Machine Translation Literacy in the age of GenAI

Aletta G. Dorst
Leiden University
a.g.dorst@hum.leidenuniv.nl

Leena Salmi
University of Turku
leena.salmi@utu.fi

Joke Daems
Ghent University
Joke.Daems@UGent.be

Maarit Koponen
University of Eastern Finland
maarit.koponen@uef.fi

Abstract

One widely used application of artificial intelligence (AI) in today's globalized world is machine translation (MT). Studies show a growing need for an understanding of how to use MT critically, or MT literacy, amongst not only translation and language students but all users. Given the current interest in using generative large language models (LLM) for translation-related tasks, the question arises to what extent MT literacy now also entails knowing how LLMs and generative AI (GenAI) work. Our paper explores how university students enrolled in translation, language and AI courses in Finland, Belgium and the Netherlands understand how MT works and what its defining characteristics are as compared to human translation (HT). We find that, overall, students consider MT distinct from HT, although many also perceive important similarities. However, some of these similarities are based on misconceptions and a tendency to humanize the technology. We argue for a need to (re)define more clearly what MT Literacy entails to empower both professional and informal users to use GenAI for translation effectively and critically.

1 Introduction

Estimated at one billion users, machine translation (MT) is now widely adopted by a variety of users, both informal and professional, for a wide range of purposes (Nurminen, 2021) in anything from low-stakes communication to high-stakes legal and medical contexts (Vieira, O'Hagan & O'Sullivan, 2020). This raises important questions about the consequences of this use: to what extent do the people that use the technology actually understand how it works? Previous work showed that, even in the context of translation studies specifically, students have misconceptions about MT and do not fully understand how it works (Salmi *et al.*, 2023). Misconceptions about technology are far from harmless. By focusing exclusively on the productivity gains made by using MT, for example, the work of translators is increasingly being devalued (do Carmo, 2020). The same is true for the way MT quality results are often presented without the necessary nuance, "creating an unrealistic and uncritical perception of MT among the general public" (Moorkens, 2022:129).

Since the launch of ChatGPT, and the ensuing hype in using large language models (LLMs), the technological landscape has only become more complex, with LLMs and generative AI (GenAI) now actively being used in translation (Kornacki & Pietrzak, 2025), raising even more questions about the need for (nuanced) understanding of technology. To verify to what extent students' conceptualisations of MT also encompass conceptualisations of GenAI, the present paper builds on Salmi *et al.* (2023), expanding the work both in number and recency (data collected until May 2024). In the following sections, we first discuss the importance of MT literacy, relating it to data and AI literacy, and highlight some of the terminological complexities related to (de)humanisation of technology and using computational metaphors to represent human cognition. We then present the methodology and discuss what our results mean for MT literacy going forward.

2 Related research

2.1 MT literacy

Building on earlier work, the concept of MT literacy was refined by Nurminen (2021:44) to encompass a user's ability to:

1. Comprehend the basics of how machine translation systems process texts
2. Understand machine translation systems' strengths and weaknesses
3. Understand how machine translation systems are or can be used for purposes that are important to the user
4. Appreciate the wider implications associated with the use of MT
5. Assimilate information from raw machine-translated texts
6. Evaluate how machine translation-friendly a text is
7. Create or modify a text so that it can be translated more easily by an MT system
8. Modify the output of an MT system to improve its accuracy and readability

While a growing number of studies has focused on MT literacy for students in translation and/or language degrees (Bindels & Pluymaekers, 2022; Dorst *et al.*, 2022; Loock & Léchauguette, 2021), little is known about the need for MT literacy among students in other disciplines (cf. Bowker, 2020). Similarly, there is little research on how professionals in different fields employ MT in their daily workflow (cf. Anazawa *et al.*, 2013; Nurminen, 2019), while the media increasingly report on incidents and malpractices resulting from imprudent use of MT. Today, MT literacy critically interacts and overlaps with information literacy (e.g. Bowker, 2021), data literacy (e.g. Krüger, 2022) and AI literacy (e.g. Ng *et al.*, 2021). Krüger argues that in parallel with the "increasing relevance of MT literacy in the professional translation process, the rise in prominence of another digital literacy can be observed, i.e. *data literacy*" (2022:248, italics original). The same holds for AI literacy: society's widespread adoption of AI tools urgently calls for a definition of AI literacy and a clearer understanding of what people need to know about how LLMs and GenAI work. Ng *et al.* (2021:2) argue that "AI literacy means having the essential abilities that people need to live, learn and work in our digital world through AI-driven technologies", and people need to be taught explicitly "how to use AI technologies judiciously, as well as to discriminate between ethical and unethical practices" (2021:2).

