Different Attitudes towards MT in the Translation Industry: A Study on the Opinions of Translators and Project Managers

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Abstract

The purpose of this thesis was to find out whether the potentially opposing views of professional translators and project managers on the use of machine translation (MT) might cause tensions in the industry and disrupt working relations. By conducting two questionnaires, which were altered to fit the profession of project managers and professional translators respectively, on the attitudes and beliefs on the use of MT and machine translation post-editing (MTPE), this thesis offers an analysis of both questionnaires individually and a mutual comparison. This thesis argues that the conflicting views on the use MT of project managers and professional translators is rooted in misunderstandings of the effort it takes translators to perform MTPE. The current study offers new insights into the attitudes and beliefs of both professional translators and project managers on the use of MT and creates a new research space for further research.

Key words: Machine Translation, Post-editing, Translators, Project Managers, Survey

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The process of writing this thesis has been challenging and involved a lot of procrastination, stress, and self-doubt. Looking back at it, I can only be incredibly proud of what I have created. However, I am aware of the fact that I would not have been able to do any of this, without the help and support of some truly wonderful people.

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Chapter 1. Introduction

"It is staggering how people who call themselves text professionals refuse to see how much time, effort and money is lost when using machine translations as textual basis. It is no less staggering to see co-workers accept the ridiculous notion that a job will pay less while it is more time-consuming and much more of an effort." (Anonymous translator, personal communication, May 15, 2021)

This direct quote, from one of the translators that participated in this study, illustrates an opinion that is shared by many other professional translators, as recent research shows (Groves and Mundt 2021; Koehn 2020; Sánchez-Gijón et al. 2019; Läubli et al. 2016). Translators have been voicing their concerns regarding the use of machine translation (MT) ever since it was first introduced in the professional translation industry in the 1950s. However, it seems that their opinions are not being heard, as machine translation is still gaining popularity in the translation industry. Recently, this rise in popularity can mostly be traced back to the launch of neural machine translation (NMT) in 2015, which led to a considerable increase in quality, and the introduction of human post-editing (PE), which is marketed as an inexpensive and productivity-boosting alternative to completely human translations. PE regards the correcting and editing of MT output in order to create a text that is qualitatively equal to that of a human translation. Though it seems to be a helpful solution to the ever-growing translation demand, translators have stated their dislike for MT and MTPE, and several studies have already shown that this is caused by a multitude of things, including falling pay rates, a decrease in productivity and even a fear of being replaced (Moorkens et al. 2016; Cadwell et al. 2017).

From personal experience, I have learned that there is generally little consideration from translation agencies for translators who do not work with MT, regardless of whether this is because of negative past experiences or a fundamental bias against MT. This disregard could actually result in a clash between the translation agencies and their translators, as the agencies keep expecting the translators to adhere to their needs and work with MT, regardless of the translators' views. I believe that the attitudes of translation agencies, specifically project managers, towards the use of MT may in fact be part of the reason why translators generally have a negative attitude towards MT, as it suggests a misunderstanding of the effort involved in MTPE. However, the existing research on the attitudes of translation agencies towards the use of MT (Torres-Hostench et al. 2016) does not include a comparison to the attitudes of translators and how possible differences might create tensions in the industry.

The aim of this thesis was therefore to find out whether professional translators and project managers have opposing or conflicting views on the use of MT and MTPE, which may disrupt their working relations. This thesis investigated this issue by conducting a survey providing data on the attitudes and beliefs towards the use of MT of both professional translators and project managers working for translation agencies. This data was collected using two surveys, one for each stakeholder group. More specifically, the survey for project managers focused on the ways in which they use and work with MT in their profession and asked questions regarding the ways in which they offer MTPE assignments to translators. Similarly, the survey for translators focused on the ways in which they use and work with MT in their profession and asked questions regarding the ways in which they receive MTPE requests from project managers. The questions asked in both surveys will ultimately provide information on the individual perception of both groups on the use of MT. A comparison of these results will provide insights into the specific differences existing between translators and project managers and their views regarding the use of MT in the professional translation industry, allowing for an analysis on how these differences might affect their working relations.

By involving project managers in a study on the different attitudes towards MT in the translation business, this thesis explores new data and provides new insights into the mutual experience of MT between translators and project managers. To the best of my knowledge, previous studies on the attitudes of translators towards MT have been limited to show only one side of the story, by either focussing on professional translators and translation students only or focussing only on translation agencies. By exploring the perceptions of both translators and project managers, this thesis aims to find out whether the different perceptions on MT of professional translators and project managers working for translation agencies cause tensions in the industry.

This thesis consists of five chapters, including the introduction as chapter 1. The second chapter establishes the theoretical framework of this thesis, providing an overview of the history of MT, discussing the evolution and different types of MT, defining post-editing and its benefits to MT, and finally, discussing previous research on the attitudes of translators towards MT. Chapter 3 establishes the methodology used in this this and provides an in-depth discussion on why and how this thesis uses surveys as a research method. Following the analysis, chapter 4 provides a discussion and analysis of the results of this study. Chapter 5 concludes this thesis with a brief summary of the contents of this thesis, a discussion of the results, and an answer to the question: Do the different perceptions of MT and MTPE of professional translators and project managers working for translation agencies cause tensions in the industry?

Chapter 2. Machine Translation

2.1 Introduction

This chapter will provide an overview of the theoretical background to the current study on machine translation (MT) and post-editing (PE) and translators' experiences with MT and PE. Section 2.1 will discuss the history of MT, providing a timeline of the most important events regarding MT. Section 2.2 will discuss the different types of MT from the 1930s until today. The theory behind post-editing and the way in which it is used today will be discussed in section 2.3. Finally, section 2.4 will discuss previous research on the experiences and opinions of translators working with MT and post-editing.

2.2 The History of MT

The general interest of linguists in MT started even before the invention of the computer and goes back as far as 1933. In that year, engineers Artsruni and Trojanskij individually worked on the automatic transfer of words from one language to another, using machines. Artsruni invented the "mechanical brain": a machine that could retrieve the target language equivalent of words and word combinations from the source language (SL) using a target language (TL) dictionary and replace those SL word combinations with TL word combinations (Vasconcellos 19881). Unfortunately, the machine did not meet its maker's expectations and proved to be inadequate. Trojanskij proposed a similar machine, as he envisioned a semi-automated translation process. According to Michael Zarechnak, this translation process can be divided into three basic steps: analysis, transfer, and synthesis. First, the source text had to be analysed and transformed into a logical form, meaning that all inflections are represented canonically; verbs are represented in the infinitive, nouns are represented in the nominative case, etc. Trojanskij called these syntactical functions "marks of the logical analysis". After that, the source text would be replaced by the target text (transfer), likewise by the marks of the logical analysis. The final step would be the replacement of all these logical analysis marks into their correct grammatical form in the target text (synthesis). The analysis and synthesis had to be carried out by people, while the only function of the machine was the transfer of one language into another. In Zarechnak's words, "Trojanskij's translation machine was an automatic dictionary which required pre- and post-editing by an editor" (Zarechnak 1979, p. 8). Unfortunately, the technical support needed for Trojanskij's translation machine to be a success did not exist until the emergence of the electronic computer (Zarechnak 1979,).

The famous 1949 memorandum of Warren Weaver created a big interest in machine translation and resulted in more research on the subject. According to Zarechnak, Weaver wrote his Memorandum based on four assumptions, specifically:

1. There is a vital need for contributing toward the worldwide translation problem.
2. The meaning of words of polysemic nature could be uniquely identified within a sufficiently large context.
3. Computers with large capacity and speed are useful tools.
4. The presence of linguistic universals could be subjected to logical analysis for identifying the common features in all language structures. (Zarechnak 1979, p. 11)

Decades later, Hutchins refers to this memorandum as "perhaps the single most influential publication in the earliest days of machine translation" (Hutchins, 2000, p. 17). According to Taube (1961), Weaver's memorandum highlights three essential messages: First, it provides logical proof for the possibility of machine translation. Second, it emphasizes how dependent the translation machine is of the meaning of the context. Finally, Taube argues that the memorandum expresses Weaver's trust in computers to fulfil the task of translating, since they proved to be very effective in cryptographic deciphering during WWII.

The possibility to incorporate computers in the automation of translation ensured the first real translation machines to be built and demonstrated to a greater public as soon as 1954. In that year, Léon Dostert directed a machine-translation project at Georgetown University in cooperation with the IBM Corporation, where a sample of Russian sentences was translated into English with the use of a very limited vocabulary, consisting of only 250 words and six grammar rules (Hutchins 2006). This experiment confirmed the possibility and feasibility of an operational translation machine (Zarechnak 1979). Research on machine translation drastically increased in the years after the Georgetown IBM experiment and the first book on machine translation was published within a year of the experiment (Locke and Booth 1955). However, after a decade of optimism, curiosity and research, developments stagnated as researchers were continuously confronted with the linguistic complexities involved in the process of creating and improving MT systems. Linguist Bar-Hillel argued that the expectations of MT were too high and that the vision of creating fully automatic MT systems that could produce the same quality as professional human translators was essentially impossible (Hutchins 2006). As a reaction to the discouraging reports, sponsors such as the military and intelligence agencies, required certainty on the benefits of their funding on actual developments. In 1966, the Automatic Language Processing Advisory Committee (ALPAC), initiated on request of National Science Foundation (NSF), issued a report called "Languages and Machines: Computers in Translation and Linguistics", in which they exclusively evaluated the use of MT to fulfil the needs of the US government and US military, regarding deciphering Russian documents and "was not concerned in any way with other potential uses or users of MT systems or with other languages" (Hutchins 2003, p. 131). The report stated that "MT was slower, less accurate, and twice as expensive as human translation" (Hutchins 2006, p. 377) and recommended that funding should be given to research on computational linguistics and mechanical tools that would assist human translators in translation. The influence of the ALPAC report was astronomical and government funding stopped immediately. Fortunately, research still continued unfunded and in 1968, only two years after the infamous ALPAC report, Systran (System Translation) was founded. The first generation of Toma's Systran was a direct translation system, which was used from 1970 onwards by the US Air Force (Anastasiou 2010). Other commercial translation systems like Logos and METAL followed in the 1980s (Koehn 2020).

