The machine translator's visibility

A postphenomenological analysis of machine translation

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This article proposes that machine and human translation differ in use and seeks to demonstrate this not by comparison, but rather using the framework from philosophy of technology known as postphenomenology. Following the work of Don Ihde and others, postphenomenology is intended to examine how technologies mediate our relations with the world. Following a short introduction to postphenomenology, the place of machine translation (MT) along Ihde's continuum of interaction types is considered, and a set of predefined dimensions are applied in order to analyse how MT mediates communication. MT is found to be hugely useful, but problematic in developers' use of training data and in how MT is described and marketed. The framing of MT contributes to heightened quality expectations and translators' alienation. The broader alienation of those disenfranchised from ICT use, who are also most affected by carbon emissions and environmental pollution, contrasts starkly with the positive effects of MT.

Keywords: machine translation, translation technology, generative AI, large language models, postphenomenology, philosophy of technology

Introduction

The answer to the question 'Is machine translation translation?' is ostensibly yes: Machine translation (MT) produces a target text version of a source text, even if the process may not conform with how we generally conceive of translation. In his review of historical definitions of translation, Asscher (2023) finds that 20th century prescriptive definitions, usually subjectless (i.e. without a clear human agent) and based on notions of equivalence, can apply to contemporary MT. This seems to be a reasonable assertion, as measurements of equivalence, in the form of

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accuracy and fidelity ratings, are still a common method of evaluating MT quality. Asscher also believes that descriptive definitions of translation, such as those introduced by Toury (2012), must include MT "if a majority of people tend to perceive MT as translation, as seems to be the case (Wang and Ping 2020, 8–9), and social norms and discourse tend to reinforce our understanding of MT as 'translation'" (Asscher 2023, 13).[1]

If we consider that MT is translation, how does it differ from human translation? There are reasons to believe that there are differences in how human and machine translated texts are used. For example, since the days of statistical MT, a threshold has commonly been set within translation memory (TM) tools above which fuzzy matches from the TM are offered rather than MT proposals, as high-value TM matches are presumed to require less editing than MT output (Tatsumi 2010). TM and MT inputs are differentiated at the target text creation stage, although for the end reader, there is no longer a clear demarcation line between human and machine translation. A rule of thumb has developed that the level of translation automation should correlate with the shelf-life, risk level, and value of a text (Moorkens 2022; Way 2013), indicating graduated automation along a cline – with MT used at the high end – but again categorising MT separately to human translation (HT). On that basis, some companies and organisations use more or less automated pipelines for translation of different types of content: so-called 'low-stakes' MT for low risk, perishable, low value content, MT post-editing for mid-tier content, and computer-aided HT for high-risk or high value content (Guerberof-Arenas and Moorkens 2023). In some organisations, this is done with the aid of automated quality estimation.[2] Each pipeline uses a conduit for communication, human or machine, but our levels of trust in the fidelity and quality of the translation product are likely to differ depending on the level of automation during the translation process (Cadwell, O'Brien, and Teixeira 2018). The consequences and repercussions of mistranslation might also differ, particularly regarding liability in the case of injury or harm (Canfora and Ottmann 2020).

The first aim of this article is to analyse whether there are differences between human and machine translation *in use*. The second is to consider what it means

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1. Rozmysłowicz (2024) associates the historical political motivations behind MT with a tendency to categorise it separately from human translation. He also suggests some self-interest from academics who dismiss MT, as it threatens "the viability of Translation Studies as an academic institution, educator of translators, and, of course, employer for translation scholars" (Rozmysłowicz 2024, 502).

2. This roughly follows the various published taxonomies of automation. For a review of these, see Vagia, Transeth, and Fjerdingen (2016).

to have much of our translation mediated by technology, now that more and more translation processes are part-automated as described in the previous paragraph. It employs the framework of postphenomenology (Ihde 1990; Rosenberger and Verbeek 2015) to examine MT in use and the ways in which it mediates our communication. Postphenomenology, which is associated with the 'empirical turn' in the philosophy of technology, draws on phenomenology and pragmatism (Reijers 2019). It explicitly centres on the human but integrates science and technology into the analysis of human interrelations with technology as a mediator. Rosenberger and Verbeek (2015, 12) call postphenomenology "a practical study of the relations between humans and technologies, from which human subjectivities emerge, as well as meaningful worlds." Crucially, and perhaps unusually, postphenomenology begins from a critical rather than negative view of technologies, considering that they are "not opposed to human existence; they are its very medium" (ibid. 13).

