Do translators use machine translation and if so, how? Results of a survey held among professional translators

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Abstract

The author conducted an anonymous online survey between 23 July and 21 October 2022 to gain insight into the proportion of translators that use machine translation (MT) in their translation workflow and the various ways they do. The results show that translators with more experience are less likely to accept MT post-editing (MTPE) assignments than their less experienced colleagues but are equally likely to use MT themselves in their translation work. Translators who deal with lower-resource languages are also less likely to accept MTPE jobs, but there is no such relationship regarding the use of MT in their own workflow. When left to their own devices, only 18.57% of the 69.54% of respondents that declared that they use MT while translating always or usually use it in the way the pioneers of MT envisaged, i.e., MTPE. Most either usually or always prefer to use MT in a whole range of other ways, including enabling MT functions in CAT tools and doing *hybrid post-editing*; using MT engines as if they were dictionaries; and using MT for *inspiration*. The vast majority of MT users see MT as just another tool that their clients do not necessarily need to be informed about.

1 Introduction

Right from the early days of machine translation (MT), it was apparent that totally replacing humans with machines for all kinds of translation was not a realistic goal since, as Warren Weaver put it in his ground-breaking memorandum, “perfect translation is almost surely unattainable” (Weaver, 1949). This was further underlined by Yehoshua Bar-Hillel, organizer of the first Conference on Mechanical Translation in 1952, who reasoned that fully automatic high-quality machine translation was not feasible. In his theoretical demonstration, Bar-Hillel described the need for post-editing “not only for polishing up purposes” but also to deal with ambiguity which is “resolvable only on the basis of extra-linguistic knowledge” (Bar-Hillel, 1960).

From these beginnings, it looked as if MT post-editing (MTPE) was shortly destined to become the predominant approach to translation, at least for technical and scientific texts. However, a few years later, the 1966 report published by the Automatic Language Processing Advisory Committee (ALPAC, 1966) cast doubt on its economic viability. The Committee concluded that, at the time, human translation could be done “faster and for less than half the price”. The ALPAC report did on the other hand promote the use of *machine-aided translation*, later known as *computer-aided translation* (CAT), which in 1966 consisted of using *text-related glossaries* compiled with the help of a computer.

After the ALPAC report, MTPE underwent a period of what Garcia (2012) defines as latency. Post-editing was still used in various projects throughout the world, but attention gradually shifted towards CAT tools, which “grew out of MT developers’ frustration at being unable to design a product which could truly assist in producing faster, cheaper and yet still useable translation” (Garcia, 2014). Initially, MT systems and CAT tools followed two separate paths of development although some attempts were made at integrating CAT tools with MT in the early 1990s. However, it was not until Lingotek produced a web-based CAT tool with MT integration in 2006 (Garcia, 2014) that the barrier between the two approaches began to break down.

CAT-MT integration makes what this paper terms as *hybrid post-editing* possible, i.e., a process whereby part of the translation is done through the post-editing of MT output and part through the editing of translation memory matches. Several CAT tools today offer even more complex features such as the automatic *repair* of translation memory matches using MT output and MT-output-based predictive typing, which make it hard to determine which type of editing the human translator is doing. Moreover, some recent studies on the two types of editing, particularly Sánchez-Gijón (2019) and do Carmo and Moorkens (2020), have noted the blurring lines between the two processes caused by improvements in the quality of MT output.

This paper presents the results of an anonymous online survey designed to gain insight into the proportion of translators that use MT during their work and the various ways they do so. Several surveys have already been conducted on the use of technology in the translation industry, and some of them also set out to measure the degree of use of MT among translators, notably the QTLaunchPad survey (Doherty et al., 2013), the Use of Machine Translation among Professional Translators survey (Zaretskaya, 2015) and the annual European Language Industry Surveys published by ELIA, et al.

However, to this author's knowledge, there have been no surveys designed to obtain details of precisely how freelance translators choose to include MT in their workflow from among the whole host of options available to them. This paper intends to fill that gap.

2 Methods

The anonymous online survey was drawn up in English, due to its international nature. The questions were inspired by an informal discussion the author launched in a private Facebook group (Translators in Italy) in February 2022, which was a *de facto* brainstorming session on how professional translators use MT during their work. The various techniques that emerged from the discussion allowed closed-ended survey questions to be designed, with the advantage of making result analysis simpler and the survey less time-consuming to take. In any case, additional *other (please specify)* options were provided so that answers that did not emerge during the brainstorming session could still be given.

