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Human-made vs. neural machine translation: A comparative analysis of human-made and machine-translated literary texts

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There seems to be a consensus that register-specific, informative texts are more suitable for automated machine translation, while form-focused texts are less so. Since there are limitations in machine translation in terms of communicative and translation competence, texts in which linguistic form, pragmatic meanings, connotations, and culture-specific elements play an important role, in addition to content, are more difficult for machine translation programs to cope with. In this paper, I will attempt to demonstrate the relevant differences that arise in the process of machine and human translation by comparing a neural machine translation (by DeepL) of a literary text ("Fatelessness" written by Imre Kertész) with the human translated text (by Tim Wilkinson). The ultimate goal of my research is to gain more insight into the quality of Hungarian–English machine translation, how corpus linguistic analysis of the source and target languages can be of further use, and what are the limitations (if any) of the use of machine translation in the translation and post-editing of literary texts.

Keywords: *machine translation, human translation, literary texts, corpus linguistic analysis, post-editing*

Introduction

In a recent study, Kenny pointed out that *"machine translation applications based on a neural network concept is considered to be the best performing type invented so far"* (Kenny 2022:43). At the same time, researchers have highlighted frequent omissions, redundant insertions and repetitions in machine-translated texts (Yamada, 2019; Loock, 2020; Teixeira, 2020). It seems that *"although the quality of neural machine translation systems has improved, there are still some areas or specific types of text where machine translation struggles"* (Donaj–Antloga, 2023:2). Hadley claims that for literature, *"the machines have a long way to go before they will be able to approach the skills of a human literary translator"* (Hadley, 2020:17). In recent years, however, research has been into the usefulness of NMT (neural machine translation) for literary translation (Fonteyne et al. 2020). At the same time, there has been a growing interest in the applicability of corpus linguistics to the machine translation of literary texts. In 1996, Jan-Mirko Maczewski (1996) proposed the acronym of CoALiTS (Computer Assisted Literary Translation Studies) *"to denote a field of research combining literary and linguistic computing with literary translation"* (Dimitrouila, 2022:105).

Methodology and Findings

The present research is corpus-based, complemented by a comparative analysis of quantifiable data found in the original Hungarian literary text ("Sorstalanság", written by Nobel Prize-winning Hungarian writer, Imre Kertész[1]) and its machine- and human-translated English versions (translated into English by Tim Wilkinson in 2004, under the title "Fatelessness"). A total of three ad-hoc 'mini' corpora will be used for the analysis. One is the Hungarian text of

[1] Imre Kertész was awarded the Nobel Prize for literature in 2002.

"Sorstalanság" ("Fatelessness"). The two other corpora have been compiled from the human[2] and machine English translations of the original Hungarian text. The results of the corpus-based (quantitative and qualitative) analysis are discussed in the dimension of the pre-editing framework proposed by Sánchez-Gijón and Kenny in 2022. In their paper, they argue that with the emergence of neural machine translation, the importance of pre-editing also increases. They claim that pre-editing should focus on three aspects in any text, namely, (1) lexical choice, (2) structure and style, and (3) referential elements (Sánchez-Gijón–Kenny, 2022:90). Therefore, by analysing the results of the corpus-based research, the main potential pitfalls in a Hungarian–English machine-translated literary text are identified in terms of lexical choice, structure and style, and referential elements.

Findings of quantitative analysis – general corpus information

In a quest to find the most relevant features of the original Hungarian and its human- and machine-translated texts, it is worth taking a look at the general characteristics of the three mini corpora (Table 1).

Table 1. General corpus information

	ST_HU	HT_EN	MT_EN
Words	55,729	80,490	70,368
Sentences	2,383	2,576	2,403
Words / sentence	23	31	29

As can be seen from Table 1, sentences in both the English human (HT_EN) and machine (MT_EN) translated texts contain more words, 80,490 and 70,368 words, respectively, than the Hungarian source language text (55,729 words). This difference in the number of words in the original and translated texts could be partly due to the morphologically analytical nature of the English language as opposed to the synthetic nature of Hungarian. English is an inflectional language with isolating tendencies, so each morpheme tends to be a separate word, whereas in Hungarian, which is an agglutinative language, suffixes and prefixes are 'glued' to the root morpheme, changing its original lexical meaning (Heltai, 2021:209). However, there is also a clear difference in the number of words in the human-translated (80,490) and machine-translated (70,368) texts. This could be explained by the translation strategies used by the human translator, but not by the machine translator, e.g. explication in the case of culture-bound terms (see Example 5), as well as the distribution of meaning, which leads to an increase in the number of words.