In the following sections, I briefly explain the MT processes considered in this article and then explain postphenomenology in more detail along with related concepts proposed by Ihde (1990) and others. These concepts will be the basis for the sections thereafter.

MT in use

A technological object, according to Ihde (1990, 70) "becomes what it "is" through its uses." The current analysis of MT in use is based on MT for dissemination (in which case MT is pushed to the human as an intermediate step in production, usually followed by post-editing) or for assimilation (in which case raw MT is chosen or provided, often to get a gist translation). The MT service may be neural MT (NMT) or generative artificial intelligence (GenAI) based on large language models (LLMs) for translation, as the latter are increasingly part of commercial translation offerings for well-supported languages.

The 2025 European Language Industry Survey (ELIS Research 2025) reports that 50% of the 179 respondents from language service companies (LSC) and 54% of the 654 independent language professionals (freelancers) said that they use MT in their translation processes. This is the first time that these figures have broached 50%, but they remain below what university staff and student respondents had estimated (63% and 58% respectively). However, this first figure may not give us the full picture, as the distinction between MT and HT in individual translators' workflows is often blurred. As mentioned, many translators receive MT proposals when there is no TM fuzzy match above a defined threshold. Some have MT prepopulated in the target language text box or work with interactive MT, whereby MT is proposed and accepted or edited by translators. Other translators use MT to get initial inspiration, typing or dictating the text themselves (Rossi and Chevrot 2019). GenAI is also used for inspiration, summarisation, rephrasing, or to help understand technical expressions (Rivas Ginel and Moorkens 2024). As translation is usually outsourced, these processes may not be part of the reported LSC figures.

Following the launch of ChatGPT in late 2022, along with the accompanying media reports, translation companies have rushed to incorporate GenAI among their offerings. GenAI tools differ from NMT in that they are not built to carry out a specified task, but are rather what ChatGPT developers OpenAI call 'general-purpose technologies' (Eloundou et al. 2023) — a good example of a technology being at its "most productive when its ultimate range of results is neither foreseen nor controlled" (Winner 1978, 98). This means that the translation capabilities of generative tools have only gradually become apparent. Translation quality appears to be competitive with NMT for well-resourced languages (Hendy et al. 2023), showing promising consideration of co-text (Castilho et al. 2023) and promising capacity for automatic translation evaluation (Kocmi and Federmann 2023), despite being trained on little aligned bilingual data (Briakou, Cherry, and Foster 2023). Although translators are sceptical about the trustworthiness of GenAI for translation tasks (Rivas Ginel and Moorkens 2025), many LSCs feel a push to implement GenAI due to pressure from senior management and hype (Moorkens, 2025).

Previous generations of translation technologies, such as TM or statistical MT, used human-readable data and followed explainable processes. Both NMT and LLM-based GenAI are examples of 'subsymbolic' machine learning, software trained on vast amounts of (usually) human data to extract patterns, and of black-box technology, as words are converted to numbers, upon which a huge number of operations are carried out. Their outputs are not easily explained. For this reason, it seems appropriate to analyse MT using postphenomenology, which is intended to help us to understand how technologies mediate human relations with the world and with one another.

Postphenomenology

The 'empirical turn' in the philosophy of technology arrived in response to previous approaches to technology that were seen as pessimistic and lacking in nuance, and is most commonly exemplified by actor-network theory, critical theory, and postphenomenology (Reijers 2019). These frameworks have been introduced to describe interactions with technology in Translation Studies, with Buzelin (2005), Abdallah (2011) and others employing actor-network theory, O'Hagan (2016) and Olohan (2017) using critical theory, and most recently, Vieira (2023) introducing postphenomenology. Phenomenology, associated with Husserl and Heidegger (Zahavi 2003), is concerned with describing (rather than interpreting) the subjective human experience, and is usually concerned with alienation from technology. Don Ihde proposed postphenomenology as an approach that combines phenomenology and pragmatism, not attempting to understand the essence of a technology, but rather how it mediates our experience, using conceptual examinations and case studies of technology in use (Aagaard 2017).

