Students are required to write their essay answers to prove their proficiency in rendering accurate translations.

Essay testing is utilized for assessing legal translation learning outcomes primarily because it provides a real-world simulation. In other words, the essay testing closely mimics the real-world scenario accurately and the essay testing methodology prepares the students better for actual translation work. The topics selected for essay testing, or parallel translation testing, in this study are drawn from the legal translation course materials. The testing includes four exam questions translation work from Indonesian to English and four exam questions translation work from English to Indonesian. For each question, there is a variety of legal sentences taken from legal documents such as contracts, agreements (e.g., end user license agreement), and statutes (including Indonesia civil code) to be translated. The total duration of the exam is two hours, providing students with ample time to complete all sections thoroughly. In addition, the composition of the exam questions allows for a balanced assessment of knowledge and skills in both Indonesian and English translations.

This essay-based test was arranged according to an instrumental criterion validated by four field experts. Validity was further tested using Pearson's correlation formula (Product Moment: $r = 0.632$), and reliability using the Inter-Rater Reliability ($\varkappa = 0.655$).

Data Analysis

Inferential statistics, adjusted to the research design and hypothesis, were performed on the obtained dataset. After the normality and homogeneity of the data had been tested, a two-way ANOVA and multiple-comparisons Tukey test were conducted.

Results

The research examined the influence of various translation technologies on the learning outcome of legal text translation across 42 students from the English Literature and English Education programme at Universitas Negeri Jakarta, as well as the Engineering program at Universitas Indonesia. Figure 1 summarises the distribution of legal text translation learning results for students using various translating technologies.

In this study, a total of 42 students were divided into three groups to determine the influence of different translation technologies on the legal text translation learning results for students. It was observed that students using Machine Learning achieved the highest score of 96, the lowest of 82, and an average of 89.68, with a standard deviation of 5.01. In contrast, students utilising Google Translate scored a maximum of 82, a minimum of 53, an average of 67.46, and a standard deviation of 9.17. Meanwhile, those who used an online dictionary reached a top score of 71, a bottom score of 53, an average of 61.67, and a standard deviation of 6.13.

Figure 1

Distribution of Legal Text Translation Learning Results for Students Who Translated Using (a) Machine Learning, (b) Google Translate, (c) Online Dictionaries.
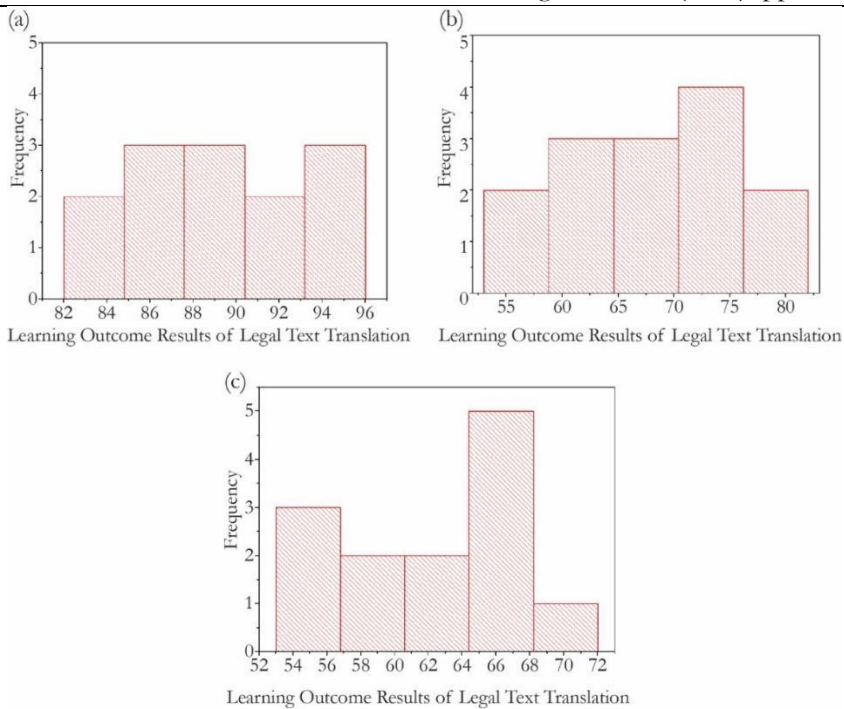
This research also examined the impact of Machine Learning-assisted legal text translation on students' learning outcomes, stratified by high and low initial placement test scores, as depicted in Figure 2. Data analysis from Figure 2a, which included a group of seven students, indicated that those who integrated Machine Learning into their legal text translation studies and had high placement test scores recorded scores ranging from 82 to 96. The mean score for this segment was 87.86, with a standard deviation of 5.36. In contrast, figure 2b shows that students with lower placement test scores who also used Machine Learning translation tools achieved scores between 85 and 96. Interestingly, this group's average score was 91.50, which was higher than their high-scoring counterparts, and they had a marginally lower standard deviation of 4.22.