One of the most relevant indicators of salient differences between original and translated texts is the mean sentence length. As the general corpus information in Table 1 shows, the human-translated English text has the highest mean sentence length (31), followed by the machine-translated text (29). Hungarian sentences in the original, non-translated text tend to be shorter (23).

It should also be noted that the human translation contains the most sentences (2,576), while the machine-translated text contains almost as many sentences (2,403) as the original (2,383), but the difference is smaller than for the human translation. This can be explained by the fact that a typical translation strategy used by human translators is the splitting or contracting of sentences. However, a salient feature of machine translation is that it translates sentences and does not tend to change sentence boundaries (Kenny, 2022:43).

[2] The human translation was made by Tim Wilkinson, who is the primary translator of Imre Kertész. Wilkinson's translation of Kertész's "Fatelessness" won the PEN Club/Book of the Month Club Translation Prize in 2005 (https://lithub.com/author/imrekertesz/).

As the general comparative corpus information above suggests, in terms of word count and average sentence length, the translated texts show a greater degree of convergence with each other than with the untranslated text, as they contain more words and denser sentences. However, in terms of the number of sentences, the machine-translated text shows a greater degree of convergence with the original Hungarian text.

Lexical choice – The analysis of keywords

In the Hungarian sub-corpus, keywords were extracted based on the frequency of their use in comparison with the Hungarian Web 2012 corpus (huTenTen12), while for the extraction of English keywords, the general English corpus (enTenTen20) was used as a reference corpus with the help of Sketch Engine.

Table 2. The most frequently used keywords in the ST, HT, and MT texts

	ST_HU	HT_EN	MT_EN
1	mostohaanya	pyetchka	stepmother
2	pjetyka	stepmother	buchenwald
3	fleischmann	citrom	pyetyka
4	ilyenképp	bandi	bandi
5	buchenwaldban	buchenwald	sütő
6	lagerältester	sütő	zeitz
7	appel	appell	pyotr
8	némelyes	brickyard	auschwitz
9	pfleger	zeitz	rozi
10	utóvégre	Lajos	appel

The ten words with the most unusual frequency in the source text can be divided into four groups. There are common words, nouns such as *mostohaanya* (‘stepmother’), adverbs, *némelyes* (‘a certain’) proper nouns, names such as, Fleischmann, and foreign (German) words, i.e. *appel*. Of the ten keywords, the use of a common noun, *mostohaanya*, an adverb, *némelyes*, and a foreign (German) word, *appel*, will be analysed in detail by comparing the source text and its human- and machine-translated versions.

The lemma *mostohaanya* (‘stepmother’) is the most frequently used keyword in the Hungarian text. Its inflected form, *mostohaanyám* (‘my stepmother’), occurs 39 times in the Hungarian text. In all instances, this Hungarian term is translated as ‘my stepmother’ in both the human- and machine-translated texts. However, given the different linguistic means of expressing and specifying reference in English and Hungarian, it would be interesting to examine how the reference to ‘stepmother’ is expressed within and outside sentences in the human- and machine-translated texts. Of the 39 examples, all references are properly specified in the human-translated text. In the machine-translated text, there are 6 examples where the reference is not properly specified. It is noteworthy that all these instances occur when the referent appears in a new sentence and the subject is not used in the Hungarian sentence. In Hungarian the use of a subject is not obligatory. Therefore, if there is no subject in a sentence, any reference to it can only be determined by relying on contextual information.

Example 1. Incorrect indication of reference (the use of inappropriate personal pronouns) in the same sentence because of the lack of a subject:

ST *(...) Rögtön dologhoz is látott, a lista szerint, amit mostohaanyám nyújtott néki át.* (p. 5)[3]
HT *…and **she** set to work straightaway, following the list that my stepmother provided **her**.* (p. 6)
MT ***He** set to work at once, according to the list my stepmother handed **him**.* (p. 5)

[3] The page numbers follow the word format arrangement of the downloaded texts under review.

As may be deduced from the example above, in the Hungarian sentence, the subject is not used. Therefore, in English, where the use of a subject in a sentence is obligatory, the translator has to specify it. To do this, the translator must rely on contextual information outside the boundaries of the given sentence or on his or her extra-linguistic knowledge. It reinforces Kenny's opinion on neural-machine translation systems, i.e. *"they might have problems interpreting reference that is based on information beyond the boundaries of a given sentence"* (Kenny, 2022:43). In Example 1, the human translator properly specifies the feminine gender of the referent, whereas the MT system uses masculine personal pronouns.