Ihde (1990, 1) wrote that, for those of us who live in industrially developed societies, daily existence is "technologically textured", from the moment we wake to the moment we sleep. The pervasiveness of technology has continued to increase since 1990, mediating and shaping our relationships with the world. His intention for postphenomenology is to provide a framework to understand these human-technology relations and the extent to which technology moulds our intentionality. Ihde argues that no technology is one thing only; technology has no single trajectory and is ambiguous, revealing or affording different uses and interactions depending on its context. The potential is not limitless, but "the "same" technology in another cultural context becomes quite a "different" technology" (ibid. 144). The affordances of a technology – the potential actions that it offers to or solicits from users – are "relative to the normativity and customs of the landscape in which it figures" (De Boer 2021, 8). A technology can simultaneously be "both something we design and use for our own purposes, and also something that influences, restricts, leads, inclines, or controls us" (Rosenberger and Verbeek 2015, 25). In postphenomenology, this key concept is known as *multistability*. It is the first of a set of concepts introduced by Ihde to describe the variable relationships between users and technology, and between users and the world mediated by technology.

A lighter, for example, can light fires but can also be used to open bottles. More recently, computers and smartphones are designed to be multistable, to afford many intended and (as in the quote from Winner) unforeseen uses (Ihde 2012). MT may also be used for 'multi' purposes: to enable social interaction, for e-discovery, reading, learning, or post-editing (Nurminen 2021), but not for *every* purpose. We cannot use it to light fires or to open bottles; there is some 'stability'. The purposes will be limited by the users' abilities. A user who can understand the source and target language may use MT for both assimilation and dissemination, using their skills to verify or correct the output from MT. A user who does not understand the source language is more likely to use MT for assimilation, trusting a system whose output they cannot verify, exposing them to risk in the case of mistranslation, but also potentially freeing them of the moral burden of a linguistic mistake for which they can blame the system. As a general-purpose technology, GenAI tools exhibit a far greater range of potential uses and less 'stability'. They can be used for the list of tasks mentioned previously, translation at the segment and document level, for related tasks such as text annotation, and for explaining discourse information with varying degrees of success (Wang et al. 2023). I draw primarily on its use for translation in the analysis of MT in the following sections.

Ihde's typology of technological mediation

Ihde (1990) proposes the following typology of four forms of technological mediation that are not mutually exclusive but rather may be placed along a human-technology continuum, with the technology progressively becoming more separate from the user. Embodiment relations apply to technology that mediates the user's perception of the world. Hermeneutic relations mediate the user's interpretation of the world. Alterity relations arise in cases where the technology becomes a quasi-other to relate with. Background relations pertain to ambient technologies, which are in one's surroundings but so familiar that they are barely noticed.

The most obvious category for MT is that of hermeneutic relations: hermeneutics is the study of interpretation and meaning, and has been established within translation at least since Steiner (1975) to examine what is comprehensible in a text under what conditions. Similarly, Ihde's (1990, 84) 'hermeneutic presence' in technology transforms an aspect of the world into something that can be read and interpreted; "not only does it occur *through* reading, but it takes shape in the interpretive context of my language abilities" (ibid.). As we interpret both the text and the object or world we experience through the text together, Ihde describes this form of mediation as 'I — (technology-world)'.

However, MT might be considered to slip into other categories of technological mediation. Postphenomenologists examine embodied mediation by using the concept of *invisibility*. For some, a technology should be invisible or as close to it as possible, an imperceptible extension of the user. Often-used examples are a pair of spectacles or a hearing aid. This appears to be the view of a research participant in a study by Szarkowska, Díaz Cintas, and Gerber-Morón (2021, 665), who likens a good subtitle to a pair of glasses: "It helps you get the picture, but it doesn't distract in any way." Ihde (1990, 70) notes the contradiction inherent in wanting technology's benefits while also wanting them to be frictionless and invisible: wishing for the technology's benefits without being aware of its presence "secretly rejects what technologies are and overlooks the transformational effects which are necessarily tied to human-technology relations."

Coming back to MT, many user interfaces with MT aim for frictionless communication. This is the intention of embodied MT tools such as the camera feature in the Google Translate smartphone app, the Pocketalk translator device, Google's Pixelbuds for audio, and the forthcoming GenAI-embedded hardware from OpenAI (Milmo 2025). For technological interaction with text, Ihde refers to the analogous concept for hermeneutic relations as *transparency*. The interface of commercial MT tools or the "increasing ubiquity of buttons and icons that direct the user to *translate now*" (Raley 2003, 299; emphasis in original) give the English-speaking user the impression of coded English source text within an all-English internet. The wish to make MT transparent or invisible harks back to Weaver's (1949) suggestion that Russian text should be thought of as English to be decoded, which Kenny, Moorkens, and Do Carmo (2020, 1) consider particularly reductive, noting that the trope of treating "foreign as English" continued into the statistical MT era in the early 2000s.

