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Machine Translation Tools: Current Use and Perceptions by French Translators

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ABSTRACT

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Technological developments have always changed human behavior and the nature of jobs. The profession of translator is no exception to the rule. This thesis addresses the topic of Machine Translation (MT). While human translators have so far always found a way to adapt to technological developments, the most recent evolution of MT might bring changes.

The objective of this thesis is to provide the commissioner (myself, a professional translator) and everybody interested in the issue with information on how French translators currently use and perceive Machine Translation (MT) tools. This thesis tried to answer the following main question and two sub-questions: how do French translators currently use and perceive machine translation tools? What is their use of such tools and what do they think about them in terms of effectiveness, quality and reliability? According to them, do machine translation tools have more advantages than disadvantages? Our research was based on the following three initial assumptions: only a small minority of professional translators use MT systems voluntarily (1); translators presume that output data from MT are often of low quality and little use (2) and translators believe that it is better to translate all the segments of a translation themselves, instead of doing post-editing (3). The data was collected following a mixed methodology involving quantitative research (online survey) and qualitative research (semi-structured interviews) targeting French professional translators.

The theoretical section explored the technical and historical context relating to MT and the Technology Acceptance Model (TAM). The finding showed that French translators do not utilize MT tools and perceive them in the same way and that perceptions of MT have an incidence on perceived usefulness, perceived ease of use and actual use. Out of this research came also the finding that there is a deficit of knowledge about MT tools and their functioning and also a need to clarify what role should be given to translators and machines in relation to MT. Even though human-machine interactions still have their best days ahead of them in the translation field, nothing, at this point, replaces human translation in terms of quality of writing.

Key words: machine translation, human-machine interaction, perceptions, technology acceptance model

CONTENTS

ABBREVIATIONS

ALPAC	Automatic Language Processing Advisory Committee
CAT	Computer-Assisted Translation
CERTT	Collection of Electronic Resources in Translation Technologies
EBMT	Example-Based Machine Translation
MT	Machine Translation
NMT	Neural Machine Translation
PEU	Perceived Ease of Use
PU	Perceived Usefulness
RBMT	Rule-Based Machine Translation
SL	Source Language
SMT	Statistical Machine Translation
TE	Translation Environment
TL	Target Language
TM	Translation Memory
TRA	Theory of Reasoned Action

1 INTRODUCTION

1.1 Research questions

Technological developments have always changed human behavior and the nature of jobs. The profession of translator is no exception to the rule. This thesis addresses this issue and focuses on Machine Translation (MT), which is the automated translation of a source-language text into a target-language text without the intervention of human translators (Irfan 2012) and dates back to the 1950s. It is one of the most important technological innovations in the translation industry.

Due to globalization and the ever-growing amount of content that needs to be translated, machine translation has constantly developed to enter today a new era with the emergence of neural machine translation (NMT). In this new approach, a computer uses deep learning (field of artificial intelligence) to build an artificial neural network to teach itself how to translate between languages with much better quality than before (Brockmann 2019). This new technology appears to be promising and may also imply changes in the way translators work. Human translators have always found a way to adapt to technological developments. But is it also the case with neural machine translation, the most recent evolution of machine translation? It would seem that translators often feel forced to comply with the requirements of translation agencies and would tend to resist the use of MT tools (LeBlanc 2013, 10–11). But what is the present situation regarding French translators in particular?

The purpose of this thesis is to provide the commissioner (myself, a professional translator) and everybody interested in the issue with information on how French translators currently use and perceive Machine Translation (MT) tools. This thesis is particularly relevant to me because it helps set its topic in the broader context of the position of human translators vis-à-vis machine translation, a debate which has been raging since machine translation took its first important steps. From the point of view of contemporary translation business, this thesis project is also interesting because it should give insights into the way my colleagues – most of them sharing the same employment status (self-employed translators) as me – use and view tools which have steadily improved in the past few years. This thesis might bring new information about the way translators and French translators in particular use and perceive MT tools.

This thesis will try to answer the following main question and two sub-questions:

- ***How do French translators currently use and perceive machine translation tools?***

1. *What is their use of such tools and what do they think about them in terms of effectiveness, quality and reliability?*
2. *According to them, do machine translation tools have more advantages than disadvantages*?

To this end, we will focus on professional translators and their use of MT in a familiar context: the Translation Environment (TE), which is a system offering diverse tools for translators « in a single integrated interface » (CERTT, n. pag.).

1.2 Initial assumptions

Based on the research of Champsaur (2013, 26), and Lagoudaki (2008, n. pag.) who believe that it is in the translators' own best interests to utilize technology, we assume that translators are willing to embrace MT if they realize it will benefit them and that they will see these benefits if they understand how MT can meet their specific needs. But, given that the translators' needs in the production process of a high-quality translation have not yet been defined and that MT is often imposed upon translators in translation workflows, it seems reasonable to believe that MT remains under-utilized because translators are generally unaware of the benefits of MT, especially if they have not used it voluntarily (Rémillard 2018). Thus, our first hypothesis is that only a small minority of professional translators use MT systems voluntarily during the translation process. If translators do not use MT voluntarily, it might be partially linked to how they view the quality of output data. Our second hypothesis is that translators presume that output data from MT are often of poor quality and little use. It thus seems plausible to make a third hypothesis: translators might believe that it is better to translate all the segments of a translation themselves, instead of doing post-editing (the process whereby humans amend machine-generated translation to achieve an acceptable final product). Assumptions 2 and 3 concern respectively acceptability and preference in a hypothetical and theoretical context, but things might be different in practical use.

2 OVERVIEW OF THE TECHNICAL AND HISTORICAL CONTEXT

Before going further, a few definitions about Machine Translation (MT) and its integration in the TE are needed. MT, like computer-assisted translation (CAT) tools, belongs to language technology, i.e., applications which aim to support humans in carrying out its language-related tasks. But, contrary to CAT tools, which include all computer applications that can support translators before, during and after the translation process by only automating « some well-defined subtasks to help translators be more efficient » (ibid.), MT can perform the translation process. Thus, it implies the automation of the whole translation process and allows the generation of a translation without human intervention.

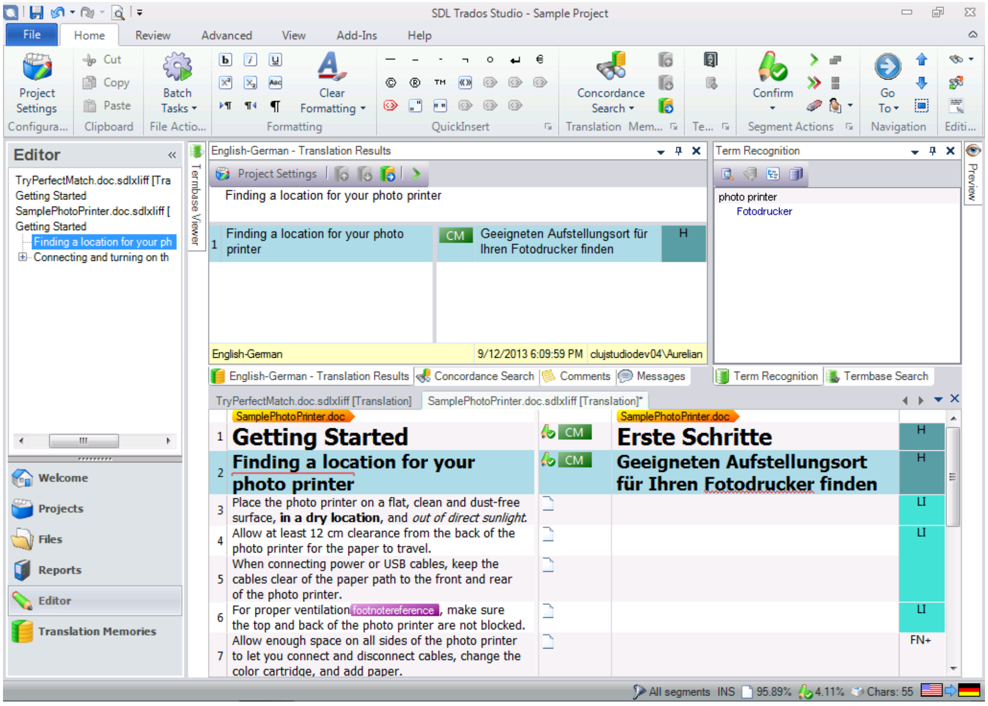

FIGURE 1. Exemple of the Translation Environnement of SDL Trados Studio, the industry-leading translation software (own screenshot)

The translation memory system management (TM system management), which is the most typical CAT tool in the translation world and the preferred tool of translators (Casacuberta et al. 2009, 135) is the main element of the TE. The TM system management operates in conjunction with a Translation Memory (TM), which a corpus of previous translations. The TM system management is thus a tool that operates and manages a resource, the TM, by allowing, among other things, the automation of some functions like the extraction of character strings already translated – which are referred to as segments and often correspond to a sentence. During the translation process, the TM system management isolates the segment to be translated and, using a matching algorithm, compares it to the other segments of the TM in order to extract a matching full or partial translation, if possible.

The extracted segments are usually full or partial human translations of the segment to be translated and are designated respectively by the terms exact or fuzzy matches (Rémillard 2018). The TM system management therefore allows the acceleration of the translation process by taking advantage of segment repetition between previous translations and the text to be translated.

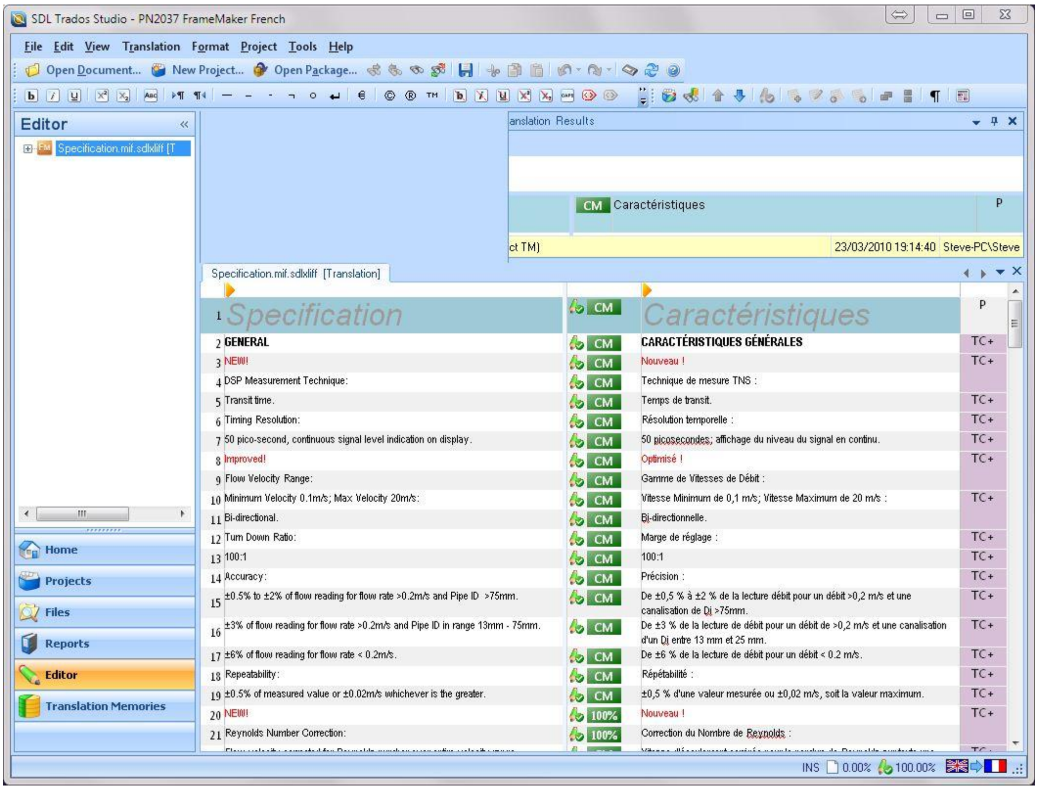

FIGURE 2. Own screenshot of a Translation Memory in SDL Trados Studio

2.1 Language processing

The idea of automatically processing languages and the translation process is not new. It predates the birth of the computer in the 1940s (Ping 2008, 162; Hutchins 2001, 5). Such research was made in the broader context of the Second World War, the development of first computers to break the German code Enigma (Koehn 2012, 15) and the following Cold War years between the United States and the Soviet Union. Even though this Machine Translation research only concerned governments and administrations, and not directly particular translators (as it is currently the case), it paved the way for the integration of such technology to the translation industry.

