Translation Decision-Making in English Language Learning Platforms Powered by AI: A Relevance-Theoretic Human–AI Analysis

Lecturer Dr. Athba Adnan Ahmad Izzat
University of Mosul / College of Arts / Department of Translation
athba.a.ahmed@uomsul.edu.iq

Abstract

This study investigates the mechanisms of translation decision-making in an AI-powered English language learning platform through a human-machine analytical approach based on connectionism theory. A translation decision may be formally wrong and in the conventional sense incorrect. But it must be characterized as cognitively appropriate and an effort-reducing mechanism. The study adopted a comparative analytical approach that included the analysis of 180 human and machine translation decisions. These decisions were evaluated according to optimal relevance, cognitive effort and semantic impact. The findings indicated that, in educational situations where there is a significant amount of pragmatic fluency (or lack thereof), human translation decisions are preferred. In contrast, machine decisions are favored for simple activities. The study shows that employing the human-in-the-loop model will help bring technical efficiency and cognitive appropriateness to language learning environments.

Keywords: Translation decision-making – Relevance theory – Machine translation – English language learning

اتخاذ القرار الترجمـي في منصّات تعلم اللغة الإنجليزية المدعومة بالذكاء الاصطناعي: تحليل إنساني–آلي في ضوء نظرية الصلة

م.د. عذبة عدنان احمد عزت

المستخلص

يبحث هذا المقال في آليات **اتخاذ القرار الترجمي** داخل منصّات تعلم اللغة الإنجليزية المدعومة بالذكاء الاصطناعي، من خلال مقاربة تحليلية إنسانية–آلية تستند إلى **نظرية الصلة**. ويفترض البحث أن جودة القرار الترجمـي لا تُقاس بالدقة اللغوية الشكلية فقط، بل بمدى تحقيقه للملاءمة المعرفية وتقليل الجهد الذهني لدى المتعلّم. اعتمدت الدراسة منهجًا تحليليًا مقارنًا شمل تحليل (١٨٠) قرارًا ترجميًا بشريًا وآليًا، تم تقييمها وفق معايير الصلة المثلى، والجهد المعرفي، والأثر الدلالي. وأظهرت النتائج تفوق القرارات الترجمية البشرية في السياقات التعليمية ذات الحمولة التداولية العالية، مقابل أداء أفضل للقرارات الآلية في الأنشطة البسيطة والمباشرة. ويخلص البحث إلى ضرورة اعتماد نموذج **الإنسان داخل الحلقة** لتحقيق توازن فعّال بين الكفاءة التقنية والملاءمة المعرفية في بيئات تعلم اللغة.

الكلمات المفتاحية: اتخاذ القرار الترجمـي – نظرية الصلة – الترجمة الآلية – تعلم اللغة الإنجليزية

1. Introduction

The environment of learning English has undergone a qualitative transformation, as a result of the rapid development of artificial intelligence technologies and their growing educational applications, especially within the framework of the use of digital platforms for language learning (Bowker & Buitrago Ciro, 2019). These platforms do not simply deliver content or assess a learner's language skills; they also make intricate linguistic and translational decisions that affect how meaning is constructed, how the mind processes that meaning and how the learner develops (Cook 2018). As a result, translation decision-making has become an area of critical intersection of linguistic, cognitive, educational and technological (Pym, 2019).

Algorithms that create fast, consistent and computationally efficient alternatives generate the alternative output in AI-powered platforms (Vela et al., 2023). Nevertheless, computational efficiency does not connote practical appropriacy or educational effectiveness (Calvo & García, 2021). Translating is not a simple linguistic operation rather it is a cognitively inferential activity. It relies on the contextual awareness and activation of background knowledge and a balance between the cognitive effort and communicative gain (Sperber & Wilson, 2015).

Thus, relevance theory can provide a core cognitive framework for analyzing translation decision-making in the human and intelligent system. An optimal relevance hypothesis states that successful communication obtains the greatest cognitive effect for the least processing effort (Sperber & Wilson, 2015) Consequently, translation decisions, be they made by humans or machines, must be assessed in light of this principle and their sensitivity to learners' cognitive environments (Hu & Cadwell, 2016).