Figure 2

Distribution of Legal Text Translation Learning Results for Students who Translated using Machine Learning with (a) High-Scoring, (b) Low-Scoring Placement Tests

(a) (b) Learning Outcome Results of Legal Text Translation
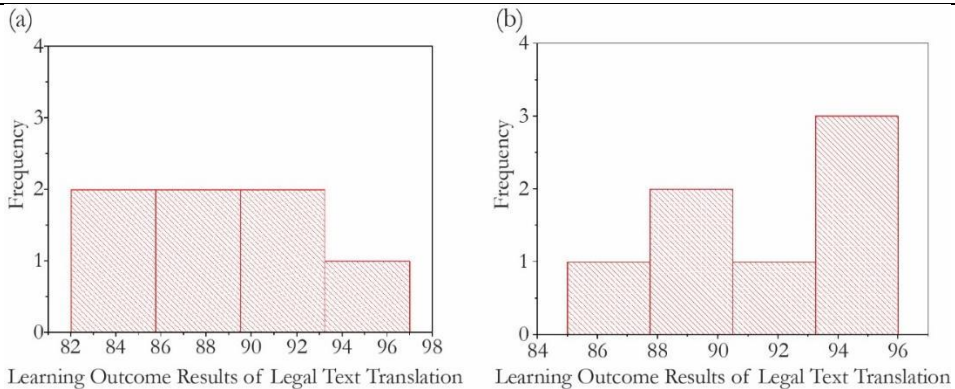
Normality and Homogeneity Test

Prior to data analysis, a normality test was performed to determine whether the obtained data for learning outcomes of legal text translation were normally distributed. The normality test was conducted on the data:

1. The learning outcomes of legal text translation using Machine Learning (A_1)
2. The learning outcomes of legal text translation using Google Translate (A_2)
3. The learning outcomes of legal text translation using Online Dictionary (A_3)
4. The learning outcomes of legal text translation using Machine Learning for Students with High-Scoring Placement Test Scores (A_1B_1)
5. The learning outcomes of legal text translation using Machine Learning for Students with Low-Scoring Placement Test Scores (A_1B_2)

The normality test was conducted using the Liliefors method. Based on a sample size of 14 students, the critical L value for A_1, A_2, and A_3 was determined to be $L_{crit} = 0.227$. On the other hand, the critical L value for A_1B_1 and A_1B_2 which were associated each to 7 students was 0.300. Subsequently, the statistical method was used to determine the L_{count} for all variables, obtaining 0.126, 0.117, 0.148, 0.207, and 0.152 for A_1, A_2, A_3, A_1B_1, and A_1B_2, respectively. Based on the test criteria, namely $L_{count} < L_{crit}$, the null hypothesis H_0 is accepted, and all sample groups are determined to be normally distributed populations.

To assess whether two sets of data have similar or different averages, they must exhibit equal variances. This research performed a homogeneity of variance test for the following groups: A_1 (students translating legal texts with Machine Learning), A_2 (students using Google Translate), A_3 (students utilising an Online Dictionary), A_1B_1 (students translating legal texts with Machine Learning with high placement test scores), and A_1B_2 (students

translating legal texts with Machine Learning with low placement test scores). Utilising Bartlett's test, we accepted the null hypothesis (H_0) if the calculated chi-square ($\chi2_{count}$) was less than the critical chi-square ($\chi2_{crit}$). The results of this test were summarised in Table 1, and confirms that the variances for A_1, A_2, A_3, A_1B_1, and A_1B_2 are equal, indicating homogeneity among the groups.

Table 1

Summary of Homogeneity Test Results on Legal Text Translation Learning Outcome

Group	Variance	Combined Variance	χ^2count	χ^2crit	Conclusion
A_1	25.10				
A_2	84.09	48.93	5.06	5.99	Homogenous
A_3	37.60				
A_1B_1	28.81	29.21	2.35	11.07	Homogenous
A_1B_2	17.83				

Interaction between the Use of Translation Technology (A) on the Learning Outcome of Legal Text Translation (Y)?