One existing framework for MT literacy training includes technical, linguistic, economic, societal and cognitive competences and highlights the importance of data literacy (Krüger & Hackenbuchner, 2022). In the context of AI literacy, Long & Magerko (2020) suggest no fewer than 17 competencies, including the need to recognise AI, understanding 'intelligence', being aware of AI's strengths and weaknesses, understanding machine learning, and learning from data. All of these definitions and frameworks show a hierarchy of complexity that aligns with Bloom's taxonomy (1956) for learning objectives: Know > Understand > Apply > Analyse > Evaluate > Create. Similarly, the European Master's in Translation Competence Framework

(2022:7) acknowledges that "MT literacy and awareness of MT´s possibilities and limitations is an integral part of professional translation competence" and translators should have a "basic knowledge of machine translation technologies". However, as argued in Salmi *et al.* (2023), what this 'basic knowledge' or 'knowing how MT works' entails is not clearly defined. The EMT Competence Framework was also published before the rise of AI tools, making the present work especially timely, as it is "important to understand existing [...] conceptions of AI in order to develop effective AI literacy interventions" (Long & Magerko, 2020:7).

2.2 (De)humanising technology and human cognition as computer processing

Salmi *et al.* (2023:301) found that students had a "tendency to humanise MT when explaining how it works", although it was impossible to know for sure whether this was a misconception or a lack of terminology to accurately express differences between humans and machines. On the other hand, work on anthropomorphism in technology suggests that "the ascription of human qualities onto non-human entities" is quite a widespread phenomenon, and that it is not entirely harmless (Placani, 2024:692). In the context of AI specifically, humanising the technology leads to overestimations of its performance, as well as distortions of people's moral judgments, such as increased (misplaced) trust in the technology (Placani, 2024). The tendency to humanise AI can be linked to general narratives where technology is characterised by words related to intelligence and emotions as well as social or ethical aspects (Ekbia & Nardi, 2017:2). In the case of MT, common narratives emphasise its human-likeness, sometimes ascribing it with nearly magical qualities (Vieira 2020:109). Conversely, depending on the translation situation, sometimes people specifically do *not* view MT in humanised terms. In a UK survey examining the perceptions of MT users, for example, the benefits of MT not being human were summarised as follows: MT is "not judgmental", there is no need to be embarrassed, and MT allows them to do things on their own without relying on others (Vieira *et al.*, 2022:905-906).

Interestingly, early models of human cognition were actually inspired by computer processing leading to the so-called 'Computational Theory of Mind' (Horst, 1999). Building on these concepts, translation could then be seen as a problem-solving activity, with translators applying rules and strategies to reach certain goals, in parallel with computers using algorithms to process data and produce output (Risku & Rogl, 2020). This shows that, even in the literature, the conceptualisation of what makes humans human and machines machines is not always clearly delineated, and they have each been conceptualised through the other. In fact, Baria & Cross (2021) warn that while the Computational Metaphor ('the brain is a computer') is "the most prominent metaphor in neuroscience and artificial intelligence", its appropriateness is highly debatable, both in terms of "whether it is useful for the advancement of science and technology" and more particularly "how it may shape society's interactions with AI" (n.p.). In many disciplines, these computational models of cognition have made way for the notion of "situated, embodied, distributed, embedded and extended cognition" (Risku & Rogl, 2020:481).

3 Methodology

In the present study we focus on the question to what extent MT literacy also entails data literacy and AI literacy by examining how university students enrolled in translation, language and AI courses in Finland, Belgium and the Netherlands understand how machine translation works and what its defining characteristics are as compared to human translation. The following subsections describe the design, methods and participants of the study.

