Do translator trainees trust machine translation? An experiment on post-editing and revision

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Abstract

Despite the importance of trust in any work environment, this concept has rarely been investigated for MT. The present contribution aims at filling this gap by presenting a post-editing experiment carried out with translator trainees. An institutional academic text was translated from Italian into English. All participants worked on the same target text. Half of them were told that the text was a human translation needing revision, while the other half was told that it was an MT output to be post-edited. Temporal and technical effort were measured based on words per second and HTER. Results were complemented with a manual analysis of a subset of the observations.

1 Introduction

In the last few years, neural machine translation (NMT) has become the state-of-the-art paradigm in the field of machine translation (MT). This fast-paced progress has shaken the translation industry and the research world, causing different reactions. Part of the research world has responded with enthusiastic claims about the quality achieved with this new architecture (Hassan et al., 2018; Wu et al., 2016), while other studies have tempered such enthusiasm, reporting less clear-cut improvements (Toral and Sánchez-Cartagena, 2017; Castilho et al., 2017).

Companies and individual professionals have started to exploit MT more than in previous years. As testified by the 2018 Language Industry Survey, for the first time more than half of companies and individual language professionals have stated that they use MT in their workflow. In the same survey repeated in 2019, only generic MT engines (Google Translate and DeepL) were chosen among the 20 most-used tools in companies’ workflow.

In this uncertain scenario, translators’ opinion on MT is likely to be mixed. In the 2019 Language Industry Survey, MT was identified as a negative trend by 20% and as a positive one by 30% of the respondents. Lack of training in MT low output quality resulting from adoption of general purpose engines, and a potential downward trend in translation rates may all explain the negative opinion (some) translators have of MT (Läubli and Orrego-Carmona, 2017), and their limited trust, leading to non-adoption of MT suggestions (Cadwell et al., 2018). Investigating how trust towards MT influences translator trainees’ behaviour towards the output, along the lines of Martindale and Carpuat (2018), is thus crucial to evaluate the likelihood that translators convincingly embrace MT.

In this contribution, we ask whether translators’ trust changes based on the task they are working on, i.e. if they behave differently when they believe they are revising a human translation (HT) vs. post-editing an MT output. We see trust as strictly related to productivity: when post-editors/revisers do not trust a text, they are likely to carry out time-consuming and potentially unnecessary searches, or perform unnecessary edits.

In our study, 47 students from a Master’s in

1A survey on trends in the language industry carried out by EUATC, Elia, FIT Europe, GALA and LINDWeb. https://bit.ly/2RpQtm2
2https://bit.ly/2ZknG1L
3https://bit.ly/2ZknG1L
translation of an Italian university, revised/post-edited the same English translation of an Italian source text composed of two academic module descriptions. Half of them were told that the translation was an MT output, while the other half was told that the text had been translated by a human translator. We measured the time each participant spent on each sentence, and the number and extent of changes they made. In what follows we summarise previous work on post-editing (PE) and trust (Sect. 2), describe the experimental setting and method (Sect. 3), outline results (Sect. 4) and draw some conclusions (Sect. 5).

2 Related work

2.1 Post-editing of MT

To the best of our knowledge, no work has been published yet on the assessment of trust towards MT as measured in a PE task. Martindale and Carpuat (2018) conducted a survey among non-professionals to understand how their trust was influenced by fluency and adequacy. The former issue is found to have a stronger negative impact on non-professional translators. More recently, Cadwell et al. (2018) interviewed two groups of institutional translators to investigate the reasons for adoption or rejection of MT suggestions. Both groups mentioned lack of trust toward MT as one of the reasons for rejecting MT segments.

Focusing on PE tasks in different languages, a number of papers have analysed how performance changes for different subjects or in different work environments, and using one or more effort categories among those listed by Krings (2001): temporal, technical and cognitive. Moorkens and O’Brien (2015) used edit distance and speed to compare the productivity of professionals and students in a PE (En–De) task, whose aim was to evaluate the suitability of the latter for translation user studies. Daems et al. (2017) examined how 10 Master’s students and 13 professional translators coped with translation from scratch and PE of newspaper articles (En–Nl), measuring translation speed and cognitive load. Moorkens and O’Brien (2015) found that students have a less negative attitude towards technology, but their productivity cannot be compared to that of professionals; by contrast, according to Daems et al. (2017) the performance of the two groups was not as different as could be expected, and indeed students were more at ease with PE than professionals.

