Rodrigo, M. M. T. et al. (Eds.) (2021). Proceedings of the 29th International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

A Review Study of the Application of Machine Translation in Education from 2011 to 2020

Yu-Yao ZHEN, Ya-Ning WU, Guang-Ming YU, Chun-Ping ZHENG*
School of Humanities, Beijing University of Posts and Telecommunications, China
*zhengchunping@bupt.edu.cn

Abstract: The progress of translation technologies has presented new opportunities and challenges to translation education, and the application of machine translation in education has received growing attention among researchers. This paper reviewed a total of 40 studies (19 empirical studies and 21 position papers) published in five SSCI-indexed and three CSSCIindexed journals during 2011 to 2020. The SSCI-indexed journals include *Perspectives, The Interpreter and Translator Trainer, Babel, Across Languages and Cultures, The Journal of Specialized Translation*. And the three CSSCI-indexed journals are *Chinese Translators Journal, Shanghai Journal of Translators* and *Technology Enhanced Foreign Language Education*. At first, this paper explored the yearly publication trend and the research themes of the journals. Then, it summarized the methodologies of empirical studies and found that a majority of the studies employed the mixed or qualitative methods with data analysis based on qualitative summaries and descriptive quantitative analysis. Major findings and pedagogical implications were provided at the end.

Keywords: Machine translation (MT); translation education; language teaching; content analysis; systematic literature review

1. Introduction

With the unprecedented development and penetration of information technology and artificial intelligence, machine translation (MT) has become an indispensable part of translation practice and has come into the focus of translation academia and industry (Loock, 2020). The progress of MT has changed the traditional methods and concepts of translator training and developed a new trend of applying MT into translation education in the digital world. Moreover, the development of translation technology has promoted studies to explore how machine translation can be integrated into translator training (Mellinger, 2017) or how translation education programs can benefit from the technology (Rodríguez-Inés, 2013). It is increasingly recognized that the technical literacy of translators is crucial to their comprehensive abilities (Man, Mo, Chau, O'Toole, & Lee, 2020). According to the literature, MT could also benefit students' language learning from the cognitive, linguistic, and affective perspectives (Lee, 2019). In an artificial intelligence era, the ability to use MT effectively during students' learning or translation practice is crucial for them to learn English as a foreign language (Tsai, 2019).

2. Literature Review

Machine translation, as a multidisciplinary subject involving lexicography, linguistics, computational linguistics and computer science, has drawn considerable attention from scholars in various areas (Sinhal & Gupta, 2014). The system of MT has been adopted by language service providers and still continues to grow in popularity within the field. Cadwell (2017) holds the view that, with further advances and promises of higher quality neural MT, it can be expected that MT will become an even more popular technology that professional translators will be compelled to engage with it. Based on the current situation and views, a variety of studies are carried out to analyze and demonstrate the growing trend of incorporating machine translation into translation curriculum (e.g., Doherty & Kenny 2014; Flanagan & Christensen, 2014). Since there are few systematic review studies on the use of MT for foreign language learning and translator training, this study aims to reveal the publication trend of the relevant studies and explore the educational applications of MT from 2011 to 2020. In addition, the pedagogical implication and suggestions would also be discussed to provide inspirations for the application of translation technology in language teaching and learning.

3. Methodology

3.1 The process of identifying journals

This research adopted the systematic content analysis as the major method for reviewing studies. Eight high-impact journals were selected, five of which are international journals, namely *Perspectives, The Interpreter and Translator Trainer, Babel, Across Languages and Cultures, The Journal of Specialised Translation*. All the five journals are indexed by Social Science Citation Index (SSCI). The other three journals are Chinese journals, namely *Chinese Translators Journal, Shanghai Journal of Translators, and Technology Enhanced Foreign Language Education*, which are all indexed by Chinese Social Science Citation Index (CSSCI).

