Do humans translate like machines? Students' conceptualisations of human and machine translation

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Do Humans Translate Like Machines? Students' Conceptualisations of Human and Machine Translation

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Abstract

This paper explores how students conceptualise the processes involved in human translation (HT) and machine translation (MT), and how they describe the similarities and differences between them. The paper presents the results of a survey involving university students (B.A. and M.A.) taking a course on translation who filled out an online questionnaire distributed in Finnish, Dutch and English. Our study finds that students often describe both HT and MT in similar terms, suggesting they do not sufficiently distinguish between them and do not fully understand how MT works. The current study suggests that training in Machine Translation Literacy may need to focus more on the conceptualisations involved and how conceptual and vernacular misconceptions may affect how translators understand human and machine translation.

1 Introduction

Recent years have seen increasing prominence of MT both inside the translation industry and in everyday settings. Although predictions of "synchronous, automated translation systems" completely replacing translators (e.g. Lehman-Wilzig, 2000) have not come to pass, MT has had an undeniable impact, not merely changing the practical realities of translation but in fact challenging the very concept of translation (e.g. Alonso and Calvo, 2015; Rozmyslowicz, 2014). The question "Is machine translation translation?" was, for example, the topic of a panel at the 2022 EST Congress.[1]

Analysing the ways HT and MT are described can be a useful way to investigate how translation is conceived by people and potentially provide insights into the nature of translation (see Chesterman, 2016). Furthermore, the way translation is discussed and described affects how it is perceived. For this reason, it is also important to examine the socially constructed narratives (see Olohan, 2017) of humans and machines as translators. Whether translation is conceptualised as a straightforward task consisting of mechanically replacing linguistic components or a creative task requiring cultural competence and social perception affects discussions of the automatability of translation (cf. Vieira, 2018). Common narratives in the popular press about the human-like or even "super human" performance of MT systems may give rise to unrealistic expectations as well as misconceptions of translation both by humans and machines (e.g. Vieira, 2020; Moorkens, 2022). One of the goals of MT literacy (see Bowker and Buitrago Ciro, 2019), for example, is to challenge such misconceptions.

To explore these issues, this paper examines short reflective texts collected from language and translation students in Finland and the Netherlands. We analyse how the students describe the process of translating and what these descriptions reveal about their conceptions of HT on the one hand, and MT on the other. We examine whether the students conceptualise HT and MT as the same or a different process, what differences and similarities they perceive, and

[1] https://www.hf.uio.no/ilos/english/research/news-and-events/events/conferences/2022/est22/program/est22-congress-program/panel-31-is-machine-translation-translation%282%29.html

Nurminen, Brenner, Koponen, Latomaa, Mikhailov, Schierl, Ranasinghe, Vanmassenhove, Vidal, Aranberri, Nunziatini, Escartín, Forcada, Popovic, Scarton, Moniz (eds.)
Proceedings of the 24th Annual Conference of the European Association for Machine Translation, p. 295–304
Tampere, Finland, June 2023.

what the reflections reveal about their conceptualisation of translation as a whole. Furthermore, we analyse potential misconceptions of translation (human or machine) that may need addressing as part of their training in translation and the use of translation technology.

2 Related Research

2.1 Conceptualising MT and Other Scientific Phenomena

While there is a rapidly growing body of research investigating how MT is used by professional translators (e.g. Läubli and Orrego-Carmona, 2017; Moorkens et al., 2018; Sánchez-Gijón et al., 2019) and translation students (e.g. Kenny and Doherty, 2014; Gaspari et al., 2015; Moorkens, 2018; Rossi, 2017), and what translators' and students' views and opinions are on using MT and doing post-editing (e.g. Dorst et al., 2022; Guerberof-Arenas, 2013; Läubli and Orrego-Carmona, 2017; Loock et al., 2022), there is to our knowledge little to no research that focuses on the way people actually conceptualise MT and how they understand the processes involved in MT as compared to HT.