Further developments in MT regarded the rise of computer aided translation systems, meant to assist human translators in the translation process. Moreover, as Hutchins states, "the Internet has had a major impact since the mid-1990s" (2006, p. 382), which manifested in the rise of statistical and neural machine translation models. These will be further discussed in the following section.

2.3 Types of MT

Machine translation has known many shapes and forms before becoming the automated data-driven system we know and use today. Generally, the evolution of MT can be divided into four types of MT, respectively: Rule-Based Machine Translation (RBMT), Example-Based Machine Translation (EBMT), Statistical Machine Translation (SMT) and finally, Neural Machine Translation (NMT).

2.3.1. RBMT

RBMT was the first type of MT and was also used during the 1954 Georgetown University IBM machine translation experiment. This system operates based on pre-programmed linguistic and grammatical rules (grammars) and unilingual, bilingual, or multilingual dictionaries (Anastasiou 2010). As Sreelekha (2017) states, RBMT is an MT system based on the human input of linguistic rules and bilingual or multilingual dictionaries. These resources include, but are not limited to, grammar analysers and generators, part-of-speech taggers, syntax analysers, bilingual dictionaries, transfer rules and reordering rules (Sreelekha 2017). There were three approaches to the use of this system, namely: the direct translation approach, the transfer approach, and the interlingua approach. The direct translation approach to RBMT consisted of a system that was created for one specific language pair, and according to Hutchins (1995), such systems must be bilingual and unidirectional, meaning that the translation only works in one direction: from one specific SL to one specific TL. The direct translation approach consisted of a system that was created for one specific language pair. In his explanation of the direct translation approach, Hutchins (2006) states that large bilingual dictionaries were compiled and stored in a memory device, "in which lexicographic information was used not only for selecting lexical equivalents but also for solving grammatical problems without the use of syntactic analysis" (p. 376). Thus, the analysis solely regards "the resolution of ambiguities, the correct identification of TL expressions and the specification of TL word order" (Hutchins 1995, p. 432). Naturally, such a superficial analysis cannot guarantee a perfect or smooth TL representation of the original text, and thus this system could only satisfy basic information needs.

The second approach to RBMT is the interlingua approach, designed to extract independent language representations from the SL text and convert it into representations of more than one TL, thus "achieving a higher accuracy than comparable linguistic methods" (Alsohybe et al 2017, p. 7). Hutchins (1995) explains that the translation process takes place in two stages: first, extraction from the SL text and translation into the interlingua (IL). Second, the conversion of the IL into a translation in the TL. The interlingua would have to be an "artificial language, an auxiliary language (...), a set of semantic primitives presumed common to many or all languages, or a 'universal' language-independent vocabulary" (Hutchins 1995, p. 432). Selecting or creating an interlingua would thus be such a complex task, that most research on interlinguas was mainly theoretical (Hutchins 2006).

The third approach to RBMT is the transfer approach, which, in contrast to the direct translation approach, relies heavily on syntactic analysis. In that respect, the transfer approach is more similar to the interlingua approach. However, while the interlingua approach consists of two stages of translation, the transfer approach consists of three. First, the SL sentence structure is analysed to determine the grammatical structure of the SL text. The SL text gets converted into conceptual SL-representations, which Alsohybe et al. (2017) refer to as an "intermediary structure". In the second stage, these SL-representations are converted into corresponding TL-oriented representations. Finally, in the third stage, the TL representations are converted into TL texts, which make up the final product of translation. In contrast to the two previous approaches, this system uses three dictionaries: a monolingual dictionary of the SL in stage one, a bilingual dictionary of both the SL and TL in stage two, and another monolingual dictionary of the TL in the final stage (Alsohybe et al 2017). Bernard Vauquois' pyramid perfectly illustrates the three different approaches to RBMT. As can be seen in figure 1, it illustrates how direct translation is a one-step-process, as the source text is (ST) directly translated into the target text (TT), whereas the interlingua approach requires not an analysis after which the source text is converted into the interlingua and then converted into the target text after generating equivalent TL representations. The transfer approach is very similar to this method, however, it does not require an interlingua, but rather analyses the ST and directly generates TT output.

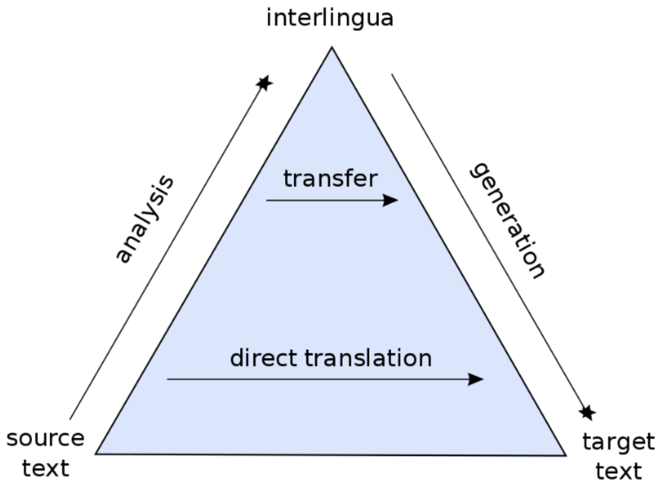

Figure 1. Bernard Vauquois' pyramid, illustrating the different approaches to RBMT (Vauquois 1968)

2.3.2. EBMT

From the 1950s until the 1980s, Rule-Based Machine Translation ruled the field as dominant MT system. However, in the early 1980s, researchers moved on from pre-programmed systems based on grammars and dictionaries to EBMT, a corpus-based machine translation system (Somers 1999). First and foremost, a corpus-based system needs a parallel aligned corpus, meaning a corpus in which source texts are presented together with their translations (or: target texts) and that the ST and TT "have been analysed into corresponding segments; the size of these segments may vary, but typically corresponds to sentences" (Somers 1999, p. 150). Nagao refers to EBMT as "machine translation by example-guided inference" and explains the phenomenon as follows:

> Man does not translate a simple sentence by doing deep linguistic analysis, rather, Man does translation, first, by properly decomposing an input sentence into certain fragmental phrases ..., then by translating these phrases into other language phrases, and finally by properly composing these fragmental translations into one long

> sentence. The translation of each fragmental phrase will be done by the analogy translation principle with proper examples as its reference. (Nagao 1984, p. 178)

According to Somers (1999), Nagao was able to identify the three principal elements of EBMT, specifically: "matching fragments against a database of real examples, identifying the corresponding translation fragments, and then recombining these to [construct] the target text" (p. 116). EBMT is often compared to the Translation Memory (TM), as both are based on an example database and reuse existing translations. However, Somers argues that the systems are inherently different, since "TM is an interactive tool for the *human* translator, while EBMT is an essentially *automatic* translation technique or methodology" (p. 115). Though Vauquois' pyramid was originally aimed at the translation process of RBMT, Somers adapted the pyramid to illustrate the process of EBMT. Somers (1999) argues that the *analysis* of Vauquois' pyramid can be replaced by the term *matching*, as the first step of the EBMT process is not to analyse the ST, but to match the ST to examples in the corpus. Furthermore, he states that, rather than *transferring* SL content to TL content, EBMT is programmed to *align* SL segments to corresponding TL segments, using the selected example sets from the bilingual corpus. Finally, Somers states that the TL segments must be *combined* again to form a correct and complete target text, in contrast to RBMT where interlingua or TL representations are *generated* into a target text.

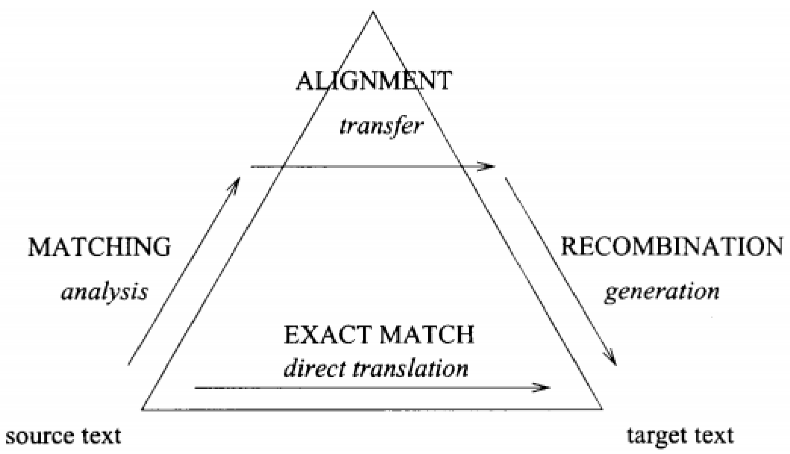

Figure 2. Vauquois' pyramid, adapted for EBMT. The traditional labels are italicized, and the EBMT labels are capitalized (Somers 1999, p. 117).

2.3.3. SMT
Within a decade of the first use of EBMT, researchers had already developed a new MT system: SMT. Though both systems are data-driven, SMT uses different types of data. While EBMT uses only a bilingual dictionary, SMT uses both a bilingual and monolingual

dictionary. Moreover, as Anastasiou states, "EBMT is distinct from SMT in that it contains symbolic translation knowledge and is not numeric in the form of a distortion and fertility probability model (by combining all parameters in the most likely manner) as SMT is" (2010, p. 22). According to Lopez (2008), SMT systems distinguish themselves from other systems through their use of machine learning methods. He further clarifies the process behind the machine learning methods as follows: "SMT treats translation as a machine learning problem. This means that we apply a learning algorithm to a large body of previously translated text, known variously as a parallel corpus (...). The learner is then able to translate previously unseen sentences" (Lopez 2008, p. 2). According to Och and Ney (2004), the use of SMT has recently drastically improved the quality of research systems." As Koehn states, "In statistical machine translation, we use both a translation model and a language model, which ensures fluent output" (2010, p. 7).

The first generation of SMT models were word-based models. In this model, words are seen as "atomic units that may be translated, inserted, dropped and reordered" (Koehn 2010, p. 6). On a word-based level, parallel corpora provide inadequate information as they are programmed to align source and target sentences, rather than words (Koehn 2010). The "disclosure of the word alignment algorithm based on expectation maximization" (Banik et al. 2020, p. 190) that followed as an answer to the alignment problem, "computes the probability of possible word alignments and collects nouns and builds an improved model of these alignments" (Koehn 2010, p. 7). In other words, when creating a translation, "the most used [i.e., most probable] meaning of a word will be used to translate that word" (Alsohybe et al. 2017, p. 5).

