Mehmet ŞAHIN
Boğaziçi University, İstanbul

Ena HODZIK
Université de Mons

Sabri GÜRSES
Üsküdar University, İstanbul

Tunga GÜNGÖR
Boğaziçi University, İstanbul

Zeynep YIRMIBEŞOĞLU
Boğaziçi University, İstanbul

Olgun DURSUN
Independent Researcher, İstanbul

Harun DALLI
University of Antwerp

Stylistic Features and Creativity in Machine Translation of Literary Texts

Human-Centred AI in the Translation Industry. Questions on Ethics, Creativity and Sustainability

Katharina Walter,
Marco Agnetta
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Stylistic Features and Creativity in Machine Translation of Literary Texts

Mehmet ŞAHIN
Boğaziçi University, İstanbul

Ena HODZIK
Université de Mons

Sabri GÜRSES
Üsküdar University, İstanbul

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Boğaziçi University, İstanbul

Zeynep YIRMIBEŞOĞLU
Boğaziçi University, İstanbul

Olgun DURSUN
Independent Researcher, İstanbul

Harun DALLI
University of Antwerp

Abstract: Computer-assisted literary translation has become a trending topic of discussion with both its possible benefits and negative impact on creativity and voice. We investigate distinctive stylistic features and the degree of creativity in the outputs generated by three English–Turkish machine translation (MT) models: (1) a customized MT model trained with literary texts, (2) a pre-trained MT model with general texts, and (3) an online MT model, namely Google Translate. We focus on two sub-genres within the literary domain: fiction and nonfiction. Our analysis of style and creativity is based on human evaluation of samples and on qualitative corpus analysis of full texts, involving identification of creative translation strategies and stylistic features. We compare the outputs of the three models with translations by two renowned translators, Nihal Yeğinobalı and Belkıs Dişbudak, on the test set. Our investigations of style and creativity involve different methods, yet we consider the possible relationship between the two in light of our findings. A higher level of creativity is observed in the human translation and in the fine-tuned model for the nonfiction; and a customized MT model trained with Turkish literary translations generates outputs stylistically closer to the human translation than a pre-trained model or an online MT tool.

Keywords: Literary translation, Machine translation, Style, Creativity, English–Turkish language pair.

1 Introduction

Computer-assisted literary translation started attracting machine translation researchers about a decade ago with experiments mainly on European language pairs (cf., e.g., Besacier 2014).[1] It has also become a widely discussed topic within Translation Studies in recent years, mostly from a critical perspective. Researchers highlighted MT's negative impact on creativity (cf., e.g., Şahin/Gürses 2019), reading experience (cf. Guerberof-Arenas/Toral 2020), and voice (cf., e.g., Kenny/Winters 2020), as well as ethical issues (cf., e.g., Taivalkoski-Shilov 2019). This line of research has proliferated, involving more language pairs and different contexts. In addition to MT, technologies such as corpus tools proved to have contributed to the translation process (cf. Youdale 2020). Nowadays, technology use in literary translation is seen as a more unexceptional practice, especially with the quick adoption of generative ar-

1 This research is funded by the Scientific and Technological Research Council of Türkiye (TÜBİTAK) under Grant No: 121K221. The research project is titled "Literary Machine Translation to Produce Translations that Reflect Translators' Style and Generate Retranslations" and Mehmet Şahin is the principal investigator.

tificial intelligence tools in writing and translation such as Grammarly and ChatGPT.

This study focuses on creativity and style in translations generated by comparatively more controllable and customizable MT models (see section 2) as well as ones produced by generic, freely available online MT tools (see section 3). Creativity and style were investigated separately as they constitute different phenomena measured with different methods (see section 4). Nonetheless, we consider there to be an overlap between these two concepts, with creativity encompassing style, while the reverse does not necessarily have to hold true (see section 5).