From the outset, two ways have been considered to automatically process languages: the linguistic approach, developed at the same time as the computer (Ping 2008, 162), and the mathematical approach, suggested by Warren Weaver in 1949 in the wake of efforts made in the area of cryptography during World War II (Hutchins 1995, n. pag.). But this latter approach, which proposed to consider translation as a decoding problem, would remain dependent on some technological developments. And it was only in 1990 that Brown and his collaborators suggested to have another look at Weaver's idea in order to create MT systems based on the exploitation of corpora. Thus, since the early 1950s, most of the research efforts have been targeted towards the linguistic approach, which resulted in Rule-Based Machine Translation (RBMT) systems. The MT research about RBMT was made with a great deal of enthusiasm until it was hampered after the publication of the ALPAC report in 1966 (Church & Hovy 1993, 239). Some researchers like Bar Hillel have begun to cast serious doubts on high quality MT systems (Kay 1980, 4). The ALPAC report recommended a target change where automatic tools should be created to help translators (Hutchins 1995, n. pag.).

Because MT was not being successful, Kay suggested in 1980 that efforts should not be directly focused on MT, but on CAT tools, which would allow a human-machine relationship based on collaboration. Unfruitful MT research have led to the design of Translation memory (TM) management systems, which were marketed in the1990s (O'Hagan 2008, 48) and have since then been adopted by professional translators.

Although some progress has been made regarding the design of TM management systems, those systems are mainly based on the automatic extraction of segments and have always been limited to repetitive documentation (Bowker 2002, 111; Casacuberta et al. 2009, 135; Macklovitch & Russell 2000, 139). Despite this limitation, researchers like Garcia (2006, 102) began advocating for utilizing these systems to process all types of documents. It is from this perspective that TE providers have also sought to expand the scope of their systems by integrating Machine Translation in the TE (Rémillard 2018).

In the following sections, we will have a look, in chronological order, at the evolution of MT systems.

2.2 Evolution of MT systems

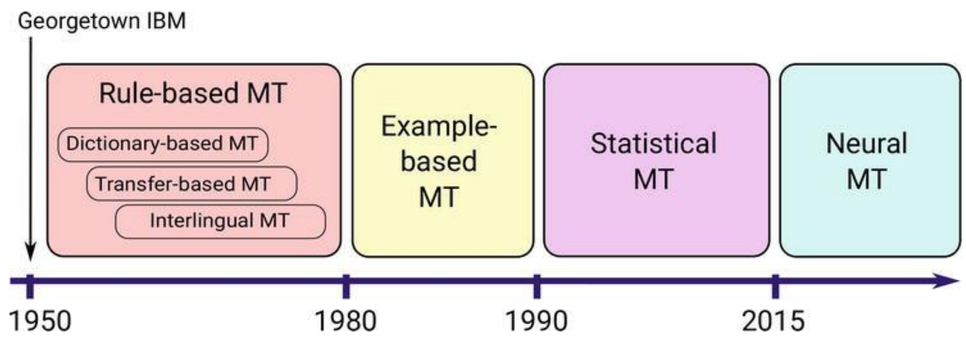

FIGURE 3. Chronological evolution of MT (Sepesy Maučec & Donaj 2019)

2.2.1 Rule-based machine translation (RMBT) systems

The post-Second World War period saw the advent of the first computers and MT was quickly viewed as an important tool because there was a need for translation between foreign languages (Cold War). But because the computers of this time had limited abilities, a pragmatic approach based on bilingual dictionaries and transfer rules was pursued. This rule-based approach has prevailed for decades and is still sought-after nowadays. (Poibeau 2017, 142)

As their name indicates, RBMT systems are based on linguistic rules, that is to say on the theoretical foundations of linguistics. Rules aim at formalizing natural language to adapt it to machine language and thus allow for its automatic processing. In concrete terms, this means that the system uses, amongst other things, a lexicon and a series of rewrite rules which constitute a grammar whose purpose is to describe a given language. Now let us take an example of Manning and Schütze (1999, 97). The rule S → NP VP means that the sentence(S) is composed of a noun phrase (NP) and a verb phrase (VP). The rules are applied recursively and then describe other possibilities of NP and VP to rewrite the categories up to words of the lexicon which are coded accordingly. For instance, the NP can comprise an article and a singular noun (the dog). The VP can be composed of an intransitive verb (barks) in order to create the phrase "The dogs barks". Since the 1980s, the indirect approach has predominated in most commercial RBMT systems such as Systran (Ping, 2008, 162).

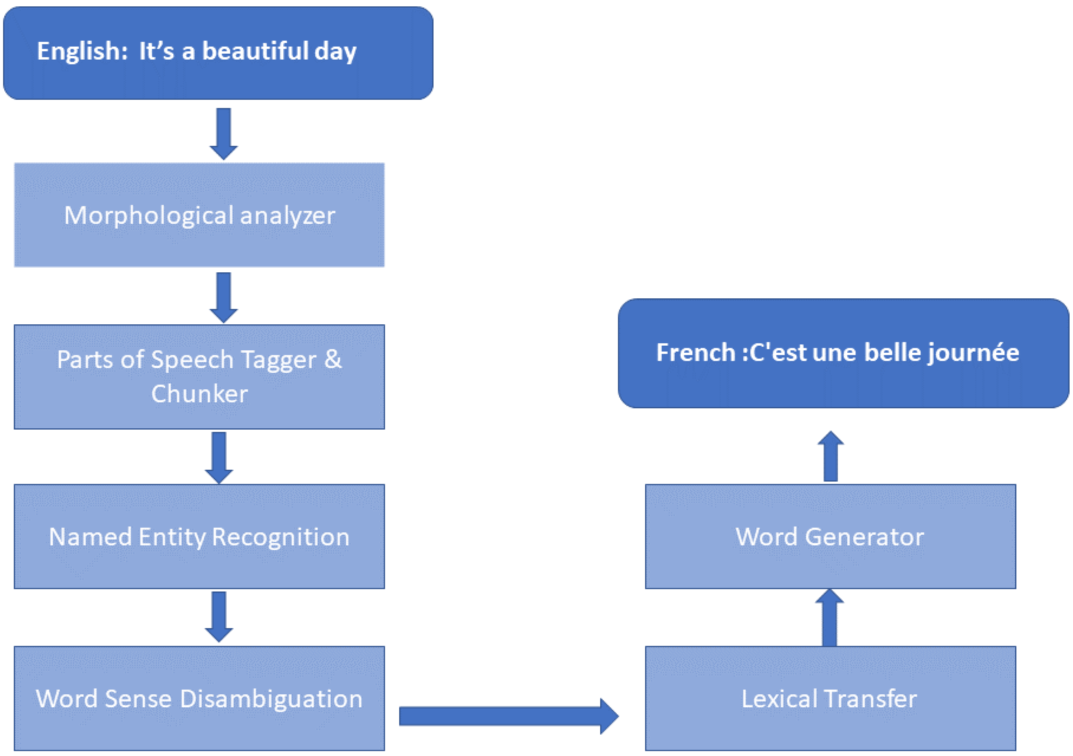

FIGURE 4. A flow diagram of a rule-based MT system (Pattanayak 2019)

However, RMBT systems suffer from structural limitations associated with their complexity and formalism. Indeed, the grammar used with those systems is context-free, i.e., is not able to take into account the context in which the category of a given word is used (Manning & Schütze 1999, 97). The disambiguation mechanism is therefore rather limited. For example, depending on the context, the word “chair” can be translated in French by “chaise” (piece of furniture) or “president” (authority). However, in a simple sentence like ”The chair addresses the meeting”, odds are that with most RBMT systems, the word “chair” will be translated in French by “chaise” because it the most common word of everyday language and presumably the word which may have been integrated in the lexicon as the first choice. (Rémillard 2018, 22)

The linguistic description is not enough. Rules do not allow us to grasp the meaning of words, a fundamental part of translation. Natural and machine language are not compatible and it is still very difficult to reconcile natural language with programming languages. Thus, linguistic programming enables computers to accomplish tasks of a linguistic nature but remains limited on a semantic level. Instead of a system which takes charge of the translation process, the programming of a system which could allow the combination of the strengths of the computer and the translator needed to be sought. While humans excel at finding solutions in the creative and artistic process involved in a translation, computers can perform routine and mechanical tasks with remarkable speed (Kay 1980, 3). According to Kay, computers should no longer be viewed as omnipotent machines but should rather be considered as a tool for humans. The advantage of such a system is that it is a language independent tool which make it possible to circumvent the problems linked to linguistic description. (Rémillard 2018, 23–25).

2.2.2 Translation memory (TM) management systems

We have already explained the difference between Translation Memory (TM) and TM management systems by stating that TM is a resource, i.e., a corpus of previous translations, and that TM management systems allow translators to exploit this resource: they indeed can take advantage of previous translations, accept or not segments which have been automatically extracted from MTs, modify it at their own discretion, draw on subsegments in order to translate or check MTs manually. It is now time to deepen our knowledge about the technical functioning of TM management systems.

Furthermore, it is important to understand the storage mechanism of Translation Memories (TM).

Storage mechanism

TM management systems can only work if they have access to TM. Data storage is an essential function that make it possible to create the corpus from which a TM management system will extract data. According to Rémillard (2018), the importation of previous translations and "on the fly" storage of segments during the translation process are the main two storage mechanisms. In order to import previous translations and store them in a TM, the TM management system implements a text segmentation algorithm, then an alignment algorithm for the SL and TL segments so that they can match. The segmentation algorithm divides the texts of the SL and TL into segments, then the alignment algorithm makes the alignment of the SL and TL segments on the basis of some linguistic or numerical characteristics within the segments. Thus, segmentation and alignment algorithms make it possible to create or update a TM, which is a parallel corpus. "On the fly" storage of segments implies that segments are added to TM as the translator translates them and can be utilized immediately. (Rémillard 2018, 28–29)

Let us now turn to the issue of the extraction of TM data. The data extraction stage is the tangible result to which accesses the translator during the translation process. Two functions are implemented during this process: the segmentation of the text to be translated and the extraction of data stored in the TM. The text to be translated should first be segmented to extract the SL segment which needs to be translated because the processing unit is the segment. This segmentation is made through the segmentation algorithm. Once the text to be translated has been segmented, the extraction mechanism comes into play to extract the TL segments stored in MT by using a fuzzy matching algorithm which calculates the similarity percentage between the SL segment to be translated and a stored segment from the SL. When a satisfying matching is possible, the stored corresponding TL segment is extracted to propose it to the translator. In addition, the “recycling” of previous translations is based on data at the segment level. Depending on the fuzzy matching percentage, three types of matches can be distinguished at the segment level: exact match, which means that the SL segment is completely identical to the stored SL segment; full match, meaning that the SL segment is identical to the stored SL segment, except for variables such as dates and numbers and, lastly, fuzzy match, which relates to segments whose degree of similarity reaches or exceeds the level of fuzzy matching established by the translator (Rémillard 2018, 30).

Lastly, it is interesting to address the question of the interactions between the translator and the system. From the TE, translators can benefit from the information collected by the TM management system. Thus, they can interact with the system, i.e., using it in interactive mode. To put it another way, the TM management system suggests segments and subsegments, then translators are free to refuse them, accept them as such or modify them in a text editor. This non-deterministic operating mode is a founding principle of CAT tools. It contrasts with the automatic mode, that characterizes the functioning of MT systems. In the latter case, the type of human-machine relationship in question is not centered on a collaboration because translators are not involved: the system makes all the decisions and provides automatically the output data. (Rémillard 2018, 32).