The way people describe a phenomenon can affect how they conceptualise that phenomenon, and examining their descriptions can provide insight into their conceptualisations (Chesterman, 2016: 18). One aspect of describing HT, for example, appears to focus on the agency and intentionality of the translator. On the other hand, Rozmyslowicz (2014) argues that MT challenges this basic assumption of agency and the perception of culture as central to translation. Rozmyslowicz (2014) conceptualises MT as the opposite end to HT on a continuum of intentionality, where MT represents mechanical decoding with no intentionality, while HT represents an intentional interpretation of the source. Not all scholars necessarily agree with Rozmyslowicz's positioning of HT as always intentional, but a detailed discussion of intentionality is outside the scope of this paper.

The integration of MT (and other technologies) in translators' processes necessitates also rethinking of the existing models regarding the translation process, both the cognitive process of a translator and the production process as a whole. Alonso and Calvo (2015), for example, argue that viewing translation technology only as support tools for translators does not fully account for their impact, and propose an instrumental model that would reflect a more instrumental and collaborative view. Along similar lines, Cadwell et al. (2018) describe translation workflows involving MT as a "double dance of agency" where interactive, adaptive MT systems in particular blur the distinction of human agents (translators) and material agents (MT).

Some authors have taken a rather dim view of this blurring, as evidenced by their metaphors. For example, Kushner (2013) talks about a "freelance translation machine" where the human translator becomes a sub-routine in the translation algorithm or an invisible interface. Mossop (2021) likens a translator using MT or translation memory suggestions, sometimes without modifications if required by the situation, to an "echoborg" controlled like a ventriloquist's dummy and repeating or echoing the words of an external artificial intelligence.

In more positive terms, the "trans-human translation hypothesis" proposed by Alonso and Calvo (2015: 135) conceives human-computer interaction in more collaborative terms as "cohesive and mutual merging between translators and their technologies" where both affect and learn from each other. Others have also considered the roles of humans and machines in this merging. For example, Massey (2021) argues that the "human added value" lies in the human translator's problem-solving process that happens on a conceptual rather than lexical level.

Discussions of conceptualising (human and machine) translation appear to have mainly focused on translation scholars and practitioners (see Vieira, 2020). To investigate perspectives outside the field, Vieira (2020) analyses how MT is portrayed in English-language news media, noting that reporting of MT was mostly positive and relied heavily on information provided by MT developers. Vieira's (2020) findings suggest that popular press reports mostly appear to conceptualise MT as infallible, emphasising its human-like behaviour and agency or even attributing to MT nearly magical powers to translate perfectly any language in any situation. Even more negative reports addressing MT errors, Vieira (2020) notes, often frame mistranslations as unexpected anomalies.

Although popular press may present misleading conceptions about MT, translator training should ensure that future translators understand it correctly and do not construct misconceptions. Misconception is defined by the Oxford English Dictionary as "a view or opinion that is false or inaccurate because based on faulty thinking or understanding". Misconceptions build barriers for students to learn and understand scientific phenomena, which is why they have been widely studied in educational sciences; the meta-analysis conducted by Soeharto et al. (2019: 248) revealed around 2,000 studies that related to misconceptions only during the years 2015-2019. In this paper, we present the concept of misconceptions and apply it to analyse data collected from translator students.

Misconceptions are usually classified into five categories: preconceived notions, nonscientific beliefs, conceptual misunderstandings, vernacular misconceptions and factual misconceptions (CUSE, 1997: 27-28). Preconceived notions are popular conceptions that have their origin in everyday experiences, such as the idea of the sun rising and setting, and nonscientific beliefs stem from religious sources or mythical teachings (CUSE, 1997: 28). Conceptual misunderstandings take place when students have a preconceived notion or a nonscientific belief about a scientific phenomenon being taught to them, and they construct an incorrect model of the phenomenon in question, based on these misconceptions (CUSE, 1997: 28). Another example of such a preconceived notion creating a conceptual misunderstanding could be the humanisation of objects, mentioned by Suprapto (2020: 52), i.e. understanding the behavior of things as human behavior. Vernacular misconceptions arise when words are used that have one meaning in everyday life and another in a scientific context (e.g., "work" or "force" in physics), and factual misconceptions are "falsities often learned at an early age and retained unchallenged into adulthood" (CUSE, 1997: 28).