2 Literature Review

2.1 Style

For the last quarter of this century, translator style has garnered significant interest, with pioneering work by Baker (2000) and subsequent contributions from Malmkjær (2003), Munday (2008), Boase-Beier (2011), Saldanha (2011), Winters (2007), and Kenny/Winters (2020), among others. Research has primarily explored two perspectives: one linking translator style to the source text author (cf. Malmkjær 2003, Boase-Beier 2011) and the other suggesting that translators have a distinct style independent of the source text (cf. Saldanha 2011).

Recent advances in corpus tools have shifted the focus from examining isolated stylistic choices to identifying broader stylistic patterns. Metrics such as type-token ratio, word/sentence length, keyness, and the frequency of morphemes and lexical categories are now used to assess vocabulary richness and structural complexity (cf. Baker 2000, Bosseaux 2001, Vajn 2009, Li et al. 2011, Saldanha 2011, Frankenberg-Garcia 2022).

While Baker's (2000) methodology primarily examines the target text, other approaches also consider the original author's style (cf. Boase-Beier 2011, 2019; Malmkjær 2003, Munday 2008). Boase-Beier acknowledges that "cultural and ideological positioning of the translator" (Baker 2000: 258, as quoted in Boase-Beier 2019: 80) is an important factor in the study of style, but emphasizes the risk of being speculative, even supported by computer-assisted analysis, since such an approach takes the study of style to a stage where various influences on translator's state of mind need to be investigated.

More specifically, keyword analysis has been employed in various studies (cf. Olohan 2004, Mastropierro 2018, Mikhailov 2021) to compare lexical items in translation corpora with those in reference corpora, comprised of texts by various translators and/or non-translated texts. Keywords are assessed not only for their frequency but also for their rarity and specificity. Analyzing their concordance—how they are used in context—reveals their grammatical, semantic, and discourse functions. For instance, Frankenberg-Garcia (2022) conducted both quantitative and qualitative keyword analyses in Portuguese-to-English translations, examining grammatical roles and broader discourse contexts. The comparison of human translations with MTs of the same texts highlighted significant differences: Human translations showed greater lexical consistency and explicitation, attributed to translators' efforts to enhance reader comprehension.

With recent developments in MT, it has also become compelling to explore whether MT systems can exhibit or mimic a translator's style. Research in literary MT has demonstrated that while MT models can achieve varying levels of success (cf. Besacier 2014, Besacier/Schwartz 2015, Şahin/Dungan 2014, Sluyter-Gäthje 2018 and Toral/Way 2018), the replication of a translator's unique style remains a complex challenge. In our previous research (cf. Yirmibeşoğlu et al. 2023, Gürses et al. 2024, Dallı et al. 2024), we investigated two key questions: Does a literary translator have a distinctive style, and if so, can MT replicate this style? To examine the unique stylistic features of a prominent literary translator, Nihal Yeğinobalı (1927–2020), we analyzed the following stylistic features:

- average morphemes per sentence,
- average words per sentence,
- type-token ratio,
- five most common morpheme combinations, and
- keywords.

We compared these features in relation to a reference corpus of 512 Turkish literary translations reflecting linguistic trends from 1946 to 2015, the translator's career timeframe. Afterwards, we fine-tuned a pre-trained MT model (cf. Tiedemann/Thottingal 2020) using 48 of Yeğinobalı's manually aligned translations. We obtained the informed consent of the translator's heirs in compliance with the pertinent copyright laws and used the fine-tuned model only for the purposes of the current research project as we are undoubtedly aware of the ethical issues around using existing translations in MT research (see Şahin/Gürses 2023). Our analysis revealed significant differences between the translator corpus and the reference corpus in the specified features, with the fine-tuned model's keywords closely matching Yeğinobalı's. Additionally, a qualitative review of texts from both the pre-trained and fine-tuned models showed substantial similarities to Yeğinobalı's style.

