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Review Article

Examining Machine Translation Use in Translation Education: Student Practices, Challenges, and Perceived Constraints in Undergraduate Programs

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Abstract

Machine translation (MT) has become increasingly accessible to students of translation, creating new opportunities for academic work while also raising questions about accuracy, contextual interpretation, and the continuing role of human translators. This study investigates how undergraduate translation students use MT tools, the difficulties they experience during their use, and their perceptions of the differences between machine-generated and human-produced translations. The study was conducted among 30 male undergraduate students enrolled in the Department of Translation and English Language at Imam Muhammad Bin Saud Islamic University. A mixed-methods research design was employed, with questionnaire data used to examine students' patterns of MT use, experiences, and perceptions. The findings indicate that students regularly use MT, particularly Google Translate, to support academic translation tasks involving unfamiliar vocabulary, specialized terminology, and linguistically demanding texts. At the same time, participants reported several weaknesses in MT output, including grammatical and semantic inaccuracies, inadequate treatment of cultural references, limited sensitivity to textual context, and variations in translation quality. Financial considerations, particularly the cost of premium translation services and specialized dictionaries, were also identified as a practical constraint. Despite the usefulness of MT as an academic support tool, students generally regarded human translation as more reliable for tasks requiring contextual interpretation, appropriate tone, cultural understanding, and nuanced meaning. The findings underscore the importance of developing MT literacy within translation education so that students learn not only how to operate digital translation tools but also how to assess, revise, and validate their outputs through informed human judgment.

Keywords: Machine Translation; Translation Education; Undergraduate Translation Students; Human Translation; Computer-Assisted Translation; MT Literacy; Translation Technology.

Introduction

In the rapidly transforming domain of translation studies, Machine Translation (MT) has redefined the traditional boundaries between human and automated linguistic mediation. Once perceived merely as a mechanical process of lexical substitution, MT has evolved into a sophisticated discipline integrating computational linguistics, artificial intelligence, and neural network modeling. Broadly defined, MT refers to the automated translation of text or speech from one language to another without direct human involvement. Contemporary research underscores that MT's progress—from rule-based and statistical systems to neural machine translation (NMT)—has revolutionized translation practices by enabling fluency, contextual awareness, and domain adaptability [1,2].

Early MT systems were grounded in manually crafted linguistic rules and lexicons, which constrained their ability to handle idiomatic, culturally embedded, or polysemous expressions. The transition to Statistical Machine Translation (SMT) and, subsequently, Neural Machine Translation (NMT) represented a paradigmatic shift in translation theory and practice. SMT's probabilistic modeling improved syntactic reliability, while NMT's end-to-end deep learning architecture enabled the system to treat entire sentences as contextualized semantic units. Consequently, MT today is not merely an auxiliary computational tool but a central participant in the evolving human–machine translation ecosystem.

The allure of MT lies in its efficiency, scalability, and accessibility. In professional and academic settings, MT facilitates rapid multilingual communication, supports terminology management, and reduces the cognitive load associated with repetitive translation tasks [3]. Tools such as Google Translate, DeepL, and Microsoft Translator are now ubiquitous, assisting both professional translators and novice learners. Their integration into language education and translator-training programs has democratized access to translation technology, empowering students to explore linguistic equivalence and stylistic variation [4,5].

However, this technological advancement is not without contention. Despite its linguistic fluency, MT continues to struggle with cultural translatability, metaphorical nuance, and emotional tone. Scholars such as Toral and Sánchez-Cartagena caution that even the most sophisticated NMT systems can misrepresent the pragmatic and stylistic subtleties that define authentic translation [6]. Likewise. It highlights that MT output, though grammatically coherent, frequently necessitates extensive human post-editing to achieve professional standards of accuracy, coherence, and cultural fidelity [7,8].