Since Zaretskaya (2015) reports that translators with advanced knowledge of IT tend to use MT more than others, it was initially decided *not* to post the survey on public websites or social media but to ask professional translators' associations to share it with their members in the hopes of reaching people with a broad range of IT skills.

The survey link was sent to 97 associations on 23 July and 2 others on 23 August 2022, ninety-five of which were members of the International Federation of Translators.

With a large population, it is commonly estimated that 385 replies are sufficient to reach a confidence level of 95%, assuming the sample is truly random. This amounts to responses from fewer than four members of each association contacted.

However, in early September, it became apparent that very few associations were willing to take part in the research: only 11 had written to say they had shared the link and one large one had replied that the survey did not align with their mission. Since the total number of responses stood at 249 on 8 September, including some incomplete ones, and the response rate was beginning to flag badly, the author decided to share the survey on Facebook, LinkedIn, Twitter, and ProZ.com using a different link (collector). Moreover, when the abstract of the presentation of this paper was published on the *Translating and the Computer 44* website, an additional question was added to identify any responses from the new channel. The data from the two populations (survey received through an association vs. survey found in a *technological* way) could therefore be analysed separately.

Most of the variables measured in the survey are non-numeric, non-parametric, categorical variables which can only take on a limited number of values, and several of the continuous, numerical variables, such as years of experience, were analysed in bands of values and therefore transformed into categorical variables. For this reason, the widely used chi-square (χ^2) test was chosen for the statistical analysis. The significance level was set to .05, as per convention, to ensure a 95% confidence level, and the online chi-square test calculator provided by Dr Jeremy Stangroom was used.[1] The results are reported in the format required by the American Psychological Association (APA): χ^2 (degrees of freedom, N = sample size) = chi-square statistic value, p = p value.

3 Results and discussion

3.1 Survey population

The survey closed as scheduled on 21 October 2022. A total of 12 of the 99 professional associations contacted had written to say they had shared the survey link with their members, although it was discovered by chance that at least 3 others had also done so without informing the author. One had written to say they would *not* share the link and none of the other associations replied at all. Survey responses were received from 452 people: 6 were disqualified since they answered that they were *not* professional translators; 301 were sent the survey link by a professional association or a member thereof (group A); 145 received the survey link from social media or a website, or from someone who found it that way (group B). Two responses were so incomplete they could not be used; other incomplete responses were used up to the question they reached.

The first step in the analysis is to see if the two groups of respondents gave significantly different replies regarding the key questions: use of MT and willingness to accept MTPE assignments.

	Never MTPE	**MTPE**
Group A	136	148
Group B	60	77
(χ^2 (1, N = 421) = 0.62, p = .430).		

Table 1: MTPE contingency table

	Use MT	**Never use MT**
Group A	197	83
Group B	93	44
(χ^2 (1, N = 417) = 0.27, p = .606).		

Table 2: Use of MT contingency table

In both cases the answers to the questions were independent of the group the respondent belonged to ($p > .05$). This may be because what Zaretskaya observed in 2015 no longer holds, or because frequenting social media and the internet is not indicative of a particularly high level of IT skill, or because predominantly tech-savvy association members tend to reply to online surveys. Whatever the explanation, there is no reason to keep the data separate from hereon in.

[1] https://www.socscistatistics.com/tests/chisquare2/default2.aspx

3.2 Respondents

The first questions aimed at getting a picture of how much experience the respondents have, the languages they work with and the way they work (freelance, in-house, etc.) to see if these factors affect their attitude towards MT.

The mean professional experience was calculated at 21.00±12.38 years.[2] Table 3 shows willingness to accept MTPE jobs according to years of experience. The bands were chosen so that there is approximately the same number of respondents in each.

Years of experience	**Never MTPE**	**Sometimes MTPE**	**Often MTPE**
0-12	30	49	24
13-19	44	45	9
20-28	57	41	16
29-70	64	33	7

Table 3: Acceptance of MTPE jobs according to experience

As experience grows, the likelihood of accepting post-editing assignments falls in a statistically significant way (χ^2 (6, N = 419) = 29.01, p < .01).