These eight journals represent quality studies from scholars in the field of translation studies, which can be helpful for the readers to grasp the research trends and research foci. In addition, all articles in the five international journals are published in English and have a wide international readership and authorship.

3.2 The process of data coding and data analysis

In the first stage, the author manually screened publications (from 2011 to 2020) in the above eight journals by referring to the titles and the abstracts. When extracting articles, only those regular fulllength research articles were selected, while book reviews, technical reports or commentaries were excluded. Due to the fact that the application of machine translation into language education is still growing rapidly, only 40 journal articles (19 empirical studies and 21 position papers) were selected after the first stage.

In the second stage, according to the coding framework by Chai, Koh and Tsai (2013), integrated with the analytical framework summarized by Macaro, Handley and Walter (2012), the preliminary framework was postulated. Then, the author used the preliminary framework for initial article analysis and code the articles.

The coded data for the systematic literature review consisted of quantitative and qualitative data. With the help of social science analysis software, SPSS 22.0, the quantitative data were analyzed mainly using descriptive statistics. While the qualitative data, mainly combined with content analysis, were categorized and summarized with the assistance of qualitative data analysis software, NVivo 11.0.

4. Results

4.1 Number of the studies published from 2011 to 2020

It can be seen from Table 1 that there are in total of 40 papers related to the applications of machine translation for translator training published in the eight journals from 2011 to 2020. In the past ten years, *Technology Enhanced Foreign Language Education* published the largest number of related papers (ten papers).

As further indicated in Figure 1, all the eight journals have published articles concerning the application of machine translation in translator education. Since 2016, an upward trend can be seen obviously largely due to the launch of Google Translate with the Google Neural Machine Translation (GNMT) system (Schuster, Johnson, & Thorat, 2016). Furthermore, the year of 2019 witnessed the largest number of publications, in which, ten studies were published in five journals.

Table 1. *Numbers of studies published by eight journals (2011 to 2020)*

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
Perspectives	0	0	0	0	1	0	2	1	0	1	5
The Interpreter and Translator Trainer	0	0	0	1	0	0	0	2	4	0	7
The Journal of Specialised Translation	0	0	0	0	0	2	0	0	0	0	2
Across Languages and Cultures	0	0	0	0	0	0	1	0	0	1	2
Babel	0	0	0	0	0	0	1	0	1	1	3
Chinese Translators Journal	0	2	3	1	0	0	0	1	1	1	9
Technology Enhanced Foreign Language Education	0	0	0	1	1	1	0	2	3	2	10
Shanghai Journal of Translators	0	0	0	0	0	0	0	0	1	1	2
Total	0	2	3	3	2	3	4	6	10	7	40

4.2 Research themes of the studies published from 2011 to 2020

Based on the content analysis, the research themes of the 21 position papers concerning three main categories (shown in Figure 2), including the instructional design of translation courses (13 papers), teaching methods (5 papers) and teaching resources (3 papers). The research themes of the 19 empirical studies were divided into three main categories (shown in Figure 3), namely the feasibility of machine translation as a tool in translation (6 papers), instructional design using machine translation (5 papers) and the adoption of machine translation and users' feedback (8 papers). Several publications covered more than one topic at the same time. As indicated in Figure 2, the instructional design of translation