Yamada (2019) compared perceived cognitive effort, amount of editing and final quality between two PE tasks carried out by students, one using an NMT output and one a PBMT output (En–Ja). While the cognitive effort was similar for the NMT and PBMT tasks, NMT output required less editing effort and led to a better final quality.

Rossetti and Gaspari (2017) measured perceived and real effort of six MA students when translating with translation memories (TM) and in a PE scenario, triangulating time measurements, think-aloud protocols (TAPs) and retrospective interviews. Results show that only suggestions coming from the TM had a positive impact on perceived task complexity and temporal effort.

Despite growing interest in PE, to the best of our knowledge trust has not been investigated in such task. Furthermore, our language combination (It–En) is relatively under-represented in PE experiments, and the text domain we are focusing on (university module descriptions) is a novel one in this scenario.

2.2 Trust

The notion of trust is a multifaceted one, which has been studied in a host of different fields. McKnight et al. (2001) report that, in three different monolingual English dictionaries, on average 17 different definitions of trust are provided. Lee and See (2004) define trust as “the attitude that an agent will help achieve an individual’s goal in a situation characterised by uncertainty and vulnerability”.

Even though human-machine relationships may develop in the same way as human-human ones (Madhavan and Wiegmann, 2007), the constructs developed to describe trust between human beings do not fully transfer to human-machine interactions (Lee and See, 2004). First, human beings, behave intentionally. Second, interpersonal trust depends on how both parties perceive the counterpart’s behaviour, which does not happen when one of the parties involved is a machine. In this case, trust follows from observation of technology performance, from understanding of its underlying architecture, and from intended use (Lee and See, 2004). Translators’ lack of trust toward MT might therefore be influenced by different factors, including inconsistency/unpredictability of its output (especially true of NMT), or misconceived expectations about its functioning.

Since several academic programs have recently
started to offer courses on MT, the next generation of translators will be the first to enter the market with some knowledge of it. Whether their trust in the technology is likely to increase as a result is still an open question.

3 Experimental setup

3.1 Goals and variables

Post-editors’ productivity was analysed with respect to the following variables: (a) translation method (students are told that the text is an MT output vs. a HT); (b) translation correctness (the translation is correct and needs to be confirmed vs. it is incorrect and needs to be edited).

3.2 Participants

47 students of the Master’s in Specialised Translation of the University of Bologna took part in the experiment. 23 participants worked on the PE task and 24 on the revision task.

Native languages of the participants working on MT were Italian (69.6%), English (4.3%) and other (26.1%). The native language of participants working on the purported revision of a HT was Italian (79.2%), English (8.3%) and other (15.5%). Although translating into English as L2 is not common practice for experiments in this field, the reality of the profession is quite different. Two surveys quoted by Pokorn (2016) revealed, respectively, that for 24% of the respondents the ability of translating into L2 is essential or important for newly employed translators and that more than 50% of 780 free-lance translators working in 80 states (including Italy) translate into L2.

All students belonged to the same cohort. This allowed us to control for (i) their PE/translation experience; (ii) their knowledge of the text type and disciplinary domains of the texts; (iii) their knowledge of English.

Regarding (i), students attended hands-on modules on CAT tools and on MT and PE as part of their syllabus. One week before the experiment, they received training on the use of MateCat, the tool used for the task (see Sect. 3.3). Also, in a pre-experiment questionnaire, they were asked how much experience they had with the revision of a HT or PEMT in a professional setting. Possible answers were: None, Little, i.e. from 1 to 5 professional tasks or Much, i.e. more than 5 professional tasks. Results are reported in Table 1 and show that the degree of expertise is similar in both groups, since the vast majority of the participants had no or little professional experience.

Regarding (ii), all subjects are likely to be familiar with the text type, since course unit descriptions address students, and are unlikely to be acquainted with the domains (pharmacy and chemistry), since their academic background is in languages and linguistics. Concerning (iii), all students are tested upon enrollment in the Master’s, a minimum of C1 CEFR being required for admission.

To collect data on participants’ opinion regarding MT, in the pre-experiment questionnaire they were asked how useful they thought MT is for translators. Results in Table 1 suggest that all participants have a positive opinion on MT, confirming the results described by Daems et al. (2017) and Moorkens and O’Brien (2015) (see Sect 2.1).

