Data Evaluation:
Machine Translationese & Post-Editese
– Basic Level

How MT integration affects the target texts we produce

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1 Introduction

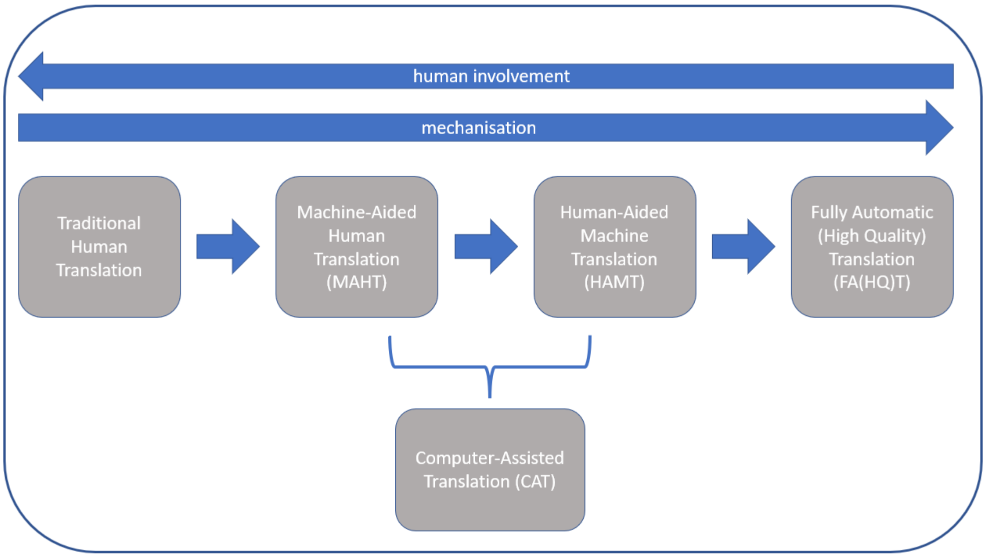

Fig. 1: Degrees of translation automation, own illustration adapted from Hutchins/Somers (1992)

For many professional translators, using machine translation (MT) systems often seems indispensable nowadays. Not only are they fast, but they also deliver excellent results. At least, that's what you'd probably think if you didn't look into the subject more closely.

In recent decades, the field of professional translation has changed dramatically, resulting in different workflows and varying degrees of translation automation. These changes are illustrated schematically in figure 1: On the left, we find the scenario of traditional human translation, where translators translated a printed version of the source text using only printed dictionaries, pen and paper. These days are long gone. After all, the digital transformation has also taken hold in the translation industry, resulting in the use of increasingly complex and powerful tools that can support translators in their daily work. Today, we find ourselves in the era of computer-assisted translation (CAT), which includes machine-aided human translation (MAHT) and human-aided machine translation (HAMT) workflows. In MAHT, the translator translates from scratch but uses tools such as terminology databases, translation memories and automatic quality checks. In HAMT, the source text is first translated by an MT system and edited by a translator afterwards (post-editing), using the tools just mentioned. Fully Automatic (High Quality) Translation without any human involvement is the ultimate goal of translation automation. However, it remains unclear whether FAHQT, i.e., fully automatic **high-quality** machine translation will ever be achieved – at least in professional translation. What we do have today is FAUT, fully automatic **useful** machine translation.

MT in general means that a computer system translates a text automatically and without direct human involvement. However, when people talk about MT these days, they are often referring to neural machine translation (NMT), which has become the de facto standard in recent years (cf. Faes 2020). In NMT, neural networks (loosely based on connected neurons in the brain) are trained on large corpora of translation data, containing aligned source and target texts. For translation, individual words are represented as bundles of numerical information (vectors, also called *word embeddings*) that encode linguistic (morphological, semantic and syntactic) information as well as the context in which the word occurs (cf. van Genabith 2020). NMT systems then draw on this information to generate an output (target text). If you want to learn more about how NMT works and how it differs from previous MT architectures, you can find excellent layperson introductions to the topic in Forcada (2017), van Genabith (2020) and Pérez-Ortiz et al. (2022).

NMT systems (e.g., public systems such as DeepL or Google Translate but also individual systems trained by private companies, etc.) are increasingly employed in the professional translation process to increase productivity. This is evidenced, for example, by the results of the annual European Language Industry Survey (ELIS 2022), a joint initiative by international associations and organizations from the language industry. On average, NMT achieves a higher output quality than previous MT architectures (cf. Bentivogli et al. 2016) and some developers even claim that their systems have achieved human parity (Hassan et al. 2018) or even a superhuman performance (Popel et al. 2020). This would mean that said MT systems would be able to deliver a translation as good as or even better than that of a human translator (=FAHQT).