The ways of describing MT in the popular press, mentioned by Vieira (2020), may lead to the general public as well as students to formulate misconceptions on MT, which is why an analysis of students' conceptualisations on MT using the classification from science education (CUSE, 1997) can shed light on how MT is understood.

2.2 MT in the Translation Curriculum

Since the early 2000s, scholars have been reflecting on how to integrate MT and post-editing into translator training curricula (Bowker, 2002; Doherty and Moorkens, 2013; Doherty and Kenny, 2014; Guerberof Arenas and Moorkens, 2019; O'Brien, 2002; Pym, 2013). Knowing how to use MT effectively is recognised as an essential competence for future translators (EMT Competence Framework 2009, 2017, 2022; Rothwell and Svoboda, 2019), as well as students more generally (Bowker, 2020; Dorst et al., 2022; Loock et al., 2022).

Already in 2009, the European Master's in Translation Network considered "knowing the possibilities and limits of MT" (EMT Expert Group, 2009: 7) a technological competence that students need to acquire in order to become professional translators. By 2017, the EMT Competence Framework acknowledged that "artificial intelligence and social media have considerably changed people's relation to communication in general and translation in particular, with machine translation applications and other language tools now commonly available on desktop and mobile devices" (2017: 2). As pointed out by the EMT Expert Group, such changes do not only influence the way the general public views translation, but also the way professionals and trainees understand the processes and agents involved in the translation workflow.

Yet the technological competence focuses more on usage than actual understanding. It involves "basic knowledge of machine translation technologies and the ability to implement machine translation according to potential needs" (2017: 9). However, the Framework does not specify what a "basic knowledge" entails, and whether students need to have a technically and scientifically correct understanding of the processes involved. The same applies to the two most commonly used definitions of MT Literacy currently in use: Bowker and Buitrago Ciro's definition refers to "comprehend[ing] the basics of how machine translation systems process texts" (2019: 88) and O'Brien and Ehrensberger-Dow's definition specifies that "MT Literacy means knowing how MT works" (2020: 145).

While in the 2022 EMT Competences Framework Technical Competence 19 mentions "data literacy", Competence 18 does not mention "machine translation literacy", even though this is a hot topic in Translation Studies. It remains rather obscure what is meant exactly by "understand the basics of MT", for example, whether this refers to history of MT, its different forms (e.g. rule-based, statistical and neural) and the operations involved in each process or something else entirely. It is also not clear whether a distinction is made between being able to use MT effectively, being able to use it ethically, and having a technically and scientifically accurate understanding how it actually works. One avenue for further investigation as well as curriculum design appears to be specifying what is involved in the "basic understanding" of MT, especially in terms of conceptualisations and misconceptions and how these affect both usage and opinion. For our current purposes, we are therefore interested in what it means for students to "understand the basics of MT" and whether this can be deduced from their conceptualisations of machine translation and the way they describe the similarities and differences between HT and MT.

3 Methodology

As was mentioned in Section 1, we wanted to know how students conceptualise the processes involved in MT and the similarities and differences between HT and MT after having been introduced to the history and basics of MT as part of a Translation module during their bachelor's or master's programme. The following subsections describe the design, methods and participants of the study.

3.1 Questionnaire

In total, 58 students took part in the study, 25 from University of Turku (Finland) and 33 from Leiden University (Netherlands). Data was gathered using a questionnaire that the students filled out in class, right after they had received a brief introduction to the history and basics of MT, including an overview of the three main types of machine translation (rule-based, statistical and neural). The questionnaire was made available online via the survey and reporting tool Webropol (https://webropol.com/) and was offered in three languages (Finnish, Dutch and English). The English version was provided as we knew that not all students were native speakers of Finnish or Dutch.