Table 4 shows the number of respondents that reported they use MT as an aid at some point in their translation workflow according to years of experience for the same ranges. Perhaps surprisingly, there is no statistically significant difference (χ^2 (3, N = 415) = 0.39, p = .941). *Young* and *old* translators are just as likely to use MT in their personal translation process.

Years of experience	**Use MT**	**Never use MT**
0-12	70	32
13-19	66	31
20-28	81	32
29-70	72	31

Table 4: Use of MT according to experience

Table 5 shows how willing the respondents are to accept MTPE assignments according to how much of their work consists of translation, expressed as a percentage of all the language services (LSs) the translator provides. The bands were chosen so that there is approximately the same number of respondents in each.

Translation as % of LSs	**Never MTPE**	**Sometimes MTPE**	**Often MTPE**
1-60	45	42	18
61-80	45	52	12
81-95	49	43	9
96-100	57	32	17

Table 5: MTPE according to translation as a percentage of all the language services provided

No statistically significant relationship was found (χ^2 (6, N = 421) = 10.20, p = .116).

[2]Two respondents indicated that they had 100 years of professional experience. Their data was not considered plausible and discarded.

Translation as % of LSs	Use MT	Never use MT
1-60	73	30
61-80	85	24
81-95	60	39
96-100	72	34

Table 6: Use of MT according to translation as a percentage of all the language services provided

No statistically significant relationship was found regarding the use of MT in the workflow either (χ^2 (3, N = 417) = 7.62, p = .055).

91.90% of respondents were freelance translators, 6.71% were in-house employees, 5.56% were employees working from home, 6.25% were volunteer translators and 1.16% had a different working relationship. Multiple answers were allowed since translators may work part-time in different ways.

Employees might have been expected to accept more MTPE jobs and use MT more often than freelancers, but the survey data shows that these two variables are independent of the way the profession is practiced (χ^2 (4, N = 471) = 4.07, p = .396 and χ^2 (4, N = 466) = 5.99, p = .200).

Employees were asked if the organization they worked for dictated the way they could use MT in their workflow. Only one answer was allowed. 64.86% of respondents said no rules were imposed, 5.41% said they were obliged to use MT and 29.73% are allowed to use MT in certain circumstances.

The circumstances mentioned amounted to not being allowed to use MT for specific jobs where privacy was an issue (1), being allowed to use MT within CAT tools (3), and being obliged to use MT if explicitly requested by the end client (7).

3.3 Translation languages

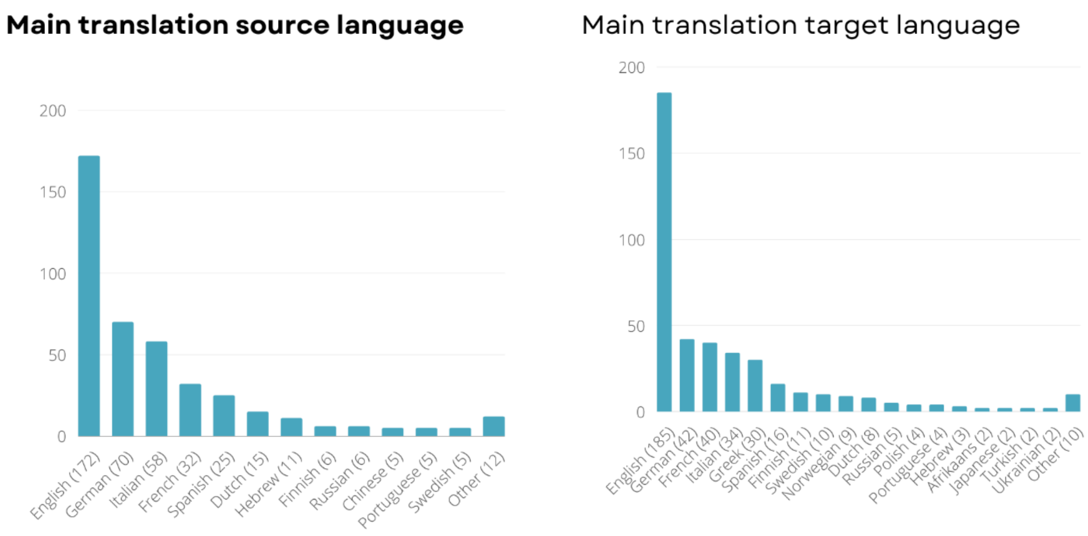

Chart 1: Main translation source and target languages

Professional translators might be expected to be more likely to consider post-editing assignments and use MT in their workflows if they work with higher-resource languages, for which the quality of MT output is normally better. To verify this hypothesis, the Digital