In Example 2, the subject is properly specified in the MT text. However, as there are three referents in the sentence, the father, the stepmother and the stepmother's mother, the MT system is unable to match the proper pronominal form (the possessive determiner, *her* instead of *his*) to the referent (*stepmother*).

Example 2. There are more referents in the sentence:

ST (...) Még folytatni akarta, de ***mostohaanyám*** meg a ***mamája*** épp végzett a hátizsákkal, s ***apám*** fölkelt a helyéről, hogy kipróbálja a súlyát. (p. 6)
HT He was about to continue but ***my stepmother*** and ***her*** mama had just finished with the knapsack, and ***my father*** got up from ***his*** seat to test its weight. (p. 7)
MT He was about to go on, but ***my stepmother*** and ***his*** mother had just finished with the knapsack, and ***my father*** got up from ***his*** seat to try the weight. (p. 6)

The examples above show that the treatment of referents could be problematic from an NMT point of view. When they are in the same sentence, there could be gender agreement problems between personal pronouns and nouns (see Example 1). In Example 2, the text alternates between different referents. In all these instances, the masculine form appears instead of the feminine form. This confirms previous research findings that there is gender bias in machine translation applications (Prates et al., 2020; Rescigno et al., 2020).

Lexical choice – the use of 'némelyes' ('to some extent')

Némelyes acts as a marker of discourse, expressing moderation, meaning 'to some extent'. It shall be noted here that the Hungarian term, *némelyes* is a rare and archaic term. It appears 10 times in the source text. There are no mistranslations in either the HT or the MT text. Even the English terms used in the two texts overlap, e.g. 'certain', 'somehow', 'somewhat'. It can also be seen that the English terms used in the HT are more varied, e.g. 'not entirely', 'a measure of', than the terms used in the MT text, e.g. 'some', 'a little'. The MT text shows relatively little variance in the translation of *némelyes*. 'Some' is used most often (4 times), followed by 'a certain' (3 times), 'somehow' (1 time), 'a little' (1 time), 'somewhat' (1 time). Neither of these, alas, has the unmistakable, original flavour of the Hungarian *némelyes*, nor its repetitive nature.

Example 3. The translation of *némelyes* with the use of 'somewhat' and 'some' in the HT and MT texts:

ST: *...sőt így nyertem csak* ***némelyes*** *pontosabb betekintést is tulajdonképp az itteni körülményekbe, föltételekbe, a társadalmi életbe, hogy így mondjam.* (p. 72)
HT: *…indeed in that way gained a* ***somewhat*** *more precise insight into circumstances here, the conditions and social life, if I may put it that way.* (p. 80)
MT: *…and even gained* ***some*** *more precise insights into the conditions, the conditions, the social life, so to speak.* (p. 68)

As for the translation of a rarely used Hungarian term, *némelyes*, which is used relatively frequently in the source-language text to express a certain degree of something, there are no mistranslations in either the human or the machine translations. Although, the meaning of *némelyes* is conveyed by different linguistic elements, some transfers overlap, e.g. the use of 'certain'. In the human translation, 'somewhat' appears the most frequently as the equivalent of *némelyes*, while in the MT text, 'some' is used the most frequently, followed by 'a certain'. It should be noted that MT works with flat and 'average' solutions (which completely lose the specific flavour of Kertész's characteristic turn of phrase, which the human translation at least tries to restore to some extent).

Lexical choice – the translation of foreign words

Another category in the list of keywords contains foreign, mostly German words. The main part of the story takes place in a German concentration camp, so some German proper nouns or common words that are regularly used in the camp remain unchanged in the Hungarian novel. One term, *appel*, appears 12 times in the source text. In the HT text, *appel* is translated as *Appell* (9 times), followed by 'roll call' (2 times) and 'muster' (1 time). The MT system treats *appel* more consistently, translating it as *appel* (11 times). In one sentence, *appel* is omitted in the MT text.