After performing the normality and homogeneity tests, a two-way ANOVA was performed to determine whether there is an interaction between Translation Technology use and Placement Test scores on Legal Text Translation learning outcomes, with the summary of the results shown in Table 2.

Table 2

Summary of Two-Way ANOVA Test on Legal Text Translation Learning Outcome

Variance Source	db	JK	RK = JK/db	Fcount= RK/RKd	F_{crit} ($\alpha = 0.05$)
Placement Test	1	154.29	154.29	5.28	4.11
Translation Technologies	2	6117.76	3058.88	104.70	3.26
Interaction	2	702.33	351.17	12.02	3.26
Error	36	1051.71	29.21		
Total	41	8026.10			

The two-way ANOVA revealed that the F-score (12.02) is greater than the critical value (3.26), indicating a significant interaction between Translation Technology use and Placement Test scores on Legal Text Translation learning outcomes. This novel insight contributes to translation studies, particularly in legal contexts, where prior research on these variables is absent, thereby enhancing the body of knowledge in language and translation disciplines.

Difference in Learning Outcomes of Legal Text Translation (Y) between students who translate using Machine Learning (A₁), Google Translate (A₂), and Online Dictionaries (A₃)?

Is there a difference?

Based on the results of the two-way ANOVA test shown in Table 2, the F_{count} of 104.70 is greater than the F_{table} of 3.26. This shows that there are differences in learning outcomes between students who translate legal texts with Machine Learning, Google Translate and Online Dictionary. The data obtained indicates a disparity in student learning outcomes when translating legal texts using different methods. Students utilising Machine Learning achieved an average score of 89.68, outperforming those who used Google Translate and Online Dictionary, with average scores of 67.46 and 61.68, respectively. It is empirically found that the learning outcomes of students who translate legal texts using Machine Learning are better than the learning outcomes of students who translate legal texts using Google Translate and Online Dictionary.

Machine Learning (A₁) vs. Google Translate (A₂)

Previously, a two-way ANOVA revealed significant interaction between Translation Technology use and Placement Test scores on Legal Text Translation learning outcomes. Based on these results, the significance in difference between translations technologies were further explored statistically using Tukey Tests, which was summarised in Table 3. The results of the Tukey Test revealed that students using Machine Learning for translation outperformed those using Google Translate, as evidenced by a Q value of 22.21 surpassing the critical score of 3.45. This aligns with past investigations which suggest that artificial intelligence (AI) and Machine Learning enhances EFL students' reading, writing, and listening skills. Moreover, these results further highlight how Machine Learning is deemed more advanced than Google Translate and is expected to evolve further.

Table 3

Summary of Tukey Test Results on Learning Results for Translating Legal Texts (a=0.05)

Data Pairs	Average	RDK	Q_{Count}	Q_{crit}
A_1	89.68	29.21	22.21	3.45
A_2	67.46			
A_1	89.68	29.21	28.00	3.45
A_3	61.68			
A_2	67.46	29.21	5.78	3.45
A_3	61.68			

Machine Learning (A_1) vs. Online Dictionaries (A_3)

The Tukey test between Machine Learning (A_1) and online dictionaries (A_3) showed a Q value of 28.00, surpassing the critical value of 3.45. This indicates that students using Machine Learning for legal text translation outperform those using an Online Dictionary. The characteristics of Machine Learning are significantly different as it demonstrates vast vocabulary storage and the ability to refine and expand its corpus, while offering more advanced features than conventional Online Dictionary technologies (Elliott & Chen, 2019).

Google Translate (A_2) vs. Online Dictionaries (A_3)

Although the Tukey test results revealed a Q score (5.78) greater than the critical score (3.45), the results are considered insignificant since the f score of 0.086 is greater than 0.050. Hence, although the Learning Outcomes of Legal Text Translation for students who performed translation using Google Translate are higher than those of students who translate using Online Dictionary, statistically the difference in scores is not significant.