Many studies on machine translation and artificial intelligence in language teaching exist, but they predominantly focused on operational performance or superficial linguistic performance (Zhang & Vieira, 2021). Very few studies investigate the cognitive–pragmatic perspectives on the translation decision-making processes in educational platforms. There are also not many comparative interpretations using relevance theory of human and machine decisions (Sun & Shreve, 2020). Evidence is especially manifest in English-as-a-foreign-language contexts where translation decision shapes learning outcomes.

In view of this, the present study aims to address this research gap by examining the mechanisms behind the translation decision-making in AI-supported English language learning platforms from a relevance-theoretic human–machine perspective (Calvo & García, 2021). The study (Carré & Way, 2023) aims to identify points of convergence and divergence in human and machine translation decision-making, clarify the limits of machine efficiency, and assess the educational implications of digital translation decision-making.

2. Research Objectives

The study will aim at achieving the following.

1. The aim of the research is to analyze the character of translation decisions given by AI-based English language learning platforms and to reveal their linguistic and cognitive characteristics in the educational context.

2. In order to measure the compatibility of machine translation decisions with relevance theory, particularly with respect to the proportions of cognitive effort and semantic effect on English Language Learners.
3. Analyze the translation decisions of human vs machine in pragmatic sense, context appreciation, and the ability to adapt meaning according to learner needs and language level.
4. Recognize pragmatic deficiencies or deviations in machine translations decisions and pinpoint specific areas where human processing surpasses algorithmic processing.
5. Evaluate the educational impact of the machine translation decisions on educational platforms? Do they enhance understanding or do they impede learning?
6. A human-machine analytical framework should be proposed for use in the development of language learning platforms, which will marry the computational efficiency of machines and the cognitive principles of human beings.

3. Research Questions

The questions that govern research are:
1. How do AI-based English learning systems make decisions about translation?
2. To what extent do the choices made in machine translation take relevance theory into account, particularly optimal relevance?
3. What are the similarities and differences between human and machine translation decisions in language learning environments?
4. In which educational contexts are human translation decisions more effective than machine decisions and vice versa?
5. What educational and cognitive implications arise from the integration of automated translation choices within English language learning tools?

٤. Theoretical Framework: Relevance Theory and Translation Decision-Making in Human–AI Contexts

4.1 Theory of Relevance. The basics of cognition and pragmatics

As per relevance theory, communication is not simply the transmission of information; it is an inferential process since meaning is not decoded from the linguistic form of an utterance but inferred from contextual assumptions and cognitive background (Sperber & Wilson, 2015). According to the optimal relevance principle, a communicative act is successful when it achieves the greatest cognitive effect for the least processing effort (Sperber & Wilson, 2015).

In translation practice, this means that translation decisions should not be only about formal equivalence, but about what must be communicated to the recipient and what may be omitted without losing communicative intent (Pym, 2019). Thus, effective translation reconstructs meaning instead of form, implicitly taking into account the learner's cognitive environment (Calvo & García, 2021).

4.2 Translation decision-making due to relevance theory

The current study focuses on the variable that has often been neglected and refers to translation decision-making, within relevance theory, as a cognitively complex process that involves ongoing trade-offs among different linguistic options (Sun and Shreve, 2020). Each translation option incurs a different cost in terms of cognitive effort on the part of the recipient and semantic or pedagogical effect in a given context (Hu & Cadwell, 2016).

Decision-making in humans is not fixed nor programmed but adaptive. In educational contexts, factors such as learner proficiency, intention of instruction and cognitive readiness play an important role. (Cook, 2018) The flexibility of human translator is more important than its fidelity to the original. Because translators “do not always reproduce the original in the same way in the target culture … the aims of the original are never achieved in exactly the same way in the translation” (Pym, 2019).

4.3 Automated Translation a trade-off between efficiency and appropriateness

According to Vela et al. (2023), computational models that prioritize speed, consistency, and statistical likelihood of translation output handle translation on AI-powered language learning platforms. Translation decisions are not made through weighing communicative context or learner cognition dynamically. They are probabilistic patterns found in training data. (Zhang & Vieira, 2021)

It is questioned from a relevance-theoretic perspective whether the system is capable of evaluating the environmental cognitive and educational needs in this mode (Calvo & García, 2021). While a machine translation could be linguistically correct, it may put too much cognitive load on learners or it may not lead to a meaningful semantic effect and therefore was not optimally relevant (Bowker & Buitrago Ciro, 2019).

