IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Translators In Transition: Assessing Sustainability And Competence In The Shifting Landscape Of Translation Professions In Response To Machine Translation Advancements

[1]Dr. Poulami Roy

[1]Assistant Professor
[1]Department of English,
[1]Netaji Nagar College, Kolkata, India

Abstract: The profession of translation has undergone changes due to the advancements in machine translation systems in recent years. As a result, translators are now expected to take on new roles and acquire new skills. While working on source texts, translators often encounter raw outputs generated by machine translation systems during the translation process. Thus in settings where machine translation is utilized, translators are required to post these outputs based on predefined criteria. This differs considerably from translation workflows where translators start from scratch with the source text. The level of editing can vary depending on the clients' expectations and the intended purpose of the text. Consequently, there is an increased emphasis on the skills and competences that translators must possess. In this article, the aim is to explore how the role of translators has evolved within the context of their competences, considering advancements in machine translation systems. The article further evaluates the skills needed for translators and post editors, and examines the necessity to redefine translator competences in light of the evolving roles translators have in an era where machine translation systems play a role.

Index Terms – **Translator-competence, Machine-translation, Profession, Sustainability, Translation market, Employability**

I. INTRODUCTION

The needs for communication and translation are currently changing. These developments are altering the roles of translators and interpreters as well as the work environments in which they practice their profession. They are being brought about by the growing internationalization of business, the creation of new forms of communication in ever-increasing digital environments, and especially the advancement of new technologies. It is vital to investigate new career paths and job search strategies where the human element is not only desirable but crucial in an era of increasing automation, where the survival of translation as a long-term human activity is being questioned (Calvo 2010). This circumstance affects training since it could include, on the one hand, expanding and redefining the duties and responsibilities expected of interpreters and translators (Angelone 2018), and on the other hand, allowing students to identify market niches to which they can apply. The process, profession, and outcome of translation have all seen significant changes in recent years due to advancements in translation technologies. Prior study has examined these effects and provided a comprehensive review of the current state of translation (Alcina, 2008). It appears that fewer studies (Pym, 2011) have provided predictions for the translation's future. Additionally, a review of the pertinent literature reveals that the majority of studies have concentrated on computer-aided translation, also known as the Translator's Workbench, which primarily uses Translation Memories (TMs) and Term Bases (TBs). However, since machine translation systems have improved in terms of translation quality, particularly in the 2010s, the focus of attention has shifted to these systems. Regarding this, past studies have demonstrated that in addition

to experts, beginners or trainees, machine translation engines are being used by translation students more and more (Korošec, 2011). It should be highlighted, however, that machine translation is still not entirely embraced by experts or adequately comprehended by novices. In this sense, Yuste (2001) called attention to trainees' misconceptions about machine translation systems and cautioned that, in the early 2000s, students' preconceptions about these systems should be dispelled through a learner-centered, pragmatic, and realistic approach. Ten years later, Korošec (2011) noted that students were using Google Translate more frequently and cautioned that they might not be aware of the benefits and drawbacks of machine translation. Similar to this, Flanagan & Christensen Paulsen (2014) recognized the necessity of teaching post-editing to translation trainees in light of the growing tendency and interest in machine translation systems, but they also emphasized the absence of uniformed guidelines for use in translator training programmes.

II. TRANSLATION INDUSTRY DYNAMICS: NAVIGATING EMPLOYABILITY AND ENTREPRENEURIAL ACUMEN

Entrepreneurship and entrepreneurial competence are closely associated concepts with employability. Entrepreneurship, which was once included in general business and economic studies, is typically connected to problems that are specifically related to starting new businesses, reviving old ones, and encouraging the innovative attitude that is necessary for advancement. Training in entrepreneurship has often been provided by business schools. But when seen through the lens of education, entrepreneurial skills have far more to do with initiative and adaptability than simply helping to launch new businesses, creative projects, or create jobs. For this reason, employability policies as they currently exist, mandate their inclusion in non-business fields like the humanities.