2.2.3 Systems based on the exploitation of corpora

Concept of corpus

Usually, a corpus is made of a set of texts. MT management systems operate with TM which are bilingual and aligned corpora also known as “parallel corpora” or “bi-texts corpora”. “A parallel corpus is a corpus composed of a set of pairs of texts in a translation context” and “an aligned parallel pair of texts is called a bi-text, from bilingual text”. (Poibeau 2017, 207). The same applies to MT systems based on the exploitation of corpora. These same kinds of parallel corpora are needed to perform translation tasks.

Example-based machine translation (EBMT)

Example-based machine translation, also called translation by analogy, was created in Japan by Makoto Nagao (1984). Nagao, noticed that professional translators usually work with pieces of text that they translate and rearrange to create full sentences and that parallel corpora include precious information that is often missing in bilingual dictionaries. As a consequence, he suggested that it would be a good idea to directly utilize pieces of translation available in existing bilingual corpora. (Poibeau 2017, 281)

Overview of how EBMT functions:

Translations made by EBMT systems involve three stages in the translation process:

- The systems look for fragments of the sentence to be translated in the corpora available for the SL.

- Based on the bilingual texts, the systems look for equivalences in the TL.

- The systems combine the translation fragments in order to get a correct sentence in the TL.

Let's try to be more specific and clearer with a concrete example inspired by Poibeau (2017, 285). We would like that the following sentence "*Procrastination is not the response to every problem*" to be translated into French by an EBMT system. Such a system would utilize a bilingual corpus and the pairs of sentences indicated below:

<u>Ex. 1</u>	Procrastination is not the response to everything. La procrastination n’est pas la réponse à tout.
<u>Ex. 2</u>	Procrastination is not the response to all student difficulties. La procrastination n’est pas la réponse à tous les problèmes éprouvés par les étudiants.
<u>Ex. 3</u>	There is a response to every problem. Il existe une réponse à tous les problèmes.
<u>Ex. 4</u>	There is a proper response to every problem. Il existe une réponse adéquate à tous les problèmes.

FIGURE 5. Sentences from a bilingual corpus utilized to translate *“*Procrastination is not the response to every problem*.”* (Poibeau 2017)

According to Poibeau (2017, 289), sentences from the SL in the EBMT system includes a series of similar words with the sentence to be translated in the TL. The EBMT system will look for equivalences in the TL. For instance, the system will get “*procrastination is not the response*” and its translation in French (“*la procrastination n’est pas la réponse*”) from examples 1 and 2”. Based on examples 3 and 4*,* it can deduct that it is possible to translate “*to every problem*” into French with “*à tous les problèmes*.” Thanks to this word association, the EBMT system is able to generate the final translation “*la procrastination n’est pas la réponse à tous les problèmes*.”

This technology took advantage of the abundance bilingual texts available at the time and abandoned the manual development of MT systems. Nevertheless, EBMT systems have certain limitations. For example, they might generate a word-for-word translation if they cannot extract sentences from the SL. “Mixing the example-based approach with a statistical analysis of very large corpora has proven to lead to very interesting results, since statistical approaches are known to have good recall and can in turn benefit from the precision of the example-based paradigm”. (Poibeau 2017, 301)

Statistical Machine Translation (SMT)

This particular type of MT which emerged in the 1950s relies on the use of mathematical models (statistics) based on the analysis of bi-text text corpora. (Nemeth 2019). The idea of this mathematical approach would remain dependent upon the availability of bilingual and aligned corpora. It was not until 1990 that Brown et al. suggested to go back to this approach in order to design that type of MT systems (Rémillard 2018, 38). SMT works according to this principle: “Given a sentence T in the target language, we seek the sentence S from which the translator produced T. We know that our chance of error is minimized by choosing that sentence S that is most probable given T. Thus, we wish to choose S so as to maximize P (S|T)”. (Brown et al. 1990).

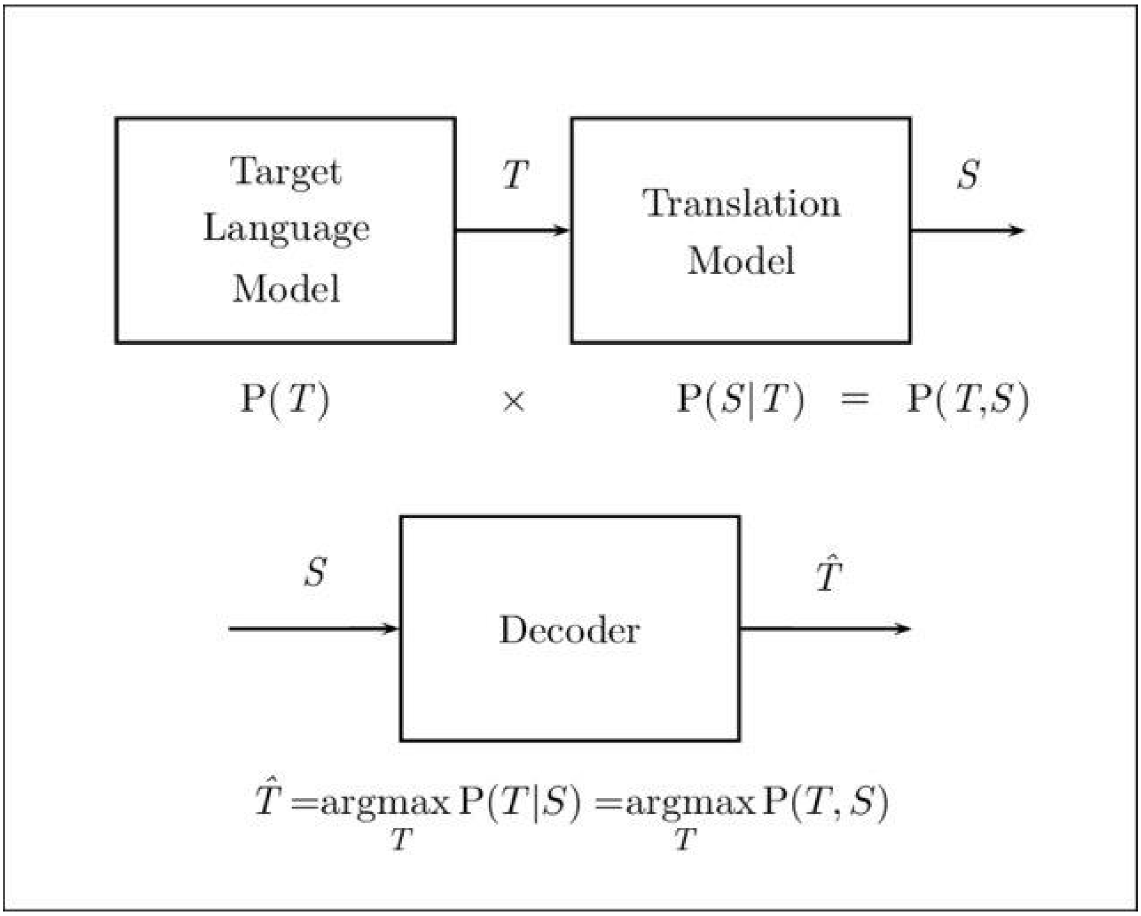

FIGURE 6. Example of a SMT system (Groves 2007, adapted from Brown et al. 1988)

For instance, SMT has been used by Google Translate between 2006 and 2016 (Google Translate now uses NMT).

2.2.4 New MT systems

Hybrid systems

According to Poibeau (2017, 364), hybrid systems (mixing different historical approaches) are now the norm. Given the great success of statistical translation systems, most systems progressively tried to integrate statistics. (see, for instance, Systran's systems). Poibeau (2017) indicates that the global idea behind hybrid MT systems is to link the abundance of existing resources with the performances of SMT. According to him, when the amount of available bilingual corpora is too small, SMT systems lose much of their appeal. (Poibeau 2017, 417–418).

Neural Machine Translation (NMT) systems

Neural networks find their origins in the biological brain. Neurons are able to transmit and process information, from which the brain shapes concepts and ideas. Artificial neural networks should be able to build complex concepts from different pieces of information assembled hierarchically (Poibeau 2017, 447). Neural networks can be applied not just to language translation but to any kind of data. For instance, neural networks have been applied in areas as diverse as images and speech recognition, stock-market prediction and music composition. The more recent neural machine translation (NMT) approach is based on deep learning technology. Deep learning is a specialized subset of machine learning, which is itself a subset of artificial intelligence. According to Poibeau (2017), deep learning met initial success in the field of image recognition. Rather than utilizing a group of predefined characteristics, deep learning usually uses large set of examples (e.g., hundreds of thousands of images) to automatically extract the most relevant features. Learning is made in a hierarchical manner: it begins with basic elements (pixels, words or characters) to identify more complex structures (segments or lines in an image; sequences of words or phrases in the case of a language) until it obtains an overall analysis of the object to be analyzed (a form, a sentence). In the case of MT, deep learning makes it possible to design systems where very few elements are given manually, so that the system can deduct the best representation from the data. NMT systems consist of two elements: an encoder (analyzes the training data) and a decoder (automatically produces a translation from a given sentence, based on the data analyzed by the encoder). The encoder and the decoder are based uniquely on a neural network where “each word is encoded through a vector of numbers and all the word vectors are gradually combined to provide a representation of the whole sentence” (Poibeau 2017, 457). NMT does not explicitly rely on word-level alignments to learn how to translate. In fact, this approach is quite similar to what translators are taught in translation schools: first, the source sentence of a text is analyzed to produce an internal representation of the meaning of that sentence, and from that internal representation the TL translation is produced. However, in most NMT systems, word-level correspondences are captured through a mechanism referred to as “attention”: as it is generating TL words from left to right, an NMT system will focus its attention at different locations within the source text, as if it was shifting its attention from word to word (Bahdanau et al. 2015, Vaswani et al. 2017). From this attention mechanism, it is possible to extract “soft” alignments between words of the source and target language of a pair of sentences, which indicate the relative importance of each SL word in generating each TL word during translation (Peter et al. 2017). In brief, the deep learning approach to MT considers directly the whole sentence without having to decompose it into smaller segments, and also considers all kinds of relations in context at the same time. Besides, the fact that these relations can be vertical (groups of similar words that can have specific positions in a sentence) or horizontal (syntactically related groups of words within a sentence) makes the approach quite flexible but also challenging (Poibeau 2017, 468).

3 TECHNOLOGY ACCEPTANCE MODEL (TAM)

3.1 An overview of the Technological Acceptance Model (TAM)

We still need to determine to what extent MT is really useful to translators. While real, technological advancements need to be validated by the community of interested users, it is worth considering whether MT addresses an actual need of translators. The first step in the adoption process of a product is a priori acceptability, which can be defined as the evaluation of that product before having any interaction with it (Rémillard 2018). Technology acceptance deals specifically with perceived usefulness (PU) and perceived ease of use (PEU) (Davis 1989).

It is at this stage that researchers specialized in human-machine interactions try to predict the acceptability of a product, i.e., its potential usage based on users' perceptions. To this end, they use different models, including the Technology Acceptance Model (TAM). We have decided to utilize this model because it is simple and has been considered as a reliable framework regarding the of acceptance of technologies (Lowry 2004). According to Koul and Eydgahi (2017), TAM is a popular model used to evaluate the behavior of people when it comes to the adoption of new technologies. As such, it is an appropriate model to use to address the translators' acceptance of MT technologies.

Morris and Dillon, who have tested and recognized the applicability of this model in the area of human-machine interactions, also specify that it was originally developed by Davis et al. in 1989 in the field of management information systems. The TAM model mainly derives from the Theory of Reasoned Action (TRA), a social psychological theory that makes it possible to consider the determining factors in the way human beings behave when using a technology (1997, 59). Davis' (1989) Technology Acceptance Model (TAM) is an information technology framework for understanding users' adoption. It predicts user acceptance based on the influence of two factors: perceived usefulness and perceived ease of use. TAM posits that user perceptions of usefulness and ease of use determine attitudes toward using the system. Consistent with TRA, behavioral intentions to use is shown to be determined by these attitudes toward using the system. According to the model, behavioral intentions to use in turn determine actual system use. In addition, a direct relationship between perceived usefulness and behavioral intentions to use is also proposed by TAM (Dillon 1997). The model is presented in the figure below.