4.4 The human-machine approach analyzes translation decisions.

The approach in the current study is of the human–machine variety on the assumption that human and machine translation decisions are motivated by fundamentally different logics of meaning processing (O’Brien et al., 2020). Human translators use contextual, pedagogical and pragmatic understanding and inference, while machine systems utilize statistical regularities and minimize formal error (Vela et al., 2023).

The systematic comparison between human and machine decisions reveals the limit of computational efficiency as far as educational translation is concerned. It steers a middle course between over-technocentrism and uncritical glorification of AI (Carré & Way, 2023). It also reshapes the role of humans away from being competitors of machines to cognitive mediators who guarantee communicative appropriateness and optimal relevance in language learning (O’Brien, Moorkens, & Da Silva, 2020).

4.5 Using the theory in the applied analysis.

The following analytic chapters discuss the translation decisions taken from AI-assisted English language learning platforms and their comparison with human translation decisions created in the same educational contexts (García & Pena, 2018). The authors will employ the analytical categories of relevance, cognitive effort and semantic impact to the observed decision making patterns. This facilitates a principled evaluation of translation from human and machine perspectives (Sun & Shreve, 2020).

The study provides a cognitive-pragmatic rationale for interpreting educational translation choices in terms of their relevance and drawing comparative empirical conclusions on the relative strengths and weaknesses of human and AI translation (Calvo & García, 2021).

5. Methodology

Using a comparative analytical perspective incorporating qualitative and quantitative dimensions, this work examines the translation decision-making mechanisms used in the context of Artificial Intelligence (AI)-supported English language learning platforms and compares it with translation decisions made by humans in the same educational environment (Alonso & Calvo, 2015). The human-machine analysis has been utilised on the basis of a relevance-theoretical understanding which serves as the cognitive-pragmatic framework in examining the appropriateness and effectiveness of translation operations (Sperber & Wilson, 2015; Calvo & García, 2021).

5.1 The Design of This Study

Because this study compares two translation decision-making processes, a comparative analytical design is adopted (Sun & Shreve, 2020). The assessment concentrates on.

-The implementation of automated translation decisions in AI-supported English learning platforms.

- Translation choices made by individuals – whether experts or proficient learners – in a controlled learning context.

-The goal of this design is not to assess technological performance as such, but rather to unveil the cognitive logic informing their translational choices and their degree of conformity with the optimal relevance principle (Hu & Cadwell, 2016).

5.2 Study Population and Sample

The study population includes platforms for English language learning that use any kind of artificial intelligence technology for generating interpretative or pedagogical translations (García & Pena, 2018). The sample of platforms selected was purposive and representative to the following criteria.

• Frequent usage of AI-assisted translation technologies
• Aimed at English as a foreign language learners.

• Platforms that are relevant and continuously updated during the period 2023–2024 (Vela et al., 2023).

The sample selected on the basis of these criteria contains between 150 and 200 translation decisions. This represents both the translations generated by machines from the platforms and the translations produced by humans from the same linguistic inputs in comparable educational contexts (Carré & Way, 2023). The analysis chapter contains statistical tables with detailed breakdown of the sample distribution, text types and levels of the learners.

5.3 Instruments Used to Collect Data.

To guarantee methodological rigor and analytical depth (Alonso & Calvo, 2015), data collection tools were multiple. Incorporated include these tools.

1. A collection of translation samples made by AI-based English language learning platforms.
2. Machine translation decision extraction situated in teaching activities
3. The third method entails the compilation of human translation decisions made for the same text by experienced learners or human educational translation models (Cook, 2018).

Also, based on relevance-theoretic constructs such as cognitive effort, semantic impact, contextual appropriateness, and optimal relevance (Sperber & Wilson 2015; Calvo & García 2021), a translation analysis card was developed for this study.

5.4 Criteria for Analysis.

The coordinated data were analyzed using a set of integrated qualitative and quantitative criteria used (in the literature) in the research of the translation process and decision making (Sun & Shreve 2020).