Considering MT as transparent may not present many problems for casual use and low-stakes MT, but in use cases with increasing risk, MT should not be transparent as it must be used with care. This is why Guerberof-Arenas and Moorkens (2023) and Melby and Lester (2024) advocate the clear labelling of raw MT. As a general rule, Frischmann and Benesch (2023) recommend that *some* friction is designed into technologies so that they are not used unthinkingly. Liebling et al. (2020) provide concrete examples of MT risk and the difficulties faced by immigrants to the United States who are dependent on smartphone apps for translation. Respondents struggle to deal with mistranslations, offensive output, or just inconvenience, as in the case of the respondent who has "lost good clients because they don't have the patience to communicate with me" (Liebling et al. 2020, 8). An alternative safeguard to transparent MT is "training in the critical and effective use of machine translation", which Bowker and Ciro (2019, 33) term 'MT literacy'. Bowker and Ciro's assertion that "informed decisions can be made by educated users, so that uses of MT would not be entirely conditioned by the technology itself" (as noted by Rossi 2020, 342) fits precisely with the notion of multistability, in that the range of affordances will vary based on the user's cultural-social context: improved MT literacy should narrow the range of potential uses based on the user's informed perception of the level of risk. From Nurminen (2021) we might also expect that affordances will vary based on the user's competence in the source, target or pivot languages, and their familiarity with the text's domain or subject matter.

We might argue that a broader AI literacy is necessary as LLM-based tools and their capacity to generate and transform text, including multilingually, are being added to existing technological tools such as search engines and text editing interfaces. Krüger (2024) proposes an AI literacy framework for translation, whereby the user will understand the technical foundations of GenAI, can measure domain-specific performance, will know how to interact with the system and apply it appropriately, and will understand the ethical and social impacts. Building AI literacy along these lines will adjust user expectations and engender effective interactions. As the user interacts with the system, prompts and exchanges are also saved by the AI system, creating a feedback loop in which technology does not just influence human behaviour, but "patterns in human behavior influence the use and even the functionality of technologies" (Verbeek 2011, 93).[3] AI literacy might also reduce the tendency to assign human qualities to technology, which is encouraged by chatbots such as ChatGPT (van Es and Nguyen 2025) or the use of agents, personalised artificial helpers within LLMs, for which we might also consider Ihde's alterity relations. Ihde (1990, 100) recognised the tendency to create technology that is a "quasi-other", so that the technology itself becomes an object of fascination rather than a mediator. Thus, chatbot-style generative tools can both enable hermeneutic relations when they translate or provide us with information, and alterity relations when they 'chat' with us.

Analysis dimensions

Technologies may be more or less transparent or invisible when mediating our relations with the world, while still shaping these relations. This shaping means that they "simultaneously magnify or amplify and reduce or place aside what is experienced through them" (Ihde 1990, 76). This will be true of any manner of mediation; the amplification need not be positive, nor the reduction negative. Some of these 'non-neutral transformations' are desired by us, but there will also be side-effects or trade-offs: "a decrease of a sense, or area of focus, or layer of context" (Rosenberger and Verbeek 2015, 16). For example, to "see the moon through a telescope is to see it close up but also to lose it in its position in the sky" (Ihde 1990, 50). In a chapter focusing on these non-exclusive dichotomies, Norwegian philosopher Arle Kiran (2015, 124) writes that meditation on these sorts of 'dimensions' represents an "important broadening of the basis on which we assess technologies, both on a societal level and on a personal one", in that they help us to move beyond assessing a technology as good or bad to an analysis of "*how* we can shape our lives in relationship *with* this technology" (emphasis in original). Kiran (2015) proposes the use of four dimensions in the analysis of technolo-

3. The notion that human actions influence technologies is also a key part of the social construction of technology theory from science and technology studies (Bijker 1999), employed in translation studies by Olohan (2017) and Sakamoto and Yamada (2020).

gies: magnification-reduction, revealing-concealing, enabling-constraining, and involving-alienating.

Magnification-reduction

Technologists *magnify* technologies when they amplify their capabilities (for example, 'Today, we're launching even more AI-powered features to provide helpful and contextual awareness when using Translate on mobile and the web.' — Gu 2023). In doing so, they also *reduce* the role of translators in creating training data, and online tools tend to bury information about their gathering of interaction data within terms and conditions. Kenny (2011, 2) notes that data-driven MT relies on humans for both data and legitimacy, data that "are assumed to contain good answers precisely because they contain translations performed by human beings." However, the crucial role of human translators in data-driven MT tends to be heavily downplayed. Source and target segments become commodified data, and the metadata that connects this data to its human creator is excised. Reijers and Dupont (2023, 24) write that MT "dissolves the identity of a work of art through its process — practice and production — that ends up being both universalised and standardised and therefore imminently exchangeable." Human input is only magnified when a benchmark — often a decomposed segment, translated by one person, and taken to represent human-level quality — has been surpassed, in which case many natural language processing (NLP) papers claim 'superhuman' performance (Tedeschi et al. 2023).