This tension between efficiency and authenticity positions MT as both a catalyst and a challenge for novice translators. For beginners—particularly undergraduate students in translation and English programs—MT serves as a cognitive scaffold that facilitates lexical exploration and initial draft production. Yet, reliance on MT without critical reflection can hinder the development of essential translation competencies, such as source-text interpretation, cultural sensitivity, and stylistic adaptation. Hence, the pedagogical question arises: To what extent should MT be integrated into translator education, and how does it shape novice translators' attitudes, strategies, and professional identities?

LITERATURE REVIEW

Conceptualizing Machine Translation

Machine translation (MT) has become an established area of translation technology, referring broadly to the use of computational systems to generate translations between natural languages. Its development has been closely connected with advances in computational linguistics, artificial intelligence, and language modelling [2]. Early MT research was largely concerned with developing systems that could represent linguistic rules and establish correspondences between source and target languages. Over time, these approaches were supplemented and, in many applications, replaced by statistical methods that learned translation patterns from bilingual corpora. The subsequent emergence of neural machine translation (NMT) introduced deep-learning architectures capable of modelling relationships between words and larger linguistic sequences, contributing to substantial improvements in the fluency of machine-generated translations [9].

The progression from rule-based systems to statistical and neural approaches has changed the position of MT within translation practice. Rather than being viewed solely as a mechanism for automatically converting one language into another, MT is increasingly understood as part of a broader technological environment in which human translators interact with automated systems. The distinction between fully automated translation and technology-supported human translation has consequently become important in translation studies. In many professional contexts, translators evaluate, modify, and post-edit machine-generated output rather than accepting it without intervention [10-12].

The usefulness of MT also varies according to the nature of the material being translated. Highly standardized and repetitive texts may be more amenable to automated processing because they contain predictable terminology and relatively stable linguistic structures. Conversely, literary, culturally specific, persuasive, and highly context-dependent texts present greater difficulties because their interpretation depends on factors that cannot always be inferred from linguistic form alone [6,13]. Consequently, advances in MT have not eliminated the need for human expertise; instead, they have altered the knowledge and skills expected of translators.

Evolution of Machine Translation Technologies

The development of MT can be viewed as a series of technological transitions, each attempting to overcome limitations identified in earlier systems. Rule-based machine translation relied on explicitly formulated grammatical rules, dictionaries, and linguistic transfer procedures. Although these systems offered a relatively transparent representation of linguistic processes, their dependence on extensive manual rule construction limited scalability and made it difficult to accommodate the complexity and variability of natural language [10-12].

Statistical machine translation introduced a different principle by using large collections of bilingual data to estimate probable translations. Rather than relying entirely on manually specified rules, statistical systems learned translation correspondences from previously translated material. This approach increased flexibility and enabled systems to deal with a wider range of linguistic structures. However, statistical systems could still generate fragmented or unnatural output, particularly when sufficient training data were unavailable for a particular language pair or domain [9].

Neural machine translation subsequently transformed the technological landscape. NMT models use neural networks to learn representations of source and target language sequences and to generate translations through learned patterns in large datasets. Research on neural approaches demonstrated significant improvements in fluency and translation quality compared with earlier statistical approaches. Nevertheless, improved readability should not be interpreted as evidence that machine systems have acquired the full interpretive capacity of human translators. Problems involving ambiguity, discourse-level coherence, cultural references, figurative language, and specialized terminology continue to require careful human evaluation [7,8].

Benefits of Machine Translation

One of the most frequently identified benefits of MT is the speed with which it can produce preliminary translations. Human translators working with substantial volumes of multilingual material can use MT to generate an initial version that can subsequently be checked and revised. This workflow can be particularly useful when deadlines are demanding or when large quantities of relatively standardized material must be processed [13]. MT therefore has the potential to increase productivity without necessarily eliminating human participation in the translation process [14].

Accessibility is another important advantage. Online translation platforms have made automated translation available to users who may not have access to professional translation services or specialized technological infrastructure. Students can use these systems to investigate unfamiliar words, compare possible formulations, and obtain an initial understanding of texts written in another language. Such accessibility has contributed to the growing presence of MT in language-learning and translator-training environments [15].