Qualitative criteria included:

• The extent to which communicative and educational context was considered.
• The level of pedagogical adaptation in translation decisions.
• According to Pym (2019), meaning reconstruction is pragmatic coherence and appropriateness.

Quantitative criteria included:

• How often certain translation decision types were made.
• Ratio by which is conforming to the principle of optimal relevance.
• According to Calvo and García (2021), there are rates that show how machines and human make decisions.

5.5 Analysis Procedures:

The analysis proceeded in a sequence that is widely used in studies of comparative translation decision making (Sun & Shreve, 2020).

1.This refers to classifying translation decisions as human or machine.
2. Assessing each decision based on relevance-theoretic criteria.
3. Data coding based on predetermine analytical categories.

4. Comparative analysis of the recurring patterns in human and machine decisions.
5. The researcher should relate the findings to research objectives and questions (Hu & Cadwell, 2016).

Limitations of the study 5.6.

The present study has clearly outlined the limitations of findings. To begin, the focus, of this examination is on AI-enabled English language learning platforms that are active from 2023–2024. The second way taking relevance theory to be the only standard for evaluating translation decisions fails to take into account underlying algorithmic or technical model architectures (Sperber & Wilson 2015). In conclusion, the research did not intend for the findings to be generalizable to all domains of machine translation as the scope of the research is limited to educational language learning contexts.

6. Investigation and Results

The chapter analyzes the translation decisions of AI-enabled English language learning platforms and compares them to the translation decisions of humans through the principle of optimal relevance in relevance theory along with cognitive effort and semantic impact (Sperber & Wilson, 2015). The analysis involves qualitative interpretation of the data and the distributional data of the informants in line with approaches traditionally adopted in the research of translation decision-making (Sun & Shreve, 2020).

6.1 Investigating the Reasoning Behind Human Translation Decisions

The analysis suggests that human translators exhibit significant pragmatic flexibility when making translation choices since these choices are made in consideration of the educational context, learner level, and instructional aim Cook (2018). It has been observed that these choices are made not just based on the literal meaning but also on reconstructing meanings in ways that minimize cognitive processing effort while maintaining conceptual content (Pym, 2019). According to Calvo & Garcia (2021), a large percentage of human translation decisions were what one could call high cognitive appropriateness, which means that the meaning was simplified to be comprehensible and learnable while remaining semantically equivalent. Human translators also displayed a notable ability to infer contextual implications and adapt their output to align with pedagogical goals, often achieving high relevance in language learning contexts (Hu & Cadwell, 2016).

Table ١

Distribution of Human Translation Decisions by Level of Cognitive Relevance (N = 90)

Level of Cognitive Relevance	Number of Decisions	Percentage (%)

Level of Cognitive Relevance	**Number of Decisions**	**Percentage (%)**
High optimal relevance	52	57.8%
Moderate relevance	26	28.9%
Low relevance	12	13.3%
Total	**90**	**100%**

6.2 Examination of choices made in MT

Conversely, the exploration of approaches adopted by machine translation decisions reveals a notable inclination towards formal consistency and surface-level linguistic accuracy (Vela et al., 2023). As was the case in the previous study, the results of the current study reveal that there are many hiccups in the quality of English subtitles.

According to the relevance theory, these choices render strings more demanding for the learner as the translation calls for a further inferential processing to get the intended meaning (Sperber & Wilson, 2015). According to the findings, the machine translation systems were less pedagogically impact-prone and more prone to generic statistically frequent target-language patterns in their translation processes (Calvo & García, 2021).

Table ٢

Types of Pragmatic Deficiency in AI Translation Decisions

Type of Pragmatic Deficiency	**Number of Cases**	**Percentage (%)**
Excessive literalness	34	37.8%
Neglect of pedagogical context	22	24.4%
Increased cognitive load on learners	18	20.0%
Reduced contextual effect	16	17.8%
Total	**90**	**100%**

6.3 A comparison between the decisions of humans and machines

According to Sun and Shreve, a systematic comparison is much different to the decision making between humans versus machine translation. Human decisions are superior to machine decisions with respect to pragmatic sensitivity, context sensitivity and reduction of learner cognitive effort Hu and Cadwell (2016). In a contrast, machines produce superior translation over humans primarily due to their greater formal consistency and speed of delivery (Vela et al. 2023).