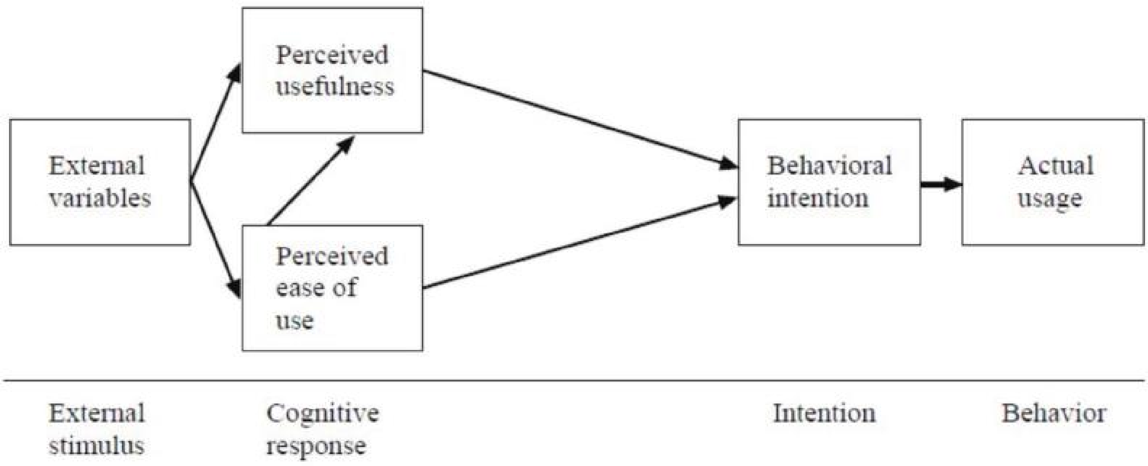

FIGURE 7. TAM model (adapted from Davis & Venkatesh 1996, 20)

“Perceived ease of use (PEU) and perceived usefulness (PU), the most important factors in the TAM, refer to the degrees to which a person believes that using technology would be free from effort (PEU) and that using technology would enhance their job or task performance”. (Scherer et al. 2019, 15). Perceived ease of use corresponds to how people view the level of work required to utilize technologies (Scherer, Siddiq, & Teo 2015).

TAM variable	Conceptualization
TAM-core variables	
Perceived ease of use (PEU)	The degree to which a person believes that using technology would be free of effort (Davis, 1989)
Perceived usefulness (PU)	The degree to which a person believes that using technology would enhance his or her job performance (Davis, 1989)
Attitudes toward technology (ATT)	A person's evaluation of technology or specific behavior associated with the use of technology (P. Zhang, Aikman, & Sun, 2008)
Outcome variables	
Behavioral intention (BI)	A person's intention to use technology
Technology use (USE)	A person's actual technology use
External variables	
Subjective norm (SN)	A person's perception that most people who are important to him or her think he or she should or should not perform the behavior in question (Martin Fishbein & Ajzen, 1975)
Computer self-efficacy (CSE)	The degree to which a person believes that he or she can perform a specific task using a computer (Compeau & Higgins, 1995)
Facilitating conditions (FC)	The degree to which a person believes that organizational and technical resources exist to support the use of technology (Venkatesh et al., 2003)

FIGURE 8. TAM variables (Scherer et al. 2019)

According to Garces et al. (2016), the adoption process of technological products is divided into the following three acceptability phases: a priori acceptability, acceptation and appropriation (ibid.). In the following sections, we will define these phases and present them from the usage perspective because it is possible to link these acceptability steps with different usage stages of MT, namely the subjective perceptions about a potential usage, the decision on a first attempt to utilize MT and the actual usage (Rémillard 2018, 56).

3.2 Subjective perceptions about a potential usage

The first step of the adoption process of a product is a priori acceptability which refers to subjective representations with regards to technological usage (Garces et al. 2016, 245). During this phase, researchers in the area of human-machine interactions try to predict the acceptability of a product, i.e., potential usage based on the user's perceptions. To do so, they use various models, including TAM. This model is predictive and not descriptive, in the sense that it allows the estimation of a priori acceptability, but does not enable the identification of the system's shortcomings (ibid. 59). On a concrete level, it allows external variables, i.e., any variable concerning the usage context, including the system's characteristics, to be taken into account (ibid.). This context makes it possible to induce a perception regarding the ease of use among potential users (effort needed to utilize the system) and a perception of usefulness (improvement of user efficiency). These two perceptions then determine the attitude and the intent regarding usage. According to Morris et Dillon, all the variables involved in the TAM model have a significant effect on the usage of given product. Perceived usefulness has a large impact on attitude and these two variables also affect the intent regarding usage, which remains the best predictor of technology acceptance (ibid., 63). However, TAM model cannot be fully applied to MT systems because machine translation is not so much assessed on its ability to as generate output data, but rather on its capacity to generate output data whose quality is good enough for users in a given context. Indeed, in the field of human-machine interactions, the interface is assessed and not output data de sortie, as in the case of MT (Hui 2002, n. pag.). This involves two differences. First, the variable concerning perceived usefulness is less applicable because users are not expected to work at the interface level, and even less when the MT system is integrated into the TE. Secondly, the perceived usefulness of MT system should depend, in substantial part, on the perceived usefulness of generated output data. This makes it difficult if not impossible to skip the assessment of this data. But despite these differences, the TAM model serves to underscore the importance of some factors, like attitude and perceived usefulness, regarding machine translation usage. (Rémillard 2018, 57–58)

3.3 Decision on a first attempt to utilize MT

The second step of the adoption process of a product is acceptance. This phase relates more specifically to the investigation of the factors that had an impact on the first interactions between the developed technology and the user (Garces 2016, 245). This step implies a decision to utilize the product in question in a particular setting. According to Morris et Dillon, first impressions would be critical for the usage of a product because they have a significant effect on attitudes towards usage (1997, 63).

According to Champsaur, there are two main usage contexts regarding MT: a usage upstream of the translation process and a usage in addition to translation tools (2013, 22). When MT is utilized to do a first translation, the translator should then take action afterwards by doing a post-editing of the translated text and the ”success of this process depends greatly on the obtained quality” (ibid.). When MT is utilized in addition to translation memories (TM), Champsaur mainly reports two steps. First, exact and fuzzy matches are inserted in the text to be translated. Secondly, the segments for which the TM management systems does not extract any matches are sent to the MT system so that it generates a machine translation (ibid., 24). After that, the translator must then do a post-editing of a text which has been translated by a machine and humans. It can also be noted that CAT tools also allow translators to translate in an interactive mode which makes it possible for a translator and a machine to collaborate in real-time at the segment level. Thus, the translator translates a segment at a time and must choose to utilize or not TM or MT data and do a post-editing if needed.

Typically, in the translation industry, two stakeholders take decisions on MT usage. Such decisions determine the usage context and the experience of translators as users. Firstly, the client or employer who usually decide to integrate MT in their workflow and utilize it upstream in the translation process. They give the translators a post-editing mandate. In this context, translators utilize MT very indirectly. Secondly, translators can choose to utilize MT voluntarily and directly in their practice. They do it mainly in two ways: they can activate the MT system in their TE or utilize a MT system outside the TE. When they activate the MT in the TE, they can choose to work in a pretranslation mode and do a post-editing afterwards or choose the interactive mode and do an interactive post-editing of MT data as they are generated. If they utilize a MT system outside the TE, they can get their text translated upstream of the translation process or have a look at MT during the translation process.

Therefore, in a context of voluntary usage, translators can make decisions about the user experience they wish to have with the MT system and the context in which they choose to do so. Besides, if they opt for MT in interactive mode, they can also exercise their free will regarding segments during the translation process and determine whether they should utilize or not the generated output data. (Rémillard 2018, 59–60)

3.4 Actual usage of Machine Translation (MT)

The third and last step of the adoption process of a product is appropriation, i.e., the actual usage of a product. According to Garces et al., this parameter should be assessed and measured (2016, 245). Indeed, it is interesting and necessary to measure not only the usage of a product, but also to assess this usage depending on the context because this context would also be important. In the case of MT, we have seen that there are two types of user experience to take into account in order to measure and assess its usage. Firstly, translators are indirect users who may not have made the decision to utilize MT or may have little control over usage context. Secondly, translators are direct and voluntary users of MT and make all decisions on its usage. To measure actual MT usage, it will therefore be essential to make a distinction between those two types of usage. Once the technology has been accepted, MT usage becomes effective or not and should be part of a specific context. One thing is sure: if translators choose to really utilize MT, i.e., in circumstances they consider appropriate, they will also have to choose to utilize or not output data during the translation or post-editing process, and that choice should imply the preexistence of a qualitative perception. (Rémillard 2018, 61)

3.5 Acceptability

Once technology has been accepted, the MT usage becomes actual or not. They are two categories of acceptability: theoretical and practical acceptability.

Theoretical acceptability

Theoretical acceptability is about utilizing the data from MT. It is a perception of acceptability which corresponds to a measure of usefulness and potential use based on a qualitative judgement. Theoretical acceptability is well assessed through a subjective measures scale. When MT is integrated into the Translation Environment (TE), segments translated by humans also compete with MT data and the qualitative perception of MT data and their utilization should also depend on the qualitative perception qualitative of human translations extracted from Translation Memories (TM). Therefore, acceptability can also be considered in terms of translator's preference between these data types. This precisely what Moorkens and Way did (2016): in order to compare the acceptability of MT data against TM data and draw conclusions about preferences, they measured (using a scale) the perceived usefulness of data according to how translators perceive the effort related to post-editing.

Practical acceptability

Practical acceptability concerns the decision to utilize or not MT data and concrete use of that data during the translation process. It measures the usefulness and actual usage of output data (the translator utilizes or not the data in question). In the TE, it means that translators insert the data in their translation and amend it (post-editing) if required. When they have the choice between data from MT and TM, the collected measure also expresses a preference. In this context, it is reasonable to assume that practical acceptability implies the production of a definitive and high-quality translation because translators have the choice to use or not use data. Practical acceptability offers many possibilities because it is not necessarily confined to a measure but makes it also possible to examine various aspects of post-editing and the production of a translation in the context of a voluntary use. (Rémillard 2018, 63–64).

Factors for understanding acceptability (p 64)

According to Rémillard (2018), in order to better understand acceptability and preference, it is necessary not only to measure them, but also cross-check the collected measures with more objective data. Otherwise, results are very general and limited to the collected measures. They do not permit the identification of certain key factors. To this end, it is necessary to collect data on the profile of respondents in order to identify some factors like attitude and perceived usefulness, which could play a pivotal role in the perception of data acceptability.

3.6 Evaluation of translations

Addressing the issue of the evaluation of translations involves asking what makes a translation a good translation. According to Poibeau (2017, 32), a decision point when dealing with translation issues is that nobody has been able to formally determine what is a good translation. Nonetheless, various criteria have been established in the literature.

There is a broad consensus that the translation of a text should be faithful to the original text, i.e., it should respect the main characteristics of the original text, the tone and style, the details of the ideas as well as its overall structure. The translation should be easy to read in the TL, and it should also be linguistically correct. Ideally, readers should not realize that they are reading a translation if they do not know the origin of the text, which implies that all formulaic and idiomatic expressions should be rendered appropriately. As a result, translators must perfectly understand the text they have to translate, but they must also have an even better knowledge of the TL. This is the reason why professional translators usually only translate into their mother language so that they have a perfect understanding and knowledge of the expressions to be used to render the source text accurately.