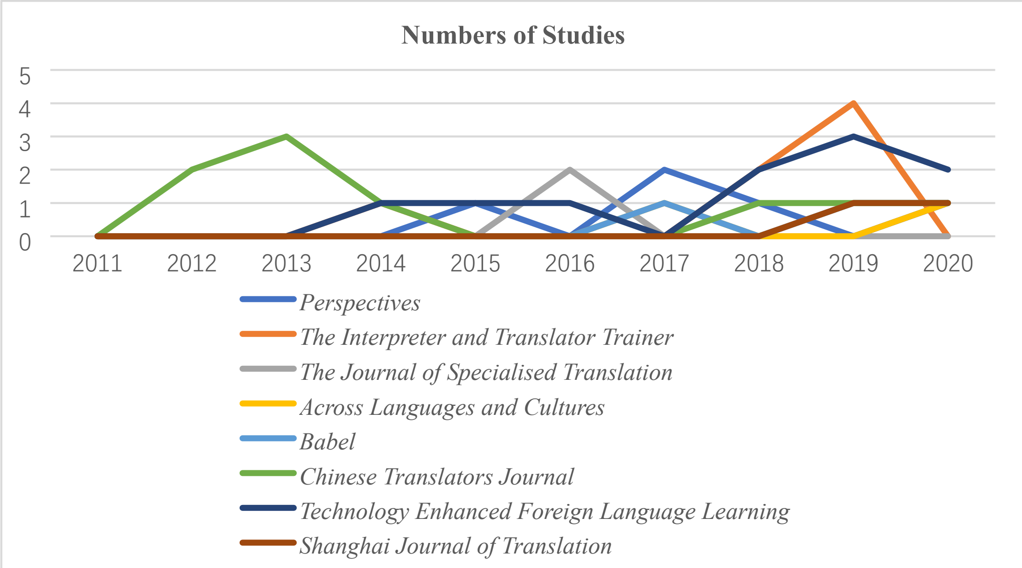

Figure 1. Numbers of Studies published by eight Journals (2011 to 2020)

courses seems to be an interesting and hot topic during the past decade. Mellinger (2017) held the opinion that different teaching modules related to MT, such as terminology management and post-editing should be integrated into the translation curriculum when providing students with MT courses.