A study comparing the 100 most commonly-occurring words from 566 MT papers taken from the ACL Anthology Reference Corpus[4] and translation studies textbooks and dictionaries found many terms in common. However, the MT papers "lacked words representing human actors (e.g. "translator," "reader," "author")" (Kageura, Miyata, and Yamada 2022, 17). This magnification of the role and agency of technology while reducing the human contribution is reflected in media reports about MT and GenAI, which are mostly positive, with a tendency to anthropomorphise the technology without revealing its data source (Vieira 2020b; Ryazanov, Öhman, and Björklund 2025). This framing is unhelpful at a time when a "lack of recognition and visibility" has been identified as a problem for the translation profession and for second language learning within the EU (European Commission and Directorate-General for Education 2022, 73).

All MT paradigms up to and including NMT magnify the sentence being translated at a cost to context from neighbouring sentences and the document as

4. This is an English-language corpus of academic papers published in the years 1979 to 2015 from the fields of NLP and computational linguistics (Bird et al. 2008).

a whole. This is also true of a great deal of commercial HT, which involves the 'peep-hole translation' focus on a single active segment within TM tools (Heyn 1998, 135). Castilho et al. (2023) find that three free online MT systems are unable to resolve a number of context/co-text-related issues,[5] with comparatively better performance from ChatGPT for translations of well-resourced languages. ChatGPT can also iteratively produce output with fewer errors if prompted to check particular words in context. A limitation to this study is that generic online MT systems were tested and the version of tested ChatGPT was quickly superceded. Several MT providers claim to offer context-aware custom MT engines, although without published evaluations at the time of writing.

Revealing-concealing

In explaining the revealing-concealing dimension, Kiran (2015) refers to Heidegger (1977, 17) and his concept of *Bestand*, which he says can be interpreted both as believing that anything in the world may be considered a resource that is on standby, waiting to be exploited, and also as our attitude to the world, influenced by technology, leading us to assume without question that efficiency is best — and usually that the way things are done with a particular technology is most efficient.[6] Other ways to be in the world and other priorities are thus concealed. This is not dissimilar to magnification-reduction, but this second dimension incorporates our behaviours. This idea of *Bestand* comes to mind regarding the reuse of data and translation databases (Troussel and Debussche 2014), and the copyright of those whose translations or text are webcrawled from the internet for MT and LLM training. Data is treated as a common resource, and thus translation data producers tend not to receive a royalty when their work is repurposed, and their input providing the key raw materials for NMT is *concealed*. This is also the case for GenAI, prompting a number of ongoing legal cases at the time of writing, including cases brought by the authors of 183,000 books used to train Meta's Llama LLM without permission (Reisner 2025).[7] Aside from the creators of original training data, there is another team of workers whose role is *concealed*, who

5. Lexical Ambiguity, Grammatical Gender, Grammatical Number, Reference, Ellipsis, and Terminology.

6. Originating with Heidegger, this dichotomy might be considered the least value-neutral. Certainly, his view of technology was rarely positive, writing that 'we remain unfree and chained to technology, whether we passionately affirm or deny it' (Heidegger 1977, 4).

7. Publishers have since moved to licence books for Generative AI training, for example Taylor & Francis' deal with Microsoft to help improve the 'relevance and performance' of their AI systems, as detailed by Battersby (2024).

test systems and provide additional data for the system's guardrails to avoid offensive and discriminatory output as part of a process known as reinforcement learning using human feedback (Ouyang et al. 2022).

The tendency to prioritise fluency in HT was criticised by Venuti in 1995 (2008): domestication is a type of concealment that renders the translation process invisible. This prioritisation is arguably also true of NMT and LLMs, but with the role of technology magnified. In *revealing* a fluent translation prediction within milliseconds, MT also *conceals* accuracy errors, making them difficult to spot (Daems and Macken 2019). MT also conceals the calculations within its black box system and the huge compute costs – and related carbon emissions – behind the machine learning systems. The likes of Rudin (2019) have called for explainability for high-stakes AI, but explainable MT has not been prioritised in research. Robbins (2019, 509) proposes that any decision that requires explanation should not use machine learning, which he terms 'opaque AI', but that an explanation is not necessary for systems that do not make decisions, as they "have a low risk of causing harm". This ignores the potential harms and biases encoded in MT output, as documented by Vanmassenhove (2019) and others.