The questionnaire opened with a description of the study, including aims and means of data collection and management, as well as contact information on the researchers involved. The students were informed of the purpose of the study, data collection and processing and asked for consent.

In the questionnaire, students were first asked to reflect on their understanding of how MT engines work and how humans translate. They were asked to consider what human translators do when they translate and which steps or activities are involved. Then they were asked to briefly answer the following questions: "Do humans translate in the same way machines do? If yes, what is similar about translating? If not, in what way is a human translator different from a machine?" It was stated explicitly that there was no word limit and that they should take approximately 10 minutes for their answer.

After writing the reflection, students were asked to specify their native language, age, university, course for which they completed the questionnaire, degree (B.A. or M.A. programme), and the start date of their degree.

3.2 Methods

In total, we received 58 reflections, of which 26 were written in Dutch, 23 in Finnish and 9 in English. The reflections were analysed in terms of (a) their answers to the overall question on how humans and machines translate (in the same or in a different way), and (b) the characteristics they mentioned in their answers as justifications to their views.

Each answer was coded for sameness vs difference and for the characteristics mentioned, linking each characteristic to the human, the machine or both. To help all authors make sense of all answers, we used DeepL to translate the Finnish and Dutch answers into English, and checked the accuracy of the translations ourselves. However, the main analysis was conducted using the original language of the reflections by authors who are speakers of the language in question. The coding for Turku students was first done by Salmi and checked by Koponen; the coding for Leiden students was first done by Dorst and checked by Zeven. All unclear, ambiguous and problematic cases were discussed among all authors to reach consensus.

The coding approach used was inductive thematic analysis. As a starting point, we used a list of data-driven characteristics that had emerged in an unpublished pilot study involving a similar reflection task with students from the Universities of Turku and Eastern Finland (Salmi and Koponen, 2022). As the question in the earlier task was slightly different, we do not include the pilot data in this analysis. The categories of characteristics were further refined inductively based on the data (see Section 4). The final list of categories, in alphabetical order, is as follows:

- Considers target audience and situation
- Considers context and whole text
- Has emotions, cognition, personality
- Has language skills
- Has vast amount of knowledge or information
- Has world knowledge
- Is creative
- Is fast
- Learns from prior material
- Makes mistakes

- Operates mechanically
- Searches for information
- Translates always the same way
- Translates directly (“word for word”)
- Understands meaning
- Uses pre-defined knowledge
- Uses probabilities
- Uses rules
- Uses vocabularies or dictionaries

The texts were coded for statements about human or machine translation that reflected these categories. Each student’s reflection could contain statements belonging to different categories, each of which was coded separately. In addition, each statement was coded to indicate whether the student associated the characteristic with human translators or MT, for example, “the machine translates fast” or “humans understand meaning, machines don’t”.

In addition, the texts were analysed to check if students had presented any false or misleading ideas about how MT functions. The preliminary analysis of the students’ misconceptions was made by Salmi (based on the originals in Finnish and English and on the translations into English from Dutch) and Dorst (based on the originals in Dutch and English and on the translations into English from Finnish). All unclear, ambiguous and problematic cases were discussed among both authors to reach consensus.

3.3 Participants

University of Turku (Finland): 25 students participated in the study. Of them, 22 were bachelor’s students and 3 master’s students. The first group of students filled out the questionnaire on 4 October 2022 during the course “Interaction and Multilingual Communication”. This course is a 5 ECTS course, compulsory for the major and minor students of French. The second group of students filled out the questionnaire on 28 October 2022 during the course “Introduction to Translation Practice” (5 ECTS elective course open to all language students on both BA and MA levels, and part of the Minor in Translation). The first group were first or second year bachelor’s students majoring in French, except one who had Spanish as their major. The students in the second group were majoring in various subjects, most of them in English or other languages. Twelve of them were bachelor’s students and three master’s students.