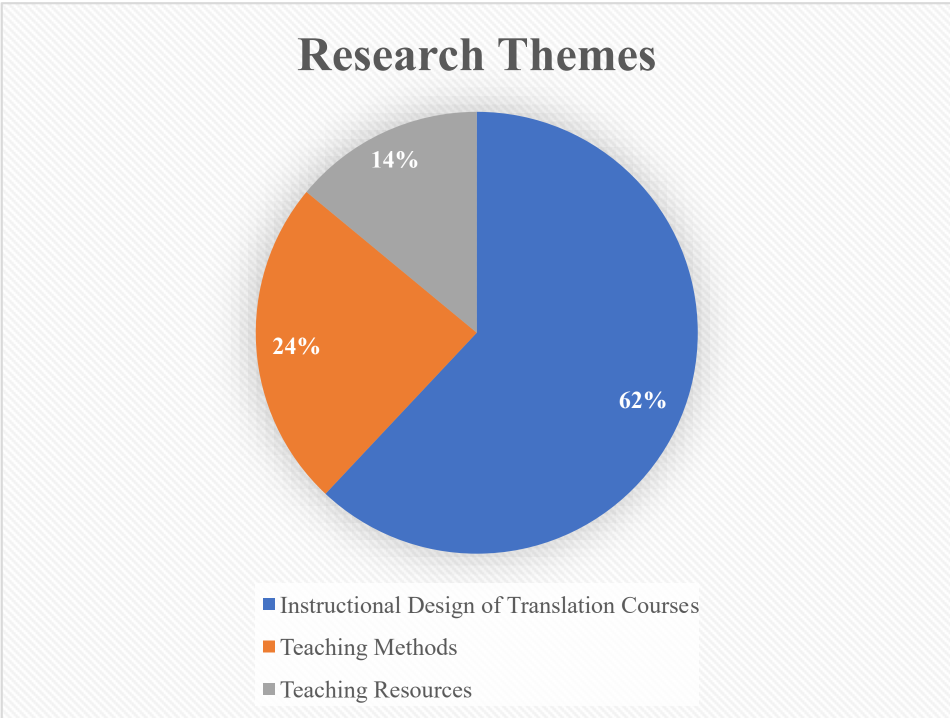

Figure 2. Research Themes in Position papers

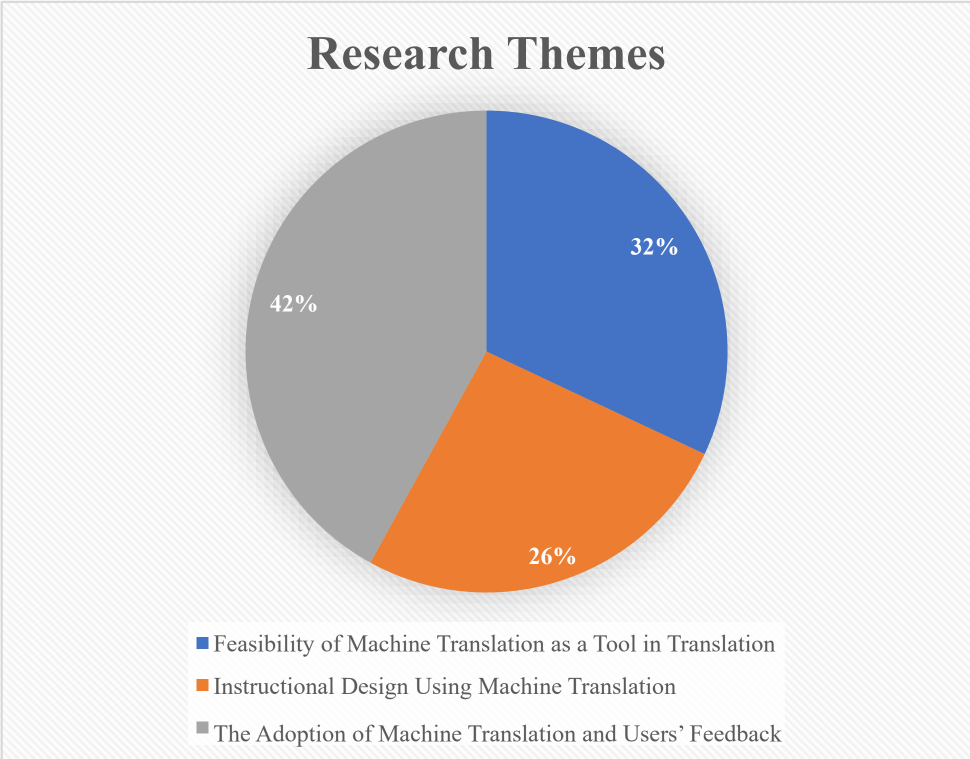

Figure 3. Research Themes in Empirical Studies.

As shown in figure 3, scholars pay much attention to feasibility of machine translation as a tool in translation and carried out several empirical studies (e.g., Jia, Carl, & Wang, 2019; Yamada, 2019). Several studies provided helpful suggestions for translation education (e.g., Doherty & Kenny, 2014). Moreover, learners' feedback to the adoption of MT and has also been studied extensively.

4.3 Data collections and data analysis of the studies published from 2011 to 2020

The position papers and empirical studies used a variety of data collection methods. For instance, Jia (2019) used five data collection methods, including questionnaires, comparative groups, retrospective written reports, key-logging and gaze data. Ortiz-Boix and Matamala (2016) adopted three collection methods consisting of questionnaires, comparative groups, and mouse clicks to conduct the research.

As Figure 4 indicates, the most frequently used data collection method is survey and questionnaire, which is adopted in 15 articles. The researchers tended to use questionnaires to investigate the application of MT and users' perceptions (e.g., Man et al., 2020).

As shown in Figures 5, the studies also used a variety of data analysis methods. For qualitative data, 16 papers used qualitative summary to categorize and summarize questionnaire and interview results (e.g., Guerberof & Moorkens 2019), mainly for analyzing respondents' feedback for using machine translation. It worth noting that only one paper used Cronbach alpha to analyze the reliability of the questionnaire (e.g., Rodríguez-Castro, 2018). For quantitative data, 17 papers used descriptive quantitative analysis.