Language Equality Metric (technological factors) was used as a measure of language resource richness (Gaspari et al., 2022). Only 22 of the 31 languages reported by respondents are rated on the European Language Grid Dashboard[3], but – fortunately – those languages account for 94% of the overall source language data and 96% of the overall target language data gathered in this survey.

Upon analysis, it was found that there seems to be a threshold under which professional translators are less likely to accept MTPE jobs (source language TDLE score of somewhere between 13807 and 14765 and target language TDLE score of somewhere between 14765 and 15414). However, as Zaretskaya (2015) observed, there is no such threshold as regards using MT in the workflow.

Respondents did an average of 81.98±18.76% of their work in their main language pair. Table 7 shows willingness to accept MTPE jobs according to the amount of translation work the translator does in their main language pair. The ranges were chosen so that there is approximately the same number of respondents in each group. No significant relationship was found (χ^2 (6, N = 421) = 2.02, p = .918).

Amount of work in main language pair (%)	Never MTPE	Sometimes MTPE	Often MTPE
100	56	41	14
90-99	47	43	13
70-89	54	47	19
10-69	39	38	10

Table 7: Acceptance of MTPE according to the proportion of work the respondent does in their main language pair

A similar contingency table was drawn up between the amount of work a professional translator does in their main language pair and whether they use MT in their workflow, again without finding any significant relationship (χ^2 (3, N = 417) = 2.06, p = .561).

3.4 Acceptance of MTPE assignments

46.56% of respondents said they never accept MTPE jobs. They were allowed to give multiple answers to explain why: “I refuse to do them” (48.21%), “I have never been offered one” (28.72%), “the rates offered are too low” (44.62%), and “other” (36.41%). The four most frequent open-ended *other* answers given amounted to (in decreasing order of frequency) a dislike for or little satisfaction from post-editing (one respondent used the expression “soul destroying”), post-editing requiring as much or more time than translation from scratch, MT giving poor results in the translator’s field of specialization, and MT output being a bad influence on the translator or leading to bad translation habits.

Some translators reported that they suspected or were sure that some of the translations they were given to revise were in reality MT output or MTPE done by non-native speakers of the target language even though they were told they were human translations or texts written by non-native speakers. These might be described as *stealth monolingual post-editing assignments*.

40.14% of respondents said they sometimes accept MTPE jobs. They were allowed to leave multiple closed-ended comments to add detail to their answer: “but I prefer to avoid them” (51.79%), “but I do not actively seek them” (60.71%), and “I am not often asked to do them” (32.14%). Respondents could also leave an open-ended comment (10.12%). The main two amounted to – from most to least common – “only if the rate is right” and “maybe I am doing them without being told”, as discussed above.

[3] Consulted on 25 October 2022

13.30% of respondents said they often accept MTPE jobs. Again, they were allowed to leave multiple closed-ended comments. 33.93% said they preferred to avoid them, and 16.07% said that they actively seek them.

Respondents could also make another comment (51.79%) not included among the closed-ended answers. The vast majority of those who wrote something said that post-editing is simply another language service, and several comments seemed tinged with melancholic resignation: "because - while I don't love them - I cannot turn a blind eye to MT and pretend it's not there."

One reason why so many translators seem to dislike post-editing may be that the rewarding part of the translation process lies in the sense of achievement attained when you elegantly express the same concept in the target language. Post-editing mostly removes this task leaving the translator the chore of dotting the i's and crossing the t's, which is felt to be less satisfying.

3.5 Use of MT at some point during the translation workflow

69.54% of respondents use MT at some point in their translation workflow (MT users). This figure is virtually the same as the *slightly more than 70% of independent professionals* reported in the 2022 European Language Industry Survey (ELIA, et al., 2022).

No significant relationship was found between willingness to accept MTPE jobs from clients and using MT as an aid while translating (χ^2 (2, N = 417) = 1.45, p = .485).