The second generation of SMT models are phrase-based models, in which phrases are "any contiguous sequences of words, not necessarily linguistic entities" (Koehn 2010, p. 8). Koehn (2010) describes the process of phrase-based SMT (PBSMT) in three steps: first, the ST sentences are segmented into phrases, meaning any units of multiple words. Second, every individual SL phrase is translated into a TL phrase. Finally, the TL phrases have to be put in the right order to follow the correct sentence structure in the TL. Koehn furthermore argues that phrase-based SMT has many benefits over word-based SMT. Not only does PBSMT exclude the issues of having too many translation options to choose from, but ambiguities are also less likely to be mistranslated as PBSMT translates ambiguous words in their phrasal context, rather than translating them as individual words with more possible meanings. Moreover, as the SMT system is self-learning, large training corpora will enable the PBMT system to learn progressively longer phrases or even entire sentences. Subjectively, Koehn adds that he considers the PBSMT system to be simpler than the word-based system. Dabre et al. (2020) state that PBSMT, compared to RBMT "requires less linguistic resources and instead requires parallel corpora" (p. 23).

The third and most recent generation of SMT models are syntax-based models, which provide an essential solution to the word reordering issue that occurs with the use of PBSMT (Farzi et al. 2017). Post states that "a number of systems make use of target-language syntax in the translation model" (2010, p. 41), which serves as a helpful tool in the reordering of TL phrases and provides more accurate translation because of syntactic analysis of the TL output. Since syntax-based SMT goes beyond word- and phrase level structures and understands sentence structures, it can produce higher quality output, even for language combinations that involve a lot of word reordering (Alsohybe 2017).

2.3.4. NMT

The fourth and final main type of machine translation is NMT. This is the most recently developed and most commonly used MT system today. The main difference between SMT systems and NMT systems, is that NMT is an ever-learning system based on neural networks. As Sutskever et al. (2014) explain, SMT and NMT are similar, but not the same. NMT is a complex and self-learning system, whereas SMT is still mostly a pre-programmed system.

Wołk and Marasek (2015) further explain that NMT systems "often belong to the encoder-decoder family in which a source sentence is encoded into a fixed length vector, that is, in turn, decoded to generate a translation" (p. 2). Considering the efficiency of NMT over other MT systems, Bentivogli et al. (2016) state that "a large recurrent network trained for end-to-end translation is considerably simpler than traditional MT systems that integrate multiple components and processing steps (p. 257). In the words of Dabre et al. (2020) "Unlike classical statistical machine translation (SMT) systems, separate lossy components such as word aligners, translation rule extractors and other feature extractors are not required" (p. 2).

Other considerations are the user-friendliness of NMT versus older MT systems. Daems and Macken (2019) state that multiple studies have argued that NMT outperforms SMT. For example, in the 2017 study by Toral and Sánchez-Cartagena, it was found that NMT performed better than SMT in fluency, inflection and word reordering. Moreover, NMT output generally requires less post-editing effort and produced less morphological, lexical and word order errors than PBSMT (Bentivogli et al. 2016). As has been mentioned before, "The core components of neural machine translation are the encoder, which takes input words and converts them into a sequence of contextualized representations, and the decoder, which generates an output sequence of words" (Koehn 2020, p. 133). One of his concerns with NMT is that "Misinformation due to mistranslation is a significant concern with neural machine translation, which sometimes prefers fluency over adequacy to the point of completely distorting the output, so it has no confidence score relation to the input" (Koehn 2020, p. 20). Koehn even proposes his own adaptation of the Vauquois pyramid, aimed at the translation process of NMT.

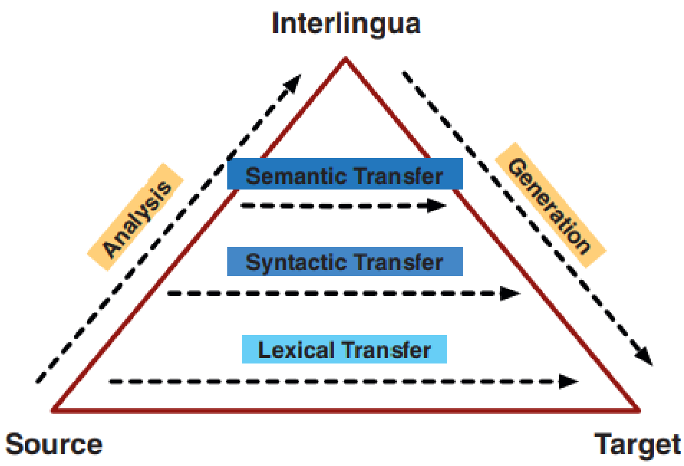

Figure 3. The Vauquois pyramid, adapted to NMT systems by Philipp Koehn (2020, p. 11).

In a fairly recent research, Wu et al. (2016) state that the strength of NMT is its ability to learn continuously and directly from the input and. NMT "typically consists of two recurrent neural networks (RNNs), one to consume the input text sequence and one to generate translated output text" (Wu et al. 2016, p. 1). Besides that, NMT makes use of Long Short-Term Memory (LSTM). However, despite its ability to keep on learning, NMT has some serious flaws, including "its slower training and inference speed, ineffectiveness in dealing with rare words, and sometimes failure to translate all words in the source sentence" (Wu et al. 2016, p. 2). Fortunately, Google's production NMT system GNMT has been designed to provide solutions for aforementioned issues. According to Antonio Toral and Andy Way (2018), NMT is particularly useful when translating literary texts, as "its performance seems to be especially promising for lexically-rich texts [...] which is the case with literary texts" and it should be able to find the cultural equivalent in different languages, rather than to do a literal translation (p. 2). Some conclusions that Toral and Way (2018) were able to draw after conducting research on the level of quality that can be attained by NMT on literary texts, are that NMT is indeed lexically rich and that the performance of NMT degrades with sentence length. According to García, though MT quality has significantly improved in many language combinations, MT output is still not considered qualitatively good enough to publish without the interference of a post-editor, with the exception of "some limited scenarios involving narrow domains, controlled languages and dedicated MT systems" (2016, p. 2). There is a lot of research arguing the feasibility of NMT from English to Spanish (Specia et al. 2010; Plitt and Masselot, 2010; Shterionov 2018), but it remains uncertain whether it is suitable for low-resource, languages. While Daems and Macken (2019) focused on the NMT output of medical texts from English into Dutch and were pleasantly surprised with how well NMT performed, Webster et al. (2020) were very dissatisfied with the results of their study on the NMT output of literary texts from English to Dutch. Other studies (Wołk and Marasek 2015; Bentivogli et al. 2016; Abu-Ayyash 2017) likewise showed the impact of text types on the quality of NMT output. Wołk and Marasek (2015) studied the use of NMT on medical texts, evaluated using statistical evaluation methods and found that "[NMT] shows promise for future automatic translation systems" (8). Unfortunately, they were not able to establish any solid conclusions as their research was fairly limited because of a lack of human evaluators of the NMT output. Bentivogli et al. (2016) and Toral and Sánchez-Cartagena (2017) produced comparable results as both studies focus on the translation evaluation of NMT output of public speeches. Both studies proved that NMT performed very well and required little post-editing effort. Surprisingly, a study by Abu-Ayyash showed that NMT has trouble with gender-based structures in technical texts in English and Arabic (2017). Though the NMT output gave satisfactory results in subject-verb agreement, the output was slightly problematic regarding adjectival-noun agreement, but very inconsistent and faulty regarding pronoun-antecedent agreement. Abu-Ayyash explains that the latter might occur because of the "huge discrepancy between English and Arabic in the pronoun system itself". Toral and Sánchez-Cartagena (2017) studied the NMT output quality of 9 language pairs, specifically: English into Czech, German, Finnish, Romanian, Russian, and Czech, German, Romanian and Russian into English. They concluded that though NMT performs well in fluency, inflection and reordering across all languages, but that NMT does not perform consistent output across languages and is lexically, still outperformed by SMT for the language combinations English-Romanian and Russian-English. Overall, the studies on NMT show that even though NMT generally performs better than its predecessors, it still is unable to produce the quality we expect from professional human translators, which is why post-editing is an important element of machine translating.

2.4 Post-Editing

In the words of Koehn, post-editing is the "crudest form of collaboration between machine and human" (2020, p. 21). It's a process whereby "the task of the post-editor is to edit, modify and/or correct pre-translated text that has been processed by an MT system from a source language into (a) target language(s)" (Allen 2003, p. 297), with the aim of "increasing translation productivity compared to unaided human translation" (Toral 2019, p. 1). Post-editors are usually experienced professional human translators, that have often been trained to perform post-editing tasks, since post-editing MT output is very different from revising human translations.

Post-editing effort can be measured using three different aspects: temporal, technical and cognitive (Jia et al. 2019, p. 10). Temporal effort is the time spent on the post-editing of MT output, technical effort regards the "mechanical operations" (Jia et al. 2019, p. 10), i.e., the actual correction actions that are involved in post-editing, and cognitive effort concerns the detection of errors and planning of corrections (Koponen 2016, p. 9). According to Krings (2001), the combination of these three efforts establishes whether or not MT output is acceptable. Jia et al. (2019)state that "The quality of the MT output is—without doubt—one of the key elements determining how much effort the post-editing task requires temporally, technically and cognitively" (p. 12). In their 2017 study towards the most common MT error types and their impact on post-editing effort, Daems et al. found that the most common errors in general were grammatical errors and adequacy errors, which manifested in errors in agreement, verb from, structure, word order, grammar, word sense, and other meaning shifts. The least frequent errors appeared in spelling and style. They found that coherence issues, other meaning shifts, grammar, and structural issues had the biggest impact on post-editing effort. In a similar research by Tezcan et al. (2019), accuracy (mistranslation) and fluency grammar were likewise the two main error types in MT output, which indicates that those two categories should be prioritized in post-editing and are determining factors for the estimated effort of post-editing.