However, the aforementioned criteria are quite subjective. What is considered as a “good” translation by someone may be a “bad” one according to another person. Furthermore, what is expected of a translation can vary radically depending on the clients, the era, the nature and complexity of the text, its usage, or even context. Technical texts are obviously not translated in the same way as literary texts. Specific adaptations of the original text are sometimes required when the text concerns a world that is remote from the world of the reader in the target language (for example, if a Chinese text from the eleventh century is translated into modern French). Translators have to choose between staying close to the original text or making use of paraphrasing to ensure comprehension (this is especially the case with historical contexts, unfamiliar events, etc.). The tone and the style of a text are also subjective notions that depends on the language in question. (Poibeau 2017, 38–40)

Human translations

The qualitative assessment of human translation is a complex endeavor. To confirm it, you only need to look at the complexity of the issue of quality (House 2008) and equivalence (Kenny 2008) or to consider the many quality assessment models regarding human translation (Catford 1965; Jakobson 1966; Nida & Taber 1969; Nord 1997; House 1997; Williams 2004), as well as the need to continue to adapt these models to the realities of the translation industry (O’Brien 2012). Thus, despite the probable absence of grammatical errors in this type of data, it should be recognized that the assessment of language and translation errors is diverse and subjective. According to Williams (2004, 14), it is perhaps one of the issues that leads to the biggest disagreements. Therefore, the assessment of human is a large area of research that goes beyond the scope of the functional assessment of systems. (Rémillard 2018, 49).

MT systems

There is a vast literature on the assessment of various types of MT systems because developers regularly assess their systems (Papineni et al. 2002; Koehn 2005; Simard & Isabelle 2009). Moreover, the fact that these systems do not generate data that comes from humans, like TM system management, make functional assessment of MT systems even more essential. In this context, the systems assessment therefore involves the evaluation of output data. Although there is no single, uniform means of assessing the quality of output data generated by MT systems, automatic and objective measures or human assessment strategies are generally used. But before discussing these methods, the most frequent assessment criteria should be briefly described.

Assessment criteria

Assessment criteria can be either quantitative or qualitative. Qualitative criteria can be set automatically and are objective. They are re not a problem because researchers just have to identify them methodically in the context of their experiments. Those criteria may be related, for instance, to post-editing effort (calculation of the number of keystrokes required to carry out a post-editing or produce an ideal version) or to the number of words in a piece of data. Qualitative criteria, for their part, are based on the nature of the observed phenomena. Thus, they are more subjective because they imply an introspective process. The most used qualitative criteria in the assessment of MT are fluency and adequacy, which refer, respectively, to linguistic form (i.e., grammar and style) and semantic equivalence (Koehn 2012, 218). Fluency corresponds to the natural character of a piece of output data. It allows all aspects of linguistic structure (morphology, spelling and grammar, typography, natural lexical usages, syntactic structure and comprehensibility of a given sentence). In the context of MT, measuring fluency corresponds to the capacity to interpret a piece of output data through meaning (Trujillo 1999, 258). Indeed, language mistakes can have an impact on output data intelligibility. Conversely, the more output data are intelligible and natural, the more they are fluent. In order to assess fluency, it is therefore better to review a piece of output data without using the piece of original output data (ibid.). Accuracy is more about the adequacy of the produced translation. It therefore corresponds to a measure of equivalence between a piece of output data and a piece of original input data. Accuracy requires the ability to interpret the intended original meaning. It is thus linked to fluency in a certain way (ibid., 259). (Rémillard 2018, 50–51)

Typology of translation errors

Studies proposing a typology of errors made by machine translation systems could be counted on the fingers of one hand because such an endeavor is difficult and subjective: on one hand, it depends on the language and on the translation system considered, and on the other hand, the identified errors are difficult to classify and often vary. However, Vilar et al. (2006) tried to propose such a typology which included different categories: unknown words (words in the source language unknown to the translation system), poorly translated words (wrong meaning, incorrect word form, badly translated idiomatic expression, etc.), word-order problems (problems related to the word order in the target language) and missing words in the target sentence. According to Vilar et al., such an analysis is possible in specific cases (especially when the language pair concerns closely related languages) and can help identify certain weaknesses in the system to resolve them later on (systematic word meaning error, etc.). This type of analysis is especially useful in the case of rule-based systems developed manually, because it allows the system developers to correct certain rules or formulate new rules when faced with the main weaknesses observed (Poibeau 2017, 470–471).

According to Poibeau (2017), in the case of statistical systems, the sources of errors are more widespread and much more difficult to correct because the systems are not intended to be modified manually. In practice, the system must be “retrained” with new data in order to correct the identified errors, but the procedure is rather cumbersome. Moreover, since training is done on very large quantities of data, errors cannot be corrected one by one, and the learning procedure cannot be fully controlled since the process is by definition global and automatic. It is thus hard to correct a specific error in the case of a statistical machine translation (Poibeau 2017, 473).

Typology of fluency and accuracy errors

Typologies of errors are also used to assess MT data and provide developers further details on the shortcomings of their systems. There are different typologies which often make it possible to meet the specific needs of a particular research and are restricted in their ability to be applied to further research (Lommel et al. 2014, 165). It is with this in mind that Lommel et al. proposed a flexible typology which can meet different needs. The basic concepts of this typology will be briefly defined below. Then, we will examine its application to identify errors and understand the links between those errors and acceptability.

Despite the recognized link between fluency and accuracy, Lommel et al. (ibid., 166) seem to want to insist on the conceptual differences between these two notions when they state that fluency does not deal with translation phenomena, but only with linguistic issues: « […] issues related to the linguistic properties of the target without relation to its status as a translation » (ibid.). They indicate that fluency includes the following linguistic errors: typography and punctuation, spelling, grammar and unintelligible (ibid., 167). The first two categories are sufficiently transparent, but it has to be said that grammar errors comprise three subtypes of errors that concern firstly the form of words (improper word forms), that is to say agreement, word category or tenses, secondly word order and thirdly function words (determiners, prepositions and auxiliary verbs). The unintelligible category applies to what researchers define as being unintelligible text. Apart from these linguistic errors, the typology includes the following accuracy errors: omission, addition, untranslated and mistranslation. Omission and addition are respectively relating to the unjustified presence or absence of words. The untranslated category concerns the production of a text fully taken from source language. Mistranslation refers to a non-equivalent word, i.e., an absence of equivalence entre between notions of source and target languages (ibid., 166). In this typology, fluency therefore relates to typography, spelling, morphology (form of words) and syntax (word order and function words), including all the translation problems associated with function words, especially the unjustified absence or addition of these words (ibid.). Thus, fluency concerns the whole structure of the language, from words to sentence. As for accuracy, it is restricted mainly to words, except for the untranslated category which may include text, so several untranslated words. Apart from these concepts, everything that is unintelligible and necessarily more difficult to grasp through the typology would enter the unintelligible category. (Rémillard 2018, 66–68).

Another interesting way to evaluate the quality of translations is to utilize the Multidimensional Quality Metrics (MQM) framework. It “presents a variety of error categories that can be drawn on to create customized metrics based on the end user’s needs, and those error categories can be used to evaluate the text as a whole (holistic method) or on a sentence-by-sentence basis, as this study did (analytic method).” (Mariana et al. 2015, 138). According to Mariana et al. (2015), “MQM was recently created by the Quality Translation Launch Pad group (QTLP 2013). It was based on many other quality evaluation tools, and most heavily draws from the LISA QA model, a model which is often used in a modified form. It was designed to be applicable to a professional production environment, (the translation industry, where translations are produced for pay) as well as a testing environment”. The MQM error categories are organized in a hierarchical manner and can be represented as follows:

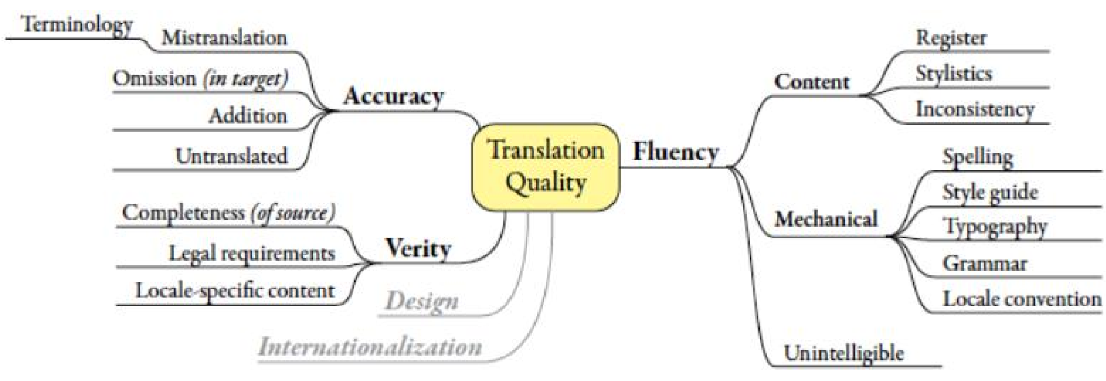

FIGURE 9. Hierarchy of error categories in the MQM framework (Mariana et al. 2015)

The chart presented below gives a good overview of the error severity and error categories in the context of the MQM framework.

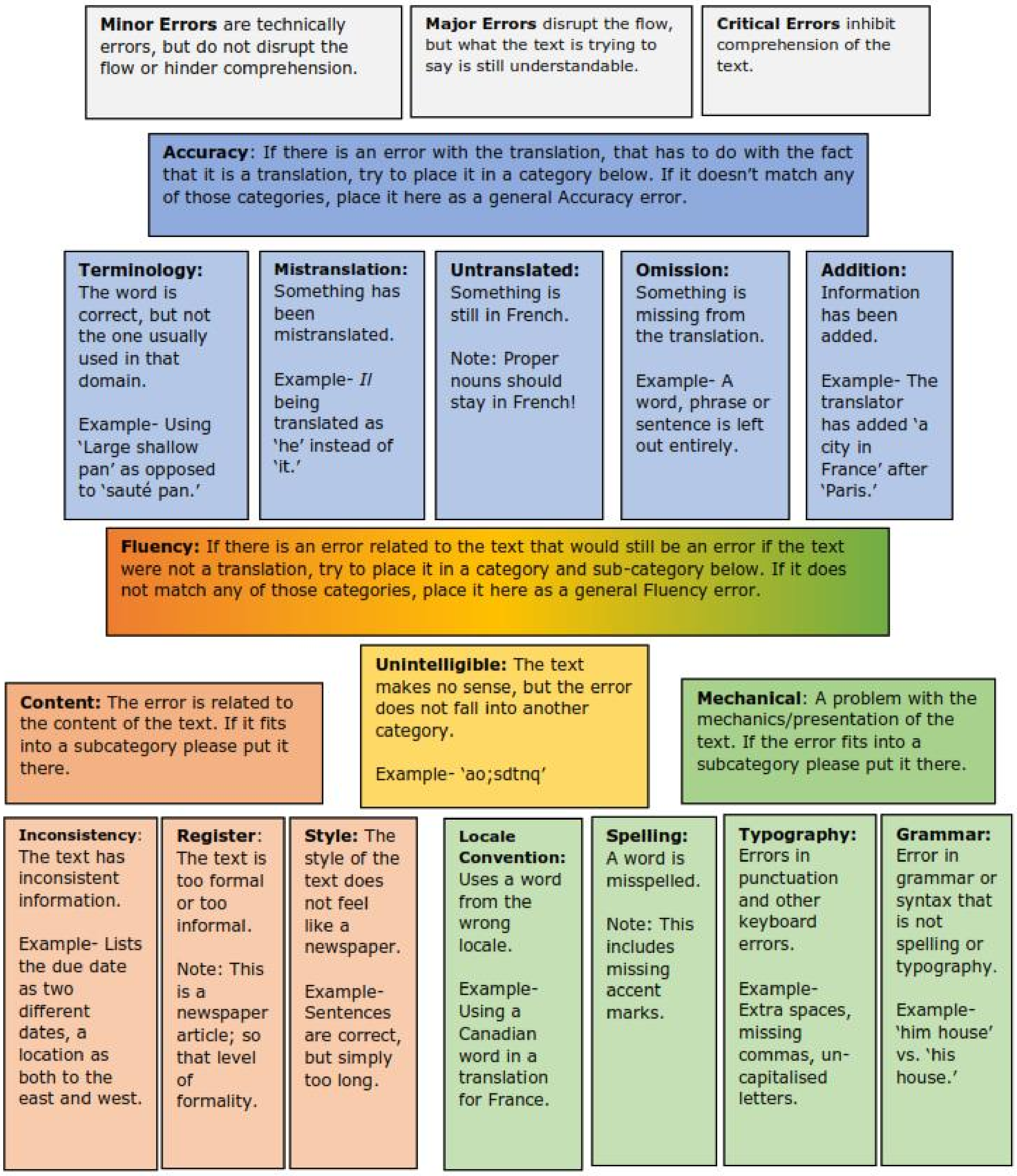

FIGURE 10. Error severity and categories utilized to help quality raters apply the MQM method (Mariana et al. 2015)

4 RESEARCH METHODOLOGY

4.1 General methodology

A mixed methodology involving numerical measurement (quantitative research) and in-depth exploration (qualitative research) has been chosen because it provides a broader and more complete vision of a problem. “The use of mixed methods turns possible to overcome the limitations of quantitative and qualitative methodologies, allowing the researcher to get rich information that could not be obtained using each method alone.” (Almeida 2018, 137). First, we wanted to find out trends and opinions. Even though, as Andrews et al. (2003) mentioned, given the fact that survey respondents need to reflect on their previous conduct, a survey may not be the ideal way to gather data (Schwarz 1999), a tool such as an online survey using closed-ended questions and allowing the respondents to make comments seems to be appropriate in order to try to reach a large number of people.