However, there is good reason to be sceptical of such claims, not least because other studies found that the output of NMT systems can be "deceptively fluent" (Way 2018), meaning that translations produced by an NMT system often read very well but may actually contain errors/inadequacies such as critical shifts in content (e.g. omissions, additions, inverted negations) or expressions and terms that are inappropriate for the text type or unfamiliar to the target audience. This deceptive fluency of NMT output poses a challenge to (future) professional translators and post-editors since it tempts them to simply adopt the translation suggestions provided by the system, making it harder for them to discover and correct issues such as those discussed above.

In this paper and the accompanying video, we will show you how you can perform a fine-grained analysis of raw (unedited) MT output, post-edited MT output and human translations produced from scratch (i.e., without MT assistance) in order to identify nuanced differences between the three modes of text production. To this end, chapters 2 & 3 introduce several concepts relevant to our data analysis. This data analysis will be discussed in detail in chapters 4 & 5.

2 Post-Editing

Correcting and editing an MT output is called post-editing (PE). Following specific quality criteria, the MT output is checked for understandability and accuracy, readability is enhanced and mistakes are corrected.[1] Post-editing can be divided into three dimensions (Krings 2001):

1. Temporal dimension: the time required to fix flaws in the MT output;
2. Cognitive dimension: the type and degree of cognitive processes that need to be engaged to fix a specific flaw in the MT output;
3. Technical dimension: the number of words that need to be deleted, inserted and rearranged (or a combination of these actions) until the text meets the quality criteria.

There are two types of PE: light post-editing (LPE) and full post-editing (FPE) (ISO 18587 2017). LPE often only serves to make the MT output understandable. Although style, terminology and/or grammar may not be flawless, the output should express the same meaning as the source text. In FPE, however, the post-editor aims to bring the quality of the MT output close to that of a human translation. Depending on the desired level of quality, the post-editor should check grammar, spelling and punctuation, ensure the correct and consistent use of terminology and harmonise style and register, among other things. There are four key problem areas that, while rarely a problem in human translation, are regularly present in MT output and hence require special attention during post-editing (Hansa-Schirra et al. 2017):

[1] A very insightful introduction to the topic of post-editing is provided by Nitzke/Hansen-Schirra (2021).

1. Unidiomatic expressions: Typical source language expressions may be translated literally if their target language equivalents are not included frequently enough in the training data of an MT system.
2. Lexical disambiguation: Due to their lack of contextual awareness and world knowledge, MT systems may fail to appropriately distinguish between multiple meanings of a word, which sometimes results in the incorrect translation of polysemes.
3. Semantic disambiguation: MT systems often refer to the most frequently used translation solution in their training material, which might not be the correct one in the respective context.
4. Syntactic disambiguation: MT systems may ignore the syntactic conventions of the target language and reproduce the syntax of the source text.

3 Linguistic Features of Target Texts

To understand how MT integration can affect the production of target texts, we can look at linguistic features of target texts produced in different translation scenarios.

3.1 Translationese

Human translations (HTs) have been found to exhibit linguistic features that differentiate them from their source texts and from texts originally produced in the target language. These features are also referred to as *laws of translation*, *translation universals* or *translationese* (cf. Mauranen/Kujamäki 2004) and include the following phenomena: simplification, normalisation/homogenisation, explicitation and interference.

Translations are assumed to be lexically, syntactically or stylistically simpler than their source texts (Laviosa-Braithwaite 2001). Lexical simplification derives from the semantic competence in our native language and can include the following strategies:

1. Using superordinate terms when no equivalent subordinate term can be found in the target language;
2. Using target language terms that come close to the meaning of source language terms;
3. Using common synonyms (or synonyms that the target audience is familiar with);
4. Transferring the functions of a source-language term to its target-language equivalent;
5. Using circumlocutions instead of finding conceptual matches for high-level words or expressions;
6. Paraphrasing where cultural gaps between the source and the target languages exist.

Syntactic simplification takes place when the complex syntax of a sentence is simplified by human translators to make the text easier to understand. In a nutshell, translators tend to break up long sentences and include a variety of possible strategies, such as the following:

1. Replacing non-finite clauses with finite ones;
2. Substituting elaborate phraseology with shorter collocations;
3. Reducing or omitting repetitions and redundant words;
4. Excluding modifying phrases and words.