According to García (2012), the ALPAC report was the reason for the development of post-editing of machine translation, as the report hinted at the improbability of a fully automatic machine translation system providing the same quality output as human translators and thus, post-editing MT output was the only way in which MT could be used. During the 1960s, post-editing was used on SMT systems by only two institutions: The US Air Force's Foreign Technology Division (FTD) and EURATOM. ALPAC considered the need of post-editing a failure of MT (Hutchins 2003, p. 133). According to García, MT and post-editing did not disappear completely after government funding stopped, but rather "retreated into more propitious environments where they were quietly pursued by institutions and enterprises that were beginning to computerize their operations" (2012, p. 296). New developments regarding the optimization of MT led to an increase in use of post-editing in general, since raw MT output was still not good enough to be published. Though post-editing was researched both theoretically and practically since the 1960s, it was not until the last decade that post-editing was performed on a large scale by the commercial language industry (García 2012). The main reason for this would be that "our technology is [only now] attaining the same sophistication as the initial ground-breaking thinking from the previous century" (García 2012, p. 306). For example, rather than post-editing SMT output, post-editing is nowadays performed on NMT output, which, according to Castilho et al. is a "significant step forward over a basic statistical approach" (2017, p. 110). Nevertheless, even NMT systems are not capable of providing near-perfect MT output, causing more post-editing effort. Therefore, pre-editing and "controlled language writing principle" are often used in combination with post-editing to "improve the translatability" and "speed up the productivity of the post-editing process", which has proved to be fruitful (Allen 2003, p. 298). In the words of Ignacio García:

> Machine translation development no longer involves mainframe computers and punch cards, but rides now on powerful computer processing and connectivity; translators no longer rely on dictation and typewriters, but on translation-memory software that can be supported by machine translation (and/or speech recognition, bringing back the dictation). (García 2012, p. 306)

Koponen (2016) rightfully argues that quality of MT output and the workability of post-editing are still rather unreliable, as MT is still not accommodated to all language pairs or text types. Though the use of MT and post-editing have already increased in the last decade, and thereby changing the role of both human translators and machines (Koponen 2016), is it unlikely that machine translation will eventually take over the field and put translators out of work, "based on the current knowledge of the potential of machine translation" (Koponen 2016, p. 13). In order to make the process of post-editing more alluring for translators, there have been attempts to make MT more adaptive and interactive, meaning that the MT system not only learns directly from the translator, but also the provides MT output suggestions based on the translators' choices (Koehn 2020).

2.5 Translators vs. MT

The general idea is that professional translators have a severe dislike for MT, which is not unimaginable. In the words of Groves and Mundt (2021), "There is an understandable tension when new technologies threaten to undermine or disrupt standard and long-held academic traditions" (p. 3). Research has given multiple reasons for this dislike, such as the ineffectiveness of MT for certain text types, low quality output, a fear of being replaced, or even because of a decrease in creativity (Cadwell et al. 2017). Koehn (2020) argues that post-editing of MT is "less enjoyable than translation from scratch" (p. 22), and Sánchez Gijón et al. (2017) found that many translators have reported that post-editing MT output costs more effort and decreases their productivity (p. 33). Another reason translators might be discouraged to work with MT, is the "issue of falling pay rates and of unclear ownership of translation databases" (Moorkens et al. 2016, p. 1). Läubli et al. researched the perspectives of translators on MT through social media posts, in which "translators might be more open and direct when expressing opinions" (2017, p. 60). Though most of the existing research into the perceptions of translators on MT concludes that translators think negatively of MT, that view is exclusive to all translators. In the study by Läubli et al. (2017), it became apparent that while a majority of translators on social media voiced negative thoughts about, specifically, the quality of MT output, a number of translators also believed that mediocre MT output is better than not being able to provide a translation at all, which might be the case for some consumers of MT who just do not have the money to pay for a professional human-made translation. Moreover, one translator even stated that "applied language technology", such as CAT tools and MT, can support translators in their demanding profession, while still allowing human translators to "make a difference in value and quality" (Läubli et al. 2017, p. 63). Besides that, some translators have spoken out about the fear some of their colleagues might have to be replaced by MT and stated that "the fear of MT is, in a way, an indicator of the competence of the translators" (Läubli et al. 2017, p. 63). Likewise, the attitudes towards MT highly depend on its use. Groves et al. (2021) found that professional translators are generally in favour of using MT if it was used as a helpful tool for students. Nevertheless, the translators interviewed in said study did point out that MT should be a tool, not a necessity.

Though research into the attitudes of translators on the use of MT, and research into the attitudes of translation agencies on the use of MT (Torres-Hostench et al. 2016) has already been done, to the best of my knowledge, there has not yet been a study comparing the attitudes and beliefs of translators to the those of project managers working at translation agencies. From personal experience, it is believed that these mutual opinions, experiences, and beliefs differ significantly, and that these differences cause tensions in the translation industry. Therefore, this thesis will not only provide new insights in the perception of translators on the use of MT by translation agencies, but also provide insights in the perception of project managers on the use of MT within translation agencies. It will do so by conducting two surveys: one aimed at the experiences and beliefs of professional translators, and one aimed at the experiences and beliefs of project managers and comparing the results from both surveys in order to establish whether the conflicting views of translators and project managers might disrupt their working relations. In the current study, a survey was chosen as the most suitable research method, as they can provide a systematic way to gather and analyse data from a specific target audience (Laaksonen 2018) and offer new insights. The next chapter will provide an in-depth discussion on the methodology of this study and how it was used to accomplish the afore-mentioned objections of this thesis.

Chapter 3. Methodology

3.1 Introduction

The aim of this study was to find out whether translators and project managers have opposing or conflicting views on the use of machine translation (MT) and machine translation post-editing (MTPE), which may disrupt their working relations. This study focuses on professional translators who are asked to perform MTPE assignments and project managers who send translators MTPE assignments.

In order to be able to establish whether translators and project managers have conflicting views and attitudes on the use of MT and MTPE by translation agencies, two questionnaires were created: one specifically focused on the perspective of the professional translators, and one specifically focused on the perspective of the project managers. This thesis will compare and contrast answers provided by both groups to gain more insight into the potentially very different experiences of both translators and project managers working with MTPE.

This chapter is structured as follows. Sections 3.2 will discuss the participants and their backgrounds. Section 3.3 will discuss the materials used in this study and explain why an online questionnaire was used as the main method of gathering participant data. Section 3.4 will describe the procedure used and provide a discussion of the creation, distribution, and processing of the questionnaire. The concluding paragraph offers a brief summary.

3.2 Participants

As stated in the introduction, this thesis focuses on both professional translators, who, at some point in their career, have received MTPE requests from translation agencies, and project managers, who, at some point in their career, have sent MTPE requests to translators. This study aims to provide further insights into how both groups experience such requests and what their views and opinions are on the use MPTE in professional translation. To this end, it was decided to take a participant-oriented approach and use surveys as the main methodology to find out more about both professional translators' and project managers' personal and individual beliefs and attitudes on the use of MT and MTPE. For the sake of clarity and to avoid repetitiveness, it should be noted that hereafter the professional translators as a participant group will be referred to as PTs (Professional Translators) and the project managers as a separate participant group as PMs (Project Managers).

Since this study focuses specifically on PTs and PMs potentially conflicting views on working with MTPE and how this may affect the interaction between PTs and PMs, only participants who had personal experience receiving or sending out MTPE assignments for a translation agency were recruited. PTs who had worked with MT in order to prepare documents or create draft translations without having been asked by a translation agency to do MTPE were not included in this research. Similarly, PMs who had worked with MT ‘behind the scenes’ to prepare documents or who had used MT output as a final translation product without involving a PT as post-editor were also not included in this study.

Section 3.2.1 and 3.2.2 provide more information on the general backgrounds of the participants included in the study. Participants were not required to provide any information about their age or gender.

3.2.1. Professional Translators

Information required about PTs concerned the amount of time they had been working as professional translators, whether or not translation is their only source of income, their native tongue, and the language combinations in which they perform translations. Figure 4 provides an overview of the work experience of participants. It shows that most participants (13 out of 24) have been working as professional translators for more than 15 years, while only 2 of the participants are relatively new to translating with 1 to 5 years of experience.

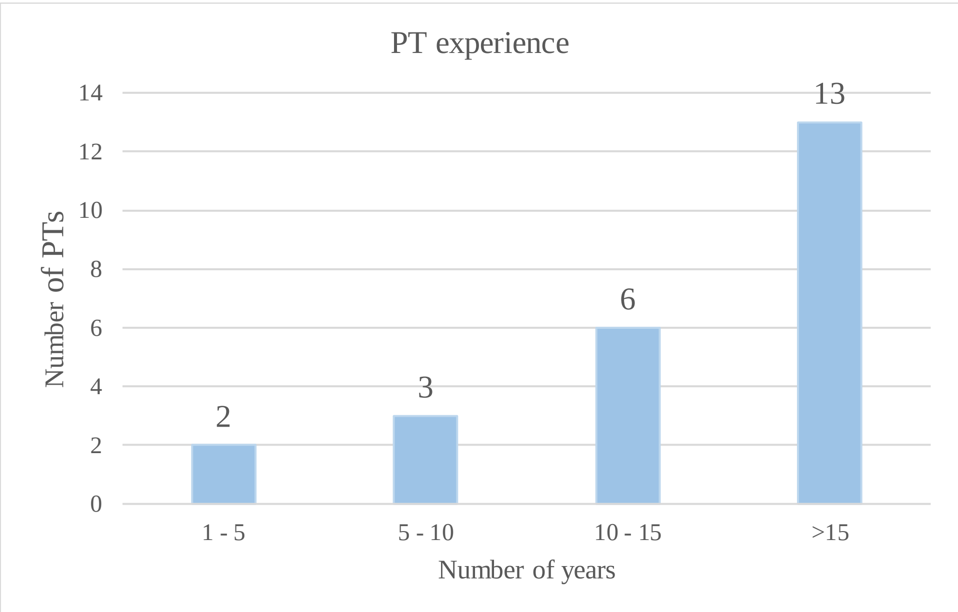

Figure 4. Work experience of PTs in years.

Regarding employment, for 16 out of 24 participants, translation is the only source of income, whereas 8 participants either have another parttime job or are financially supported by their spouse.