Style in literary machine translation continues to be a topic of interest to scholars in Translation Studies. Hansen (2024) worked on adapting machine translation to individual human translators for young adult fiction books. The edited book titled *Computer-Assisted Literary Translation* (Rothwell et al. 2024) features three chapters touching upon style and creativity by Winters/Kenny, Dorst, and Šplíchalová. Winters/Kenny (2024) continued their inquiry into Oeser's voice and style through keyword analysis. Dorst (2024) compares human translation and Google translation of a literary text with a focus on the transfer of metaphors in the target language. The researcher concludes that "the creative, more clearly literary metaphors appeared to be the easiest to translate, most likely since direct translation is simply the most suitable solution" (Dorst 2024: 183). Lastly, Šplíchalová (2024) explores how corpus tools can be employed to identify intensional functions in literary texts with an aim to help translators create the same stylistic effect in the target text.

In our previous study with a focus on English–Turkish literary machine translation, we investigated style in literary translation and showed that "adapting a pre-trained model to the works of a translator increases the BLEU score by about 45–56% on the literary data and captures the translator's style 18–40% better in terms of cosine similarity compared to the pre-trained model" (Yirmibeşoğlu et al. 2023: 426). Although style and creativity have started to be discussed more intensively within the context of generative artificial intelligence tools in the last couple of years, investigating these aspects in literary translation in more controlled settings can contribute to research in both Translation Studies and Natural Language Processing.

2.2 Creativity

Creativity presupposes some unexpectedness, novelty, originality from the agent. Yet, not everything which is unexpected is creative, and creativity has many definitions. Building on Kußmaul's (2000) work on creativity in translation which considers creativity as an inherent component of any translation activity, translation and interpreting scholars elaborate on the topic from different perspectives (e.g., Cercel et al. 2017). For instance, it is even argued that "creativity in translation work and in the translation workplace is not necessarily restricted to linguistic aspects" (see Risku et al. 2017). In the same volume, Schreiber (2017) argues that creativity can be observed in instances where there is no standard solution for a specific translation problem in the language pair in question. Literary translation, in this respect, is likely to offer more opportunities for translators to produce creative solutions. As Hermans puts it:

> Works of art in particular are expressions of creative selfhood which shape the language in which they are conceived as much as they are shaped by it. To grasp the singular genius of creative authors, one must know the language they had at their disposal and gauge how they moulded it, even awakening meanings the authors themselves may have been unaware of. (Hermans 2019: 229)

Translation as a human activity, too, is often more than a mere transfer of the source text to the target language, involving "rewriting" (Lefevere 1992) and adaptation, particularly in the literary domain.

The increasing degree of accuracy of MT tools for many genres in major languages has made creativity one of the distinctive features of translation. Turell (2004: 5–6) points out that "[w]hen looking at plagiarism in literature one has to bring into discussion the question of imitatio—a common practice in literary production in all centuries and civilizations—understood as a steering wheel of creativity." Yet, in today's mainly profit-oriented publishing sector practices, the imitation of creative solutions is viewed as an indicator of plagiarism when comparing translations of the same source text—usually classics or best-sellers—conducted by different translators (cf., e.g., Gürses 2007: 9–16; Şahin et al. 2015: 205–213).

Trained with previous translations, MT is expected to show a limited level of creativity. The effect of MT on creativity was first investigated by Şahin/Gürses (2019) in a study with novice translators who were fourth-year students in a translation and interpreting studies BA program. The researchers focused on the impact of MT-aided retranslation activity on novice translators' creativity in literary texts for the English–Turkish language pair. They compared translations by novice translators with four previously published translations of the novel *Robinson Crusoe* by Daniel Defoe. The parts in the source text that would require creative solutions are marked and the solutions by each translator were evaluated based on the following categories:

- "literal translation,
- [imitation of the] MT solution (literal, creative, or erroneous translation),
- creative solution (going beyond literal translation),
- undertranslation (not conveying the message fully),
- mistranslation (conveying the message incorrectly), and
- untranslated (omitting the whole unit)" (Şahin/Gürses 2019: 28).

The researchers concluded that students were able to create more original solutions when they had no help from MT.