The respondents that said they never use MT at any point in their translation workflow gave the following reasons (multiple answers were allowed): "because the kinds of texts I translate do not lend themselves to machine translation" (51.64%); "because it harms the quality of the final translation" (42.62%); "because of GDPR/privacy issues" (34.43%); "I have experimented with it but do not find it useful" (31.97%); "I have never tried to integrate it into my workflow" (29.51%); "because my employer/client(s) specifically ask(s) me not to use it" (18.85%); "because it is *unprofessional*" (16.39%), and "other" (20.49%).

Among the *other* open-ended answers given, three respondents said that MT quality was not good enough in the languages they worked with, two said they could not afford good MT output, two did not want to provide the engines with training data and put their jobs at risk, one said it harms their language skills and one only translates handwritten documents.

3.6 MT engines

81.40% of MT users said they use one or more cloud or web-based MT engines, as shown in Chart 2 (multiple answers were allowed).

MyMemory is a large public translation memory and not an MT engine. However, the service also provides machine translations from Google Translate and Microsoft Translator.[4]

50.85% of web-based MT engine users said they pay to use the following MT engines (multiple answers were allowed): DeepL (102), Google Translate (20), ModernMT (9), Microsoft Translator (4), and other engines (7). The others use the free versions.

18.59% of MT users use custom MT engines (multiple answers were allowed): 37 of these use engines provided by employers/clients, 17 use their own engine and 3 use other engines. ModernMT, mentioned in the question about web-based engines, utilizes user-uploaded corpora (translation memories) and adds translated segments to its training data on the fly (Germann et al., 2016). It should therefore be regarded as a custom MT engine built by the translator. However, 8 of the 9 respondents that stated they use ModernMT said that they did *not* use custom MT engines, possibly because they did not know what a custom MT engine is. The respondent that answered that they use KantanMT, on the other hand, replied correctly. With hindsight, perhaps the survey question should have provided a definition of the term. The

[4]https://site.matecat.com/support/managing-language-resources/machine-translation-engines/

data given above has been adjusted to include the ModernMT users, but it would be reasonable to assume the true figures might be higher.

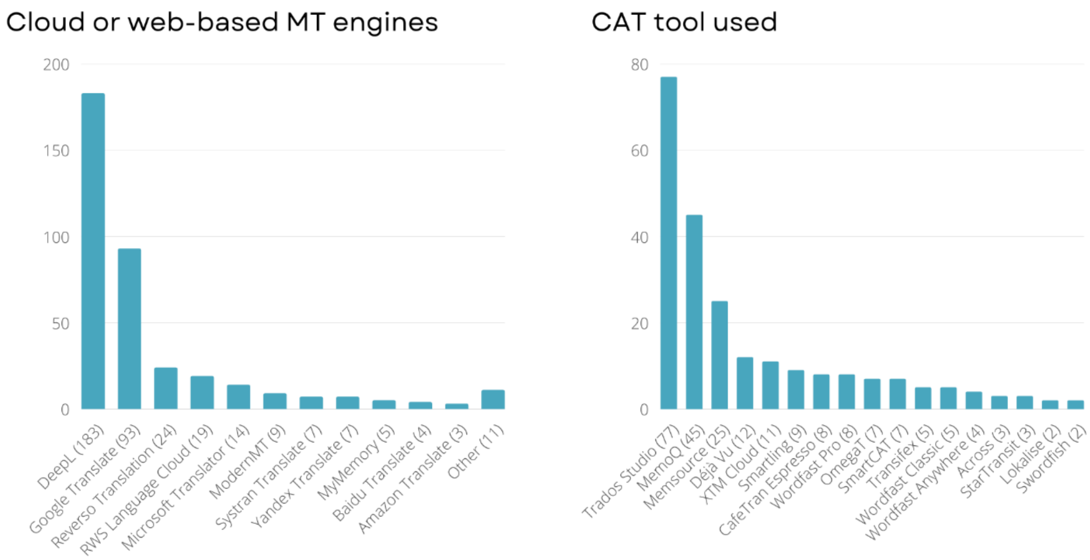

Chart 2: Cloud or web-based MT engines and CAT tools used

1.07% of MT users said they use one or more non-web-based MT engines, not including custom MT engines. Only one person named a non-web-based MT engine: OPUS-CAT. One translator said their clients use a non-web-based MT engine without stating which. And one respondent said that their client provides a penalized translation memory containing MT output. This working method is also suggested in a training manual on using MT with the CAT tool memoQ (Pawelec, 2021).