3.3 Task

The same text was used for both the MT PE task and the HT revision task. It was composed of two course unit descriptions – for a course on chemistry and one on pharmacy – written in Italian. The English version was produced with a state-of-the-art off-the-shelf NMT system, which ensures the high-quality of the target text used for the experiment.

The final version of the text was the result of a two-step procedure. First, to make sure the text could be believed to be a HT, we checked for possible mistakes typical of MT systems. To establish which sentences were (in)correct, three evaluators were asked to assign each sentence to one

| Question                  | Answers     | MT part | HT part |
|--------------------------|-------------|---------|---------|
| Professional experience  | None        | 91.3%   | 95.8%   |
| with MT/PE               | Little      | 8.7%    | 0%      |
|                          | Much        | 0%      | 4.2%    |
| MT usefulness for translators | Not useful | 0%      | 0%      |
|                          | Useful      | 82.6%   | 70.83%  |
|                          | Very useful | 17.4%   | 30.43%  |

Table 1: Results of the questionnaire on participants’ professional experience and opinion on usefulness of MT, split by type of task (HT or PE).
of the following categories: (i) correct (the meaning of the source sentence is conveyed in the target text and no editing is required); (ii) incorrect (the meaning of the source sentence is conveyed in the target text but edits are required. In this case, evaluators were asked to annotate the part of the sentence that should be edited); (iii) wrong (the meaning of the source sentence is not conveyed in the target text). The final decision as to the correctness of each sentence was made by majority vote. None of the sentences was labelled as wrong.

A small amount of edits were performed in order to have half correct sentences and half incorrect ones in the data set (see Sect. 3.1). At the end of this procedure, the text consisted of 60 sentence pairs, corresponding approximately to 670 source words in total.

Participants worked in MateCat. A project – including a termbase – was assigned to each of them.

A week before, students were given basic information about the experiment. After reading the instructions, students started working autonomously. In the instructions they were invited to work as they normally would. They were asked to deliver a target text of publishable quality, but encouraged to use the provided target text as much as possible and not to over-edit. Researchers were present in the lab throughout.

3.4 Evaluation methods

Productivity was measured in terms of HTER (Snover et al., 2006) between the original text and the participants’ edited version, and in terms of words per second (WPS). The latter was obtained by converting MateCat time measurements on a segment level into seconds and dividing them by the number of words in the target text.

Two separate linear mixed models were built, one for each dependent variable, i.e. HTER and WPS. In both cases, the independent variables (or fixed effects) are categorical, i.e. translation method (MT/HT), and translation correctness (correct/incorrect). We included in the model an interaction of the two, with participant and segment as random effects.

Random effects were tested for significance using the likelihood ratio test. Following Gries (2015), a model including all fixed and random effects was built and compared using ANOVAs against different models, each excluding one of the random effects. If the difference between the two models was significant ($p < 0.05$), the random effect was kept in the model.

4 Results

Tables 2 and 3 summarise significance and estimates for the effects of the two linear mixed models. Figure 1 shows the distribution of HTER and WPS values for individual segments split by translation method and correctness.

4.1 HTER analysis

As expected, in Figure 1 HTER is higher for incorrect sentences overall. While differences between PEMT and HT revision in both cases are small, HTER values for correct MT sentences are slightly higher than values for correct HT sentences.

Moving on to results of our linear mixed model, the two random effects participant and segment do have a statistically significant impact on the HTER scores (see Table 2), i.e. the observations for the same segment or for the same participant are strongly correlated. Using a mixed model guarantees that the effect of these correlations on the dependent variable is controlled for. Translation correctness is the only fixed effect with a statistically significant impact on HTER, while neither translation method nor its interaction with translation correctness significantly impact on it.

The model thus shows that the number of edits changes significantly only between correct and incorrect sentences, while the amount of edits performed on HT and MT sentences does not differ significantly. The effect of the interaction was not significant either, i.e. no significant change in HTER scores is observed in HT revision and MT PE across translation correctness conditions.
The similarity of the HTER values is confirmed by estimates in Table 3, where HTER is only slightly higher for MT sentences (+1.702), while the opposite happens in incorrect sentences, where HTER is higher for HT revised sentences (+1.799). We conclude that HTER does not provide evidence of a lack of trust toward MT and that behaviours observed for both translation methods are similar.

