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MACHINE TRANSLATION-BASED LEARNING AS AN ALTERNATIVE LEARNING STRATEGY IN THE TRANSLATION COURSE FOR FIFTH-SEMESTER STUDENTS AT UNIVERSITAS INDRAPRASTA PGRI

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Abstract: The rapid development of artificial intelligence (AI) has brought major changes to education, including translation learning. One of its most visible implementations is machine translation (MT) — tools such as Google Translate and DeepL — which are now able to produce contextual translations through Neural Machine Translation (NMT) systems. This study aims to describe the implementation of MT-based learning in the Translation course and to analyze students' perceptions of its effectiveness. A descriptive qualitative approach was employed, involving fifth-semester students and the lecturer of the Translation course at Universitas Indraprasta PGRI, Jakarta, as participants. Data were collected through observation, in-depth interviews, and documentation, and were analyzed using the interactive model of Miles, Huberman, and Saldaña. The finding shows that integrating machine translation into the learning process improved students' translation quality, critical thinking, linguistic awareness, and learning autonomy. Students used MT not as a substitute for their own translation ability but as an initial aid that was followed by analysis, discussion, and post-editing. The study concludes that MT-based learning can serve as an innovative and pedagogically sound alternative strategy for teaching Translation in higher education, provided it is guided by lecturers within a critical and ethical framework.

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INTRODUCTION

The advancement of artificial intelligence (AI) has significantly affected many aspects of life, including education and translation practice. One of the most widely used implementations of AI is machine translation (MT), such as Google Translate, DeepL, and ChatGPT Translator. MT is no longer merely a professional support tool; it has increasingly been adopted within language-learning contexts as well.

Machine translation has evolved from literal, rule-based translation into Neural Machine Translation (NMT) systems capable of producing increasingly accurate and contextual output. This evolution presents both challenges and opportunities for English Language Education students, particularly in the Translation course, where students often struggle to grasp context, find natural equivalents of meaning, and remain faithful to the source text. Lecturers, in turn, need effective learning strategies so that students do not merely depend on machine-generated output but learn to critically analyze and improve it.

Traditionally, the Translation course has focused on developing human translation skills — analyzing the source text, understanding cultural and linguistic context, selecting appropriate translation strategies, and producing a natural and acceptable target text. However, given the dominance of MT in the language industry, ignoring these tools in an academic setting is no longer realistic; students already use them, and professional translators must interact with MT as part of their daily work.

Integrating machine translation into the learning process can therefore become an attractive alternative strategy. Rather than merely using MT to translate, students learn to evaluate, compare, and post-edit machine-generated output. This approach shifts translation learning away from a purely theoretical exercise toward one that is more contextual, interactive, and relevant to current technological developments.

From a technical standpoint, MT approaches can be data-driven or based on parallel corpora (Bhattacharyya, 2015). Neural Machine Translation (NMT) represents a newer approach that employs recurrent neural network (RNN) architectures in its encoder and decoder, trained on parallel corpora; NMT has been shown to outperform Statistical Machine Translation (SMT) across a range of language pairs (Junczys-Dowmunt et al., 2016). Attention-based NMT, now widely used by MT researchers, efficiently reads an entire sentence or paragraph to capture context and core meaning before generating output word by word, focusing on different parts of the input at each step to gather the semantic detail needed for the next output word (Goodfellow et al., 2016). Related studies have compared SMT performance for English–Indonesian translation using RNNs and N-gram language models (Hermanto et al., 2015), as well as Japanese–Indonesian translation using SMT and attention-based NMT (Adiputra & Arase, 2017).

Despite these advances, tools such as Google Translate and DeepL still cannot guarantee fully accurate translation, even though they provide a useful general picture of a text. Based on a preliminary survey conducted through informal class observations and brief interviews with approximately 25 fifth-semester students at the beginning of the academic year, it was found that many rely heavily on Google Translate or DeepL to understand English-language course materials. They became aware of this habit only after realizing gaps in their understanding during classroom discussions.

This study is guided by the following research questions: (1) How is MT-based learning implemented in the Translation course? (2) What are the advantages and disadvantages of MT-based learning compared with traditional translation-teaching methods? (3) How do students respond to, experience, and perceive MT-based learning? (4) What learning strategies are appropriate for integrating MT into the Translation course to improve students' translation competence? (5) What challenges arise in implementing MT-based learning, and how can they be addressed?

The study assumes that the MT tools used provide an adequate baseline translation that students can analyze and improve, that students possess sufficient foundational knowledge of translation theory and technique, and that both lecturer and students are willing and able to use MT technology as part of the learning process. It is limited to the use of MT as a pedagogical aid rather than an examination of MT's underlying technical development, and its findings are context-bound to the Translation course at the institution studied rather than broadly generalizable.