3.7 *Pure post-editing*

51.79% of MT users reported they do *pure post-editing* (always = 5.36%, usually = 13.21%, sometimes = 16.43%, rarely = 16.79%), which is when the translator decides to deal with their own translation project as if it were a post-editing assignment. In other words, they receive a source text to translate from their client, machine-translate the entire text, and then carry out a full post-editing on the output. This can be done in a CAT tool or by feeding the source text to an MT engine and post-editing the output file in a word processor. Perhaps unsurprisingly translators who do not accept MTPE assignments from clients are also less likely to do *pure post-editing* for themselves (χ^2 (1, N = 406) = 7.31, $p < 0.05$).

	All MT users	**Those who never accept MTPE assignments from clients**
Pure MTPE	145	47
No pure MTPE	135	79

Table 8: Translators who do *pure post-editing*, all MT users vs. those who do not accept MTPE assignments

3.8 *Hybrid post-editing*

33.21% of MT users do *not* use or enable MT functions in their CAT tools and 13.72% do not use CAT tools at all. The remaining 53.07% enable or use MT in the ways shown in Table 9 (multiple answers were allowed). By enabling MT functions, many of the translators are effectively doing *hybrid post-editing*, in other words, a process whereby part of the translation is done through the post-editing of machine translation output and part through the editing of translation memory matches. The CAT tools which respondents reported they enabled MT functions in are shown in Chart 2 above (again multiple answers were allowed).

Machine translation when there is no exact match	55.78%
Machine translation when there is no good fuzzy match	43.54%
Machine translation to integrate or *repair* fuzzy matches	16.33%
Machine translation through predictive typing	20.41%
Other way (please specify)	23.13%

Table 9: How MT is enabled in CAT tools

Six respondents used the *other way* reply to specify that they keep the MT output in a side CAT tool window and only copy it into the translation if they think it is useful. Three others machine-translate whole paragraphs or the whole document and keep the output as reference, in one case in the form of a translation memory.

3.9 MT as a dictionary

In this use, the translator takes a single word, expression (phrase), or whole sentence and feeds it to an MT engine. This can be done with a specific function inside a CAT tool by selecting a segment or part thereof. It can also be done when using a word processor to do a translation with add-ons, such as GT4T[5] or IntelliWebSearch[6], which can even be used as alternatives to enhance the built-in MT functions in CAT tools. A less sophisticated technique entails the translator simply opening an online MT engine in a browser window and copy-pasting parts of the text.

77.93% of MT users use MT engines as if they were dictionaries in the following ways (multiple answers were allowed): by feeding in whole sentences to find the translation of an expression in context (67.70%); by feeding in whole sentences to find the translation of a single word in context (65.93%); by feeding in expressions on their own (63.72%); by feeding in single words on their own (46.46%); by feeding in lists of related terms, e.g. nations, species of plants, names of pharmaceuticals, etc. (21.24%) and *other similar ways* (8.41%).

18.58% of respondents reported they prefer to use an MT engine for the purposes described above rather than using a traditional dictionary. One respondent specified that they fed their queries to two different MT engines to have a "range of options". It should be noted that the web interface of all the top eight engines shown in Chart 2, excluding ModernMT, give dictionary-like results if a single term is input, complete with definitions and alternative translations. The DeepL web interface also gives alternative translations for whole segments and, together with Systran, allow the user to click on any word in a segment (source or target) to see a definition of that word.

3.10 MT for *inspiration*

This use also regards individual sentences, words, or expressions (phrases), much as described for the dictionary-like uses, but this time the aim is not to solve a vocabulary problem, but to be *inspired*. One respondent clarified how this can be done: "I translate passages or sentences myself and then use the MT on the source text to see what it comes up with, and I may adjust my translation on that basis or indeed completely ignore the MT text. The MT never takes the lead but can sometimes be useful as a supplement."

[5]https://gt4t.net
[6]https://www.intelliwebsearch.com/version-5/api/

A total of 86.21% of MT users use MT this way.

74.80% of MT users use MT to overcome what Michael Cronin defines as blockage, when – as he puts it – the "word or the expression or the equivalent allusion will not come, the textual whole does not seem the right fit and try as you might, there seems to be no way out, the words refuse to come to your rescue" (Cronin, 2003).