Example 4. The translation of *appel* as 'Appell' in the HT and 'appel' in the MT texts:

SL: *Buchenwaldban a Zeltlager lakói részére nincs **appel**,* (p. 43)
HT: *At Buchenwald there was no **Appell** for the inmates of the Zeltlager* (p. 47)
MT: *In Buchenwald, there is no **appel** for the inhabitants of the Zeltlager,* (p. 40)

Example 5. The translation of *appel* as 'roll call' in the MT text:

SL: *...este az **appel**, no meg, persze, az értesülések – ennyivel kellett beérnem, ennyi volt egy nap rendje.* (p. 40)
HT: *…the issuing of rations, **roll call** in the evening, and not forgetting, of course, the bits of news* (p. 44)
MT: *…the food distribution, the **appel** in the evening* (p. 37)

The machine translation follows the source-language usage more closely, as the German term appears unchanged in the machine translation, as can be seen in the examples above. However, there is one instance where *appel* is missing from the MT text. In the human-translated text, the term *appel* (roll call) is specified by means of 'explicitation'. This type of translation strategy, i.e. the explicitation of a term requires such extra-linguistic knowledge that goes beyond the boundaries of a given sentence or text. For this reason, such a solution is unlikely to appear in the machinetranslated text.

Structure and style – the analysis of 3-4 n-grams

A 3-4 n-gram is a sequence of three to four words such as 'I could see' or 'I could see it'. Analysis of 3-4 n-grams can be used to predict how a given sequence will appear in a text (Jurafsky–Martin, 2024). As such, they also provide information about the underlying syntactic structure of a text and its most common sequences.

Table 3. The analysis of the use of 3–4 n-grams in the ST, HT, MT texts

	ST_HU	HT_EN	MT_EN
1	no meg a (16)	I could see (48)	I had to (68)
2	s mondtam neki (13)	I had to (44)	I could see (45)
3	hogy így mondjam (12)	in front of (35)	I could not (39)
4	hogy úgy mondjam (11)	I could not (34)	a kind of (37)

5	az én számomra (9)	as it were (32)	in front of (36)
6	de hát nem (7)	in the end (31)	I did not (35)
7	egy koncentrációs táborban (7)	as far as (31)	I didn't (35)
8	az én szememben (7)	I did not (31)	that it was (34)
9	a fiúk is (6)	I told him (29)	I don't (31)
10	de hát a (6)	that I had (28)	that he was (31)

The table above shows that there are fewer 3-4 n-grams in the Hungarian text than in the English texts. The reason for this lies in the different syntactic nature of Hungarian and English. Hungarian is a synthetic language, which means that grammatical cohesion is provided by prefixes or suffixes attached to the root word. In English, which is an analytical language, function words provide grammatical cohesion in a given sentence, and the order in which they are used carries additional information. As a result, English is thought to have a more fixed order of sequences in a given text.

It is noteworthy that the most frequent n-grams in the Hungarian text are *no meg a* ('and the'), which is an additive functional structure with no actual meaning, and *s mondtam neki* ('and I told him/her that'), which is used as a way of introducing a subordinate clause, a way of narrating, followed by *hogy így mondjam* ('to put it this way') and *hogy úgy mondjam* ('to put it that way'). These most frequently used n-grams reflect the narrative nature of the original Hungarian literary text as well as the special narrative, bleak of the fact tone of the author.

The Hungarian expression *egy koncentrációs táborban* ('in a concentration camp') sets the main theme, as the main part of the story takes place in Buchwald, a concentration camp. Other frequent 3-4 n-grams, *az én számomra* ('for me'), *az én szememben* ('as far as I could see'), are linguistic devices that can be used to express the subjectivity of the main character, the narrator, who tells the story in the first-person singular, through his subjective lens.

In the human- and machine-translated texts, different patterns in 3-4 n-grams can be observed. In the human-translated text, *I could see* is the most frequently used 3-4 n-gram, while in the machine-translated version it ranks second. *I had to* is frequently used in both, although it is the most frequently used sequence of items in the machine translated text. It appears 68 times in the machine translated text, making it the most common 3-4 n-gram in all texts. Presumably, this also reinforces the idea that the MT system relies on n-grams that are also common in natural language. However, there is a risk that the machine-translated text loses its specific, unique characteristics. A look at the most frequently used n-grams, *I had to*, *I could*, *I could not*, *in front of me* leads to the suspicion that the recurring pattern in the text is a subjective, first-person singular recollection of events that are perceived by the narrator as external constraints imposed on him.