MT may also support terminology-related work. In technical and specialized translation, consistency in the treatment of recurring terminology is an important consideration. When machine translation is combined with translation memories, terminology databases, and other computer-assisted translation technologies, translators can develop workflows that improve consistency and reduce repetitive effort [16,17]. The usefulness of this approach, however, depends on the quality of the underlying data and on the translator's ability to identify inappropriate suggestions [18].

From an educational perspective, MT can provide opportunities for students to engage in comparative analysis. Instead of treating an automatically generated translation as a final answer, learners can compare machine output with the source text, identify errors, propose alternatives, and justify their revisions. Groves and Mundt [19], for example, demonstrated the potential of MT to support language learning, while later pedagogical research has emphasized the value of using machine output as material for critical analysis and post-editing practice [15,16]. In this sense, MT can become a learning resource when students are explicitly taught how to interrogate its output.

Limitations and Challenges of Machine Translation

Despite substantial technological progress, the quality of MT remains dependent on language pair, text type, domain, and contextual complexity. A translation may be grammatically fluent while nevertheless conveying an inappropriate meaning. This distinction between surface fluency and communicative adequacy is particularly important because users may interpret a polished machine-generated sentence as evidence of complete accuracy [6,20].

Semantic ambiguity represents another persistent challenge. Words and expressions can acquire different meanings depending on their linguistic and situational contexts. Human translators can draw upon wider discourse, background knowledge, communicative intentions, and cultural information when deciding between possible interpretations. MT systems, although increasingly capable of using contextual information, can still select inappropriate meanings when the available linguistic evidence is insufficient or ambiguous [7,16] (Table 1).

Cultural and pragmatic interpretation creates further difficulties. Expressions that depend on shared cultural knowledge, humour, irony, metaphor, or social conventions may not have direct equivalents in another language. Effective translation therefore requires more than identifying lexical correspondences. It may involve reformulation, adaptation, explanation, or deliberate retention of culturally specific elements. Research has repeatedly shown that such dimensions remain challenging for automated systems, particularly when the intended meaning is implicit rather than directly expressed [6-8].

Consistency and coherence at the discourse level are also important concerns. A system may generate individually plausible sentences but fail to maintain terminology, reference, tone, or stylistic consistency across a longer document. Such problems become particularly relevant in academic, professional, literary, and specialized translation, where relationships among sentences and sections contribute substantially to meaning [16] (Figure 1).

Another concern is the possibility of inappropriate dependence on MT. When students use automated translation without evaluating its output, they may overlook errors or reproduce machine-generated formulations that they do not fully understand. In translator education, this creates a pedagogical dilemma: a tool that can provide valuable linguistic support may also reduce opportunities for students to develop independent translation strategies if it is used as a substitute for analysis [5,15]. Effective integration therefore requires explicit instruction in verification, revision, and post-editing.

Discussions

The study adopted a mixed-methods research design to examine undergraduate translation students' use and perceptions of machine translation (MT). The design combined quantitative measures with qualitative responses to provide both an overview of students' MT-related practices and a deeper understanding of the experiences underlying those practices. The quantitative component focused on measurable patterns, including the frequency with which students used MT, the difficulties they experienced, and their views concerning the usefulness and reliability of machine-generated translations. The

Table 1: Profile and Data-Collection Characteristics of the Study.

Characteristic	**Description**
Research design	Mixed-methods
Study setting	Department of Translation and English Language, Imam Muhammad bin Saud Islamic University
Academic year	2022–2023
Initial questionnaires distributed	35
Valid questionnaires analyzed	30
Response rate	85.7%
Participant gender	Male
Participant level	Undergraduate
First language	Arabic
Foreign language studied	English
Sampling approach	Purposive sampling
Main research instrument	Structured questionnaire
Questionnaire items	10 Likert-scale statements
Response scale	1 = Strongly Disagree to 5 = Strongly Agree
Expert reviewers	5 specialists in applied linguistics and translation studies
Reliability coefficient	Cronbach's α = 0.75
Quantitative analysis	Frequencies, percentages, means, standard deviations, *t*-values and significance levels where applicable
Qualitative analysis	Thematic analysis

qualitative component drew on participants' written comments to provide additional explanations and perspectives that could not be fully represented through numerical responses [13].