86.40% of MT users use MT for a second opinion when they are not entirely happy with their own translation of a word, phrase, or sentence.

The concept of using MT to escape from one's idiolect and add variety to a text, mentioned by 59.20% of MT users, seems to contradict the findings of some authors that report that MT leads to lexical impoverishment (Farrell, 2018; Volkart, 2022). However, if the translator already has a solution in mind or has previously translated a word or expression in a certain way elsewhere in the same text and is looking for a synonym, then using an MT proposal instead of their own idea has the effect of adding variety, which can be an important factor in the quality of the translation of creative texts.

In the *other similar way* box (9.60%), one respondent wrote "I feed larger chunks of text into DeepL, sometimes paragraphs […] This enhances the quality of the output since the MT has more context." In December 2020, the author carried out a series of experiments which revealed small differences in the translation DeepL provides when fed whole paragraphs rather than the single sentences that make up the same paragraphs. This feature is however not documented on the DeepL website (last consulted on 23 September 2022).

3.11 MT for comic relief

25.86% of MT users reported that they use MT for an occasional giggle to brighten up their working day. However, several translators used the *other similar way* box (completed by 22.67% of respondents) to clarify that they do not intentionally use it this way but enjoy the odd chuckle when MT happens to produce entertaining output.

3.12 Other uses of MT

The only other uses of MT in the translation workflow that truly do not fit into one of the previous categories (3.7 to 3.11) were the back translation of incomprehensible parts of source text written by non-native speakers into their native language (3 respondents), and as a sort of double-check to prevent omissions or mistakes during the revision process (1 respondent). All the other replies could be reclassified as answers to other questions.

3.13 Transparency

Respondents were asked if they tell their employer/client(s) that they use MT in their workflow.

Always	8.49%
Sometimes	25.83%
Never	65.68%

Table 10: Answer to "do you tell your employer/client(s) you use MT in your workflow?"

Those who answered *sometimes* also specified when. The most common replies - in descending order of frequency – are "if asked", "when the client has specifically asked for MT to be used", "when the translator decides to do *pure MTPE*", "when I think they should know" and "when they know already".

Respondents were then asked if they explained precisely how they use MT when they tell their employer/client(s) that they use it.

Always	25.81%
Usually	17.20%
Sometimes	20.43%
Rarely	10.75%
Never	25.81%

Table 11: Precise explanation of the use of MT

3.14 Other language pairs

86.62% of MT users who work with more than one language pair reported that there are no significant differences in the way they use MT in pairs other than their main one. The reasons given by the respondents who use MT in a different way according to language pair can mainly be categorized as (from most to least common): “MT output is better/worse for the other language(s)” and “because my knowledge of the other language(s) is weaker”.

4 Conclusion

This paper reports the results of an anonymous online survey conducted between 23 July and 21 October 2022 designed to establish the proportion of translators that use MT in their translation workflow and the various ways in which they do.

Although it was found that translators with more experience are less likely to accept MTPE assignments than their less experienced colleagues, it was seen that they are equally likely to use MT themselves in their own translation work.

As might be expected, translators who work with lower-resource languages are less likely to accept MTPE jobs, but – perhaps surprisingly – there is no such relationship regarding the use of MT in their workflow.

Attitude towards using MT and accepting MTPE jobs was also found *not* to depend on how much of a professional translator’s work consists of translation compared with the other language services they provide, the way the translator works (freelancer, in-house, etc.) or the proportion of translation work the translator does in their main language pair.

When left to their own devices, only 18.57% of the translators who use MT in their workflow (69.54%) always or usually use it in the way the pioneers of MT envisaged, i.e., MTPE. Most either usually or always prefer to use MT in a wide range of other ways. These may be classified as using or enabling MT functions in CAT tools and doing *hybrid post-editing*; using MT engines as if they were dictionaries; using MT for *inspiration*; and even using it for comic relief, although this seems more likely to be incidental rather than deliberate.

The vast majority of MT users (91.51%) do not feel that it is always necessary to inform their employer/client(s) that they use MT in their workflow and 65.68% never do so. The impression is that translators today see MT as just one of the many tools they have available to them and not so special as to need pointing out.

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