3.1 Questionnaire

In total, 173 students agreed for their data to be used in the study, 47 from University of Turku (Finland), 82 from Leiden University (Netherlands), 15 from University of Eastern Finland

(Finland), and 29 from Ghent University (Belgium). Data was gathered using an online questionnaire that the students filled out in class or as homework. The questionnaire was made available via Webropol (https://webropol.com/) and was offered in Finnish, Dutch and English. The English version was provided because 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 the way they translate? 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. Finally, students were asked to specify their native language, age, university, course for which they completed the questionnaire, degree, and the start date of their degree. Unfortunately, we did not ask for more specific information regarding their previous experience in translating or using translation technology. Future research could explore in more detail to what degree previous experience influences students' conceptualisations of MT and AI.

3.2 Methods

In total, 173 reflections were analysed, of which 55 were written in Dutch, 62 in Finnish and 59 in English. The reflections were analysed in terms of (a) their answers to the overall question whether humans and machines translate differently or in the same way, and (b) the characteristics they mentioned to explain 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. Reflections often contained statements belonging to different categories, each of which was coded separately. It should be noted that these characteristics represent themes: students did not need to use the exact words of the category label. For example, both "MT produces instant translations" and "machines can go through millions of texts instantaneously" were coded as "Is fast". DeepL was used to translate the Finnish and Dutch answers into English. 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 and UEF students was first done by Salmi and checked by Koponen; the coding for Leiden and Ghent students was first done by Dorst and checked by Daems. All unclear, ambiguous and problematic cases were first discussed by the language team and then amongst all authors to reach full 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). These categories were further refined inductively based on the data after the first round of data collection in 2022 (see Salmi *et al.* 2023). After the second round of data collection in 2023-24 a final list of categories was established, including a number of new categories that emerged from the new data. The previously analysed part of the dataset was also rechecked against these new categories to verify whether similar issues could be found. The final list of characteristics, in alphabetical order, can be found in Table 2.

3.3 Participants

University of Turku (Finland): 47 students participated, 39 B.A. and 8 M.A. The first group (n=10) filled out the questionnaire in October 2022 during a 5-ECTS course on intercultural communication, compulsory for the major and minor students of French. The second group (n=15) filled out the questionnaire in October 2022 as part of a 5-ECTS elective course on translation practice, open to all language students, and the third group (n=22) as part of the same course in October 2023. The first group were first-year bachelor's students majoring in French, except one second-year student who had Spanish as their major. The students in the second and third group were majoring in various subjects, most of them in English or other languages. Some of them had translation studies as a minor, and may have completed or been enrolled in a translation technology course at the time of the survey.

Leiden University (Netherlands): 82 students participated, from three different cohorts: 10 B.A. students in October 2022 during a 5-ECTS elective minor course on multilingual translation; 23 M.A. students in November 2022 during a 5-ECTS compulsory course on translation technology; and 4 M.A. and 45 B.A. students in April 2024 during a 5-ECTS elective minor course on AI and the Humanities. The first group was predominantly enrolled in language degrees (especially English, Japanese and Korean) without any prior courses on translation or translation technology; the second group were all enrolled in the 1-year M.A. in translation and had completed a 30-ECTS Minor in Translation during their B.A.; and the third group came from a wide range of degrees, including several exchange students from abroad. This latter group were all enrolled in a Minor in Digital Humanities but we do not know if they had previously taken any courses on translation or translation technology.

University of Eastern Finland (Finland): 15 students participated, 14 B.A. and 1 M.A. The students filled out the questionnaire in April 2024 during a 3-ECTS compulsory course for translation students, elective for other students at UEF, on translation studies. Most were students in the English or Russian translation degrees or the Swedish language degree, with some students from other subjects. Most of them had completed at least one translation course and were enrolled in a translation technology course at the time of the survey.

Ghent University (Belgium): 30 students participated. The first group, consisting of 5 postgraduate students enrolled in a programme on Computer-Assisted Language Mediation and 5 M.A. students enrolled in the European Master's in Technology for Translation and Interpreting, filled out the questionnaire in October 2023 during a 5-ECTS elective course on machine translation and post-editing. Five of the students had a background in translation, but only two indicated they used MT during their studies. Some of the students could have been enrolled in an elective course on terminology and translation technology at the same time, but since they participated in this survey during the first MTPE class, their exposure to translation technology would have been limited. The second group, consisting of 20 M.A. students enrolled in the 1-year Master's in translation, filled out the questionnaire in November 2023 during a 3-ECTS obligatory course on terminology and translation technology. They could have encountered translation technology during an introductory course in the 2nd B.A. year, and - depending on their language combination – have been allowed to use translation technology during their translation work for other courses, but they had no experience post-editing.