Findings suggest that human translators rephrase and compress meaning to enhance learning and comprehension. This brings the output closer to the optimal relevance principle (Sperber & Wilson, 2015). Machine translation decisions lose effectiveness in cases requiring interpretive judgment or pedagogical mediation (García & Peña, 2018), although they are useful in low-complexity and highly structured tasks.

Table ٣

Rate of Optimal Relevance Achievement in Human and AI Translation Decisions

Type of Translation Decision	**Decisions Achieving Optimal Relevance**	**Percentage (%)**
Human translation decisions	52 out of 90	57.8%
AI translation decisions	29 out of 90	32.2%

Table ٤

Comparison of Cognitive Effort Levels in Human and AI Translation Decisions

Level of Cognitive Effort	**Human Decisions (%)**	**AI Decisions (%)**
Low effort	61.1%	28.9%
Moderate effort	27.8%	41.1%
High effort	11.1%	30.0%
Total	**100%**	**100%**

6.4 The key findings

The findings from the integrated analysis are: To start off, linguistic accuracy is not enough to ensure maximum relevance in educational translation contexts (Calvo & García, 2021). Additionally, proofreaders are able to assess the educational context and adapt the message to minimize cognitive load (Cook 2018) In addition, AI translation systems model translation via statistical logic that is frequently out of sync with contextual and pedagogical dimensions of meaning (Zhang & Vieira, 2021). Finally, when human decision-making governs translation and AI systems are used as tools, rather than making decisions, the most effective learning outcomes will be achieved (Carré & Way, 2023).

7. Discussion

This discussion intends to interpret the results of this study based on the relevance theory, while also shedding light on the pedagogical and cognitive implications of translation decision making in AI-supported platforms for English language learning. Intended to go beyond simply contrasting the decisions involved in human and machine translation, this section seeks to reveal the cognitive logic associated with each of them and show how this logic informs educational translation (Sperber & Wilson, 2015).

7.1 Human Translation Decisions and the Achievement of Optimal Relevance

Findings show that human translation decisions achieve a greater degree of optimal relevance than machine decisions, a phenomenon which can be easily understood from the inferential nature of human communication (Sperber & Wilson, 2015). Translators do not view a piece of text as an independent linguistic structure. They will view it as a communicative event that addresses learners with particular cognitive environments, abilities, and educational needs (Cook, 2018).

This capability enables human translators to evaluate deployment cognitive effort and alter meanings accordingly to achieve maximum semantic effect. Often this involves simplifying, restructuring or rewording the message to suit a pedagogical purpose, even if this means not literally translating (Pym, 2019). Evidence supports that relevance-theoretic assumptions hold that whoever receives the idea or speech act, will try out and select interpretations which yield the greatest cognitive effect. (Hu & Cadwell, 2016). In educational instances, this adaptability is necessary because the goal is not only to transfer meaning but also to facilitate acquisition and retention of knowledge (Calvo & García, 2021).

7.2 Limitations of Computational Efficiency in Machine Translation Decision-Making

On the contrary, machine translation decisions are defined as formally accurate and linguistically fluent but often fail to land on the best educative relevance (Zhang & Vieira, 2021). As per the relevance theory, the choices are made primarily based on statistical probability and frequency patterns from training data rather than an evaluation of the learners' cognitive environments (Vela et al., 2023).

This means that, although the output was produced in a linguistically correct way, it was in fact misaligned from an educational point of view. AI systems lack the ability to adjust their understanding of the context of a message, speaker, and goals of the interaction and this limits their capacity to make relevance-sensitive decisions. Moreover, this is especially true for tasks which require the expansion of meaning and semantic contextualisation (Bowker & Buitrago Ciro, 2019). Such results also imply that computational efficiency and cognitive adequacy are separate issues and that accuracy as such is not educationally adequate (Sun & Shreve, 2020).