Guerberof-Arenas/Toral (2020, 2022) also focused on creative aspects in MT, post-edited MT, and human translation in two related studies. In their later study, to measure the level of creativity, the researchers counted "the number of creative solutions (shifts) provided for a given problem posed by the [source text] ST" (2022: 190). They used a Dynamic Quality Framework (DQF) combined with Multidimensional Quality Metrics (MQM) to classify errors according to the following categories: Accuracy, Fluency, Terminology, Style, Design, Locale Convention, Verity and Other. They marked the source text with 15 different units of creative potential such as metaphors, idiomatic phrases, wordplay and puns, onomatopoeias, neologisms, and rhyme and metrics. The reviewers classified the units of creative potential as reproduction, omissions, errors, and creative shifts, a term which refers to "translations that deviate from the ST" by means of abstraction, concretization, and modification. Although the researchers created a customized MT model trained with English–Catalan literary data, their findings were in line with the ones by Şahin/Gürses (2019): The outputs were quite literal and post-editing such outputs hindered translators' creativity.

English–Turkish literary MT was further investigated by Şahin/Gürses with a focus on the attitudes of novice and professional translators towards using online MT tools in the process. They argued that "the human-machine interaction may have decreased the participants' sense of immersion in the act of 'translation.' In other words, the interaction probably caused a certain level of confusion about their role. Were they editors, or translators?" (2021): 197).

In her book titled *Translation and Creativity*, Malmkjær (2020: 28) argues that "[p]eople engage in creativity spontaneously in view of their humanness, but creativity can be nurtured and trained, and guidelines can be provided for such efforts." This argument is in fact the backbone of translator education, where novice translators still outperform MT or generative AI tools. Nevertheless, it seems worth investigating whether MT systems can be "nurtured" for creative outputs. MT outputs are usually not considered copyrightable because they are not regarded as original or creative. In fact, as Malmkjær observes, "it is extremely rare that two translations of the same text into the same other language are exactly alike, either in a translation classroom or in a more professional context" (2020: 39). It is also important to see whether this applies to customized MT models or not. In other words, identifying the level of creativity and distinctive stylistic features in customized MT outputs can modify our current understanding of copyright and our perception of the distinctions between human and artificial intelligence.

3 Methodology

In our study we address the following question: What are the distinctive stylistic features and the degree of creativity in the outputs (a fiction and a nonfiction literary work) generated by three English–Turkish MT models, namely (1) a pre-trained MT model with general texts, (2) a customized MT model trained with literary texts, and (3) Google Translate, a freely available online MT system? We are also interested in investigating the degree of proximity of the outputs produced by the abovementioned systems to human translation in terms of style and accuracy.

3.1 Texts

We used two different texts in our study. One representative each from a fictional and a nonfictional genre:

Fiction: *Ağ* (*Under the Net*) (1954) by Iris Murdoch (1919–1999) was translated in 1993 by Nihal Yeğinobalı (1927–2020), an author-translator. Interestingly, earlier in her career, back in the 1940s, she had published two novels under a fake American name after facing rejection from publishers for her own work. *Under the Net* echoes her experiences, as it portrays a writer who has become a translator after a poorly received novel. Notably, Yeğinobalı revealed her authorship of those pseudotranslated novels around the time she translated Murdoch's book, creating an intriguing parallel.

Nonfiction: Belkıs Dişbudak (1938–) has been working as an interpreter and literary translator for about 60 years. She has published around 200 translations and her translations from Ayn Rand, Trevanian and Tom Robbins have been most popular. *The Bookseller of Florence* (2021) is a nonfiction novel by the novelist Ross King (1962–). Dişbudak translated another nonfiction novel by King called *Brunelleschi's Dome* (2000) in 2010. It was about 180 pages long. When another publisher republished the translation in 2020, he also asked Dişbudak to translate King's latest book about the booksellers in Italy. And she translated *The Bookseller of Florence* (*Floransa Kitapçısı*) in her 80s, a book three times longer than the first one, about 500 pages long. The book has massive footnotes and bibliography. Even though these books are categorized as nonfiction, they can be put under fictionalized history books since the narration is very stylized. The translation was published in 2023.