Leiden University (Netherlands): 10 bachelor’s students and 23 master’s students participated in the study. The bachelor’s students filled out the questionnaire on 19 October 2022 during the course “Multilingual to Dutch Translation” (5 ECTS elective course in the Minor in Translation). The master’s students filled out the questionnaire on 24 November 2022 during the course “The Translator’s Tools” (5 ECTS obligatory course in the MA Linguistics: Translation). The bachelor’s students were enrolled in various programmes, though most majored in English Language and Culture, Japan Studies or Korean Studies. The master’s students were all enrolled in the 1-year Master’s in Linguistics, track Translation. They had all completed a Bachelor’s Degree in languages and a Minor in Translation.

4 Results

Table 1 shows the results for the first question posed to the students, namely “Do humans translate in the same way machines do?”, divided by the students’ university. “Both” indicates that they have responded by saying that there are both similarities and differences between HT and MT. “Unclear” indicates that the student’s text did not directly answer the question in a way that it could have been interpreted as belonging to any of the other categories. For example, a student who only wrote some general remarks about how humans translate but did not mention MT at all.

	Finland	Netherlands	All
Same	1	4	5
Different	14	24	38
Both	8	5	13
Unclear	2	0	2
Total	25	33	58

Table 1. Students’ views on if humans and machines translate in a different or in a similar way.

Results of the analysis on the characteristics mentioned by students are presented in Tables 2 and 3. Two characteristics not previously mentioned in the pilot study emerged: the use of logic and the use of previous experience.

The characteristics students associated with both humans and machines are listed in Table 2.

Characteristic	Human	Machine
Uses pre-defined knowledge	6	13
Uses rules	5	12
Operates mechanically	4	10
Learns from prior material	4	7
Uses previous experience	7	2
Makes mistakes	3	6
Uses vocabularies	4	5
Is fast	1	5
Has a vast amount of knowledge/information	1	2

Table 2. Characteristics associated with both humans and machines.

The characteristics students associated either mainly with humans or mainly with machines are shown in Table 3.

Characteristic	Human	Machine
Considers context and the whole text	27	5
Considers the target audience and situation	19	0
Understands meaning	15	0
Has world knowledge	11	0
Has emotions, cognition, personality	11	0
Has language skills	9	1
Is creative	5	0
Searches for information	2	0
Uses probabilities	0	9
Translates directly	0	8
Translates always the same way	0	3
Uses logic	0	2

Table 3. Characteristics mainly associated with humans or machines.

The pilot study by Salmi and Koponen (2022) suggested some differences between BA and MA students. However, a comparison regarding the respondents' level or background is not included in this paper due to space limitations.

5 Discussion

As Table 1 shows, the majority of the students consider HT and MT to be different at least in some ways, namely 38 out of 58 (66%) and an additional 13 students (22%) who opted for "Both". Only 5 out of 58 (9%) consider HT and MT to be essentially the same, though their answers indicate that this similarity is not complete, or perhaps metaphorical rather than literal, and that there are still differences between the two even if they cannot put their finger on what this difference is [emphasis added]:

L04, translated from Dutch: **I think that to a certain degree** people and machines translate the same way. Both make use of a database that they have acquired to see whether they can retrieve something from it.

L23, translated from Dutch: **I think that in principle** people translate the same way as machines, because both make connections between the words of the source text and the associated translations of the target text. Both have access to a vocabulary from which the right words can be chosen.