The other interpretation of *Bestand*, revealing the technologised method and concealing other ways that things could be done, is relevant for MT and language learning. MT has been revealed as a shortcut for language students. Surely MT is the most efficient way for them to produce text in their second language? Groves and Mundt (2021) believe it unrealistic to assume that students writing in a language other than their own will not resort to MT, an opinion supported by empirical studies with French university-level students (Loock, Léchauguette, and Holt 2022), and secondary school students in the UK (Organ 2023). Loock, Léchauguette, and Holt (ibid.) also note that students are usually unable to detect MT errors. The assumed corollary here is that students' language learning will be affected by MT. Carré et al. (2022) suggest that this need not be negative, and that MT can be used to support language learners. Parasuraman et al. (2000) warn of potential skill loss from automation, but this assumes that the skills have been learned in the first place. Furthermore, the availability of free online MT for over 25 years may give the impression that MT is the way to translate. Many translation companies and organisations have created pages that assert the value of professional translation to explain why one might want to pay for translation work, pushing against the *transparency* of the technology that tends to conceal other ways to carry out translation.

Enabling-constraining

In *enabling* some modes of interaction, technologies simultaneously *constrain* others, making them less likely or appealing (Ihde 1990). This comes back to the idea of *multistability* and what is afforded by a technology. In "enabling us to do specific things, technologies simultaneously shape *how* we do these things, and thereby divert our attention from other possible ways" that they may be done (Kiran 2015, 131). Most obviously, MT enables instantaneous multilingual communication for languages that the user does not know, enabling them to both produce comprehensible text in another language and to receive comprehensible text. This is undoubtedly hugely important and is not fully counterbalanced by constraints. However, MT also constrains variability in expression, defaulting to the most common words from training data, with less common words appearing rarely or not at all (Vanmassenhove, Shterionov, and Way 2019). For translators, it enables productivity as documented in the section on MT in use, but also constrains creativity to the extent that one respondent to Guerberof Arenas and Toral (2022) likens it to a corset. Toral's (2019) analysis of four datasets containing texts produced using MT, post-edited MT and HT finds that post-edited MT tends to retain similar sentence length and part-of-speech distribution to source texts, and to produce lower lexical variety and lexical density than HT, tending towards what Catford (1965) terms 'formal correspondence'. The caveat here is that only one of Toral's datasets (Chinese-English) contains only post-edited NMT, with the others mixing NMT with statistical and rule-based MT.

MT also constrains production of a translation tailored for a particular *skopos* in its raw form, as machines cannot have communicative intent or produce text with a purpose, that is, "a writer intention and a reader expectation" (Sager 1994, 51).[8] This constraint is also true for MT for dissemination, as post-editors are encouraged to work at speed and to retain as much raw MT as possible, thus limiting the human input. Contrastingly, humans are capable of ostensive communication, motivated by an intention to inform. This is less problematic for generative tools, which with generic prompts are likely to produce lots of purposeless text, particularly at the time of writing when the barrier for use is low: the cost of development and computation is effectively subsidised by huge investment and is thus not reflected in charges for access (Heath 2024). However, with carefully iterated, detailed prompts, it can be possible to produce good quality translations for a specified purpose in high resource languages, such as English-Spanish (e.g. Ray et al. 2025).

8. This is another reason why Asscher (2023) believes that subjectless (i.e. without a clear human agent) definitions of translation may be applied to MT.

Training data is a constraint more generally, as insufficient training data will cause quality issues and out-of-domain data will be unlikely to result in good output for a specific field. Say, for example, our source text is a transcript of a personal conversation, we might receive inappropriate output from an MT system trained primarily on European Commission legislative TM data. Marketing material in the life sciences domain might not be best served by an MT system trained for software documentation. Training data is necessarily historic, which constrains the translation of new words or neologisms. However, the use of byte pair encoding to break words down to most commonly-occurring chunks in NMT training can help with coining translations for what Kolb, Dressler, and Mattiello (2023) call 'occasionalisms': new compounds, derivations, and blends in literary texts. More problematically for LLMs, freely available data seems to be running out (Longpre et al. 2024).

Involving-alienating

The final dimension proposed by Kiran (2015), involving-alienating, is intended to be inherently ethical, and as such entails a moral value or judgement. Ihde tends to be critical of dystopian generalisations about technology and thus avoids discussion of alienation, but his perspective of the non-neutrality of technology allows for some value judgement. Kiran's (2015, 136) proposal is for a nuanced evaluation to assess technologies "in terms of the opportunities and hindrances they pose for us to create for ourselves a good life." A user's life should be better with an involving technology than it would be without it.