Explicitation takes place when translators render ambiguous or implicit source text passages in a less ambiguous/more explicit manner in the translation. This can include the following strategies (cf. Laviosa-Braithwaite 2001):

1. Using interjections to better express the characters‘ thoughts or to put emphasis on a given interpretation;
2. Adding modifiers, qualifiers, and conjunctions to achieve greater transparency;
3. Adding information and explanations as well as repeating previously mentioned details to achieve more clarity;
4. Using precise renderings of implicit or vague data;
5. Providing more accurate descriptions;
6. Adding names to geographical locations;
7. Using clear pronouns when they are ambiguous to clarify references.

Normalisation, also referred to as homogeneisation, refers to the assumption that translations are more conventional in their use of language than their source texts. This includes changes in vocabulary, syntactic structure or style to make the text more accessible and familiar to the target audience (cf. Laviosa-Braithwaite 2001).

Interference refers to the tendency of translating the source text literally rather than employing one's linguistic knowledge of the target language (cf. Laviosa-Braithwaite 2001). The extent of interference depends on the professional experience of the translator and on sociocultural conditions. For example, translators may adopt language patterns from the source text (e.g., adopting verbal style when translating from English into German).

3.2 Machine Translationese and Post-Editese

Interestingly, MT output also shows typical tendencies distinguishing it from its source texts, from human from-scratch translations and from texts originally produced in the target language, which is called *machine translationese* (cf. Vanmassenhove et al. 2021). For example, Vanmassenhove et al. (2021) found a decreased lexical richness in NMT output compared to the corresponding source texts, i.e., a less diverse vocabulary. The authors call this phenomenon "artificially impoverished language". Also, when NMT systems encounter text that is not reflected in their training data, they often resort to a rather linear translation of the source text (cf. Ahrenberg 2017). So, raw MT output is assumed to be artificially impoverished and to show signs of source text interference.

Post-edited MT output (MTPE) also exhibits patterns which differentiate it from human from-scratch translations, which is called *post-editese* (cf. Toral 2019). Specifically, Toral (2019) found post-edited MT output to be lexically simpler and closer in sentence length and part-of-speech sequences to its source texts than human from-scratch translations. Patterns present in the MT output (machine translationese) can therefore be reflected in post-edited versions of this output (although often to a lesser degree).

3.3 Priming

Priming is a psychological effect that unconsciously influences the way we perform a task based on something we've experienced before (cf. Carl/Schaeffer 2019). This may cause us to reproduce what we've experienced or to perform the task faster, perhaps putting less cognitive effort into it.

Priming effects have been identified in both HTs from scratch (priming by the source text, resulting in translationese) and in post-edited MT output (priming by the raw MT output, resulting in post-editese). It is important to note, however, that these effects are stronger in post-editing than in HT. Reading and working with a more or less fluent and idiomatic *target-language* text makes it harder for us to come up with alternative translation solutions and can unconsciously affect our choice of post-editing strategies. In a nutshell, post-editors are generally less likely to drastically change the MT output than translators without MT assistance are likely to deviate from the source text in their translations. Please note, however, that not all instances of translationese and post-editese are necessarily caused by priming. They may also be caused by external factors in the translation production network, such as time pressure, instructions to perform only light (instead of full) post-editing, etc.

4 Data Collection and Evaluation – Video Tutorial

In order to put theory into practice, we‘re now moving on to analysing three different translation scenarios (see figure below) with the aim of identifying nuanced linguistic differences between the texts produced in these scenarios: (1) a raw (i.e., not post-edited) NMT output, (2) five post-edited NMT outputs (MTPE) and (3) five human translations from scratch (HT). These texts were kindly provided by Kerstin Rupcic and produced in the course of her MA thesis on the potential of NMT in legal translation (published in Rupcic 2021).

We focus our analysis on the two concepts of *lexical density* and *lexical variety* (which will be discussed in more detail in the video) and we start from the following hypothesis: Both lexical density and variety will be lowest in raw NMT output (as a form of artificially impoverished language), higher in MTPE (where post-editors will likely compensate for some but not all instances of this artificially impoverished language) and highest in HT (where translators are completely unaffected by this artificially impoverished language). Once we have performed our analysis, we'll look at whether there really is a difference between the different translation scenarios as stipulated in our hypothesis and we'll discuss the potential consequences for us as (future) professional translators and post-editors. This way, you can see for yourself how MT may influence the target texts we produce.