Figure 5 provides an overview of the native tongue of the participants. It shows that a majority of the participants (11 out of 24) are native speakers of Dutch. Among the participants there are also 7 native speakers of English and 3 native speakers of German. Two participants stated that they were raised bilingually and thus considered themselves native in two languages. Of those two participants, one stated to be native in Dutch as well as English; the other participant in Dutch and German.

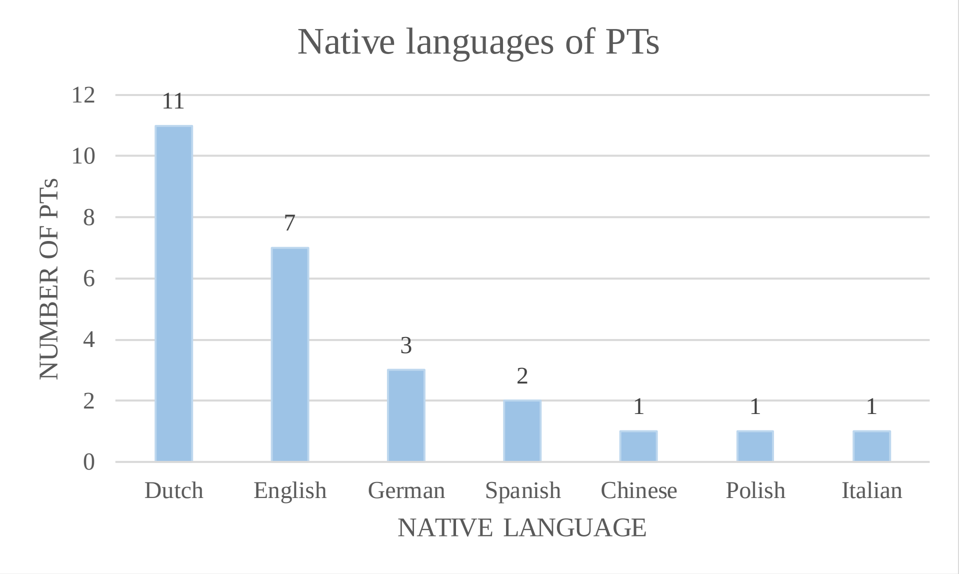

Figure 5. Native languages of PTs.

Table 6 shows an overview of participants' preferred language combinations for translations. It shows that most of the participants (14 out of 24) translate from Dutch into English, or from English into Dutch (7 out of 24). Less popular language combinations among the participants are Dutch into Polish, Chinese, Italian, French, or Russian.

English into Dutch	7	29.2%
English into German	3	12.5%
English into Polish	1	4.2%
English into Italian	1	4.2%
English into Spanish	2	8.3%
Dutch into English	14	58.3%
Dutch into German	3	12.5%
Dutch into Polish	1	12.5%
Dutch into Chinese	1	4.2%
Dutch into Italian	1	4.2%
Dutch into French	1	4.2%

Dutch into Russian	1	4.2%
German into English	3	12.5%
German into Dutch	3	12.5%
Polish into English	1	4.2%
Polish into Dutch	1	4.2%
Italian into English	1	4.2%
Italian into Dutch	1	4.2%
Total	24	100%

Table 6. Participants' preferred language combinations for translations.

All participants are freelancers working for a variety of employers. It is important to consider that these PTs might also work for employers outside of the Netherlands, since not all of the PTs are Dutch nationals.

3.2.2. Project Managers

For the PM questionnaire, a total of 16 participants were recruited. Essential background information about these participants regarded the amount of time they had been working as a project manager at the translation agency they currently work for and the country where they are located. Figure 7 provides an overview of the work experience of participants. It shows that most participants (10 out of 16) have only been working as project managers at their current employer for 1 to 5 years, while only six participants have over 5 years' experience.

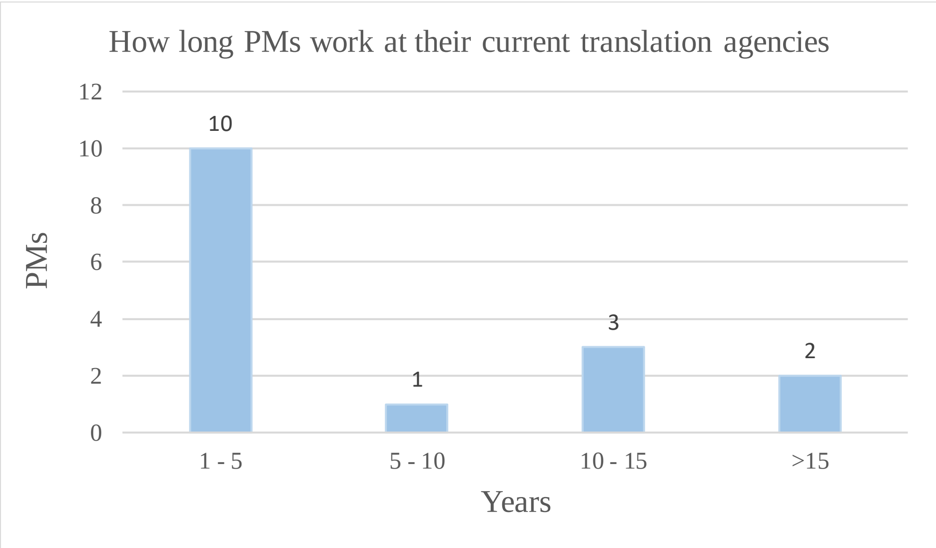

Figure 7. Number of years PMs have worked at the translation agencies they currently work for.

Table 8 provides a representation of the countries where the translation agencies participants work for are located. It shows that a majority of the participants, 12 out of 16, are located in the Netherlands.

The Netherlands	12	75%
The United Kingdom	1	6.5%
Poland	1	6.5%
Spain	2	12.5%
Total	16	100%

Table 8. Location of the translation agencies participants work for.

3.3 Materials

The current study adopts surveys as a research method. Laaksonen (2018) defines a survey as "a methodology and a practical tool to collect, handle, and analyse information from individuals in a systematic way" (p. 5). As mentioned in Saldanha and O'Brien (2013), the terms 'survey' and 'questionnaire' are often used as synonyms, however, Langridge and Hagger-Johnson (2009) explain that 'survey' refers to the design of the study, whereas 'questionnaire' refers to the instrument of the study. These terms will be used accordingly throughout this thesis. Matthews and Ross (2010) define questionnaires as "(1) a list of questions each with a range of answers; (p. 2) a format that enables standardized, relatively structured, data to be gathered about each of a (usually) large number of cases" (p. 201). The reason questionnaires were chosen as data gathering method, rather than for example interviews, is because they provide a fixed set of questions, identical for each participant of the same participant group and therefore, allows the researcher to "generalise the findings to a broader community" (Fulford & Granell-Zafra, 2005, p. 7), in this case, translators and project managers in general.

As the research aim of this thesis is to find out whether translators and project managers have opposing or conflicting views on the use of MT and MTPE, which may disrupt their working relations, it is helpful to divide this research question into multiple sub questions. Before it is possible to answer the main research question, the following sub questions must be answered:

1. What do the different backgrounds tell us about the attitudes of translators towards MT and MTPE?
2. What are the experiences of translators of working together with translation agencies who offer them MTPE assignments?

3. When do translators consider MT to be suitable to aid in professional translations in general?

4. What do the different backgrounds of project managers tell us about their attitudes towards MT and MTPE?

5. When do project managers consider MT to be suitable to aid in professional translations in general?

6. What are the personal experiences of project managers in working together with translators and offering them MTPE assignments?

Both questionnaires focus on three things: finding out more about the backgrounds of the participants; finding out more about the professional work experience of working with MTPE; and lastly, finding out more about the personal attitudes of participants towards MT and MTPE. Appendix A offers the full PT questionnaire and Appendix B the full PM questionnaire.

3.4 Procedure

The process of designing the survey involved: (1) determining the survey questions; (2) selecting and recruiting the participants for both questionnaires; (3) realize the task description; (4) conducting the survey.

Qualtrics was used as the instrument to create and distribute the questionnaire. The questionnaire for PTs consisted of 16 questions, including 8 open questions and 8 multiple choice questions. The questionnaire for PMs consisted of 13 questions, including 7 open questions and 6 multiple choice questions. Participants were allowed to skip questions that did not apply to them. Using Qualtrics' tool for 'skip logic', a number of questions were selected as conditioned multiple-choice questions. In these cases, when the possible answers were either 'Yes' or 'No', and 'Yes' was selected, participants were redirected to the next question, allowing them to explain their answer. If 'No' was selected, participants were redirected, skipping the explanation question. In the PT questionnaire, this concerns question 11; in the PM questionnaire, this concerns questions 7 and 11.

Recruitment of the participants for the PT questionnaire consisted of three phases: first, possible candidates were selected from a substantial database of translators, accessible through the author's work environment. As stated in section 3.2, the only requirement to be considered an appropriate candidate for participation was experience in working with MT and MTPE as requested by translation agencies. In the second phase all possible candidates were sent an elaborate e-mail by the author, explaining their participation was requested for a participant-oriented study on translators' perspective of working with MT/MTPE, and offering more information on the purpose of the study and its design. The e-mail also contained a disclaimer, stating that participation would be voluntary and completely anonymous. Phase three consisted of answering e-mails from possible candidates who responded to the recruitment e-mail. Those who agreed to participate in the study received a link to the questionnaire in Qualtrics and were thanked for their participation in advance. Since the questions in the questionnaire were written in English, participants were encouraged, but not obliged to answer the open questions in English as well. A total of 24 participants was recruited to fill in the questionnaire for translators.

Two different strategies were used to recruit participants for the PM questionnaire. First, possible candidates were selected from a database of project managers, accessible through the author's personal work environment. After this selection process, possible candidates received a recruitment e-mail providing the necessary information; those who agreed to participate, received a second e-mail containing a link to the questionnaire in Qualtrics. Identical to the recruitment of translators, the only requirement was that possible candidates had experience sending PTME assignment to translators. 6 project managers were recruited via this selection procedure.