4 Results

Table 1 shows the results for the question whether humans and machines translate the same way or differently. "Both" indicates responses 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 could be interpreted as belonging to any of the categories.

One student only wrote some general remarks about how humans translate but did not mention MT at all, while the other mainly reflected on their own experiences when translating.

	Turku	**UEF**	**Leiden**	**Ghent**	**All**
Same	2 (4.3%)	0 (0%)	6 (7.4%)	0 (0%)	8 (4.6%)
Different	27 (57.4%)	10 (66.6%)	53 (64.6%)	20 (69%)	110 (63.6%)
Both	16 (34%)	5 (33.3%)	23 (28%)	9 (31%)	53 (30.6%)
Unclear	2 (4.3%)	0 (0%)	0 (0%)	0 (0%)	2 (1.2%)
Total	47 (100%)	15 (100%)	82 (100%)	29 (100%)	173 (100%)

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

Table 1 shows that the majority of respondents (63.6%) answered that humans and machines translate in a different way, and nearly all of the remaining (30.6%) saw both similarities and differences. Of the whole group, only a few stated that humans and machines translate the same way. While the precise percentages vary to some extent, the same pattern can be seen across all four universities.

Table 2 shows the characteristics (in alphabetical order) students associated with either humans or machines, or both.

Characteristic	**Human**	**Machine**	**Both**
Considers context and the whole text	74	4	7
Considers target audience and situation	50	0	0
Has a corpus / data / database	1	35	3
Has emotions, cognition, personality	33	0	0
Has experience	20	0	2
Has language skills	24	1	2
Has world knowledge	55	0	2
Is a language learner / non-native speaker	0	6	0
Is creative	27	0	0
Is fast	1	27	0
Learns from prior material	0	6	10
Makes mistakes	3	19	3
Operates mechanically	0	16	4
Searches for information	9	0	3
Translates directly ("word for word")	0	30	3
Translates the same way every time	0	3	0
Understands meaning	46	0	1
Understands nuances	40	0	0
Uses logic / reasoning	6	3	1
Uses predefined knowledge	0	11	9
Uses probabilities / algorithms / statistics	0	34	1
Uses rules	2	14	11
Uses vocabularies / dictionaries	3	4	8

Table 2. Characteristics associated with humans, machines, or both. New or updated categories marked in boldface.

When contrasting Table 2 with the findings from Salmi *et al.* (2023), the same overall pattern emerges but most contrasts between MT and HT are now much clearer, in part because some categories were updated to make more fine-grained distinctions, including the difference between having ′knowledge′ vs ′information′ discussed below. As a result, certain characteristics that were previously classified as belonging to both HT and MT due to a relatively low number of instances are now MT-specific – i.e. 'Is fast', 'Makes mistakes' and 'Operates mechanically' – while 'experience' and 'knowledge' are now clearly associated with humans. The new category 'Understands nuances' is also quintessentially human, as are 'Considers context and whole text', 'Considers target audience and situation', Has emotions, cognition, personality', 'Has language skills", 'Has world knowledge', 'Is creative', and 'Understands meaning'. Characteristics typically associated with machines are 'Has a corpus, database, a lot of data', 'Is fast', 'Makes mistakes', 'Operates mechanically' and 'Translates directly'. In addition, 'Learns from prior materials', Uses predefined knowledge, 'Uses rules' and 'Uses vocabularies and dictionaries' are considered either MT-only or both MT and HT, though the low number of mentions indicates these associations are weak. The counts also show that participants have a much clearer idea of what sets HT apart from MT than the other way around.

While Salmi *et al.* (2023) focused on what these characteristics reveal about common misconceptions in students' conceptualizations of MT, the current paper will focus on the issue of humanisation of technology, relating it to human embodied cognition and the terminology that is central to defining artificial intelligence and machine translation.