METHOD

This study employed a descriptive qualitative approach aimed at providing an in-depth account of how MT-based learning was implemented as an alternative strategy in the Translation course. A qualitative design was chosen because the research focused on understanding processes, perceptions, and experiences within a technology-based learning context rather than on numerical measurement. As Creswell (2014) explains, qualitative research seeks to understand the meaning individuals or groups ascribe to a social phenomenon; accordingly, this study emphasized exploring fifth-semester students' learning experiences in using machine translation as part of their translation practice.

The study was conducted in the English Language Education Study Program at Universitas Indraprasta PGRI, Jakarta. Translation is a compulsory course offered in the fifth semester, designed for students who have previously completed foundational English grammar and reading comprehension courses. At this level, the expected competency is for students to be able to translate various general and academic texts accurately, focusing on meaning equivalence and target-language acceptability. The site and participants were selected purposively because both the lecturer and the students in this cohort were already familiar with using technology in language learning, making them an ideal sample to evaluate MT-based strategies.

Participants were fifth-semester students enrolled in the Translation course and the lecturer teaching the course, selected through purposive sampling based on relevance to the research objectives (Sugiyono, 2019). The study involved 10–15 students and one lecturer, a number considered sufficient to yield rich and representative data on the phenomenon under investigation.

The object of the study was the implementation of MT-based learning as an alternative strategy in the translation-learning process, including students' perceptions, responses, and the strategy's effectiveness in improving their translation understanding.

Three main techniques were used to obtain valid and comprehensive data. Observation was conducted during Translation classes that incorporated MT tools (e.g., Google Translate, DeepL, or Bing Translator), during which the researchers recorded student activity, classroom interaction, and how students used MT as a translation aid. In-depth, semi-structured interviews were conducted with the lecturer and several students to gather information on their perceptions, experiences, and the obstacles encountered in MT-based learning; the semi-structured format allowed flexibility while keeping the discussion focused on the research topic. Documentation involved collecting students' translation output, teaching materials, and reflective learning notes, which were used to corroborate the observation and interview data.

Data were analyzed interactively following the model of Miles, Huberman, and Saldaña (2014), comprising three main steps: data reduction, in which data from observation, interviews, and documentation were selected, focused, and simplified according to the research focus; data display, in which the reduced data were organized into descriptive narratives illustrating patterns of MT use in learning; and conclusion drawing and verification, in which interpretations and conclusions were formed regarding the effectiveness of, and challenges in, MT-based learning. Source and method triangulation were applied throughout the analysis to strengthen the credibility of the findings.

RESULT AND DISCUSSION

Result

The result describe how MT-based learning was implemented as a translation-course strategy for fifth-semester students at Universitas Indraprasta PGRI. In this model, MT was used as an initial translation aid, followed by structured sessions of analysis, discussion, and revision. Data were drawn from classroom observation, analysis of students' translation output, interviews, and students' reflective notes.

3.1 Improvement in the Quality of Students' Translations

An analysis of students' translation assignments revealed an improvement in translation quality following the implementation of MT-based learning. Before this strategy was implemented, students' translations tended to be literal, closely following the structure of the source language, and paying insufficient attention to the context of the target language. Common errors included unnatural word choices, stiff sentence structures, and the use of terminology that was not appropriate for an academic context. After the implementation of MT-based learning, students demonstrated improved ability to evaluate and revise their translations, resulting in texts that were more communicative, acceptable, and easily understood by readers of the target language.

Table 1 Examples of Improving Translation Quality Through Post-Editing

Source Text	Students' Initial Translation	MT Output	Translation after post-editing
The rapid development of technology affects the way people communicate.	*Perkembangan cepat teknologi mempengaruhi cara orang berkomunikasi.*	*Perkembangan teknologi yang pesat memengaruhi cara orang berkomunikasi.*	*Perkembangan teknologi yang pesat memengaruhi cara manusia berkomunikasi.*

This example shows that students were able to choose more natural diction appropriate to the Indonesian target context, indicating a shift from formal equivalence toward more dynamic equivalence in their translation choices.

3.2 Post-Editing Skills and Translation Error Analysis

The results of the classroom observations show that students are able to identify translation errors produced by MT, particularly in terms of collocations, lexical choices, and sentence structure. Students do not simply accept the machine translation output at face value, but instead analyze and revise it based on the context of language use.

Table 2 Example of Error Analysis and Revision of MT Results

Source Text	Students' Initial Translation	MT Output	Translation after post-editing
This method enhances students' critical thinking skills.	*Metode ini meningkatkan keterampilan berpikir kritis siswa.*	*Istilah kurang sesuai konteks di perguruan tinggi.*	*Metode ini meningkatkan keterampilan berpikir kritis mahasiswa.*

The data shows that students understand the importance of the target reader's context in translation. The post-editing process helps students develop their analytical and decision-making skills in translation.