In the past few years, there has been a growing emphasis on narrowing the division between university education and professional application. This emphasis revolves around enhancing employability, a term often defined as the capability to secure meaningful initial employment, pursue self-employment, sustain ongoing employment, and navigate the labor market. Despite the common interchangeability of employability and employment, as highlighted by Rodríguez (2017), it is crucial to recognize that these two concepts carry distinct meanings. Therefore, employability should be viewed as a comprehensive process, not merely as a straightforward employment track record (Rodríguez, 2017).

Professional translation services are typically linked to written results. Nonetheless, in the highly multimodal digital world of today's information society, spoken mode should not be disregarded. Since various studies already stated that one modality can teach us about the constraints, conventions and norms of the other, in the context of interpreter training, it is therefore worthwhile to investigate the issues in translator training that address these modalities, spoken included. This implies that sight translation, which serves as a transitional tool between oral and written translation, ought to be given more weight in both professional translation and translation education. Some of the key components of entrepreneurial competence include understanding the labour market, having confidence in one's own skills, knowing how to seize chances, creating a demand for one's services and offering additional value, being adaptable and showing initiative. This is why, as Galán-Mañas (2018) suggests, entrepreneurial competence fosters not only the start-up and self-employment of businesses, but also the development of transversal skills, the ability to adapt to a changing market, and even the management of both personal and professional life.

III. FROM MANUAL TO AUTOMATED: UNDERSTANDING THE INDUSTRY SHIFT WITH MACHINE TRANSLATION

The last few years have seen significant changes in the language services industry as a result of ongoing technology advancements that have been incorporated into processes for translation and localization (ELIS, 2022). These days, the first tool that springs to mind when discussing translation technology is one that has either recently made news or been at the core of the major disputes voiced on social media: Machine Translation (MT). To be able to explain the stated quality advances in today's machine translation engines, it is necessary to address the historical developments in machine translation. In this sense, it is well known that the first machine translation engines were created as Rule-based systems that operated on only language rules. But until the last ten years, corpus-based approaches gained traction due to the acquisition of huge data, which included bilingual or multilingual texts, and the use of corpus tools to align these texts. Both academic and professional research have made use of these previous methods to some degree. Nonetheless, it may be argued that machine translation engines were not well known until 2016 following Google's announcement of a novel strategy known as Google Neural Machine Translation (Reichert, 2016). Neural Machine Translation is distinct from its statistical predecessors, although sharing the usage of aligned texts, as it is specifically engineered to operate on neural networks (Forcada, 2017). In addition to integrated machine translation (MT),