For the many users whose communication needs are enabled by MT it is an involving technology. There is more content being created than can possibly be translated by humans, although it's arguable whether much of this content really needs to be translated. The International Data Corporation predicts that the global datasphere will grow by 24.4% annually to reach over 384 zettabytes by 2028, with a growing proportion of time-sensitive data (Wright 2024). Free online MT is proving useful to many people, with Google Translate reaching 1 billion app downloads in 2021, translating 250,000 hours of captions daily, and 20 billion webpages per month (Diño 2021). According to Reijers and Dupont (2023, 21), "utopian claims that MT may bring together people from different nations, cultures, and persuasions are justified and illustrate genuine contributions to fostering a global understanding." Qualitatively, we see the usefulness of MT to individual African immigrants living in Umbria in Italy, whose need for translation arises "several times in a day, and therefore cannot always be fulfilled by a language professional" (Ciribuco 2020, 189), or for immigrants to the Netherlands as part of a suite of strategies to understand Dutch healthcare communication (Valdez and Guerberof-Arenas, 2025). The fluency of NMT both *involves* and *alienates* monolingual users: their input becomes the source text, but they are required to put their faith in an incomprehensible output, assuming that it will not expose them to risk. However, as their expertise in the use of MT grows, perhaps by trial and error, users show ingenuity in avoiding the pitfalls of unverified MT. Among Ciribuco's interviewees, those with better Italian language ability learned that MT is fallible and began to rely less on the technology as they gained MT literacy. In keeping with multistability, Ciribuco (2020, 191) found that while MT helps with basic needs for some, "more proficient (or better connected) asylum seekers may develop more complex relations with the tool, integrating it with other activities and a wide network of teachers and mediators." Relatedly, Nurminen (2021, 151) found techniques employed by MT-literate users to avoid mistranslation, including checking pictures and multimodal elements in source texts, submitting the same material to different MT tools for comparison, and adapting source texts to improve MT output. While this suggests a technology that is not transparent, in that users adapt to the technology rather than the technology adapting to them, the fact that users go to such lengths also suggests that MT is involving and useful.

It is also clear that MT is alienating to many translators who see it as a threat to their sustainable livelihood. As Vieira (2020a) shows, this is not so much about the technology itself as the business practices around it relating to work processes and remuneration. The task of post-editing tends not to be popular due to the associated reduction in translators' agency. Although this unpopularity is likely to relate to a perception that the role of post-editor is less valued than that of translator (Sakamoto 2019), it also relates to the effective outsourcing of the act of translation to an unreliable machine. It is increasingly clear that GenAI and the accompanying hype is even more alienating for translators, as translator associations and organisations, one after another, release statements decrying its use and refusing to participate.[9] As mentioned previously, the common practice of trawling for all available data and reusing as much as possible of it without compensation for its creators is increasingly alienating for authors, translators, and artists of many sorts.

More broadly, information and communication technologies (ICT) are alienating for a huge proportion of the global population. The UN agency for ICTs,

9. See, for example, the European Council of Literary Translators' Associations statement at https://www.ceatl.eu/tools-of-the-trade/statement-on-artificial-intelligence; the American Translators Association https://www.atanet.org/advocacy-outreach/ata-statement-on-artificial-intelligence/; the Institute of Translation and Interpreting https://www.iti.org.uk/discover/policy/slow-translation-manifesto.html.

the International Telecommunication Union (ITU 2024), reports that 68% of people globally had access to the internet in 2024. This figure hides further disparities such as the global digital divide between countries and regions, and the grey digital divide between generations. If MT and generative tools are involving and useful for this 66%, this can only heighten the divide between them and the rest. According to the ITU, only 27% of individuals in low-income countries accessed the internet in 2024, with further disparities between this group – only 11.3% of individuals in Burundi had access, for example. These happen to be the countries most affected by climate change. Meanwhile, Luccioni, Jernite, and Strubell (2024), amongst others, have spotlighted the huge carbon emissions caused by the transformer models behind NMT and LLMs, while the IEA (2023) estimated that global datacentre energy consumption was between 240 and 340 terawatt hours in 2022, which is more than the national consumption of some countries. At present, GenAI accounts for a far smaller proportion of energy requirements than serving video or cryptocurrency mining, but it is projected to grow quickly. Some of the least developed countries try to bring in money by recycling ICT waste in informal or 'backyard' facilities with no environmental controls and low labour costs, causing damaging pollution (Williams 2011), an issue for all technologies, but for high compute power processes such as machine learning in particular. Cronin (2019, 516) is clear on where our priorities should lie in this particular trade-off, writing that:

> Humans are dependent for their survival not on developing technologies that will leave Nature behind in the ascent to a post-material Cloud of cyber possibility but on resituating technology within the carrying capacity of a planet with finite resources and an ever shortening timeline of climatic viability.