You can access the DataLit^{MT} Repository on GitHub and download all relevant files: the source and target texts, the video and the Excel file "lex_variety_density" (incl. solutions, more on that in the video). For our analysis, we use simple freeware tools that help us collect and evaluate data and draw conclusions from our findings. To follow the different steps, you'll need these tools:

- Microsoft Excel
- AntConc (Anthony n. d.a)
- TagAnt (Anthony n. d.b)

In the video, we'll explain the tools and how to best use them for analysing the different texts. However, if you are unfamiliar with AntConc, we recommend that you watch the following tutorials before watching the video.

1. AntConc 4 – Tutorial 1 Getting started (Anthony 2022a)
2. AntConc 4 – Tutorial 4 File tool basics (Anthony 2022b)
3. AntConc 4 – Tutorial 8 Word list tool basics (Anthony 2022c)

That's it, you can start the video now. If you like, you can come back later to look at some examples of the analysis results in chapter 5.

5 Analysis Results – Examples

In this chapter, we will discuss a few interesting text passages from our analysis. We explain the differences between the target texts produced in the different translation scenarios (NMT, MTPE, HT) and we will attempt to interpret the analysis results in order to make them more tangible.

On average, the human translations show slightly higher lexical density values (the difference ranges from 0.486 to 0.522) than the post-edited texts (0.447 to 0.477). The NMT output has the lowest lexical density (0.443).

5.1 Differences in Part of Speech and Style – Part one

Example 1:

Source text	NMT	HT_B7	MTPE_A3
By using this website you are agreeing to be bound by these terms and conditions **('these Conditions')** and [...] subject to any additional terms and conditions that are **applicable** to that service.	**Durch die Nutzung** dieser Website erklären Sie sich damit einverstanden, an diese Geschäftsbedingungen **(„diese Bedingungen")** und [...] unterliegen Sie den zusätzlichen Bedingungen, die auf diese Dienstleistung **anwendbar** sind.	**Mit der Nutzung** dieser Website stimmen Sie den folgenden allgemeinen Geschäftsbedingungen **(folgend „Bedingungen" genannt)** sowie [...] stimmen Sie allen zusätzlichen Bedingungen zu, die für diese Dienste **Anwendung finden**.	**Durch die Nutzung** dieser Website akzeptieren Sie diese Geschäftsbedingungen **(„diese Bedingungen")** und [...] unterliegen Sie den zusätzlichen Bedingungen, die auf diese Dienstleistung **anwendbar** sind.

In example 1, the source sentence starts with "By using". The NMT output and the post-edited output show an obvious translation (*Durch die Nutzung*), while the human translation uses *Mit der Nutzung*, which is the more preferable translation in this context as it adheres to German legal genre conventions. However, the transformation of the gerund into a nominal construction, which is common in legal texts, can be found in all targe texts.

Another interesting observation is that the NMT output and the post-edited text closely resemble the source text at the end of the respective sentences. The word "applicable" was translated literally (*anwendbar*) by retaining the adjective. However, in the HT, the adjective was transformed into a nominal expression (*Anwendung finden*), which again is the preferable choice in a legal context (it is also more formal).

We can find another literal translation in the parenthesis. The source text passage reads "these Conditions", which was translated literally (*diese Bedingungen*) in all translation scenarios but the HT. There it reads *folgend „Bedingungen" genannt*. This is an example of increasing lexical density: The NMT output and the post-edited output retained the determiner and the noun, while the human translation added two content words (*folgend*, *genannt*).

Example 1 shows that the HT used context-appropriate translations, while the NMT output and the post-edited text closely resemble the source text. Consequently, genre conventions were often not adhered to.

Example 2:

Source text	NMT	HT_B6	MTPE_A3
You are **to abide** by the following **rules**:	Sie **müssen sich an** die folgenden **Regeln halten**:	Sie **sind zur Einhaltung** der folgenden **Vorschriften verpflichtet**:	Sie **müssen** die folgenden **Regeln einhalten**:

In example 2, two interesting text passages show how closely the NMT output and the post-edited output resemble the source text. Firstly, both translated "to abide" with *müssen*, meaning the verbal construction was retained, while we can find a nominal and more appropriate translation in the HT (*sind zur Einhaltung verpflichtet*), which also corresponds to a higher register. Lexical density is also increased by adding the content words *Einhaltung* and *verpflichtet*.

Secondly, the NMT output and the post-edited output used *Regeln* for "rules", which is inappropriate in this context. In the HT, on the other hand, we find the more context-appropriate translation *Vorschriften*. Again, we can see that the post-edited output is very similar to the NMT output, while the translator tried to find an appropriate translation that respected German legal genre conventions.