Legal Text Translation Outcomes for Students using Machine Learning with Different Placement Test Scores

The study delved into the effects of Machine Learning tools on the translation of legal texts and their subsequent influence on student performance (refer to Figure 2). It was observed that students with higher initial test scores, who utilised Machine Learning for translation, achieved

results ranging from 82 to 96, with an average of 87.86. Conversely, those with lower initial scores also benefited from the technology, surprisingly outperforming the former group with scores from 85 to 96 and an average of 91.50. This outcome suggests that Machine Learning tools may level the educational playing field, offering substantial support to students regardless of their starting academic proficiency.

Discussion

Interaction between the Use of Translation Technology (A) on the Learning Outcome of Legal Text Translation (Y)?

Previously, the two-way ANOVA performed in this study revealed significant interactions between the use of Translation Technology when used on Legal Text Translation learning outcomes. Notably, researchers like Akbari & Sahibzada (2020) argue that assessment test results cannot be directly used as a reference for the final Learning Outcome. They argue that each student has unique characteristics and different motivations when taking the Placement Test. Intelligent but unmotivated students often approach Placement Tests with indifference, resulting in poor scores. Additionally, previous investigations from Ananda et al. (2018) and Wang et al. (2020) further suggest that it takes diligence, perseverance, and enthusiasm to complete problem exercises consistently and achieve maximum learning results. This suggests that the effectiveness of technology in enhancing student learning is inseparable from the student's enthusiasm to complete practice questions, dedication, and persistence.

This research confirms a relationship between Translation Technology use and Legal Text Translation performance. The results of this study highlight the significant role of cognitive aspects (such as intelligence in Placement Tests) and affective aspects (like diligence and perseverance when completing practice questions) in shaping learning outcomes. Therefore, this study provides new empirical evidence and complements existing literature by Akbari & Sahibzada (2020) and Wang et al. (2020).

Difference in Learning Outcomes of Legal Text Translation (Y) between students who translate using Machine Learning (A$_1$), Google Translate (A$_2$), and Online Dictionaries (A$_3$)?

Is there a difference?

The two-way ANOVA tests presented in this study determined that the learning outcomes of students who translate legal texts using Machine

Learning are better than the learning outcomes of students who translate legal texts using Google Translate and Online Dictionary. Recent research underscores the growing use of translation technologies, such as Machine Learning algorithms and platforms like Google Translate, in legal text translation. These tools are becoming essential for enhancing productivity and efficiency, particularly in developed countries. Abrams (2019) found that technology enhances writing and the educational process. Conversely, Elliott & Chen (2019) observed that not all technologies aid learning productivity in China, with Ioannou & Ioannou (2020) suggesting a preference for adaptable technologies that foster a positive user experience. In this context, Machine Learning technologies are perceived to better meet user needs for customization and engagement compared to Google Translate.

Notably, the findings of this study align with past studies which state that technology enhances language learning outcomes. Quality translation results were achieved by adhering to methodologies recommended by Chun (2019), particularly through the creation of a Machine Learning corpus.

Machine Learning (A_1) vs. Google Translate (A_2)

The results of the Tukey Test statistically determined that students using Machine Learning for legal text translation outperformed those using an Online Dictionary. The findings in this investigation corroborate the results of Elliott & Chen (2019) and Ioannou & Ioannou (2020), indicating a preference for adaptable technology that fosters a positive learning connection, impacting learners' outcomes. Unlike google translate, emerging Machine Learning technologies are modifiable, making them flexible to meet the needs of EFL learners. Consequently, Machine Learning technology facilitates better legal text translation outcomes due to its adaptability and the positive learning relationship it supports, leading to higher translation learning outcomes compared to Google Translate.

Machine Learning (A_1) vs. Online Dictionaries (A_3)

Similar to the previous results, the performed Tukey test determined that students using Machine Learning for legal text translation outperform those using an Online Dictionary. One of the reasons behind this outcome can be traced back to the ability of Machine Learning technologies to allow translators to collaborate and even replicate past translations. While digital dictionaries assist vocabulary acquisition (Wang et al., 2020), they are insufficient for producing accurate translations. Machine Learning technology is thought to surpass Online Dictionary tools by enabling collaborative translation efforts and the replication of previous translations.

Specifically, Machine Learning algorithms support the inclusion of any text, including ESP-specific content, into its database. Online Dictionaries, however, do not allow direct user contributions of ESP corpus. Users can propose new words for inclusion in dictionaries such as Oxford or Collins; however, the content of these digital dictionaries is generally established by their editors. This limitation can be challenging for ESP translators, as Online Dictionaries focus on vocabulary rather than contextual sentence meaning.