4.2 Words per second analysis

Figure 1 shows that WPS is higher for correct sentences than for incorrect ones, while it is similar for PE and revision in the two conditions.

As in Sect. 4.1, the $p$ values in the WPS column of Table 2 confirm the statistically significant effect of the two random effects (participant and segment) on the dependent variable. However, in this case neither the two fixed effects (translation correctness and translation method), nor their interaction have a significant effect. This means that differences in terms of WPS between correct and incorrect sentences are not statistically significant. Similarly, significant differences between HT revision and PE were not found. When considering the interaction of translation method and translation correctness, WPS does not change significantly.

Looking at Table 3 we can see that, as expected, participants were more productive on correct sentences than on incorrect ones, but values do not vary substantially. WPS is higher (+0.106) for correct MT sentences than for correct HT sentences, while for incorrect sentences productivity in terms of WPS is higher (+0.010) for HT than for MT.

Combining these results with those in Sect. 4.1, we can confirm that students did not trust MT less than HT or vice versa.

4.3 Qualitative analysis

Given that neither translation method nor its interaction with translation correctness were found to significantly affect technical and temporal effort, we performed a qualitative analysis on a subset of the sentences. Segments with the highest difference between MT and HT in terms of mean HTER were examined.

Concerning Example 1 in Table 4, in both revision and PE, the same number of participants made the right decision, i.e. no edits. In the HT condition most of the participants who edited the sentence only changed the preposition. In the MT condition, terms were changed as well, resulting in a higher HTER score for MT (25.6) than for HT (17.3). Similarly in Example 2, most post-editors changed verb tenses or nominalised verbs. Mean HTER was 11.4 for MT and 6.79 for HT: most revisers did not edit the sentence.

Regarding incorrect sentences that were edited less in PE than revision, it would seem that revisers paid more attention to issues in the text than post-editors did. For example, all three occurrences of reaction in Example 3 should be plural and the term provided by the termbase is Alkyl halides rather than Haloalkane. 58.3% of the revisers spotted both issues, while only 34.78% of the post-editors did. As a result, mean HTER was 57.2 for HT revision and 43.4 for PE.

In Example 4, it would be sufficient to add the word examination at the end. However, in the HT condition most of the participants (54%) carried out a number of other edits applying to the whole sentence. Post-editors carried out unnecessary edits to a lesser extent (4.8%), such that mean HTER was 48.9 for HT and 43.8 for MT.

5 Discussion and limitations

In this contribution we have compared post-editor and reviser trainees’ trust towards MT and HT based on HTER and WPS (see Table 2 and 3). According to two linear models, significant changes were only found between HTER on correct and incorrect sentences.

No evidence of a lack of trust towards MT emerged. This behaviour confirms the positive opinion on MT stated in the pre-experiment ques-
Table 4: Examples of correct and incorrect outputs with large HTER differences between HT and MT.

| Ex. | Sent. type | Text | Correctness |
|-----|------------|------|-------------|
| 1   | OUTPUT    | Drugs during pregnancy, in children and in the elderly | Correct |
|     | PE        | Drugs in children, in the elderly and during pregnancy | |
|     | REVISION  | Drugs during pregnancy, for children and for the elderly | |
| 2   | OUTPUT    | Finally, possible technical solutions to reduce the use of solvents and their recycling will be discussed | Correct |
|     | PE        | Finally, possible technical solutions for solvent usage reduction and solvent recycling will be discussed | |
|     | REVISION  | Finally, possible technical solutions to reduce the use of solvents and to enable their recycling will be discussed. | |
| 3   | OUTPUT    | Haloalkane reactions (metal reaction, elimination reaction) | Incorrect |
|     | PE        | Alkyl halides reactions (metal reaction, elimination reaction). | |
|     | REVISION  | Alkyl halides reactions (metal reactions, elimination reactions). | |
| 4   | OUTPUT    | The requirement to take the test is to have taken the Microbiology | Incorrect |
|     | PE        | The requirement to take the test is to have taken the Microbiology examination. | |
|     | REVISION  | Only the students who passed the Microbiology test can take the exam. | |

Table 4: Examples of correct and incorrect outputs with large HTER differences between HT and MT.
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