5 Discussion

Table 1 showed that across all universities roughly two-thirds consider MT and HT to be different and roughly a third consider them to exhibit both similarities and differences. If we divide the answers according to time period – 2022 (Turku and Leiden), 2023 (Ghent, Turku, UEF) and 2024 (Leiden) – the distribution remains the same, suggesting that the increased visibility of GenAI has not radically changed the way students understand how machine translation works. However, some of the answers do indicate that students make a distinction between traditional MT and LLMs. More importantly though, the presence of 'bias' and 'hallucinations' in LLMs is sometimes explicitly related to LLMs behaving more like humans than traditional MT:

> *L60, English original:* However, like humans, machines can and do make mistakes when translating. Especially LLMs such as GPT who are tasked with translation can produce hallucinations, i.e. outputs that are significantly lesser in quality than desired. This can be compared to how humans may alter sentence structure or grammar rules when translating from one language to another without meaning to, a common occurrence with people who are multilingual. Furthermore, bias exists in both human and machine translation alike.

One issue in teaching MT literacy has been whether it is necessary for users to understand the difference between rule-based, statistical and neural MT. We would argue that for MT in the age of GenAI there is a much greater need for students to understand how data, LLMs and GenAI work and how the processes involved are distinct from human behaviour and cognition.

Looking at Table 2, the categories 'Has emotions, cognition, personality', 'Has experience' and 'Has world knowledge' account for 108 of participants' comments about human translation, while they are never labelled as typical of MT. Only very rarely are they seen as typical of both (twice for 'Has experience' and twice for 'Has world knowledge'). This offers support for the situated, embodied approaches to cognition (Risku & Rogl, 2020). Most comments suggest that there is something typical about 'the human experience' and of 'being in the world' that sets human translation apart from MT:

L70, English original: I feel as though there is something we acquire from the human experience that allows us to sense the nuances in meaning and feeling when it comes to expressing things that machines simply cannot do.

L81, English original: To me, the crucial difference is that humans have a lived experience of being in this world. This gives them a unique experience of the meaning of certain words and phrases, which is informed by their culture, upbringing, and day to day use of the language.

It is this lived experience that gives people the 'world knowledge' that many of the participants deem essential to human translation. This world knowledge covers our consideration of the target audience and purpose of the translation, but also our understanding of nuances as well as the tone and emotional value of the text. It is what enables humans to understand cultural references, humor, and implicit meaning. The answers provided by the students show that in their conceptualisation of human translation context, culture, emotions, nuance and creativity are inextricably linked, and this complex interaction is exactly why machines cannot translate the way humans translate:

L52, English original: human translators can incorporate emotional nuances, humor, and cultural sensitivity into their translations. [...] Algorithm-driven machines, on the other hand, have a hard time dealing with these subjective and emotional factors.

L43, English original: Humans possess cultural and emotional intelligence, allowing them to understand nuances, idioms, and context, which profoundly influence translation accuracy and quality. Emotions imbue human translations with empathy, tone, and cultural sensitivity, making them more adept at capturing the subtleties of language. In contrast, machines rely on algorithms and statistical models to translate, lacking emotional comprehension and cultural awareness.

T05, translated from Finnish: The machine cannot understand intonation, emotion and nuance in language. These, however, affect the translation considerably.

T18, translated from Finnish: The human brings a human tone to the translation; the human understands emotions better than the machine and can play around with words creating a possibly more flowing text.

On the other hand, the concept of 'experience' is sometimes interpreted more as 'gaining experience through practice' in a way that suggests students are using the Computational Metaphor to draw parallels between humans and machines and the way they 'learn' and 'search for information':

L19, translated from Dutch: A neural network formed on a large bilingual corpus is to some extent comparable to how a human translator gains 'experience' with the two languages over a lifetime.

G10, translated from Dutch: The language data from a translation machine can also be compared with people's language experiences and knowledge,, all of which play a role in their translations.

T11, translated from Finnish: The brain has a word storage where one searches for information, which word would fit the translation. Previous experiences can also tell how some term/word has been translated previously and in which context.