In a second phase, semi-structured interviews with some of the survey respondents willing to give more details about their experience with MT is a good way to better understand the trends and perceptions highlighted in the survey.
I used my professional network and specialized platforms like Proz to find translators willing to participate in my research.
Regarding data analysis, we utilized statistics to interpret, compare and find correlations for the survey. We also analyzed the interview transcripts to identify themes and relate them to each other through conductive and deductive thinking (coding). The survey and interviews were made in order to collect quality data that make it possible to answer the research questions (how do French translators use MT tools and what do they think about them in terms of effectiveness, quality and reliability? According to them, do machine translation tools have more advantages than disadvantages?).

4.2 Methodology for the online survey

The survey design comprised three stages: the selection of samples, the survey design in and its online release. Once the samples have been chosen (French speaking professional translators targeted through my network or Proz), we designed the online survey on SoGoSurvey, which offers an interesting package for students. The survey was accessible from August 14th to September 18th 2021. It consists of 24 questions, so that it is not too long and does not require too much time to complete. Most of them are based on TAM. “The TAM questionnaire is easily adapted to a particular technology for a given user community and provides a reliable predictor of critical success factors in technology uptake for that community” (Lowry 2004, 2). The first four questions are relatively general. First, the respondents are asked for consent to take part in the survey. Then, they are asked for their gender, age and academic background.

4.3 Methodology for the interviews

The persons chosen for the semi-structured interviews were those who were willing to answer more qualitative questions about their experience with MT (question 24). Only three translators were interested in such an interview. Interviewee 1 is a woman with 13 years of experience in translation. Interviewee 2 and 3 are male translators with respectively 7 and 10 years of experience in the field. Because all of them were based in France, the interviews were conducted online via Microsoft Teams and recorded. The interviews comprised 9 questions. The first two questions were introductory questions regarding their professional experience as a translator and the aspects of their work they particularly enjoy and enjoy less. Questions 3 and 5 concerned specifically perceived usefulness. Question 7 and 8 were MT technologies.

5 DATA ANALYSIS

5.1 Online survey results

In total, 25 people answered the survey. Most of them were women (76%), with two people who did not wish to reveal their gender. Such a result is not surprising because there is a higher female/male ratio than a male/female one in the translation industry (European language industry survey 2020). Regarding the age of the respondents, the mean age was 48.3, the minimum being 32 and the maximum 80; two people did not wish to answer. We could regret that younger translators (under 30) did not take part in the survey because their use and perceptions of MT might have been different (e.g., a possible better acceptance of MT tools). Question 4 was also in line with our expectations, a vast majority of respondents having an academic background in languages (68%). On average, the respondents have been working as translators for 14.4 years. Questions 6 and 7 aimed at understanding the impact of MT on translators. Question 6 results are quite interesting because they seem to reveal that, for a large majority of respondents (60%), MT has had a major impact on them and as the results for question 7 show, especially on their working methods. However, about one quarter of respondents (24%) think that MT has not made a big difference in their work.

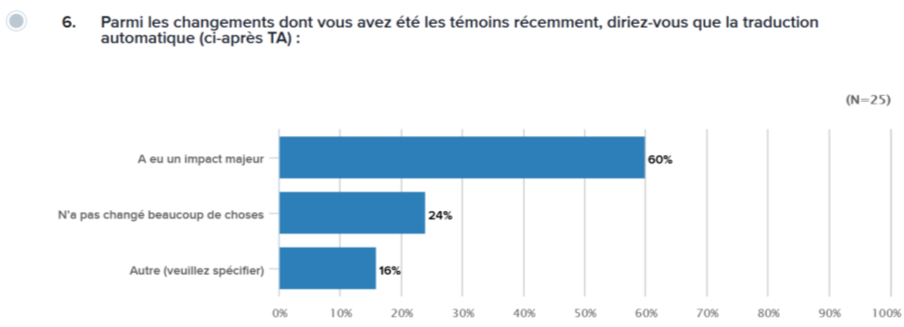

FIGURE 11. Answers to question 6

Besides the working methods, the results for question 7 show that the respondents believe that MT affect mainly the kind of work they do and the quality of their work (answer for respectively 44% and 40% of the population).

Questions 8 to 11 aimed at getting information about how translators utilize MT. Question 8 concerned the context in which translators use MT. It revealed that 76% of respondents utilize MT only in some cases. 20% of respondents never utilize it and only one person utilizes MT consistently and irrespective of text nature. Those results show that a large majority of respondents do not use MT consistently (76%). Translators might utilize MT if they feel it is appropriate (text type) or required by a client. Question 9 focused specifically on the frequency of use of MT. The results for this question reveal that a majority of respondents (52%) utilizes MT rather frequently (every day or week). The rest of the respondents utilize MT every month (20%), several times during the year (17%), or never (9%). Question 10 results showed that most respondents (62%) do not know the type of MT system they are working with, which might seem a bit surprising. It appears that there might be a knowledge gap about the MT tools translators are utilizing. That said, almost 40% of respondents know the type of MT system they are working with (mainly hybrid systems). The answers for question 11 indicate that, in a high proportion (76%), the MT systems translators are utilizing are part of a translation environment.

Question 12 looked at the respondents' preferences regarding MT. It was interesting to see the differences among translators.

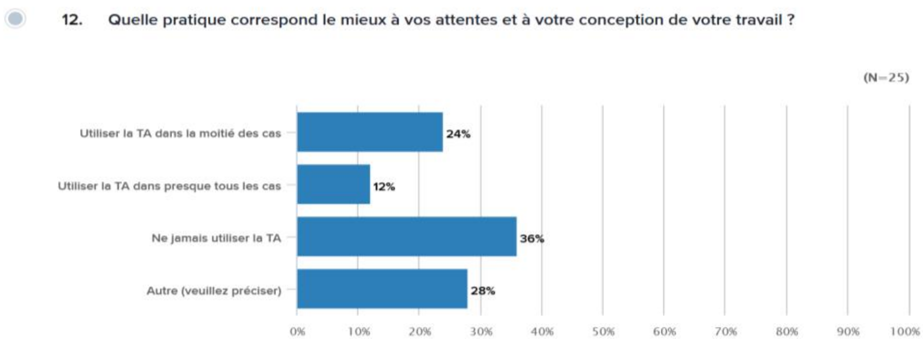

FIGURE 12. Answers to question 12

There is indeed an opposition between one third of the respondents who would prefer never to utilize MT and the rest of the respondents who are willing to utilize this technology in their work. Nevertheless, preferences also differ among this larger group: while 24% of respondents would be willing to use MT in half of the cases, 12% would like to utilize MT in nearly all cases and 28% would prefer to utilize this technology only in specific cases, e.g., when it is imposed by the client, when texts are particularly suitable for using MT or as a last resort.

Question 13 concerned perceived ease of use of MT systems. A large majority of respondents (67%) agreed that MT systems are easy to use. The following question aimed at understanding if translators had control over the use of MT tools. And it seems to be the case because 64% of respondents do not have to utilize a MT system to do their job. Question 15 was about perceived usefulness, and more specifically about efficiency. There were opposing views on that subject: while 46% of respondents said they believed they were not more efficient when they utilized MT, 38% thought on the contrary that they were more efficient. This result was also reflected in the interviews. It would be interesting to try to understand the reasons behind that trend. Are translators less efficient when they utilize MT tools because the tools are inadequate or do translators need some training to improve the way they work with such tools? Question 16 measured perceived ease of use. The results are fairly clear: 59% of respondents believe that is not the case, which would mean that it would be easier for them not to utilize MT and do a translation without the intervention of a machine. Question 17 concerned perceived usefulness about MT tools. Almost 60% of the respondents were under the impression that the quality of their work did not increase with MT. A third of the respondents thought the contrary. Question 18 was about the reliability of MT tools that translators utilize. It seems that there is a disagreement on that subject: while 41% believe that such tools are reliable, 38% do not find them reliable. There is also some debate over the question of the output quality: while 41% believe that MT output data can be utilized in most cases, 37% do not share this view. The point of question 20 was to determine if translators were afraid of MT and found it useful. It appears that a large majority of respondents (64%) view MT as very worrying (20%) or rather worrying (44%). But at the same time, 36% of the respondents find MT rather useful (28%) or very useful (8%). The last three questions concerned perceived usefulness. Very interestingly, at the question 21 (Would you say that MT has more advantages than disadvantages?), a majority of translators answered no (56%). That would mean that most respondents believe that MT technology is not that useful and mature yet. Regarding the benefits of using a MT system, it seems that a majority of respondents (a little more than 45%) think that these benefits are not clear (44% indicate that they are clear to them).

5.2 Interviews results

In total, three translators took part in the interviews. We would have expected more participants but it seems that most translators were mainly interested in answering the survey, which take less time than the interviews. The survey results seem also to indicate that some translators are mistrustful of machine translation. Three main themes emerged from the interviews. They will be discussed in this section.

1. MT is a present-day reality and will increasingly be used in the future

Interviewee 1 works with MT when she does post-editing. In that case, clients utilize their own MT tool to generate an automatic translation. The translators amend it in a second phase. Interviewee 1 has been doing post-editing for a short time because her clients have only recently started requiring it. She also utilizes DeepL (MT tool) when she does not for sure how to formulate a sentence in French because it can give a direction for building a sentence correctly. But according to interviewee 1, translators should not be afraid about that global trend because currently, it is inconceivable that machines could replace the translator's work. Humans and machines need to work together.

Interviewee 2 and interviewee 3 think that knowing how to utilize MT tools will be a necessity in the future because the translation market demands it. Interviewee 2 has little experience of MT because after mixed experiences with this technology, he tends to refuse projects involving this technology. For him, even though machines have made progress, their level remains well below than that of human translators. According to interviewee 3, who does post-editing from time to time, MT tools should not be viewed as competitors but as a valuable in some cases (e.g., repetitive texts with little ambiguity) because MT tools can help improve productivity. He believes that machines and humans can work hand in hand and that human translators will not be replaced anytime soon.

2. MT tools still present problems in terms of quality and reliability

There is a consensus among interviewees about that point. According to interviewee 1, at the moment, utilizing MT tools or doing post-editing after that some MT tools have been utilized can sometimes be frustrating because the benefits are not so clear. She stressed that she or colleagues of hers have sometimes the impression that utilizing MT rarely saves time because checking every segment translated by a MT system is time-consuming and that quality changes significantly MT systems. Interviewee 2 said he does not like to utilize MT because every time he did post-editing projects, the quality of the translation was poor (especially in terms of style). Interviewee 3’s view is in line with what interviewee 1 suggested: when he knows which MT system has been utilized by a client, he would rather not do the post-editing of the machine translation and would prefer do the whole translation by himself because the pretranslation made by the machine might not be very reliable.