When we relate the similarity judgments to the characteristics students refer to in order to support their decision, it becomes clear that they understand the differences between HT and MT predominantly through the characteristics that are typical of human translators. Only four characteristics are clearly associated with machines by students in this data – *Uses probabilities, Translates directly, Always translates the same way,* and *Uses logic* – and the total counts for these are low. Even though the questionnaire was filled out during an introductory tutorial on MT, it is telling that after having been told how different MT systems work, only 9 out of 58 (16%) mention probabilities and only 8 (14%) remark on the fact that MT normally retains source text structures and translates word-by-word. Moreover, the idea that MT would be consistent in formulating the translation (coding *Always translates the same way*) is not true for NMT systems.

The scores for the characteristics that students clearly associated with humans are much higher and a more accurate reflection of the actual differences between HT and MT. In total, eight characteristics are associated more with humans, of which *Considers context and the whole text* appears to be "the defining characteristic" with 27 mentions (even though 5 students also associated context with machines), followed by *Considers target audience and situation* (19 vs 0), *Understands meaning* (15 vs 0), *Has world knowledge*

(11 vs 0) and *Has emotions, cognition, personality* (11 vs 0). A variety of explanations are in fact brought together under these labels. For example, a number of students mention that humans understand humor, sarcasm, irony or implicit meaning, while others mention that humans understand nuances and reflect on social norms and values and take cultural differences into consideration.

Most students contrast the differences between humans and machines:

T03, translated from Finnish: When a human translates, they do quite a lot of background work. They consider the context of the translation, think about the target audience for whom the translation is being made and look at the text holistically in terms of the reading experience. This is not something a machine can do. A machine is able to do translation work that requires repetition and to process huge amounts of material, which would be laborious for a human.

Interestingly, only 5 students mention that humans are (more) creative, a point often made in academic research on machine translation and post-editing, especially in a literary context (see Guerberof-Arenas and Toral, 2020). This may be due to the students' limited experience in doing translation themselves – many novice translators translate quite literally – and in doing MT and post-editing on different genres and text types. Two of the students, in fact, mention that they are not familiar enough with the processes involved either in MT or in how humans translate to decide on the difference or similarity. For example, T15 starts their answer by saying (our translation from Finnish): "To be honest, I'm not familiar enough with the principles of machine translation to give an informed answer as to the extent to which the human translation process resembles that of a machine."

In those cases where students indicated that both humans and machines consider context, a difference is sometimes made between basing the decision how to translate a particular word in context on experience/instinct/feeling versus on data:

L01, translated from Dutch: The main difference lies in how context is understood: in case of a word with different meanings, a human can look at the sentence, and sense from experience which translation is most suitable. A machine does this not on the basis of feeling, but on the basis of data.

It is also clear that different students mean different things by "context": some use it to refer to word meaning in the context of the sentence, others to the context of the whole text, and others to the context outside of the text, so situational context:

L17, translated from Dutch: A machine is only concerned with the text itself. Although it can take context into consideration, it does not look at the underlying meaning, the purpose, or the possible audience.

As for the misconceptions the students might have, our preliminary analysis suggests mainly cases of conceptual misunderstandings (a construction of an incorrect model of the phenomenon in question, CUSE, 1997: 28), including the humanisation of objects (Suprapto, 2020: 52), as well as some vernacular misconceptions (present when words are used that have one meaning in everyday life and another in a scientific context, CUSE, 1997: 28). For example, four students (T04, L02, L21 and L28) explain that MT first creates a word-by-word translation based on a vocabulary and then applies rules (example from L02, originally written in English): "Machine translation goes word for word and then attaches grammar rules and the like while most human translators go sentence per sentence."

This is, of course, true for rule-based MT systems, but not for others, and can be considered (at least partially) a conceptual misunderstanding.

Another example of a conceptual misunderstanding as construction of an incorrect model is the idea, suggested by L12 and L33, that in translating, machines first convert text to numbers or code, after which they turn it back into text. Here, the students relate the functioning of MT to the functioning of a computer in general. There is also a tendency to humanise machine behavior in several students' responses where they talk about machine "thinking" (L03 and L07), "making guesses" (T24), "having difficulty recognising" (L5), "paying attention to" something (L05), or learning (quote from L30, originally written in English): "On top of that, machines are only able to apply rules that they have either been taught to use or that they have been able to figure out from the context of translations that they have already been given".