The use of a mixed-methods approach was appropriate because the research addressed both behavioural and perceptual dimensions of MT use. Numerical data made it possible to identify general tendencies within the participant group, whereas qualitative information helped explain how students interpreted their experiences with MT. Combining the two forms of evidence therefore provided a more comprehensive account of students' engagement with translation technologies than either approach would have provided independently [10-14].

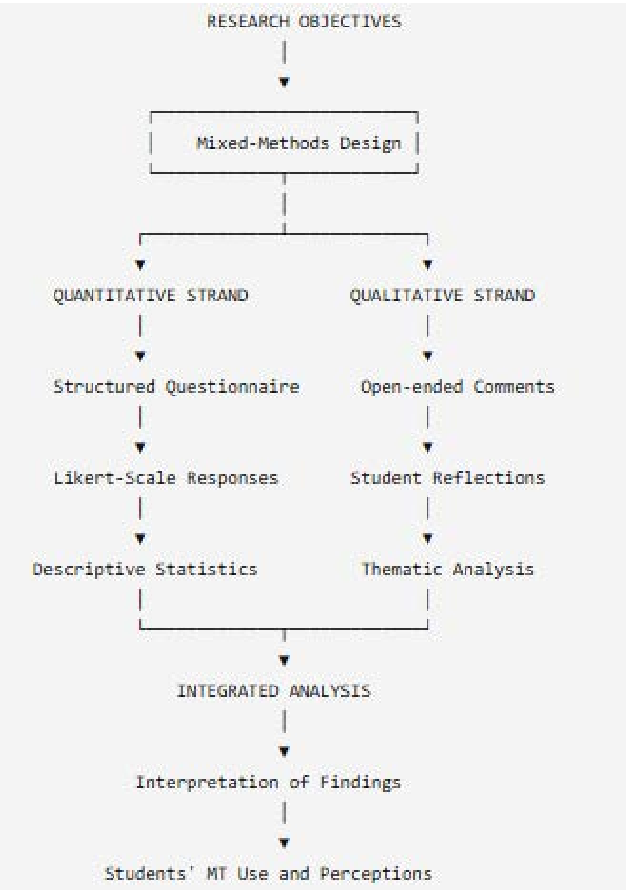

Figure 1: Research Methodology Framework.

Participants and Sampling

The study involved 30 male undergraduate students from the Department of Translation and English Language at Imam Muhammad bin Saud Islamic University during the 2022–2023 academic year. The participants were enrolled as full-time students in the translation program. Arabic was their first language, while English was studied as a foreign language.

A purposive sampling approach was used to obtain a relatively consistent group of participants with direct experience of translation-related academic activities. Restricting the sample to students within the same institutional and program context helped reduce variation associated with differences in academic environments, language backgrounds, and curricular exposure. The sample was primarily intended to provide exploratory evidence concerning students' experiences rather than to support statistical generalization to all translation students in Saudi Arabia [15-18].

Thirty-five questionnaires were initially distributed, of which 30 were considered complete and suitable for analysis. The resulting response rate was 85.7%. Questionnaires containing incomplete responses were excluded from the final dataset. Although the number of participants was relatively limited, the sample was considered appropriate for the exploratory nature of the investigation. Nevertheless, the findings should be

Table 2: Questionnaire Dimensions and Analytical Focus.