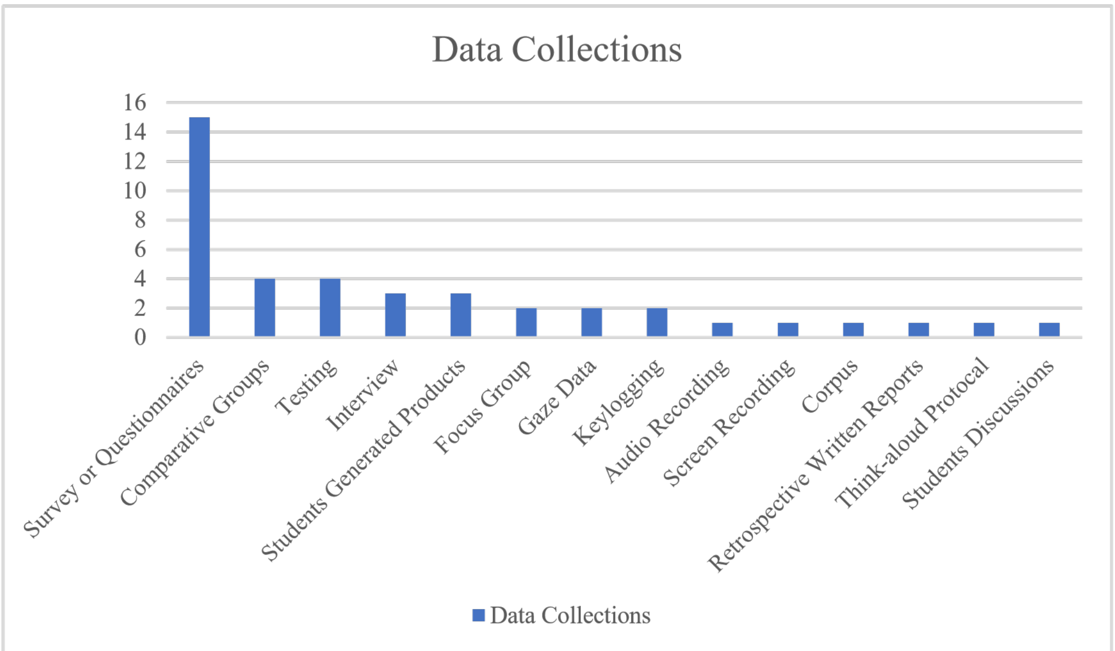

Figure 4. Data Collections of the studies from 2011 to 2020

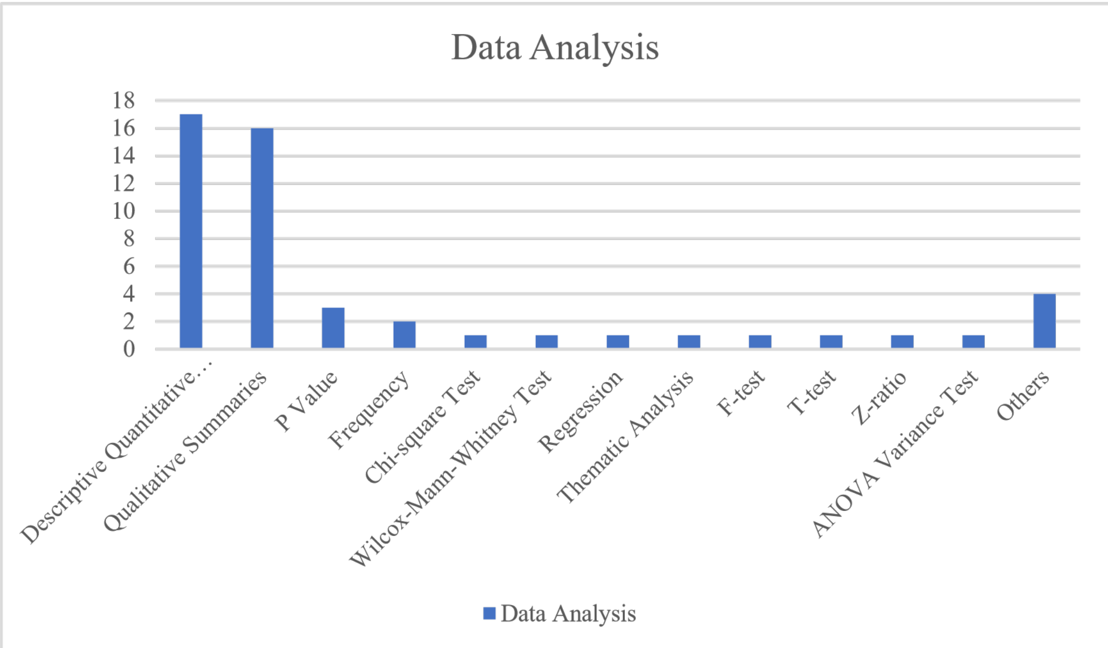

Figure 5. Data Analysis of Studies from 2011 to 2020

4.4 MT selected by the studies published from 2011 to 2020

As shown in Figure 6, a total of five articles clearly indicates the type of machine translation used, of which one used SMT alone, two used NMT alone, two used at least two different types of MT at the same time, and there were no cases of RBMT alone in the selected articles.