Secondly, possible candidates were recruited through a private group, called *Vertalerskoffiehoek*, on the social media platform Facebook. Rather than personally and individually selecting possible candidates, a general message was posted to the private group, explaining the purpose of the message, the purpose of the study, clarifying the design of the study and most importantly, containing a statement that participants had to be familiar with working with MT and MTPE. Naturally, this message also contained a disclaimer on the voluntary and anonymous participation in the research and a statement saying that if members of the private group were willing to participate in the research, they were allowed to send the author a private message after which they would receive a link to the questionnaire in Qualtrics. This recruitment procedure thus consisted of only two steps: recruitment of possible candidates via social media and providing the candidates with the link to the questionnaire after volunteering to participate in the research. This recruitment procedure yielded another 10 project managers. Hence, a total of 16 participants were recruited to fill in the PM questionnaire. Again, all participants were encouraged, but not obliged to answer the open questions in English.

The PT questionnaire was accessible from 27 April 2021 until 15 May 2021. The PM questionnaire was accessible from 5 May 2021 until 15 May 2021. The results were exported from Qualtrics into MS Excel for analysis. The next chapter will elaborate on these results.

Chapter 4. Results & Analysis

4.1 Introduction

This chapter will provide an in-depth analysis of the results from the two questionnaires. Section 4.2 will discuss the results from the questionnaire for project managers, and section 4.3 will discuss the questionnaire for professional translators. Section 4.4 will then compare and contrast the two, discussing the impact the differences in opinions may have on the working relations of the two groups.

4.2 Results of translators' questionnaire

The PT questionnaire consisted of 16 questions regarding their backgrounds, their attitudes on the use of MT in general and their professional experience in working with MTPE. As was discussed in chapter 3, most of the participants had been working at translators for more than 15 years and are Dutch nationals. A more detailed overview of the participants' backgrounds is provided in section 3.2.1.

Participants were asked what text types they generally translate. Figure 9 provides an overview of their answers. They were not given examples. Every area of expertise that is displayed in figure 9 below was mentioned by the participants themselves. Nevertheless, for the sake of consistency, 'manuals' were grouped under 'technical', and 'website texts' were grouped under 'marketing/commercial'. Figure 9 shows that legal texts (12 out of 24) and marketing texts (11 out of 24) were the most popular areas of expertise among the participants. Medical texts and IT texts were the least popular among participants as both were only mentioned once. Two participants also mentioned to be comfortable translating any type of texts and did not provide further specification.

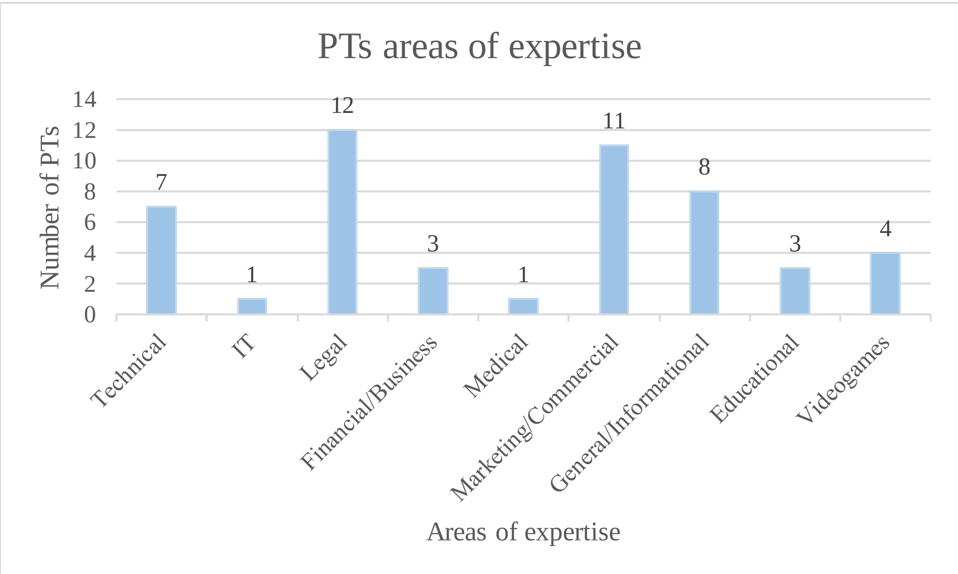

Figure 9. PTs areas of expertise.

Table 10 provides an overview of the number of times PTs receive MTPE assignments from translation agencies. It shows that most participants (12 out of 24) receive MTPE assignments once or twice a month. Only five participants receive MTPE assignments 2-3 times a week. Moreover, 16 out of 24 participants stated that these requests come from multiple translation agencies, whereas eight participants receive these requests from one specific translation agency. Knowing that all of the participants are freelancers working together with multiple translation agencies and knowing that half of the participants only receive MTPE assignments once or twice a month, we can conclude that the translation agencies they work with are not actively incorporating MT into their translation services.

Less than once a month	3	12.5%
Once or twice a month	12	50%
Once a week	4	16.7%
2-3 times a week	5	20.8%
Daily	0	0%
Total	**24**	**100%**

Table 10. Amount of times PTs receive MTPE assignments.

When asked if PMs always explicitly state that the assignment concerns MT output rather than human translation, half of the participants (13 out of 24) said ‘Yes’. Disappointingly, nine participants said that PMs explicitly state this information “most of the time”, and two participants stated that they do not. This might be an important cause for any tensions between PTs and PMs, as it could potentially create trust issues. It goes without saying that trust is a very important aspect in all business relations, so once that trust is broken, the relationship will undoubtedly be affected.

The participants were also asked about the rates they are generally offered for MTPE assignments. Their answers have been displayed in table 11, which shows that a third of the participants (8 out of 24) are offered a word rate of 4 cents, and a quarter 5 cents (6 out of 24 participants). Only one participant was offered 8 cents for MTPE assignments and surprisingly, this participant translates from Dutch to English, which, unlike Dutch-Chinese or Dutch-Russian, is not a low resource language combination. Two of the participants explicitly stated that they considered a word rate of 4 cents or less to be “way too low”, and one mentioned that they would rather be offered an hourly rate for MTPE assignments.

2 cents per word	3	12.5%
3 cents per word	3	12.5%
4 cents per word	8	33.3%
5 cents per word	6	25%
6 cents per word	3	12.5%
8 cent per word	1	4.2%
Total	**24**	**100%**

Table 11. Word rates offered for MTPE assignments.

When asked how often they accepted MTPE assignments, seven out of 24 PTs stated that whether they accept or deny, depends on the text type. For example, one of the participants mentioned that if they notice the MT output concerns a commercial text, they will automatically deny the assignment. Only three participants stated that they always accept MTPE assignments, regardless of text type, deadline, or word rate, while four participants stated that they always deny MTPE assignments. Table 12 provides a detailed overview of these results.

Always	3	12.5%
Depends on the text	7	29.1%
Depends on the deadline	6	25%
Depends on the word rate	4	16.7%
Never	4	16.7%
Total	**24**	**100%**

Table 12. How often PTs accept MTPE requests.

While 15 out of 24 participants claimed not to favour any translation agencies over others, nine participants stated that they were more likely to accept MTPE requests when they come from a specific translation agency. The reasons differed from high quality MT output and recognition of which texts are suitable for MT (6 out of 9) to the close relationship they have with the agency (4 out of 9). One participant mentioned that they were more likely to accept MTPE requests from a specific agency because of the rates they offer.

Interestingly, the majority of participants (16 out of 24) did not notice a decline in new assignments from agencies after rejecting MTPE, although eight participants indicated that they did.

Table 13 provides an overview of the ways in which participants evaluate whether MT output is worth the effort involved in PE. It shows that almost half of the participants (10 out of 24) perform a very detailed proof-reading of the output, whereas only four participants stated that they do not evaluate the output, as they believe the translation agency should evaluate the output before sending the assignment. One participant mentioned that they checked the deadline to assess how much time they were expected to spend on it, and judging by that, they would consider whether the effort involved in PE was worth it or not.

Closely proof-reading	10	41.7%
Quick scan	7	29.2%
Checking the grammar	2	8.3%
Checking the deadline	1	4.1%
No evaluation needed	4	16.7%
Total	**24**	**100%**

Table 13. How PTs evaluate the compatibility of MT output

The answers to the question, “Which types of texts do you consider to be easier to post-edit rather than to translate from scratch, if any?” were again quite diverse. Figure 14 provides an overview of the answers given by the translators. Eight participants stated that they considered manuals to be easier to post-edit rather than to translate from scratch, as they often consisted of short sentences with easy sentence structures. Similarly, four participants stated that they consider standard legal texts to be easier to post-edit rather than to translate from scratch as they often require very little post-editing effort. Six of 24 participants stated that they do not consider any type of texts to be easier to post-edit than to translate from scratch.

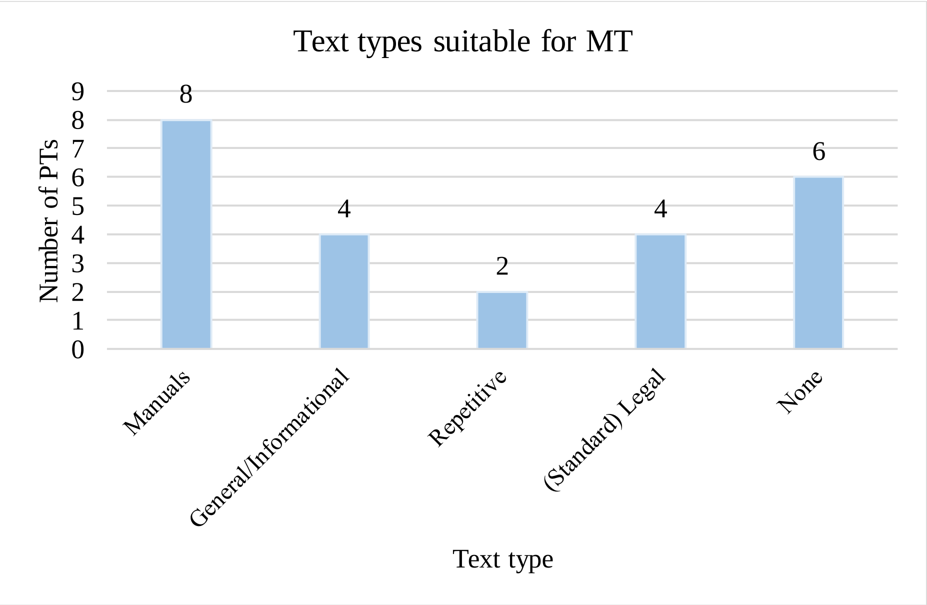

Figure 14. Text types easier to post-edit than to translate from scratch according to PTs.