other tools that help with translation include computer-assisted translation tools (CAT), which employ digitalized term bases, translation memories, and integrated MT to speed up and ease the translator's work (Garcia, 2014). These technologies are used, for instance, when a client uploads a file requesting a quote for a translation utilizing AI-powered platforms. Through this process, the format, the text's specialist domain, and its word count are identified. In a scenario in which a customer fails to provide a glossary for a job involving a machine translation system, the engine may still be able to accurately translate the terminology provided by the client if there are numerous instances of the terms' proper translations in the parallel corpus. The machine-learning methods enable patterns to be identified that show the probability that a target word or phrase is the translation of a specific source word or phrase, just like with normal lexical items. These are ultimately stored in the phrase-table for easy access during decoding. Naturally, machine translation (MT) is far faster than human translation. While it is generally acknowledged that human translators can translate 2,500 words on average per day, machine translation (MT) engines can do the same throughput in about sixty seconds, making MT a useful tool for translation projects requiring rapid turnaround times. MT can produce translations along with a confidence score, which indicates how accurate the translation is based on its knowledge. The quantity of training data required to seed an MT engine is always limited, therefore no matter how big the amount is, the MT engine is unlikely to ever have full lexical coverage of the documents that need to be translated. MT system developers frequently report these objects—known as out-of-vocabulary items—as a critical sign of the likelihood that the system will be able to translate the documents that it encounters effectively. These elements, which are absent from the training set but present in the test set, are referred to as 'out-of-vocabulary' items, and MT system developers frequently cite them as a crucial sign of the system's propensity to translate documents correctly. A few recent studies have addressed translation quality in machine translation systems in the context of speed and productivity advantages. It goes without saying though, that machine translation is still in need of human aid during both the pre- and post-production phases. Because of this, before any translation project is considered finished and sent to the client or the initiator, the machine translation outputs need to be edited by a person. Post-editing is a new area of practice and research that has emerged as a result of this necessity. The correction of a translation result produced by a machine translation engine is the definition of post-editing given in one of the first studies (Allen, 2003). Regarding the categories or levels of post-editing, there exist two types: light post-editing and full post-editing, also referred to as partial or complete post-editing, respectively. The distinction lies in the fact that light post-editing involves editing minor errors, whereas full post-editing entails the detection and correction of both minor and major errors. Determining the appropriate level of post-editing is contingent upon the intended purpose of the translation. However, the selection of the right option can pose challenges, with the translator or post-editor often navigating a balance between the client's quality expectations and the compensation for the work. In such situations, it becomes essential for translators or project managers, if involved, to inquire about the purpose of the translation from the client or initiator before commencing any post-editing task. Relatively large business companies possess the operational and logistical strength to integrate new language technologies into their workflows, like AI-powered supplier management, neural machine translation, and other technological solutions, which are out of the reach of small businesses and can increase their profits and revenue through automation. As it has been seen, the majority of the language services industry is made up of freelancers, who have even more challenges when it comes to implementing these new technologies. To reduce expenses, companies might put more money into automating workflows. Nunes Vieira (2020) made the following suggestion: translators are not scared of technology in and of itself, as they frequently utilize it; rather, they are afraid of the ways in which big businesses utilize technology for their own specific benefit and the potential effects this may have on their working conditions. This highlights the concern of whether dubious business practices or technology pose a threat to the translating profession.

IV. BEYOND AUTOMATION: RECOGNIZING THE UNIQUE STRENGTHS OF HUMAN TRANSLATORS

To the best of our knowledge, no MT developers of cutting-edge engines in academia can be accused of inflating their performance, even though MT capabilities are frequently overstated in the commercial world. Yet, some translators enjoy showing off the areas where machine translation fails, frequently with amazing outcomes. The reality about MT's capabilities rests somewhere in between these two counterproductive extremes, even while we agree that it is not and never will be flawless.

However, some of the factors that lead to MT's underperformance are also those areas that make humans shine. Because of this, it may be difficult for a layperson to comprehend just why MT commits the kinds of mistakes that it does. There are some types of translations that human translators routinely produce, but which