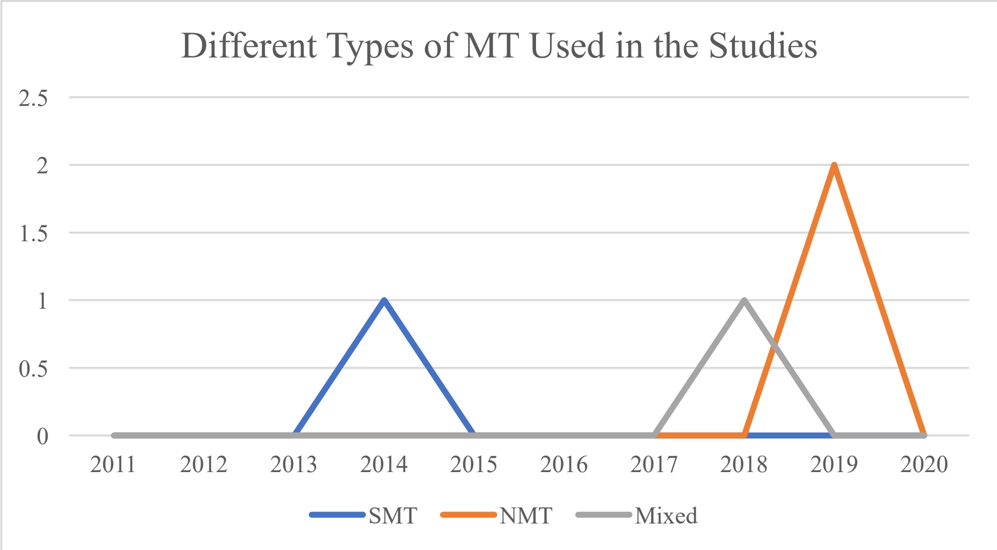

Figure 6. Different Types of MT Used in the Studies

It can be seen that Rule-Based Machine Translation (RBMT), an earlier MT approach, has no longer been studied extensively in the recent decade, and the research field of MT has attached more importance to SMT and NMT. Around 2016, neural-based machine translation (NMT) was initially introduced by Google Translate. Deeply affected by that, the research focus gradually shifted from the application of SMT to NMT or mixed types of MT technologies.