3. There is a deficit of knowledge about MT tools and their functioning and thus related training needs

According to interviewee 1, because machine translation has been a reality for a few years and the fact that more and more clients are interested in using this technology, it is important that translators remain up-to-date on that subject. Machine translation has always been discussed in translation schools but there might be a lack of practical training. Interviewee 1, who knows some translation teachers mentioned that some of them had a hard time determining what to teach in practice to students because they are not proficient enough and have limited experience in the subject.

Interviewee 2 referred to the fact that it is necessary that translators follow trends in their field and continually learn throughout their careers. Otherwise, they might be unable to keep up with technology. Interviewee 2 wondered if students were now taught how to use MT tools and do post-editing. According to him, even though he is not very fond of post-editing, it would be important to reflect on the place of that activity in the training of translators.

Finally, interviewee 3 highlighted the fact that a deficit of knowledge not only concerns translators but all stakeholders in the translation industry, especially the clients. He said that, in order to meet their expectations, we should clarify with them the level of quality it is possible to reach with a specific MT tool and what role should be given to translators and machines.

5.3 Key findings

After analyzing data through a survey and semi-structured interviews, we have information enabling us to give answers to our research questions (how do French translators use MT tools and what do they think about them in terms of effectiveness, quality and reliability? According to them, do machine translation tools have more advantages than disadvantages?). It appears that French translators do not utilize MT tools and perceive them in the same way. Even if most respondents (56%) indicated that they would say that MT has more disadvantages than advantages, they also acknowledge that MT is a present-day reality and that this technology will increasingly be utilized in the future. Most respondents are divided about the current levels of quality and reliability reached by MT. But at the same time, they are willing to utilize this technology in their work, find it useful and effective in some cases (repetitive texts with little ambiguity, when there is a need to reformulate a sentence) and tend to consider it as threatening. In line with the results of Rossi & Chevrot (2019), our findings showed that the way MT is viewed has implications for perceived usefulness, perceived ease of use and actual use. Lastly, out of this research came also the finding that there is a deficit of knowledge about MT tools and their functioning and also a need to clarify what role should be given to translators and machines in relation to MT.

6 CONCLUSIONS AND DISCUSSION

6.1 Discussion of results

In the end, it seems that our first hypothesis (only a small minority of professional translators use MT systems voluntarily during the translation process) is wrong because the online survey we made shows that 64% of respondents do not have to utilize a MT system to do their job. The translators who took part in our study have usually control over the use of MT tools. The results might have been different with another sample of respondents. It also seems that professional translators mastering Information Technology seem to utilize MT tools more often than the ones less proficient in this area (Zaretskaya 2015). Regarding our second and third hypothesis (respectively that translators presume that output data from MT are often of low quality and little use (2) and that translators believe that it is better to translate all the segments of a translation themselves, instead of doing post-editing (3), the results from the survey and the interviews seem to indicate that on one hand, there is some debate among respondents over the question of the quality of output data (while 41% believe that MT output data can be utilized in most cases, 37% disagree).

According to the findings of the 2019 study carried out by Rossi and Chevrot, the majority of translators who responded declared that MT output data was relevant for them to check terminology, get new ideas and in a limited number of cases. A third of respondents mainly utilized MT to avoid wasting time. The interviews we conducted confirm this last point. Besides, it appears that due to poor quality of translation, many translators still hesitate to utilize MT tools (Zaretskaya, 2015). On the other hand, if the MT tools are perceived as not very effective or of poor quality, translators are under the impression that doing post-editing does not save them time. Therefore, they tend to prefer to do the translation themselves or utilize previous human translations. These findings are in line with Rémillard's study (2018): translators prefer human translations and human data from translation memories.

After analyzing the collected data and results, it seems that Rossi and Chevrot's amended version (2019, see Figure 13 below) of the third TAM proposed by Venkatesh and Bala (2008) is more relevant that TAM original version because it takes into account more variables and above all, is applied to MT.

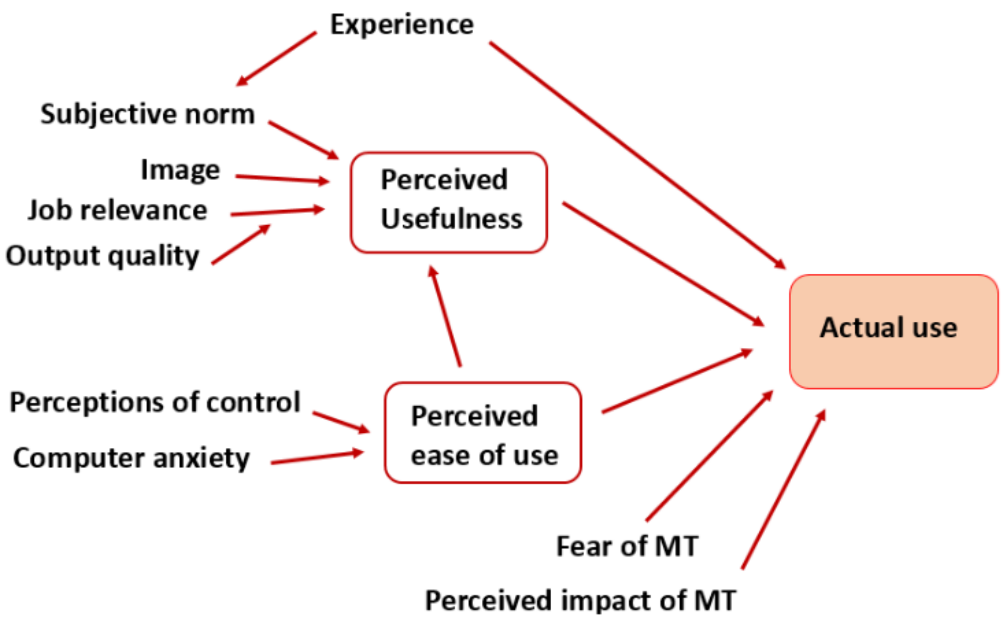

FIGURE 13. Rossi and Chevrot's amended version of TAM3 (2019)

We can see above the different factors having an impact on PU, PEU and actual use. This new version illustrates also our findings: the way MT is viewed affects perceived usefulness, perceived ease of use and actual use. Further research could for instance examine to what extent experience, perceived impact or fear of MT might influence the actual use of MT by French translators.

6.2 Research limitations

After answering our research questions, we must admit that the interpretation of our conclusions has some limitations. First of all, they are heavily dependent on the answers, choices and comments made by the translators who agreed to participate in our survey and interviews. Furthermore, we can't ensure the representativeness of the survey's sample. As a result, it is difficult to determine to what extent our results are valid for all French translators. Secondly, our findings are based on a relatively small data sample. Obviously, we did not review all possible situations. However, the analysis of the behaviors of French professional translators enabled us to, humbly, start better understand how they currently utilize and perceive MT tools. Thirdly, because a lot of subjectivity is involved, the way we interpret our findings entails also limitations. A lot of subjectivity is involved. It was also interesting to examine the latest developments in MT (neural systems), even if most translators usually do not know much about the functioning of this new technology or the technical aspects of MT.

6.3 Closing remarks

Although some people might not like it, MT systems are now utilized by professional translators and are here to stay because real and continuous technological advancements are being made (neural MT for instance). It is very likely that MT’s usefulness will increase over the next few years. But only focusing on technological developments without consulting the translators would not be a wise because they remain a key part of the translation process. Besides, getting more translators involved in the development of MT tools could improve their understanding and adoption of MT technology. Therefore, it is in their interest to start discovering this technology and voice their concerns in a constructive way in order to empower themselves for using MT in adequacy with their practices. Otherwise, translators would have to undergo unavoidable technological changes. They should get interested in MT to discover themselves the strengths and weaknesses of this technology.

Although MT systems seem to answer some translation needs (post-editing), a lot of work remains to be done to better understand their usefulness. A realistic use of MT, which involves the intervention of a proficient user and a balance between the tools capacity in a given context and the translation activity, is a necessity (Rémillard 2018). The perception of quality depends on many factors and we have only reviewed some them. Further research is needed to better understand such a complex topic. The progress achieved by machine translation seem to support the productivity and profitability goals of language service providers. As suggested by Rémillard (2018), thanks to the appropriation of technology, language service providers tend to want to constantly increase their productivity and make sure that their operations are profitable. But despite all the technological advancements made so far, the production of a high-quality translation still depends on human translators. Indeed, translating a sentence always requires the use of thinking skills. It is not possible to translate a sentence without understanding it. Put another way, more than just the meaning of a word, it is the whole sentence structure that must be taken into account because, depending on the context, a word may sometimes have different meanings in a same document. While MT can be useful for understanding a text globally, it can quickly become a counterproductive instrument for translators when they are working on technical or ambiguous texts.

It is highly likely that MT tools will not be able grasp all the specificities of technical areas such as law or medicine. Besides, MT tools have not yet managed to improve their performance regarding the general style of a translation (Sepesy Maučec & Donaj 2019). Apart from a few integrated common expressions, a MT tool will translate a text literally. But sometimes, it is necessary to reword a sentence so that it becomes clearer and more fluid when people read it. This is where the aesthetic sense of human translators, which MT tolls will always lack, really comes in because those tools will propose a text in a target language with the same structure and style as the source language and without any sentence adaptation or restructuring. Machine translation is far from being useless but it should be utilized with caution.

It can be very convenient for translators to save time and ”lay the groundwork” but machine translation should always be reviewed, corrected and approved by a human translator. Lastly, and above all, it should be avoided when dealing with topics which are too technical or ambiguous context. Human-machine interactions still have their best days ahead of them in the translation field. The profession of translator has certainly evolved but the job is here to stay for some time. As Poibeau (2017) has expressed it very well, the fact that “computers beat the world chess champion in 1997 and the world Go champion in 2016, but that no computer is able to translate accurately between two languages shows the complexity of natural languages” (Poibeau 2017, 482) and of the translation process. This process involves indeed high-level cognitive and linguistic capabilities that machines do not have. Translators are indeed required to master two languages (SL and TL) and be able to reformulate complex sentences. These kinds of skills are not directly available to machines.

“Artificial systems are still in their infancy from this point of view and are very far from the capacities of human beings when it comes to reasoning, inferring, and reformulating”. (Poibeau 2017, 553). At this point, nothing replaces human translation in terms of quality of writing. For how long exactly? Only the future will tell.

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APPENDICES

Appendix 1. Original online survey

Page 1

Outils de traduction automatique (TA) : utilisation et perception des traducteurs/trices de langue française

Le présent questionnaire s'inscrit dans le cadre de mon mémoire de Master (MBA) portant sur la manière dont les traducteurs/trices de langue française utilisent et perçoivent les outils de traduction automatique. Il me permettra de recueillir des données actuelles à ce sujet.

Je vous remercie par avance de bien vouloir répondre spontanément aux différentes questions qui vous seront proposées. Vos réponses sont anonymes et confidentielles.

* Informations obligatoires

* 1. Consentement (question obligatoire)

J'ai au moins 18 ans et je consens à participer à la présente étude.