A glance at the 3-4 n-grams of the source text and its human and machine translated counterparts can provide some information about the main recurring theme in the texts. The results of the n-gram analysis suggest that the narrator's subjective recollection of the events forms the main part of the story. The events are also perceived as external constraints, but the perception of their harshness is mitigated by the relatively distant perspective of the narrator.

Referential elements – The use of personal pronouns

In the case of the Hungarian-English translation, due to the different morphological nature of the two languages, the use of referential elements, namely personal pronouns, is one of the recurring problems in the post-editing of machine-translated texts. The explanation for this is that Hungarian is a pro-drop language, i.e. it omits pronouns that are considered superfluous. Hungarian is also a genderless language, i.e. personal pronouns always include the appropriate (inflected) form of the neutral third-person gender-neutral pronoun (*ő*), unlike the English *he*/*she* distinction. Therefore, when translating from Hungarian into English, from a genderless, pro-drop language into a gendered, subject-dominant language, it is necessary to specify not only the referent but also his/her gender. In other words, in the Hungarian-English translation, the personal pronouns have to be inserted and the referential function has to be clarified and made more specific. In many cases, however, this requires recourse to linguistic factors or information beyond the scope of the sentence or even the text. It is therefore worth examining the extent to which the use of the personal (subjective) pronoun *he*/*she* and the possessive adjective *his*/*her* differ in the two translations.

Table 2. The use of personal pronouns in the HT and MT texts.

	HT	MT
he	985	1,150
she	199	124
his	557	619
her	194	136

It can be concluded that *he* (1,150) and *his* (619) are used more often in the machine-translated text than in the human-translated version (985 and 557 occurrences, respectively). However, when it comes to the use of feminine pronouns, the human-translated text contains more items (*she*, 199 times, *her* 194 times) than the machine translated text (*she* 124 times, *her* 136 times). This can be explained by the fact that machine translation tools can show gender bias and tend to provide masculine defaults (Prates et al., 2020; Rescigno et al., 2020).

English has a pronominal gender system, meaning that it has masculine, feminine, and neuter forms of the third-person singular pronoun, whereas gender-neutral languages, such as Hungarian, do not express gender in the third-person singular pronoun. When translating pronouns between these languages, the machine translation system inevitably provides either feminine or masculine translations of originally gender-neutral words (Farkas–Németh 2022:2). Thus, when it comes to specifying the gender of a given gender-neutral personal pronoun in the English text, the human translator relies on his or her extra-linguistic, situational or general knowledge to specify it. In machine-translated texts, however, the use of masculine personal pronouns dominates.

Discussion

The aim of this paper is to demonstrate how a corpus-based analysis of a literary text, complemented by a qualitative analysis, can assist the work of a translator. To this end, the quantitative findings of the corpus-based analysis have been examined in the triple dimension of Sánchez-Gijón and Kenny (2022) in order to gain more insight into the specific lexicon, style and structure, and referential elements of the source and target language texts. With regard to the author's particular style, the analysis of keywords and n–grams has provided clues. The distanced and relativised tone of the narrative is embodied by discourse markers (e.g. *némelyes*) that relativise the degree of perception. This finding is corroborated by an analysis of the source text, which highlights the bleak, matter-of-fact tone with which the protagonist-narrator describes life in a concentration camp with a tight, distanced objectivity (Tempus Public Foundation, 2020). The detailed and qualitative analysis of the quantitative results identified some recurring differences between the human and machine translations of the source text. The most noticeable differences were in the reference to a person or the definition of a foreign word, outside the boundaries of a particular sentence or even the whole text.

Conclusion

Unprecedented and ever-improving developments have redefined the translation process and pushed the boundaries of what machine translation can do. There seemed to be a consensus that for literary texts, *"machines have a long way to go before they will be able to approach the skills of a human literary translator"* (Hadley, 2020:17). Nevertheless, there has been a growing interest in how machine translation can be applied to the translation of literary texts. Some researchers now argue that corpus-based approaches to identifying the uniqueness of a literary work can assist the human translator and also highlight the potential pitfalls of translation. With such knowledge, the quality of a machine-translated literary text could even be improved.

The combination of corpus-based methods and qualitative analysis of a text prior to human or machine translation of a source-language text greatly facilitates the translation process and leads to better target-language texts. At the same time, they provide invaluable insights into how meaning is created from linguistic and extra-linguistic information, and how such information can be accessed by machines. This paper has attempted to use corpus linguistic methods to illustrate the peculiarities of the original text and to suggest how post-editing can consciously compensate for the losses caused by machine 'intelligence'.

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