Example 3 (lexical variety):

Source text	NMT	HT_B7	MTPE_A5
[…] not to **promote** or **advertise**, or **engage in** any other form of **marketing**, [...].	[…] nicht für andere Formen des Marketings zu **werben** oder zu **werben**, [...].	**Werbeaktivitäten** [...] sind nicht zulässig, [...].	**keine Reklame, Werbung** oder andere Formen des Marketings zu **veröffentlichen**, [...].

In example 3, we can see that the human translation exhibits less interference from the source text and a higher **lexical variety** than the respective NMT output and the post-edited output. Instead of retaining the verbal construction and translating "promote or advertise, or engage in […] marketing" literally (which would lead to quite a long and complicated sentence), the human translator only used the noun *Werbeaktivitäten*, which exactly describes the content of the source sentence. This leads to a shorter sentence with a nominal construction.

The NMT output shows the strongest interference from the source text as it uses a literal translation. Moreover, the two source language verbs "promote" and "advertise" are translated with the same target language verb *werben*, which reduces lexical variety in the NMT output. This is probably because NMT systems tend to prefer the translation solutions most frequently used in their training data and to ignore less frequent words (Vanmassenhove et al. 2019).

The post-editor compensated for these tendencies only to some extent by translating the verbs "promote" and "advertise" with the nouns *Reklame* and *Werbung*. At text level, both the NMT output and the post-edited output A5 have a lower lexical variety than the HT B7.

5.2 Differences in Part of Speech and Style – Part two

Example 1:

MTPE_A5	HT_B9
erklären Sie sich damit **einverstanden**, […].	stimmen Sie der **Anerkennung** […] zu […]
wenn Sie eine bestimmte Dienstleistung […] **nutzen**	im Falle **einer Nutzung** unserer Dienstleistungen
Bitte lesen Sie diese Bedingungen; sie sind **wichtig**.	sie sind **von großer Wichtigkeit**
wenn wir von einem Gericht […] dazu **aufgefordert oder angeordnet werden**	im Falle **einer Aufforderung oder Anweisung**
Sie **müssen sich an** die folgenden Regeln **halten**	Sie **sind zur Einhaltung** der folgenden Regeln **verpflichtet**

These text passages in example 1 show examples of the different frequency of noun use in a post-edited text (MTPE_A5: 75 nouns total) and a human translation (HT_B9: 91 nouns total). As you can see from these numbers and in the example above, the translator uses the nominal style more frequently than the post-editor. This is characteristic of legal German and adheres to the prevailing genre conventions.

Example 2:

Source text	HT_B7	NMT	MTPE_A5
If you **purchase** or **acquire** goods or services from any third parties	Beim **Kauf** oder bei der **Nutzung** von Waren oder Diensten von Drittanbietern bestehen jegliche Verträge	Wenn Sie Waren oder Dienstleistungen von Dritten **kaufen** oder **erwerben**	Wenn Sie Waren oder Dienstleistungen von Dritten **kaufen** oder **erwerben**

It is also interesting to note the lower number of verbs in this human translation (HT_B7: 19) compared to the post-edited output (MTPE_A5: 27). Often, one of the reasons for a lower number of verbs in HTs (from English into German) is a preference for nominal constructions, which can be related to the use of an impersonal style (outlined in example 3 below).

Example 3:

HT_B7	NMT	MTPE_A5
Beim Kauf oder bei Nutzung von Waren oder Diensten von Drittanbietern […]	**Wenn Sie** Waren oder Dienstleistungen von Dritten **kaufen** oder **erwerben** […]	**Wenn Sie** Waren oder Dienstleistungen von Dritten **kaufen** oder **erwerben** […]
Persönliche **Angriffe** auf andere **sind untersagt**;	**Sie dürfen** niemanden persönlich **angreifen**	niemanden persönlich **anzugreifen**;
Folgende Regeln **müssen eingehalten werden**	**Sie müssen sich** an die folgenden Regeln **halten**	**Sie müssen sich** an die folgenden Regeln **halten**
es dürfen keine beleidigenden oder obszöne Inhalte **veröffentlicht werden**	**Sie dürfen** keine Schimpfwörter oder Obszönitäten **vorbringen**	keine Schimpfwörter oder Obszönitäten **zu veröffentlichen**

With the insights from the previous examples, we can look at instances of impersonal style in this HT compared to the NMT output and this post-edited text. Interestingly, the NMT output and the post-edited text are relatively similar. The post-editor only made a few changes. In contrast, we can see that the human translator prefers to use impersonal constructions (e.g., *es dürfen* instead of *Sie dürfen*, or *Angriffe sind untersagt* instead of *Sie dürfen niemanden angreifen*), which is also characteristic of legal German.