5. Conclusion

The present research is a review study of 40 studies selected from eight high-impact academic journals concerning the application of MT in education. Content analysis method was employed and a coding scheme was constructed from aspects of publication trend, research themes, data collections and analysis, and the types of MT in studies. Drawing upon the findings, we conclude that MT has become an increasingly important technology in the translation studies and teaching practice. Through the effective integration of the MT with translation and language teaching, educators can make the most advantages of the MT to cultivate and improve students' technical literacy and translation efficiency.

Acknowledgements

This research is funded by the Teaching Reform Project for Postgraduate Education of Beijing University of Posts and Telecommunications (Grand No. 2021Y011） and the Fundamental Research Funds for the Central Universities (2019XD-A04).

References

Cadwell, P., O'Brien S., & Teixeira C. S. C. (2018). Resistance and accommodation: factors for the (non-) adoption of machine translation among professional translators. *Perspectives*, *26*(3), 302-321.

Chai, C. S., Koh, J. H. L., & Tsai, C.-C. (2013). A Review of Technological Pedagogical Content Knowledge. *Educational Technology & Society, 16*(2), 31-51.

Doherty, S., & Kenny, D. (2014). The design and evaluation of a Statistical Machine Translation syllabus for translation students. *Interpreter and Translator Trainer, 8*(2), 295-315.

Flanagan, M., & Christensen, T. P. (2014). Testing post-editing guidelines: how translation trainees interpret them and how to tailor them for translator training purposes. *Interpreter and Translator Trainer, 8*(2), 257-275.

Guerberof, A. A. & Moorkens J. (2019). Machine translation and post-editing training as part of a master's programme. *Journal of Specialised Translation,* (31), 217-238.

Jia, Y., Carl, M., & Wang, X. (2019). How does the post-editing of neural machine translation compare with fromscratch translation? A product and process study. *Journal of Specialised Translation,* (31), 60-86.

Lee, S.-M. (2020). The impact of using machine translation on EFL students' writing. *Computer Assisted Language Learning, 33*(3), 157-175.

Loock, R. (2020). No more rage against the machine: How the corpus-based identification of machinetranslationese can lead to student empowerment. *Journal of Specialised Translation,* (34), 150-170.

Macaro, E., Handley, Z., & Walter, C. (2012). A systematic review of CALL in English as a second language: Focus on primary and secondary education. *Language Teaching, 45,* 1-43.

Man, D., Mo, A., Chau, M. H., O'Toole, J. M., & Lee, C. (2020). Translation technology adoption: evidence from a postgraduate programme for student translators in China. *Perspectives-Studies in Translation Theory and Practice, 28*(2), 253-270.

Mellinger, C. D. (2017). Translators and machine translation: Knowledge and skills gaps in translator pedagogy. *Interpreter and Translator Trainer, 11*(4), 280-293.

Ortiz-Boix, C., & Matamala, A. (2016). Post-editing wildlife documentary films: A new possible scenario? *Journal of Specialised Translation,* (26), 187-210.

Rodriguez-Castro, M. (2018). An integrated curricular design for computer-assisted translation tools: developing technical expertise. *Interpreter and Translator Trainer, 12*(4), 355-374.

Rodriguez-Ines, P. (2013). Electronic target-language specialised corpora in translator education Building and searching strategies. *Babel-Revue Internationale De La Traduction-International Journal of Translation, 59*(1), 57-75.

Schuster, M., Johnson, M., & Thorat, N. (2016, November 22). Zero-shot translation with Google's multilingual neural machine translation system. Google Research Blog. Retrieved from https://research.googleblog.com/2016/11/zero-shot-translation-withgoogles.html

Sinhal, R., & Gupta, K. (2014). Machine Translation Approaches and Design Aspects. *IOSR Journal of Computer Engineering*, *16*, 22-25.

Tsai, S.-C. (2019). Using google translate in EFL drafts: a preliminary investigation. *Computer Assisted Language Learning, 32*(5-6), 510-526.

Yamada, M. (2019). The impact of Google Neural Machine Translation on Post-editing by student translators. *Journal of Specialised Translation,* (31), 87-106.