4.3 Results of project managers' questionnaire

The PM questionnaire consisted of 13 questions regarding the general backgrounds of the participants, their beliefs of MT in general and their professional experience in working with MTPE. As discussed in the previous chapter, most participants have a working experience as PMs of 1 to 5 years and are located in the Netherlands. A more detailed overview of the participants' backgrounds is provided in section 3.2.2.

In order to learn more about the ways in which PMs use MT and MTPE, participants were asked about the machine translation programme they use. Table 15 provides an overview of the participants' answers and shows that most of the participants (13 out of 16) use some version of DeepL. Of those 13 participants, eight use DeepL Pro and five use DeepL Pro integrated as a plugin in Trados. Both versions are paid and secured services. Only two out of 16 participants said they use Google Translate, which is a free online, unsecured MT system. Having a secured MT system is especially important when using MT on confidential documents, such as financial statements or certain legal documents. However, though data might not be secured when using Google Translate, the quality is similar, according to Reber (2019), who states that "the choice of translation service plays a minor role" (pp. 113-114). Nevertheless, Reber also mentions that DeepL has a more extensive vocabulary than Google Translate, hence DeepL is "slightly more precise than Google Translate" (p. 113). Smartling is very similar to Trados and just as DeepL Pro and Lokalise, is a secured and paid environment which offers MT services as well.

DeepL (Pro or Trados plugin)	13	81.25%
Google Translate	2	12.5%
Lokalise & Smartling	1	6.25%
Total	**16**	**100%**

Table 15. Machine translation programmes used by PMs.

Participants were also asked about the language combinations they consider suitable for MT. Table 16 provides an overview of all the specific language pairs PMs considered suitable. The answers do not include the responses of three participants, of whom one stated that they considered "all DeepL supported language pairs" suitable for MT. According to the DeepL website, the programme currently supports 24 languages, specifically: Bulgarian, Chinese, Czech, Danish, Dutch, English, Estonian, Finnish, French, German, Greek, Hungarian, Italian, Japanese, Latvian, Lithuanian, Polish, Portuguese, Romanian, Russian, Slovak, Slovenian, Spanish, and Swedish. Among these languages there are currently 552 possible language combinations (support.deepl.com 2 May 2021). The other participant of the three stated that "languages belonging to the same language family to form appropriate language combinations for MT". Thus, Slavic languages, Germanic languages and Romance languages can be matched within their own language family and form language combinations suitable for MT. The third participant not included in the table stated that any Western European language (French, Spanish (including regional variations), Dutch (including Flemish Dutch), Portuguese, Luxembourgish, German, and Catalan) could be translated into English. Table 16 shows that the most popular language combinations among PMs are Dutch into English (11 mentions) and English into Dutch (8 mentions).

English into Dutch	8	50%
English into German	5	31.5%
English into Polish	2	12.5%
English into French	3	18.5%
English into Spanish	6	38%
Dutch into English	11	68.5%
Dutch into German	2	12.5%
Dutch into Polish	2	12.5%
Dutch into French	2	12.5%
Spanish into English	4	25%
German into English	4	25%
German into Spanish	2	12.5%
French into English	3	18.5%
French into Spanish	2	12.5%
Italian into Spanish	2	12.5%
Total	**16**	**100%**

Table 16. Language combinations mentioned to be suitable for MT according to PMs.

Participants were provided with a list of text types and asked to select all text types they considered suitable for MT. Figure 17 provides an overview of the results and it shows that most of the PMs (11 out of 16) considered legal texts to be suitable for MT. Nine participants selected technical texts to be most suitable for MT. Other areas of expertise that the participants considered suitable for MT included IT, financial, economic, and informational texts. What these text types have in common is that they are often standardized texts, such as manuals (technical), contracts or policies (legal), and financial statements (financial/economic). One of the PTs commented the following on the use of standardized texts in MT: “Standardized texts are easier to post-edit, because even with changes there is probably little difference in production between post-editing and translating from scratch”.

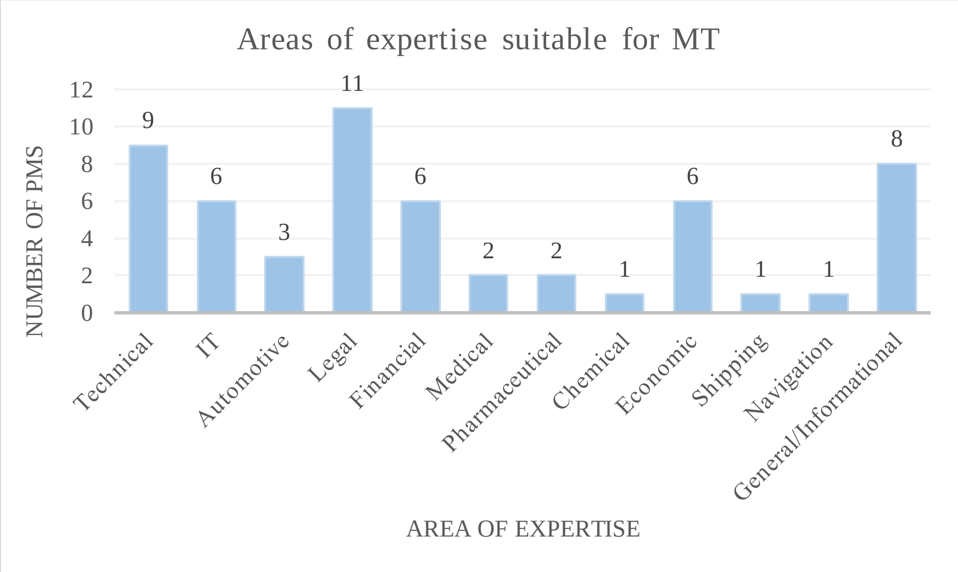

Figure 17. Areas of expertise/Text types most suitable for MT according to PMs.

Participants were also asked how often they send MTPE requests to translators. Their answers are presented in table 18, which shows most participants (12 out of 16) stated that they send MTPE requests no more than once or twice a month. By contrast, two participants stated that they send MTPE requests every day. No PMs stated that they send MTPE requests less than once a month.

Less than once a month	0	0%
Once or twice a month	12	75%
Once a week	2	12.5%
2-3 times a week	0	0%
Daily	2	12.5%
Total	**24**	**100%**

Table 18. How often PMs send MTPE assignments.

Among the 16 participants, 13 stated that they have never sent a translator MT output to post-edit without making explicit that the assignment concerned MT output rather than human translation. However, three participants stated that they had done so, and explained that it was either because they believed the translators would be more likely to accept the assignment if they thought it concerned a human translation (two out of three) or because they had just started working with MT and did not want the translators to be influenced or biased in advance (one out of three).

Another important consideration in working with MTPE is the payrate offered to translators. Table 19 provides an overview of the PMs average offered rates for MTPE. Roughly a third (6 out of 16) stated that they offered 3 to 6 cents per word for MTPE assignments, depending on the quality the translator delivers and the difficulty of the text. Two participants stated that they offer translators an hourly rate for MTPE, rather than a word rate. Surprisingly, two participants stated that this information was confidential.

3-6 cents per word	6	37.5%
4 cents per word	4	25%
4-5 cents per word	2	12.5%
Hourly rate à 30 EUR	2	12.5%
Confidential	2	12.5%
Total	**16**	**100%**

Table 19. Rates offered for MTPE assignments.

The PMs listed several reasons why translators decline MTPE requests. Table 20 illustrates the results and shows that, according to the PM participants, most translators declined because they do not work with MT in general (11 mentions). Other reasons PMs said translators had given them for declining MTPE included that they did not consider the source text to be suitable for MT (8 mentions) or that the word rate was too low (6 mentions).

The offered word rate was too low	6	37.5%
The source text was not suitable for MT	8	50%
They generally don’t work with MT	11	68.75%
They could not meet the deadline	1	6.25%
Other	3	18.75%
Total	**16**	**100%**

Table 20. Reasons translators have given for not accepting MTPE requests, accompanied by the number of PMs who have mentioned this reason.

The majority of the PM participants (14 out of 16) said that they do not send fewer new assignments to translators who have rejected MTPE assignments. Of the two participants who stated that they do, one explained that it is because the agency they work for wants to standardize MT in their workflow, while the other explained that the agency simply did not have the budget to work with those translators anymore.

4.4 Answers to the research questions

Before the main research question can be answered, it is important to discuss the sub questions stated in section 3.3. These questions were as follows, and will be discussed respectively:

1. What do the different backgrounds tell us about the attitudes of translators towards MT and MTPE?
2. What are the experiences of translators of working together with translation agencies who offer them MTPE assignments?
3. When do translators consider MT to be suitable to aid in professional translations in general?
4. What do the different backgrounds of project managers tell us about their attitudes towards MT and MTPE?
5. When do project managers consider MT to be suitable to aid in professional translations in general?
6. What are the personal experiences of project managers in working together with translators and offering them MTPE assignments?

When we take into account that half of the PTs (11 out of 24) are native speakers of Dutch with more than 15 years of experience being a translator (13 out of 24), of whom translation is the only source of income (16 out of 24), it becomes evident that the results to the questionnaire for PTs are mostly a reflection of the attitudes of Dutch translators who are "veterans" in the translation industry. Therefore, it is not surprising that many of these participants translate from Dutch to English (14 out of 24). The outcome of the questionnaire is thus mostly—but not entirely—representative of this specific group of people. Their experiences of with translation agencies offering them MTPE assignments were diverse. Half of the translators (12 out of 24) said that they receive MTPE requests once or twice a month, and only four out of 24 PTs stated that they never accept these assignments, regardless of text type, deadline, or word rate. While a little more than half of the translators (15 out of 24) stated that they were not more likely to accept MTPE assignments if they were sent by a particular translation agency, nine indicated that they were, either because of a good working relationship or because of the trust they have in the quality of that agencies' MT systems. Unfortunately, eight of the 24 translators had experienced a decline in new translation assignments from agencies after not accepting MTPE assignments. Nevertheless, the PTs had very similar opinions on the suitability of MT, as manuals, general or informational, and standard legal texts were mentioned by multiple PTs as text types that are most suitable for MT. Likewise, nearly half of the PTs (10 out of 24) stated that they closely proof-read the MT output in order to evaluate whether it is worth the PE effort.