ESP translation requires more than just vocabulary. It requires translators to translate lengthy and complex sentences necessitated by the nature of the legal language itself. In contrast, this task can be done more easily with the help of Machine Learning technology through the corpus. This proves particularly beneficial for ESP translators dealing with legal texts, as they can exchange vocabulary and standardised sentence translations, thus enhancing the quality of legal text translations (Wang et al., 2020).

Beyond mere vocabulary acquisition, ESP translators require proficiency in translating complex legal sentences, a skill that Machine Learning technology supports effectively. Research indicates that Machine Learning technology contributes to superior learning outcomes and is rapidly advancing (Gayed et al., 2022; Vázquez-Cano et al., 2022). The finding also complements the research by Fauzan et al. (2022), which empirically demonstrated that learning EGP is more effective when students create their own corpus rather than relying solely on Online Dictionaries.

Based on the research that was conducted and the research of previous researchers, it can be concluded that the Learning Outcome of Legal Text Translation with the help of Machine Learning technology provides better translation results when compared to the Learning Outcome of Legal Text Translation with the help of Online Dictionary.

Google Translate (A₂) vs. Online Dictionaries (A₃)

The Tukey test revealed that students using Google Translate for legal text translation slightly outperformed those using an Online Dictionary. However, the difference in their scores was not statistically significant. Supporting evidence from Abidin et al. (2020) highlights Google Translate's efficiency and superiority in providing translations across more than 100 languages, contributing to its widespread use for English to Vietnamese and Arabic to Malay EGP translations. The comparative study of student learning outcomes in translating legal texts reveals distinct advantages of Google Translate and Online Dictionaries. Google Translate excels in handling lengthy legal sentences, while Online Dictionaries offer precise differentiation between ESP and EGP vocabularies and crucial collocation reviews for coherent legal text translation. Despite these differences, research by Abidin

et al. (2020) indicates Google Translate's superiority in translation quality over Online Dictionaries, particularly in Arabic to Malay EGP translations. Additionally, Google Translate's ease of use, cost-free service, and support for over 100 languages further enhance its appeal. With these reasons, Google Translate remains superior to Online Dictionary in terms of providing translation results.

Legal Text Translation Outcomes for Students using Machine Learning with Different Placement Test Scores

The results of this study showed that the use of Machine Learning technologies for legal text translations outperformed the learning outcomes of students using Google Translate and online dictionaries. Interestingly, students with lower placement test scores achieved higher results for legal text translations compared to those with high placement test scores. After a discussion with the training instructor and analysing the observer's note during the training, it is believed that despite having lower placement test scores, these students exhibited a high level of curiosity and active participation, which may indicate a strong intrinsic motivation to improve. During the post training discussion, all of observers and the training instructor agreed that the strong motivation to improve is associated with one's grit.

Despite criticisms of grit, such as those presented by Credé (2018) who argues that the concept of grit's impact is often overstated, grit or tenacity has still been increasingly recognized as a critical factor for success, transcending innate intelligence or placement test scores. Grit, as explored by Angela Duckworth, is not merely about perseverance but encompasses a passionate commitment to a chosen path (Duckworth et al., 2007). Angela Duckworth's definition of grit emphasises a blend of focused desire and a resilient, hardworking spirit. Grit acts as an internal compass, guiding individuals through challenges in education and learning, proving to be an indispensable non-cognitive trait that supports enduring achievement. Moreover, motivation plays a crucial role in the success of prospective students in placement tests. High motivation correlates with high scores, while a lack of it leads to carelessness and lower scores (Akbari & Sahibzada, 2020).

The practice of sorting learners into groups based on their abilities gauged by placement test score is a common strategy among educators and researchers. However, this method is not without controversy, as it can provoke adverse reactions from parents and educators, highlighting the need for sensitivity in its implementation, particularly when assigning students to lower-tier groups. While ability grouping enhances student performance and

classroom management, critics cite the potential for negative labelling and unequal attention distribution, which could lead to a divide between high and low-ability students, as dangers for its use. This dichotomy underscores the complexity of educational strategies and the importance of balancing academic objectives with the psychological well-being of students.

Educational theorists Reis & Renzulli (2018) have suggested a variety of student grouping models that extend beyond the traditional high-low dichotomy. These include groupings based on learning products or methods, collaborative or individual learning preferences, subject interests, and even instructional styles. While each model has its pros and cons, with Steenbergen-Hu et al. (2016) strongly advocating for flexibility, suggesting that any grouping model can be effective if not applied rigidly. However, the prevailing cognitive focus in Indonesian education often overlooks this, as evidenced by placement tests that categorise students with lower scores as having inherently limited abilities, rather than recognizing the potential mismatch between the student's learning style and the test's design.