- Oui
- Non

2. Vous êtes :

- Une femme
- Un homme
- Vous ne souhaitez pas répondre

3. Quel âge avez-vous (veuillez utiliser 0 si vous ne souhaitez pas répondre) ? :

Create a Survey

Page 1

4. Dans quel domaine avez-vous effectué votre formation académique ?

- Lettres et langues (p. ex. école de traduction)
- Sciences humaines et sociales
- Droit et sciences politiques
- Économie et gestion
- Sciences et technologies
- Santé
- Autre (veuillez préciser)

5. Depuis combien de temps exercez-vous le métier de traducteur/trice ?

Caractères restants: 100

6. Parmi les changements dont vous avez été les témoins récemment, diriez-vous que la traduction automatique (ci-après TA) :

- A eu un impact majeur
- N'a pas changé beaucoup de choses
- Autre (veuillez spécifier)

7. Diriez-vous que la TA affecte (cochez SVP les affirmations avec lesquelles vous êtes d'accord) :

- La quantité de travail que vous accomplissez
- Le type de travail que vous faites

Create a Survey

- Autre (veuillez spécifier)

7. Diriez-vous que la TA affecte (cochez SVP les affirmations avec lesquelles vous êtes d'accord) :

- [ ] La quantité de travail que vous accomplissez
- [ ] Le type de travail que vous faites
- [ ] La qualité du travail que vous réalisez
- [ ] La manière dont vous travaillez (vos méthodes de travail)
- [ ] Vos relations avec vos clients et/ou votre employeur
- [ ] Aucune des affirmations susmentionnées

8. Dans quel cadre utilisez-vous la TA ?

- De manière systématique et quel que soit le type de texte
- Seulement dans certains cas
- Jamais

9. Si vous n'utilisez pas la TA de manière systématique, quand y avez-vous recours ?

- Tous les jours
- Toutes les semaines
- Tous les mois
- Plusieurs fois par an
- Autre (veuillez spécifier)

10. Si vous travaillez avec la TA, veuillez donner quelques précisions sur le type de système de TA dont vous vous servez. Le système de TA est :

- À base de règles
- À base statistique
- Hybride (à base statistique et de règles)
- Autre
- Je ne sais pas

11. Le système de TA est intégré à un environnement de traduction (comme SDL Trados, MultiTrans, Transit NXT, etc.)

- Oui
- Non
- Je ne sais pas

12. Quelle pratique correspond le mieux à vos attentes et à votre conception de votre travail ?

- Utiliser la TA dans la moitié des cas
- Utiliser la TA dans presque tous les cas
- Ne jamais utiliser la TA
- Autre (veuillez préciser)

13. Les systèmes de TA sont, de manière générale, simples à utiliser.

- Tout à fait d'accord

13. Les systèmes de TA sont, de manière générale, simples à utiliser.

- Tout à fait d'accord
- D'accord
- Pas d'accord
- Pas du tout d'accord
- Je ne suis pas en mesure de répondre ou n'ai aucun point de vue sur la question
- Autre / commentaires

14. Je ne suis pas tenu(e) d'utiliser un système de TA pour remplir mes fonctions.

- Tout à fait d'accord
- D'accord
- Pas d'accord
- Pas du tout d'accord
- Autre / commentaires

15. Je suis plus efficace lorsque je l'utilise la TA.

- Tout à fait d'accord
- D'accord
- Pas d'accord
- Pas du tout d'accord
- Je ne suis pas en mesure de répondre ou n'ai aucun point de vue sur la question
- Autre / commentaires

16. Il est plus facile pour moi de travailler avec la TA (aussi bien en ce qui concerne les tâches que j'assume que la charge cognitive).

- ○ Tout à fait d'accord
- ○ D'accord
- ○ Pas d'accord
- ○ Pas du tout d'accord
- ○ Je ne suis pas en mesure de répondre ou n'ai aucun point de vue sur la question
- ○ Autre / commentaires

17. Je travaille mieux et la qualité de mes traductions s'améliore lorsque j'utilise la TA.

- ○ Tout à fait d'accord
- ○ D'accord
- ○ Pas d'accord
- ○ Pas du tout d'accord
- ○ Je ne suis pas en mesure de répondre ou n'ai aucun point de vue sur la question
- ○ Autre / commentaires

18. Les outils de TA que j'utilise sont fiables.

- ○ Tout à fait d'accord
- ○ D'accord
- ○ Pas d'accord
- ○ Pas du tout d'accord
- ○ Je ne suis pas en mesure de répondre ou n'ai aucun point de vue sur la question
- ○ Autre / commentaires

○ Autre / commentaires

19. Les données de sortie de la TA sont généralement utilisables.

- ○ Tout à fait d'accord
- ○ D'accord
- ○ Pas d'accord
- ○ Pas du tout d'accord
- ○ Je ne suis pas en mesure de répondre ou n'ai aucun point de vue sur la question
- ○ Autre / commentaires

20. Avez-vous l'impression que la TA :

- ☐ Constitue une grande menace
- ☐ Constitue une menace dans une certaine mesure
- ☐ Je ne suis pas en mesure de répondre ou n'ai aucun point de vue sur la question
- ☐ Est inutile
- ☐ Est plutôt utile
- ☐ Est très utile

21. Diriez-vous que la TA présente plus d'avantages que d'inconvénients ?

- ○ Oui
- ○ Non

○ Non

22. Les bénéfices de l'utilisation d'un système de TA me semblent clairs.

- ○ Tout à fait d'accord
- ○ D'accord
- ○ Pas d'accord
- ○ Pas du tout d'accord
- ○ Je ne suis pas en mesure de répondre ou n'ai aucun point de vue sur la question
- ○ Autre / commentaires

23. Pensez-vous que des compétences spécifiques sont nécessaires pour utiliser la TA ?

- ○ Oui
- ○ Non

24. Seriez-vous disposé-e à répondre à d'autres questions de nature qualitative relatives à vos expériences avec la TA ?

- ○ Oui
- ○ Non
- ○ Si tel est le cas, veuillez indiquer ici vos noms et prénoms ainsi que votre adresse de messagerie :

Merci de votre patience ! Votre contribution est très précieuse !

Appendix 2. Open questions used in semi-directed interviews and their translation

1. Depuis combien d’années travailles-tu comme traducteur/traductrice professionnel-le ? *How many years have you been working as a professional translator?*

2. Qu’apprécies-tu particulièrement dans ton travail et quels aspects de celui-ci apprécies-tu moins ?
Which aspects of your work do you particularly enjoy and which parts do you enjoy less?

3. Pourrais-tu décrire l’utilité de la traduction automatique dans ton travail ?
Could you tell how useful is Machine Translation to your work?

4. Quels outils de TA utilises-tu ? *What MT tools do you utilize*?

5. A contrario, t’est-il arrivé de penser que la traduction automatique n’était pas d’une grande aide voire te freinait dans ton travail ? Pourrais-tu donner un exemple, illustrer une telle situation ?
By contrast, have you ever thought that MT was not of great assistance or could hinder your work? Could you give an example, illustrate such a situation?

6. Pourrais-tu m’indiquer comment sont générées les données de sortie d’une traduction automatique ? As-tu déjà rencontré des difficultés vis-à-vis de tels résultats ?
Could you tell how the output data of a MT are generated? Have you ever encountered any problems with those results?

7. À ton avis, quelle sera l’utilisation future des technologies de TA par les traducteurs ?
What is your opinion about the future use of MT technologies by translators?

8. As-tu déjà entendu parler de la traduction automatique neuronale ? *Have you ever heard of neural MT ?*

9. Pour finir, as-tu des remarques, des commentaires à propos des outils de traduction automatiques ? As-tu autre chose à ajouter ?
Finally, do you have any questions, remarks or comments about machine translation tools? Is there anything that you would like to add?

Je te tiens à te remercier chaleureusement de ta participation.
Thanks a lot for participating!

Appendix 3. Transcript of an interview (in French)

1. Depuis combien d'années travailles-tu comme traducteur/traductrice professionnel-le ? *How many years have you been working as a professional translator?*

13 ans

2. Qu'apprécies-tu particulièrement dans ton travail et quels aspects de celui-ci apprécies-tu moins ? *Which aspects of your work do you particularly enjoy and which parts do you enjoy less?*

J'aime mon métier, ce contexte avec différentes cultures, différents domaines. Je pense que c'est ma principale source de satisfaction au travail. J'aime le fait de pouvoir m'organiser comme je veux, la flexibilité. En ce qui concerne la frustration, de faire plus en plus de traduction technique, qui ne plaît pas toujours et de pas pratiquer les langues à l'oral, je regrette un peu.

3. Pourrais-tu décrire l'utilité de la traduction automatique dans ton travail ?
Could you tell how useful is Machine Translation to your work?

J'utilise la traduction automatique quasiment uniquement pour débloquer des situations de traduction. Par exemple, si je ne sais pas comment formuler une phrase en français, je vais la mettre dans un logiciel de TA et voir ce qui sort. Je ne vais pas forcément reprendre la phrase telle quelle mais elle va m'aider à reformuler. Parfois, si je ne suis pas sûre du sens de la phrase source, je vais regarder ce que la TA propose tout en gardant des réserves.

4. Quels outils de traduction automatique utilises-tu ? *What MT tools do you utilize*?

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5. A contrario, t'est-il arrivé de penser que la traduction automatique n'était pas d'une grande aide voire te freinait dans ton travail ? Pourrais-tu donner un exemple, illustrer une telle situation ?
By contrast, have you ever thought that MT was not of great assistance or could hinder your work? Could you give an example, illustrate such a situation?

Oui, dans un cas de post-édition demandé par un client. Le client traduit d'abord avec son outil de TA, puis il nous demande de faire de la post-édition après. Mais en réalité, après avoir traduit plusieurs projets, j'en viens à la conclusion que je passe au moins autant de temps, sinon plus, à effectuer de la post-édition que si j'avais traduit le texte moi-même dès le départ. Peut-être que je n'ai pas encore trop l'habitude, que je ne connais pas encore trop son outil de TA. Du coup, je suis obligée de vérifier les segments un à un, de vérifier si le sens est correct, si on ne pourrait pas reformuler différemment, et finalement, je trouve qu'on ne gagne pas de temps.

6. Pourrais-tu indiquer comment sont générées les données de sortie d'une traduction automatique ? As-tu déjà rencontré des difficultés vis-à-vis de tels résultats ?
Could you tell how the output data of a MT are generated? Have you ever encountered any problems with those results?

Je ne sais pas précisément. Je crois qu'il y a un mélange de règles de grammaire qui sont apprises par la machine et un traitement de tout un ensemble de traductions antérieures, je ne sais pas si on pourrait dire un corpus, un pool de pleins de segments antérieurs qui ont été traduits et qui sont recoupés les uns avec les autres, pour dire bon bah, ça serait ça la traduction idéale, je suppose. En général, je réutilise ces données de sortie. Après, ce que je trouve assez fréquent, c'est qu'on a du mal à avoir du recul par rapport à la TA. Ok, le sens est bon, mais est-ce que vraiment on dit comme ça en français? En soi, le sens est bon, mais est-ce qu'il n'y aurait pas une manière plus fluide ? Parfois, on ne va pas chercher plus loin que ce qui est proposé et on est à la limite du faux-sens. Tous les sont à leur place et ça passe.

7. À ton avis, quelle sera l'utilisation future des technologies de TA par les traducteurs ?
What is your opinion about the future use of MT technologies by translators?

Je pense qu'on ne pourra pas éviter la TA, c'est parti de toute façon. Et encore, je pense qu'en fait, nous, chez MLI, on s'y est mis un peu tard car on a un client qui nous a dit il y a deux ans qu'on allait se mettre à la TA, donc on s'est adapté. Mais on a découvert que nos traducteurs freelance font ça depuis très longtemps. On est un peu en retard sur le sujet, mais c'est inévitable que les jeunes traducteurs qui arrivent sur le marché vont devoir avoir utiliser ses outils là. Je pense aussi que les mémoires de traduction et la TA ont leur intérêt, à condition de bien savoir les utiliser.

8. As-tu déjà entendu parler de la traduction automatique neuronale ? *Have you ever heard of neural MT ?*

Oui, j'avais déjà entendu l'expression, mais je n'aurai pas su quoi mettre derrière exactement.

9. Pour finir, as-tu des remarques, des commentaires à propos des outils de traduction automatiques ? As-tu autre chose à ajouter ?
Finally, do you have any questions, remarks or comments about machine translation tools? Is there anything that you would like to add?

C'est le grand sujet du moment, très prisé des étudiants. C'est un sujet intéressant qui divise la communauté de traducteurs. Je pense qu'il faudrait surtout des formations, en fait. Et aussi clarifier quel rôle on veut donner à la machine. A l'heure actuelle, il n'est pas pensable que la machine puisse remplacer le travail du traducteur. Il faut que l'humain et la machine travaillent ensemble. Il faudrait clarifier avec toutes les parties prenantes la qualité que l'on peut espérer avec la TA et quelle serait la place de la post-édition dans la formation des traducteurs.

Je te tiens à te remercier chaleureusement de ta participation.
Thanks a lot for participating!