5.3 Explicitation/normalisation

The following examples illustrate how HT adheres to German legal genre conventions by translating more freely. At the same time, they show examples of translationese.

Example 1:

Source text	HT_B6
If you purchase or acquire goods or services from any **third parties**, even if you have been directed from this website to **them**, any contract you enter into with those **third parties** and any use you make of **their website** is a matter between you and **them**.	Im Falle eines Kaufs oder Erwerbs von Waren oder Dienstleistungen von **Drittparteien** erfolgt jeglicher Vertrag, den Sie mit **der Drittpartei** schließen, und jegliche Nutzung **der Website der Drittpartei** zwischen Ihnen und der **Drittpartei**, selbst wenn Sie von dieser Website an die jeweilige **Drittpartei** weitergeleitet wurden.

In this translation, we can see an example of both normalisation and explicitation. On the one hand, repeating the noun *Drittpartei* instead of using pronouns ("them", "their") makes the translation more explicit and precise. On the other hand, it also adapts the text to another characteristic of legal German: reducing the ambiguity of the text as much as possible (explicitation).

Example 2:

Source text	NMT	HT_B7	MTPE_A5
We do not endorse, and we are not responsible for [...].	Wir befürworten nicht [...] und sind nicht dafür verantwortlich.	Macmillan Publishing Limited übernimmt keine Haftung für [...].	Wir sind nicht für [...] verantwortlich und befürworten diese nicht.

This is an example of explicitation and it shows that the NMT output and post-edited output closely resemble the source text. Here, "we" is translated literally (*wir*), while the human translator used the name of the company (*Macmillan Publishing Limited*) instead of the personal pronoun. This is not only more appropriate in legal texts but also a clearer and more formal solution (normalisation).

6 Conclusion

In conclusion, our data analysis mostly verified our hypothesis concerning lexical variety. It tends to be higher in HT than in NMT output and post-edited texts. This seems logical: It's easier for translators to translate more freely and draw on a larger vocabulary in from-scratch translation because they do not have the target language suggestions of the NMT output as a reference (which may prime them). As NMT systems tend to favour translation solutions that are most frequently used in the training data, lexical variety may be reduced in raw MT output as less frequent words get "lost in translation" (Vanmassenhove et al. 2019). This decrease in lexical variety can be described as a form of simplification, which was discussed as a potential translation universal (translationese) in section 3.1. Therefore, we could say that machine translationese tends towards simplification. Also, when NMT systems encounter text that is not reflected in their training data, they often resort to a rather linear translation of the source text. So, raw MT output will often show more signs of source text interference than corresponding human translations.

Additionally, adhering to prevailing genre conventions is characteristic of HT. Professional translators tend to use nominal constructions when translating into (legal) German (while English often prefers verbal constructions). They are also more likely to opt for a higher degree of formality and use the impersonal style more often.

Our assumptions about lexical density were also generally verified. It tends to be lowest in NMT, higher in MTPE and highest in HT. However, Toral (2019), for example, is unsure whether the degree of lexical density is a systematic difference between the different translation scenarios or not.

Post-editing seems to counteract the machine translationese effects only to a certain extent, as, for both lexical variety and lexical density, the post-edited texts achieved results similar to the NMT output or were somewhat in between NMT and HT. Again, this could be both due to a priming effect by the MT output or due to external factors in the translation production network, such as time pressure or instructions to perform light instead of full post-editing.

But what does that mean for us as future translators? Since post-editing is increasingly implemented in the professional translation process, professional translators often find themselves in the role of post-editors. Since post-editing usually comes with a discount or similar methods to decrease translation costs, the MT output must often be edited to the desired level of quality with as little effort as possible. To be able to do this without compromising final translation quality, professional translators should keep in mind that MT output exhibits patterns of machine translationese, which have to be compensated for by translators in order to avoid producing target texts that show instances of post-editese. Being aware of patterns of machine translationese and post-editese (and of potential MT-induced priming effects), translators may be better equipped to spot and revise passages in the MT output requiring their human intervention in a more efficient manner. In this way, neural machine translation could fulfil its promise as a tool for enhancing translation productivity (FAUT) without compromising final translation quality.

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