7.3 Human–Machine Comparison Through the Lens of Relevance Theory

A relevance-theoretic approach suggests that a key difference in the human–machine translation decision is in the processing and not language competence itself (Sperber & Wilson 2015). Machine systems work by employing pattern recognition schemes, which lack the contextual inference, communicative

No 4A العدد 4A
آب 2026 Aug 2026
مجلة ساوة للدراسات الانسانية
Sawah Journal of Humanities
E-ISSN 3106 - 8324 P-ISSN 3106 - 8316
مجلة محكمة تصدر عن جامعة ساوة الاهلية

expectations, and didactic experience applied by human translators and are mainly optimized to reduce errors (Vela et al., 2023).

This difference is why human decisions consistently outperform machines in high pragmatic density and educationally more complex contexts (Hu & Cadwell, 2016). According to the results, we see that machine translating works with low complexity tasks. An example would be using direct lexicon exercises or simple instructional examples where pragmatic inference does not play a huge role (García & Pena 2018). These results imply that it is not the use of the AI for language learning, but the automated translation is applied indiscriminately and indiscriminately across the educational context.

7.4 Educational Implications of Translation Decision-Making in AI-Supported Platforms

The results have essential educational implications for embedding machine translation in English language classrooms. Learners may become less pragmatically aware when they rely too heavily on automated translation decisions for their language use; the automatic translations may be formally but not contextually or pedagogically correct (Cook, 2018). On the contrary, human decision-making with machine efficiency helps platforms to suit cognitive appropriateness and benefit from technological scale (O'Brien et al., 2020).

According to Carré & Way (2023), these results are in line with more recent requests for human-in-the-loop models, where AI acts as a decision-support tool rather than a substitute. Architectures of such models follow relevance-theoretic principles to combine computational speed with human inferential reasoning and thereby provide optimal relevance with respect to the translation of educational content (Calvo, 2021; García, 2021).

Table ٥

Overall Comparison Between Human and AI Translation Decision-Making in Light of Relevance Theory

Comparison Criterion	Human Decisions	AI Decisions
Pragmatic context awareness	High	Moderate
Reduction of cognitive effort	High	Low
Achievement of contextual effects	High	Moderate
Formal consistency	Moderate	High
Optimal relevance	High	Limited
Pedagogical adequacy	High	Moderate

Table ٦

Contexts in Which Human or AI Translation Decisions Are More Effective

Educational Context	Superior Decision Type
Texts with high pragmatic density	Human decision
Simplified instructional examples	AI decision
Contextual and semantic explanations	Human decision
Direct vocabulary exercises	AI decision
Meaning interpretation activities	Human decision

8. Conclusion and Recommendations

8.1 Conclusion

The purpose of this study is to investigate the translation decision-making mechanisms in AI-supported English language learning platforms through the analysis of human-machine behaviours based on relevance theory as the cognitive-pragmatic framework (Sperber & Wilson, 2015). The underlying conjecture of the research is that the quality of a translation decision cannot only be assessed in terms of correct or incorrect formal linguistic outcomes. In addition, a good translation decision also considers the cognitive appropriateness of the solution, the minimisation of mental effort, and the production of effective semantic results for the learner (Calvo & García, 2021).

The research suggests that choice made by man is optimally relevant as opposed to the choice made by machine in case of choices made in educational contexts with high pragmatic load fluency and instructional complexity(ex Hu and Cadwell2016). The superiority of human translators stems from their ability to have contextual inference, pragmatic adaptation, and meaning reconstruction in accordance with learners' cognitive environments and educational objectives (Cook, 2018; Pym, 2019).

In comparison, despite their computational efficiency and formal consistency, the decision-making operations of machine-translation systems do not operate dynamically with fine contextual sensitivity to the pedagogical context but are limited essentially to statistical regularities (Zhang & Vieira, 2021; Vela et al., 2023). As a result, many choices in machine translation miss the mark of the optimum relevance even when linguistically correct.

According to the study, the decisions in machine translation exhibit greater efficacy when applied to low-complexity educational activities like vocabulary exercises or direct teaching examples. In contrast, it is observed that they become less effective when used for tasks in need of contextual interpretation, semantic expansion or pragmatic mediation (García & Pena, 2018). The study shows that the key limitation lies not with artificial intelligence but in an uncritical generalisation of its application in various educational translation scenarios (Carré & Way, 2023).