3.2 MT Training

Our first model is an English–Turkish Transformer model[2], pre-trained on general text (on more than 108M sentences) from various domains as part of the OPUS-MT project by Helsinki-NLP. The second model is the same OPUS-MT model, which we fine-tuned with literary translations by renowned Turkish translators for 5 epochs with a batch size of 64 on 4 Tesla V100 GPUs. According to best practice guidelines, all translators or their heirs gave us permission to use the translations to train MT for research purposes (as explained in detail in footnotes 3-5). The literary fine-tuning dataset consists of 91 manually aligned books from 3 different translators

2 See <https://huggingface.co/Helsinki-NLP/opus-mt-tc-big-en-tr> (01.07.2025).

(Nihal Yeğinobalı[3], Sabri Gürses[4], Belkıs Dişbudak[5]) with a total of 517,488 sentences (see Table 1).

Translator	Sentences	Books
Yeğinobalı	322,822	62
Gürses	98,462	14
Dişbudak	96,204	15
Total	**517,488**	**91**

Table 1: Datasets used for fine-tuning OPUS-MT

3.3 Analysis

This section explains the criteria for selecting samples for the qualitative analysis. We also provide a detailed list of the translation strategies used to code translation solutions in different

3 The Nihal Yeğinobalı corpus was digitized with the informed consent of her heirs in compliance with the pertinent copyright laws. The digitization process involved procuring physical copies of the texts for scanning, revising the optically recognized digital versions, and manually aligning the target texts with their respective source texts to train the machine translation engine.

4 The texts that form part of the Sabri Gürses corpus, which consists of 14 translations from English, were collected as digital texts by himself. The project members accepted responsibility to protect them and not to use them in other works or for any other purposes. These texts were automatically and manually aligned to train the MT engine for the purposes of the current project. The texts will be deleted afterwards from all locations and will not be included in any reference corpora.

5 Due to the limited availability of most materials in electronic form, we obtained informed consent from Belkıs Dişbudak to digitize her texts and asked her for the digital versions while complying with relevant copyright laws. We declared to use them only for our work and not to use or share them in any other reference corpora or for any other purposes and to delete them afterwards.

outputs. Finally, we give brief information about the annotators and the inter-rater reliability.

3.3.1 Samples

We took two samples, each consisting of 50 segments (sentences) from the test books. The selection criteria were as follows: 10 random samples were selected from sentences with the highest BLEU and BERTscore F1 values (50^{th}, 60^{th}, 70^{th}, 80^{th} and 90^{th} percentiles).

For the automatic evaluation of the machine translation models, we used BLEU, BERTscore, and COMET scores. Automatic evaluation of style is based on the methodology employed by Yirmibeşoğlu et al. (2023), where the stylistic features such as average morphemes per sentence, average words per sentence, type-token ratio, and keywords are counted, and their average normalized frequencies are converted into vectors. Each translation is represented as a separate vector, and their similarities to the translations by Nihal Yeğinobalı or Belkıs Dişbudak is assessed based on the cosine similarity of these vectors. In this comparison, higher cosine similarity indicates a closer style match between two texts.

3.3.2 Human Evaluation

Our analysis of style and creativity is based on human evaluation of samples and on qualitative corpus analysis of full texts, involving identification of creative translation strategies and stylistic features. We compare the outputs of the three models and the available human translations on the test set. We used a rubric of translation strategies adapted from Şahin et al. (2018), who compiled a set of translation strategies using a variety of sources (cf. Vinay/Darbelnet 1958/1977, Nida 1964, Vázquez-Ayora 1977, Margot 1979, Newmark 1988, Delisle 1993, Chesterman 1997, Molina/Hurtado Albir 2002). The researchers coded translation solutions in different translations of the same source text to identify the level of similarity and pinpoint plagiaristic works. Table 2 presents the strategies used in the current study. The strategies are divided into the three major semiotic categories: syntactic, semantic, and pragmatic (see Appendix A for the codes for each category).