Most PMs in this study (12 out of 16) work for Dutch translation agencies and have 1 to 5 years of work experience as PMs (10 out of 16). Therefore, the results of the questionnaire for PMs are mostly representative of Dutch PMs with less than 5 years of experience in the business. Most of them shared the same or similar opinions on the suitability of MT, as 11 out of 16 PMs considered the language combination Dutch to English to be most suitable for MT. Regarding text types, legal (11 out of 16), technical (9 out of 16) and general/informational texts (8 out of 16) were considered most suitable for MT. The majority of the PMs (12 out of 16) stated that they offer MTPE assignments to translators no more than once or twice a month, at a word rate somewhere between 3 cents and 6 cents per word (12 out of 16). Whenever translators declined such assignments, 11 out of 16 PMs stated that this was mostly because these translators expressed that they generally do not work with MT.

The most important aspects to consider when comparing PTs' and PMs' perception of the use of MT are whether PTs and PMs agree on when to use MT, whether PTs and PMs agree on rates, and whether there is mutual honesty, consideration and trust between PTs and PMs when using MT. Though the PTs and PMs have very similar ideals regarding the suitability of MT with regard to text types and language combinations, the word rates that PTs are currently offered are too low according to the PTs themselves. The PTs were given the opportunity to share any additional comments about MT and they displayed the following sentiments:

Anonymous PT 1:

> When the type of text is suitable for MT and the MT software is well developed and constantly updated, the translation process can actually be sped up. However, in many (I would say most) cases the post-editing process ends up taking the same time as an actual translation (at half the rate!). (Personal communication, April 30, 2021)

Anonymous PT 2:

> MT would be no problem if the rates were commensurate with the effort, which is often not the case. For one, I would prefer an hourly rate to word rate. (Personal communication, May 12, 2021)

Anonymous PT 3:

> It is staggering how people who call themselves text professionals refuse to see how much time, effort, and money is lost when using MTs as textual basis. It is no less

> staggering to see co-workers accept the ridiculous notion that a job will pay less while it is more time-consuming and much more of an effort. (Personal communication, May 15, 2021)

What these three quotes have in common, is that all three of these PTs consider the rate offered for MTPE assignments to be disproportionate considering the effort it takes. From personal experience and the data gathered in this study, it becomes obvious that project managers do not have a sufficient understanding of how much effort is involved in MTPE. This lack of understanding also becomes visible from the data on how many PTs (8 out of 24) see a decline in new assignments after not accepting MTPE assignments, even though only two out of 16 PMs confirmed that they have done so in the past.

Contrary to the sentiments of the PTs, the PMs were very positive about the use of MT in the professional translation industry:

Anonymous PM 1:

It's an amazing transformation of the translation industry. (Personal communication, May 17, 2021)

Anonymous PM 2:

I think MTPE will be 'the future' of translation (whether translators like it or not), but it will never fully replace human beings. (Personal communication, May 10, 2021)

Anonymous PM 3:

MT is an addition to the translation service industry. It offers a solution for those who are not able to pay the full cost of regular human translations. (Personal communication, May 6, 2021)

Moreover, though the intentions of the PMs were good, it is very misleading to send translators MT output to post-edit and presenting it as a human translation in need of revision. The amount of effort and time spent on post-editing do not match that of a regular revision, so it is very discouraging to translators when they are offered (often) half of the rate they would otherwise receive for MTPE assignments, while still having to put in that extra effort. This does not contribute to a healthy and happy work relationship, which then leads to translators favouring certain translation agencies over others. Ultimately, the combinations of these factors will most certainly lead to a disrupted work relation. Hence, this survey has shown that translators' and project managers' opposing and conflicting views on the use of MT do result in disrupted work relations.

Chapter 5. Conclusion

The purpose of this thesis was to find out if the opposing views of PMs and PTs on the use of MT caused a disrupted working relationship between the two. It should be taken into consideration that most of the participants for this research were either native Dutch translators or project managers based in the Netherlands. Hence, the results are not representative of PMs and PTs all over the world. This is related to the fact that the questionnaire for PTs was distributed amongst the author's limited personal contacts and the questionnaire for project managers was distributed via a Facebook group and the author's limited personal contacts. Hence, more research with a larger and more diverse group of participants must be done to be able to make generalizations about PMs and PTs across the world, rather than mainly in the Netherlands. An alternative to the current study would be, recruiting and selecting participants via worldwide translator- and translation agency platforms, such as ProZ.

The thesis assumed that there would be differences between the attitudes of PTs and PMs on the use of MT. This suspicion was indeed confirmed, as PTs and PMs did not only disagree on suitable pay rates, but also disagreed on the convenience of MT: whereas PMs considered MT to be a positive transformation of the translation industry, PTs mostly consider MT and MTPE to be more effort for less money. Moreover, not being transparent in the kind of assignments PMs send to PTs, might result in the PTs being less likely to accept new MTPE requests from that specific agency. Unfortunately, this might also result in the agency sending fewer or no new translation assignments to those PTs. These misunderstandings may then create a snowball-effect and inevitably cause considerable tensions between the PTs and the PMs. I believe many of these tensions could easily be solved if we offer PMs more insight into the problems translators face when working with MT output.

Previous research already pointed out the negative perceptions PTs have of MT and the positive attitude translation agencies have on the use of MT; however, this study provides data on both PTs and PMs simultaneously and offers a direct comparison of the attitudes of both groups in order to find out whether their opposing views create tensions in the work environment and disturb healthy working relations.

The current study includes a total of 40 participants and focuses mainly on Dutch PTs and PMs. Therefore, more research is needed in order to generalize the current findings, including a larger and more diverse group of both PTs and PMs. Yet the current study offers some interesting first insights into the current working situation in the Netherlands and suggests that there is much to be gained from fostering mutual understanding between PTs and PMs and increasing PMs' understanding of the working conditions of professional translators when engaging with MT output. This thesis clearly shows that the opposing and conflicting views of professional translators and project managers in the Netherlands on the use of MT do indeed cause tensions and disrupt healthy working relations.

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Appendix A.

Translators' questionnaire exported from Qualtrics

Start of Block: Default Question Block

Q1 How long have you been a translator?

○ 1-5 years

○ 5-10 years

○ 10-15 years

○ More than 15 years

Q2 Is translation your only source of income?

○ Yes

○ No

Q3 What is your first language?

____

Q4 What are your preferred source and target languages for translation work?

____

Q5 What type of texts do you generally translate?

____

Q6 How often do you receive requests for the post-editing of machine translation (MTPE)?

○ Daily

○ 2-3 times a week

○ Once a week

○ Once a month

○ Never

Q7 Who sends you these MTPE assignments?

○ One specific translation agency

○ Multiple translation agencies

Q8 Do project managers state explicitly whether the assignment concerns post-editing of machine translation or regular editing?

- ◯ Yes
- ◯ Most of the time
- ◯ No

Q9 What is the average word rate translation agencies offer you for MTPE?

____

Q10 How often do you accept MTPE requests?

- ◯ Always
- ◯ It depends mostly on the deadline
- ◯ It depends mostly on the word rate
- ◯ It depends mostly on the type of text
- ◯ Never

Q11 Are you more likely to accept MTPE requests when they come from a specific agency?

◯ Yes

◯ No

Skip To: Q13 If Q11 = No

Q12 Please explain why you are more likely to accept MTPE requests from certain agencies over others.

____

Q13 Have you noticed a decline in new requests from agencies after rejecting their MTPE requests?

◯ Yes

◯ No

Q14 How do you evaluate whether the quality of the MT output is worth the effort involved in post-editing?

____

Q15 Which types of texts do you consider to be easier to post-edit rather than to translate from scratch, if any?

____

Q16 Do you have any additional comments regarding machine translation and/or post-editing?

____

End of Block: Default Question Block

Appendix B.

Project managers' questionnaire exported from Qualtrics

Start of Block: Default Question Block

Q1 How long have you been a project manager at the translation agency you currently work for?

- ◯ 1-5 years
- ◯ 5-10 years
- ◯ 10-15 years
- ◯ more than 15 years

Q2 In what country is the translation agency you currently work for located?

____

Q3 What translation programme do you use? For example, DeepL, Kantan, Google Translate...

____

Q4 What language combinations do you generally consider to be suitable for machine translation (MT)? Mention all that apply.

____

Q5 Which text types do you generally consider to be suitable for MT? Select all that apply.

- ▢ Technical
- ▢ IT
- ▢ Medical
- ▢ Pharmaceutical
- ▢ Chemical
- ▢ Legal
- ▢ Financial/Economic
- ▢ Marketing/Advertising
- ▢ Shipping/Navigation
- ▢ Automotive
- ▢ General/Informational

Q6 How often you do send machine translation post-editing (MTPE) requests to translators?

◯ Daily

◯ 2-3 times a week

◯ Weekly

◯ Monthly

Q7 Have you ever sent a translator MT output to post-edit without making explicit that the assignment concerned MT output rather than human translation?

◯ Yes

◯ No

Skip To: Q9 If Q7 = No

Q8 Please explain why. For example, because the quality is not different, because the work itself is not different or because translators are more likely to accept an assignment if they expect it to be a human translation...

____

Q9 What word rate do you offer translators for MTPE assignments?

____

Q10 What are the main reasons translators have mentioned for not accepting MTPE requests? Select all that apply.

- ▢ The offered word rate was too low
- ▢ They could not make the deadline
- ▢ The source text was not suitable for MT
- ▢ They generally don't work with MT
- ▢ Other

Q11 Do you send fewer new translation assignments to the translators who reject MTPE assignments?

- ○ Yes
- ○ No

Skip To: Q13 If Q11 = No

Q12 Please explain why. For example, most of the work you have to offer is MTPE, you would like to standardise working with MTPE or you don't have the budget to work with them...

____

Q13 Do you have any additional comments regarding machine translation and/or post-editing?

____

End of Block: Default Question Block