In closing

As noted in the introduction, there is often no clear demarcation line between human and machine translation, even though we categorise them separately. Kay (1982, 72) wrote that translation takes place along a technology continuum, with "fully automatic translation at one extreme, and word-processing equipment and dictating machines at the other". Hutchins and Somers (1992) extended this with their widely cited translation technology continuum, with computer-aided translation bridging human and machine translation. This is also the impression we get when we look at the various typologies of automation, which differentiate between a machine offering several alternatives (as in TM tools) and a single alternative (as in MT to be post-edited) (Vagia, Transeth, and Fjerdingen 2016). As

Ihde (1990, 80) notes, "all writing entails technologies" — HT is still mediated by technology, albeit to a lesser degree than MT and LLMs. However, HT and MT in use still differ in many respects.

The dimension of magnification-reduction is one way of highlighting the role of technology in MT and the concomitant reduction of the human role. This message is reinforced in NLP research and the media, by the use of the ill-defined term AI and assignation of human-like qualities to machines, leading to an impression that the technology, rather than vast increases in data, is behind improved MT and LLM performance. Ihde (1990, 98) warns that "to characterise computer "intelligence" as human-like is to fall into a peculiarly contemporary species of anthropomorphism". The importance of data for MT is highlighted by the contrast between high- and low-resource MT and the difficulties and workarounds to create useful systems when data is scarce. Data-driven MT and LLMs change how we think about and understand text. Text changes from being the dominant mode of communication to data, to be harvested and processed. The complexity of machine learning conceals the processes by which text is translated or produced, adding to the magnification of the role of technology and, at times, to unrealistic expectations of MT quality.

Expectations and trust differ between HT and MT. This is despite — and the cause of — much hybridity in translation production. Good HT is adapted to the reader, conforming to purpose, brief, and translation norms, whereas MT requires the end user to adapt to it in order to avoid incomprehension and risk. As users gain experience with MT, they learn to limit their trust and to work around its limitations. Users adapt to the MT rather than vice versa. The concept of multistability is useful in describing this interaction: the design of MT (or, especially, an LLM) does not define the boundaries of our interactions with it, and these interactions change based on our knowledge and experience.

In enabling instantaneous translation, often with impressive output quality, MT constrains lexical diversity, struggles with co-text, and lacks communicative intent, sometimes producing biased output. This does not stop it from being a hugely useful and involving technology for millions of users worldwide, and for many translators who are happy to work with it. For many translators it is an alienating technology that exteriorises the translation process. This is not the same as Plato (1925, 9:275a) decrying writing because it will "discourage the use" of one's own memory. Mastery of a task has been shown to be a key indicator of job satisfaction (see Moorkens 2020), thus the automation of this role will reduce satisfaction for many translators.

MT and AI in general are also alienating for those across the digital divide, who are without access to ICT for one reason or another. Their usefulness serves to exacerbate the divide, and this negative impact on the least developed countries is compounded by the uneven effects of climate change, the environmental pollution in which ICT is implicated, and the relative lack of scientific information in languages other than English (Neylon, Kramer, and Diprose 2022). Current efforts in green or sustainable AI are generally narrow in scope and have not yet proved effective (Heilinger, Kempt, and Nagel 2024).

An earlier draft of this text used the term 'dichotomies' to describe dimensions from postphenomenology, suggesting that they are binaries, which Tymoczko (2000, 36) argues "do not work very well in translation studies" given that "the best of binaries tend to break down". These particular dichotomies, however, are not mutually exclusive: a multistable technology is likely to both magnify and reduce, both enable and constrain. These dimensions seem to be applicable to MT and LLMs, giving us language to describe phenomena and, perhaps, new ways to think about translation technologies. The concepts from postphenomenology also echo Venuti (2008), who argues that a tendency to prioritise fluency in (human) translation makes it appear transparent, concealing the work of the translator. As a lens through which to examine our interactions with technology, postphenomenology cannot tell us whether or not MT is translation, but it can provide us some direction to consider what contemporary MT is and how it shapes our interactions with the wider world.

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