Students excelling in Placement Tests are increasingly leveraging Machine Learning technologies for translating legal documents with superior accuracy. This trend is supported by the proficiency these students display in English, which enables them to create the extensive and precise corpus that are integral for Machine Learning applications. Such capability is crucial for the success of Machine Learning in translations. In the specialised domain of legal translation, Machine Learning technology emerges as a powerful tool for those with high linguistic aptitude, offering a modern complement to traditional methods and potentially enriching educational outcomes. Nevertheless, it is imperative for students to approach Machine Learning with due diligence, respecting the complex and nuanced nature of legal texts. When applied with care, Machine Learning can be an invaluable resource in honing the translation skills of proficient students, ensuring both precision and the retention of intricate legal meanings.

The integration of the ESP linguistic corpus into Machine Learning platforms has significantly enhanced the educational experience for students with low scores in their placement test. This innovative approach has not only improved learning outcomes but has also elevated the quality of translations produced by the students. A notable advantage of Machine Learning technology is its ability to grant access to a vast database of corpus, previously compiled by various users, thus eliminating the need for individual data entry by students. Furthermore, the findings of this study corroborate the notion that the adoption of cutting-edge technology in educational settings substantially contributes to the attainment of superior learning outcomes. Such advancements align perfectly with the concept of Personalized

Learning, as advocated by Thomas in 2018, underscoring the pivotal role of tailored educational methodologies in fostering academic success.

This research has effectively bridged a previously unaddressed gap in the literature by examining the impact of different learning technologies on the proficiency of legal text translation. It was found that students employing Machine Learning techniques surpassed those relying on Google Translate or online dictionaries in terms of performance. Notably, Machine Learning enables individuals from diverse educational backgrounds the opportunity to achieve proficiency in a new subject, in this case legal text translation. This study underscores the empowering role of Machine Learning technology in enabling students from fields as varied as Engineering and English Literature to achieve satisfactory results.

Conclusion

The present study investigates the relationship between the use of translation technology on the learning outcome of legal text translation, additionally examining whether differences were present based on the type of translational technology used and TOLES placement scores of students.

In answering Research Question 1, the use of translation technology indeed impacted the learning outcomes of legal text translations, but this effect differed depending on the type of technology used.

To answer Research Question 2, we found that students obtained the highest scores in learning performance through Machine Learning, compared to Google Translate and Online Dictionaries. Learning results in legal text translation were also higher using Google Translate than Online Dictionaries, although not a statistically significant degree. Findings suggested that Machine Learning was most beneficial for improving students' learning results, in addition to garnering students' interest and engagement effectively. Students agreed that the presence of a corpus aided immensely in translating legal texts, as well as in collaborating with other students to generate translations of increasing quality.

Interestingly, our findings in answering Research Question 3 also showed that students with low placement test scores obtained better legal text translation outcomes compared to their high-scoring counterparts. Students with lower test scores often displayed more grit, persistently striving towards their objectives, which led to superior outcomes in legal text translation compared to those with higher scores. In planning the model of an ESP classroom, it would be of benefit to increase and develop the use of Machine Learning, in comparison to Google Translate and Online Dictionaries, by students.

Our findings support the notion that through Machine Learning, students (regardless of their previous disciplines) can become a legal translator. In Indonesia especially, this type of technological support will become a critical stepping stone in meeting legal translational industry and national interests by shortening the current gap between untranslated and translated documents through learning and capability support.

While the findings of this study suggest that there exist benefits for academia to adopt novel, industry-adjacent technologies; the present research does have limitations that future studies should overcome. This study could be improved through further testing within additional learning environments (i.e., university-level, training centres, cross-city, cross-country, online with sufficient sample size). This study was also conducted on semester 5 university students with certain characteristics; further research could perhaps focus on professional/field-established participants or fresh graduates. Additionally, a longitudinal design to this research would also benefit from insight towards intermediate and advanced-level legal text translation. Finally, another valuable extension of this research would be to compare Machine Learning with additional different types of Machine Translation tools, such as DeepL or ChatGPT specifically for legal translation outputs to investigate if they yield different results.

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