An incorrect model is constructed also by T12 who argues (our translation from Finnish): "Humans and machines, translation memories for example, both explore their prior knowledge and try to find the correct equivalents of words in the target language". While the exploration part is indeed in a way true, the type of pre-defined knowledge the machine and human employ can be considered fundamentally different, and the student confuses MT and translation memories. While this clearly is a conceptual misunderstanding, this might also be interpreted as a vernacular misconception based on the idea of seeking something in a "memory".

Relating this back to the similarity judgments, it could be argued that for most of the students who opted for "HT and MT are the same" this judgment may be based on a vernacular misconception or lack of accurate terminology. For example, L04 cited above argued that both use a database to translate. In a technical sense, neither humans nor neural MT retrieve previous translations from a database the way CAT tools or translation memories do, though the answer can also be taken to suggest that "database" is used in a more metaphorical sense to mean any kind of previously stored information. Similarly, L23 mentioned that both have access to a vocabulary and make connections between words, yet it is unclear whether they realize that the way human vocabularies work and the way word meaning is determined in neural MT are fundamentally different processes.

Similar misconceptions and technical inaccuracies can be identified in the answers from the "both similar and different" students as well. L24 appears to be aware of the lack of accurate terminology and adds quotation marks to "read" and "instinct" in their explanation (originally written in English): "In some ways, the neural MTs translate the same as humans: they "read" many different texts (data) and then develop an "instinct": for humans an almost subconscious knowledge of when something (a sentence in a language) is wrong or right, and for machines a developed strategy." This use of quotation marks illustrates that the student understands that machines do not behave like humans.

6 Concluding Remarks and Future Work

In this paper, we have illustrated that teaching students "the basics of MT" is not a straightforward task as far as students' conceptualisations of the translation processes involved is concerned. Even though most students seem to have a reasonable understanding of the ways in which MT is different from HT – especially in terms of how human translators take context, purpose, audience and effect into consideration and thus have important "added human value" – their answers also point to certain conceptual and vernacular misconceptions and a tendency to humanise MT when explaining how it works.

One question that remains as far as we are concerned is whether it is in fact necessary for students to develop the technical competence of *understanding* how MT works (in terms of programming, being able to train and customise systems, and running metrics) in order to develop the technical competence of *using* MT systems effectively and ethically. Translator training programmes appear to focus more on developing post-editing skills – which we agree is a translation competence rather than a technical competence. The question remains then whether training should include more computational competence depending on the meaning of "basic knowledge of machine translation technologies" (EMT Board and Competence Task Force, 2022: 9).

While a lot of attention has been paid to training translation students how to use different MT systems and do post-editing in different genres, far less attention appears to have been paid to assessing (also formally) how students understand the different processes involved and whether misconceptions affect either their usage or their perception or both. Paying attention to misconceptions is important, as they may build barriers for students to learn about MT and direct their reasoning to incorrect notions of what MT is. As future professionals, whether working in language industry or in public service positions, they need to understand the uses and limits of MT in order to be able to "implement and advise on the use of present and future translation technologies", as the EMT Competence Framework (2022: 9) puts it.

Further research is still needed to uncover the best way to introduce MT to translator trainees. In our future work, we intend to continue analysing the existing data for possible differences between students in terms of their experience and background, as well as collect some more data. Students may not only be struggling with difficulties in using different systems and identifying different errors, but also with conceptualising the process they are involved in and what their own role is in that process as opposed to the machine. One area for future exploration would thus be to try and determine whether translator trainees have actual misconceptions or simply lack the accurate terminology to explain how MT works and how MT is different from HT. Do students actually think that Google Translate and other MT engines "understand", "decide" and "get confused"? In fact, the verbs they use may as well be short-hand for processes they cannot define in technical terms.

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