T12, translated from Finnish: The human and machine, such as translation memories, both look into their previous knowledge and try to find in their memory correct equivalents for target [sic] language words. They are connected by a relatively mechanical search for equivalents.

A similar example of the Computational Metaphor can be seen in the comment made by T27, who connects databases to both humans and machines, concluding that their translation processes are similar:

T27, translated from Finnish, emphasis added: Both modern MT and a human translator translate based on translation memory, searching **their database** for matches for the specific situation. At this level, the translation process is similar, but the translation memory of a human does not consist of such an extensive repository of options as that of a machine translator.

Here, one problem lies in the fact that many of the central concepts in machine translation, machine learning and artificial intelligence draw on the Computational Metaphor and the

Computational Theory of Mind. The terminology of these fields is fundamentally metaphorical in nature, obscuring the difference between what is essentially human and what typical of machines. In Finnish, this blurring of the two domains is particularly noticeable: both 'knowledge' and 'information' translate as 'tieto', and the word 'tieto' also appears in the Finnish equivalents of 'computer' ('tietokone' – knowledge/information machine) and 'database' ('tietokanta'). Although the majority of the respondents in Finland do think that machines and humans translate differently (Table 1), this may influence some of the students' thinking and reasoning, when comparing humans and machines. For example:

T12, translated from Finnish, emphasis added: The human and machine translation processes have some similarities, but they are not entirely identical. For example, humans and translation memories, **both explore their prior knowledge** and try to find the correct equivalents of words in the target language. What they have in common, therefore, is a relatively mechanical search for equivalents.

Even though the respondents make a difference between how MT and humans work, they still express themselves in ways that do not make a difference. In the following example from EF03, we have emphasized the words where the original in Finnish has the word 'tieto':

EF03, translated from Finnish: One difference between a human translator and a machine is how creatively and extensively humans can use their **knowledge/information** and **information**-seeking skills to find useful sources to come up with a translation. The **knowledge/information** a machine has depends on the texts it is given and how it is programmed to use those texts. Humans, on the other hand, can search more freely for **knowledge/information** from sources that are not necessarily directly related to the subject but can help in the translation process.

The example shows that it has not always been possible to distinguish between "information" and "knowledge" when analysing the responses. Understanding the degree to which a person's native language and its inherent ambiguities influence their conceptualisations and an analysis on the differences between groups of respondents writing in Finnish, Dutch and English is out of scope for this paper but could be a subject of further research.

6 Concluding remarks

The present study explored how university students enrolled in translation, language and AI courses in Finland, Belgium and the Netherlands understand machine translation and its defining characteristics as compared to human translation, with a focus on what their conceptualisations reveal about the need for more data literacy and AI literacy as part of MT literacy. Building on Salmi *et al.* (2023), the additional data collected showed that across the four universities and three countries approximately 60% of the students considered human and machine translation to be distinct, and around 30% identify both similarities and differences. The characteristics that are assigned to either humans or machines, or both, reveal that students have a relatively clear idea of what sets human and machine translation apart. Most of the quintessentially human characteristics identified can be related to human beings having embodied cognition and world knowledge that encompasses emotions, lived experience, as well as cultural and social awareness.

On the other hand, some reflections revealed a tendency to follow the computational theory of mind in comparing the way humans use their experience to the way a machine's database and 'memory' operate, indications that people may be either humanising the technology or dehumanising people. There were also indications that this tendency may be even stronger for our understanding of LLMs and GenAI, as seen in references to machine 'hallucinations' and 'bias'. It is the terminology itself – using human terms to define machine concepts – that leads to a possibly misleading and potentially dangerous humanisation of MT and AI more generally. There is a clear need to conduct more research on this topic, including a more extensive exploration of how different languages draw the boundaries between humans and machines, i.e. whether they distinguish between knowledge and information, memories and databases. As for pedagogical implications, there is a clear need to include data and AI literacy more systematically in modules where MT is used or taught. Such courses should also take into account informal uses of the technology and explicitly address students' previously formed conceptualisations about translators, both human and machine. MT literacy should help students understand how the technology works without obscuring the differences between humans and machines. At best, this blurring is only misleading and fosters misconceptions. At worst, it lures people into overestimating the machine's capabilities and putting too much trust in its "good intentions".

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