machine translation is presently incapable of doing. Naturally, because MT lacks 'real world knowledge', it can only translate syntactically. Kay (2014) defines the Syntactic Model of Translation as memorizing short translations (lexical items), which can be rearranged, and a long translation is a series of short(er) translations. Moreover, human translators possess the expertise to generate high-quality texts even when the original content is poorly written, illogical, ambiguous, contradictory, or inconsistent. This frequently occurs in a globalized context where English serves as the lingua franca, compelling authors to produce texts in the language, even without the requisite skills. In many instances, English documents may not be the original source language but have undergone translation through a third-party language, whether by a professional translator, an inexperienced translator, an unqualified translator, or via machine translation. Professional translators deliver translated texts that accurately express the meaning, capture textual nuances, follow grammatical standards, and even take on unique spellings at the clients' request. Additionally, any discrepancies in the translation have the capability to have been found and fixed already. A text's contradictions and inconsistencies can be easily spotted by human translators, thanks to their trained eyes and well-tuned reading skills. In order to prevent conflicts, experienced translators are able to discreetly point out mistakes to their clients. It is evident that human translators produce a finished result rather than a by-product, as machine translation (MT) typically produces, when viewed through a language lens. By crafting a new final text in a foreign language for a particular new audience, translators, who are also accomplished writers, recreate meaning. Because the final result has been provided, the target text can be relied upon, negating the need to invest further time and funds. On one side of the language pair, the majority of MT engines developed to date have English. It is well known that, from a syntactic standpoint, translating from MT into English is usually always easier than translating from English since MT is somewhat morphologically impoverished, making lexical selection of verbal and nominal forms with the same roots considerably easier. MT faces a significant challenge when determining pronominal referents to choose the most appropriate translation for circumstances when there is no gender differentiation. Prior until recently, all machine translation (MT) systems translated a sentence at a time without taking context into account. This obviously is not how people understand language, either when they are monolingual or translating. Consequently, MT can never reliably interpret extra-sentential pronominal referents in a right manner. For even similar-structured languages, MT struggles to distinguish between meanings. Given that it lacks both plural and conjugation, Chinese is an excellent example of a language where ambiguity is ingrained. The incredibly basic nature of Chinese grammar contributes to its confusion. Human translators, as opposed to machine translation, can ensure a high-quality translation for languages with highly dissimilar structural patterns because they can preserve or clarify ambiguities when necessary, delete superfluous information, and categorize the text in a meaningful way. Part of the problem with MT development and enhancement has been reducing translation to essentially a two-language mastery task. Proficiency in critical reading, pragmatism, and the ability to take into account extra-textual elements like context, the author's intentions, the receivers' expectations, ceremony conventions, and much more are necessary for successful translation. Machines and humans operate and 'think' differently. This does not imply that they cannot be reconciled; on the contrary, programmers and computational linguists may be able to merge the two methods of information processing once they have gained more translation expertise. Explicit and implicit memories work best together. Given MT's rapid information processing speed, human translators stand to gain a great deal from it if computational linguists collaborate closely with translators, take text genres into account when building data sets, and go much farther than they have in the past in adopting both a semantic and a cognitive approach.

V. CONCLUSION

'Communication' will be the most sought-after personal talent in the future, predicts Coursera (2022). This is consistent with the current analysis, which ranks digital marketing, e-commerce specialists, and digital content creation at the top of the list of possible industries. For people in the language services market, the industry's increased turnover is also very positive news. Despite the pivotal role linguists play in the development and evaluation of Machine Translation (MT) systems, and the ongoing collaboration of human translators in research and development, a paradox emerges in post-editing. Even though studies demonstrate that translators are considerably faster in post-editing compared to translating from scratch, they consistently report a perceived decrease in speed. This discrepancy is influenced by various factors such as stress, fear, pride, knowledge, satisfaction, and financial considerations (O'Brien 2014). The reluctance of some human translators to embrace MT in their daily work stems from a sense of threat posed by automation. However, it is evident that MT has not yet reached the same level of quality as professional human translators, and post-editing may lack the intellectual stimulation found in translating from the ground up. In reality, human translators are primarily concerned with the lack of recognition and understanding of their profession in a globalized context where

multilingual communication is crucial for humanity, despite the consensus acknowledging that MT falls short of the capabilities of human translators. With the advent of new professional profiles and training, it is possible to view any threat as potentially present opportunity. It is possible to identify various sectors with notable growth that are anticipated to become more relevant in the near future by analyzing the effects of digitalization and automation on the language services industry and looking at the various fields that the current market is targeting. Furthermore, when it comes to technology, those working in the language services sector have three options: resistance, collaboration, or reinvention. Accepting cooperation and innovation must be the best course of action going forward. To reject technology and launch an anti-AI and anti-MT campaign is absurd. Even before it begins, that campaign is an unwinnable conflict. Training for fields that will become more and more relevant in the future is therefore the answer. More importantly, it is time to go beyond the one-size-fits-all model of translation, especially when it comes to literary translation and the various responsibilities that translators play outside of 'just' translating, like those made possible by digital publishing. Given that technology is one of the primary forces transforming the profession through the advancement of machine translation and the emergence of new workflows, more research into the function of technology and its effects on professionalization would be captivating.

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