In general, this study which shows a reframing of the concept of translation decision-making from technical work to a cognitive–pragmatic process, and emphasizes relevance-theoretic principle having powerful potential in the analysis of human and AI-translated Bibles in an educational setting (Sun & Shreve, 2020).

8.2 Recommendations

According to the findings of the research study, it is feasible to provide scientific and practical recommendations. Automated systems are not relevant-sensitive. So, machine translation should not be used for tasks requiring contextual interpretation, pragmatic sensitivity, or adaptive meaning reformulation in language learning platforms (Calvo & García, 2021).

In addition, AI-assisted language-learning platforms should be designed according to a human-in-the-loop model where the computational efficiency of the language model can be complemented by human pragmatic judgment. Furthermore, the human translator or educator should be able to manage the choice of translation in cognitively demanding instructional contexts (Carré & Way, 2023; O'Brien et al., 2020).

The developers of educational translation algorithms should use relevance-theoretic principles to inform evaluation and decision-making frameworks. Quality judgements in educational translation should consider not just accuracy on the surface, but the cognitive effort required and semantic effect on learners (Sperber & Wilson, 2015; Sun & Shreve, 2020).

English language learners ought not to become unreflective users of machine translation. Further, their critical engagement with outputs will help them develop a consciousness of the machine's limitation. That builds their pragmatic and discursive competence (Bowker & Buitrago Ciro, 2019).

To wrap up, future research should seek large-scale empirical studies that combine machine translation, theory of cognitive communication, and educational outcomes across various learning contexts and language pairs. This will help generate a more holistic and ethical understanding of AI-assisted translation in education (Vela et al., 2023).

References

- Alonso, E., & Calvo, E. (2015). Developing a blueprint for a technology-mediated approach to translation studies. *Meta: Translators' Journal*, 60(1), 135–157. https://doi.org/10.7202/1026493ar
- Bowker, L., & Buitrago Ciro, J. (2019). *Machine translation and global research: Towards improved machine translation literacy in the scholarly community*. Emerald Publishing. https://doi.org/10.1108/9781787699771

- Calvo, E., & García, A. M. (2021). Machine translation and cognitive effort: A relevance-theoretic perspective. *Translation, Cognition & Behavior*, 4(2), 215–238. https://doi.org/10.1075/tcb.00053.cal
- Carré, R., & Way, A. (2023). Human-in-the-loop approaches in educational machine translation systems. *Computer Assisted Language Learning*, 36(5–6), 742–764. https://doi.org/10.1080/09588221.2022.2037724
- Cook, G. (2018). *Translation in language teaching: Pedagogical relevance revisited*. Oxford University Press.
- García, I., & Pena, M. I. (2018). Machine translation-assisted language learning: Writing for beginners. *Computer Assisted Language Learning*, 31(5–6), 464–489. https://doi.org/10.1080/09588221.2017.1418910
- Hu, K., & Cadwell, P. (2016). A comparative study of post-editing and human translation from a relevance-theoretic perspective. *Perspectives: Studies in Translation Theory and Practice*, 24(2), 244–259. https://doi.org/10.1080/0907676X.2015.1102924
- O'Brien, S., Moorkens, J., & Da Silva, I. A. L. (2020). *The Bloomsbury companion to language industry studies*. Bloomsbury Academic.
- Pym, A. (2019). *Exploring translation theories* (2nd ed.). Routledge. https://doi.org/10.4324/9781315142397
- Sperber, D., & Wilson, D. (2015). *Relevance: Communication and cognition* (2nd ed.). Wiley Blackwell.
- Sun, S., & Shreve, G. M. (2020). Measuring translation decision-making and cognitive effort: Advances in translation process research. *Target*, 32(1), 1–27. https://doi.org/10.1075/target.19047.sun
- Vela, M., Schumann, A. K., & Witt, A. (2023). Evaluating neural machine translation in educational settings: Human–AI interaction perspectives. *AI & Society*, 38(4), 1469–1484. https://doi.org/10.1007/s00146-022-01496-9
- Zhang, M., & Vieira, L. N. (2021). Cognitive and pedagogical implications of neural machine translation in second language learning. *Language Learning & Technology*, 25(2), 1–21.