Dimension	Main Focus	Key Issues Examined
MT Usage	Students' engagement with machine translation	Frequency of use, academic translation tasks, purposes of MT use
MT-Related Challenges	Problems experienced when using MT	Linguistic accuracy, semantic interpretation, cultural appropriateness, technical concerns
MT versus Human Translation	Comparative perceptions	Accuracy, reliability, contextual understanding, cultural sensitivity
Pedagogical Use	Educational value of MT	Learning support, vocabulary assistance, drafting, translation practice
Human Intervention	Need for translator judgement	Verification, revision, correction, post-editing
Overall Perception	Students' general evaluation	Usefulness, limitations, dependence, and perceived role of MT

interpreted within the boundaries of the study population. Research involving larger samples, female participants, and students from different Saudi universities would provide opportunities for broader comparison in future investigations (Table 2).

A structured questionnaire was used as the principal instrument for data collection. The questionnaire was selected because it allowed information concerning students' MT practices and perceptions to be gathered in a consistent format. Standardized questions also enabled responses to be compared across participants and summarized quantitatively [19].

The questionnaire provided an opportunity for participants to express their views in their own words. These responses supplied qualitative information concerning students' experiences with MT and helped clarify some of the issues identified through the quantitative component [20]. Thus, the questionnaire functioned as the central data-collection instrument for both strands of the mixed-methods design.

Conclusion

This study concludes that machine translation (MT) has become a useful resource in the academic translation practices of undergraduate students. Students use MT primarily to support tasks involving unfamiliar vocabulary, difficult texts, and the preparation of preliminary translations. However, their experiences also reveal important limitations, particularly concerning semantic accuracy, contextual interpretation, cultural sensitivity, and consistency of output. These findings suggest that although advances in MT have improved the quality and accessibility of automated translation, machine-generated text still requires careful evaluation and human intervention. The study further concludes that MT should be incorporated into translation education as a complementary technology rather than as a replacement for human translators. Human expertise remains essential for interpreting context, conveying cultural meaning, selecting appropriate tone, and making informed translation decisions. Translation programs should therefore emphasize MT literacy, critical evaluation, and post-editing skills so that students can use automated tools responsibly and effectively. Such an approach can enable future translators to benefit from technological advances while maintaining the linguistic, cultural, and analytical competencies that remain central to professional translation.

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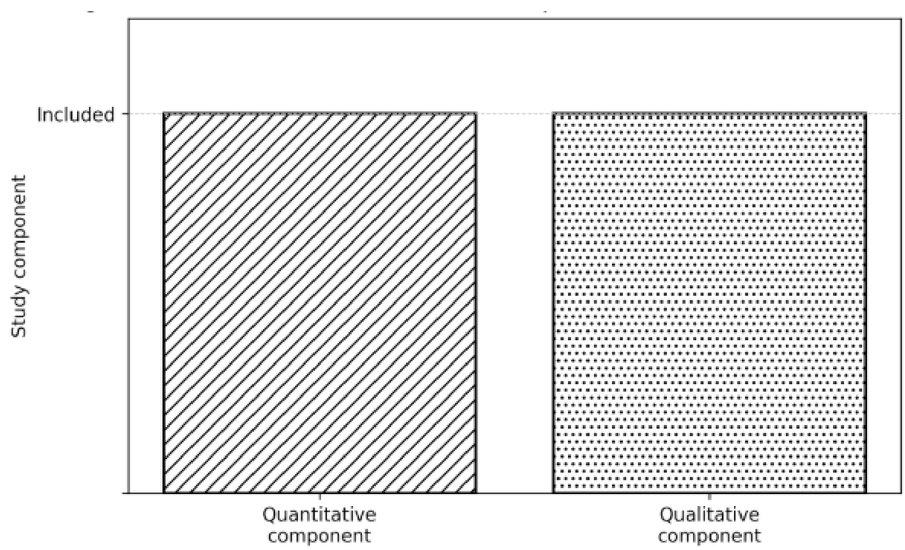

Figure 2: Quantitative and Qualitative Components of the Mixed-Methods Design

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