3.3 Student Attitudes and Responses toward MT-Based Learning

Interview and reflection data showed that most students responded positively to MT-based learning. Students reported that MT helped them grasp the meaning of the source text more quickly and provided an initial draft that could be further developed. As one student reflected, machine translation helped them understand the content of a text, while also making them aware that the output still needed revision to fit the Indonesian context. This response indicates that students developed a critical awareness of MT's limitations and understood their own active role in the translation process.

Discussion

The findings suggest that MT-based learning can serve as an effective alternative strategy in the Translation course. The improvement in translation quality shows that MT use helped students understand the difference between formal and dynamic equivalence: through post-editing, they learned that a good translation must not only preserve the form of the source text but also convey meaning naturally and acceptably in the target language. This shift aligns with the technological characteristics of modern Neural Machine Translation (NMT) systems discussed earlier. Because attention-based NMT is capable of reading entire sentences to capture core context and produce relatively fluent baseline translations, students are no longer bogged down by basic syntactic restructuring or literal translation. Instead, the sophisticated output of NMT inherently compels students to engage in higher-order post-editing—focusing heavily on dynamic equivalence, pragmatic nuances, and cultural acceptability to ensure the target text is entirely natural for human readers. Ultimately, this indicates that MT-based learning helped students internalize the principle of meaning equivalence in translation practice.

Students' revisions also tended toward more communicative and natural translations. They simplified sentence structures, adjusted word choices, and paid attention to the readability of the target text, showing that MT-based learning supports the development of reader-oriented translation competence.

Within this study, MT was not positioned as a replacement for students' translation ability but as a learning aid — a trigger for discussion, analysis, and reflection in the translation-learning process. Students were trained to remain critical of machine output and to recognize that translation quality still depends fundamentally on human translator competence.

These findings carry important pedagogical implications for translation teaching in higher education. MT-based learning can enhance learning quality, student motivation, and the relevance of the Translation course to current technological developments. With appropriate lecturer guidance, MT can be used ethically and educationally to support the achievement of course learning outcomes — consistent with prior work cautioning that uncritical reliance on MT may hinder the development of critical thinking and productive language competence (O'Neill, 2019), and that MT output often falls short in handling cultural, idiomatic, and pragmatic aspects of language, making the lecturer's facilitating role indispensable (Somers, 2003).

CONCLUSION

Based on the findings and discussion regarding the implementation of MT-based learning as an alternative strategy in the Translation course for fifth-semester students at Universitas Indraprasta PGRI, several conclusions can be drawn:

- **First, MT-based learning proved effective in improving the quality of students' translation output.** Students produced translations that were more accurate, acceptable, and comprehensible after undergoing analysis and post-editing, with MT serving as an initial aid that helped them grasp source-text meaning while prompting critical revision.
- **Second, it contributed to the development of students' critical and analytical thinking in translation.** Students no longer passively accepted machine output but were able to identify linguistic errors, select more appropriate diction, and adapt translations to target-language context, indicating that translation learning became oriented toward process as well as product.
- **Third, from an affective standpoint, MT-based learning had a positive impact on students' attitudes and motivation.** This was reflected in more positive responses, greater confidence, and more active participation, making the Translation course more relevant to contemporary translation practice in the digital era.
- **Fourth, MT-based learning can be adopted as an innovative and applicable alternative strategy for teaching Translation in higher education.** However, this is provided that lecturers act as facilitators who guide its ethical and pedagogical use in support of course learning outcomes."

Several recommendations follow from these conclusions. Lecturers teaching Translation are encouraged to integrate MT in a planned and directed manner, using it primarily as an initial aid followed by analysis, discussion, and post-editing activities so that students continue to develop critical thinking and translation competence. For initial post-editing practice, it is highly recommended that lecturers start with general or academic texts (such as news articles, formal letters, or scientific abstracts) before advancing to highly idiomatic or culturally bound texts (like literature), allowing students to focus on basic structural and contextual adjustments. Study programs and institutions are encouraged to support technology-based Translation learning through training, ethical-use guidelines for MT, and the introduction of Computer-Assisted Translation (CAT) tools within the curriculum, in preparation for the demands of the translation profession. Students are encouraged to use MT wisely as a learning aid rather than an instant solution, continuing to build their linguistic competence, contextual understanding, and cultural sensitivity. Finally, future researchers are encouraged to extend this study using different approaches, such as quantitative or experimental designs, a wider range of text types, longer-term investigation of MT-based learning outcomes, or integration with other CAT tools.

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