Syntactic	**Semantic**	**Pragmatic**
unit shift cohesion change transposition noun phrase structure verb phrase structure sentence structure change naturalization loan	word choice emphasis change paraphrase	addition omission free translation theme/rheme change discursive creation coherence change paratextual visibility explicitation/implicitation cultural adaptation linguistic amplification linguistic compression variation modulation compensation illocutionary change

Table 2: Translation strategies according to the three semiotic categories

Four annotators—senior university students majoring in translation and interpreting studies—worked on the samples of outputs. A pilot analysis was conducted using a test translation. Two annotators were assigned for each sample dataset. The source of the outputs was not revealed to the annotators to avoid bias (see Table 3).

EN	#1	#2	#3	#4
"What do you mean?" she said.	"Ne demek istiyorsun?" dedi.	Ne demek istiyorsun?' dedi.	"Ne demek istiyorsun?" dedi.	'Ne demek istiyorsun?' dedi.
Both resemble the dynamism of water which runs through many channels to find its own level.	Her ikisi de birçok kanaldan geçerek kendi düzeyini bulan suyun dinamizmini andırır.	Her ikisi de pek çok kanaldan geçerek kendi seviyesini bulan suyun dinamizmini andırıyor.	İkisi de, birçok kanallardan akıp geçerek sonunda kendi düzeyini bulan suyun dinamizmini andırır.	Her ikiside kendi seviyesini bulmak için birçok kanaldan geçen suyun dinamizmine benzemektedir.

Table 3: Sample annotation spreadsheet

Established methods of inter-rater reliability are based on methods such as Cohen's kappa, Krippendorff's alpha and other metrics that take agreement by chance into account. However, the number of categories involved in our approach, as well as the interchangeable nature of these categories leads to results that indicate little to no inter-rater reliability with these approaches. As a step in the direction to refine our categories and annotation guidelines, we have measured the inter-rater reliability based on simple match/no match percentage in several scenarios.

These scenarios are designed to mitigate the drawbacks of these complex annotation requirements. Exact Annotation Match occurs when two annotators use the same set of style codes. Partial Annotation Match happens when two annotators share at least one style code. Exact Category Match applies when two annotators use the same categories without counting duplicates; these categories can be syntactic, pragmatic, or semantic as described in Table 2. Partial Category Match takes place when two annotators have at least one category in common. Literal or nonliteral match involves converting annotations into literal (if annotated as 1 or if there is no annotation) or nonliteral before comparison.

4 Results

This section provides the results of both automatic and human evaluation. The former involves three different metrics as well as cosine similarity whereas the latter is based on manual coding of text samples by four annotators. We also provide the results of the inter-rater reliability and the reflections of the annotators.

4.1 Automatic Evaluation

The style vector cosine similarity shows that the fine-tuned model is the closest to the original translator's style, while the pre-trained model is even further away than Google Translate in terms of stylistic features. This shows that the base pre-trained model's lower stylistic similarity is being counteracted with the fine-tuning process, and the fine-tuned model also performs better than the pre-trained model according to the other evaluation metrics not related to style (see Tables 4–5).

Ağ (Fiction)*	**BLEU**	**BERTScore F1**	**COMET****	**Style Vector Cosine sim.**
Google Translate	10.93	0.746	67.5	0.853
Pre-trained	9.27	0.724	79.7	0.807
Fine-tuned	**14.32**	**0.751**	**81.9**	**0.944**

Table 4: Automatic evaluation scores and style vector cosine similarity for the fiction

Floransa Kitapçısı* (Nonfiction)	**BLEU**	**BERTScore F1**	**COMET****	**Style Vector Cosine sim.**
Google Translate	**10.50**	**0.732**	64.2	0.899
Pre-trained	9.11	0.712	77.4	0.850
Fine-tuned	9.77	0.717	**78.7**	**0.909**

Table 5: Automatic evaluation scores and style vector cosine similarity for the nonfiction

While automatic evaluation provides valuable evidence of stylistic convergence, it might prove insufficient in catching the subtleties of language used in literary and creative texts. Thus, although time-consuming and prone to bear a certain level of subjectivity, human evaluation is needed to supplement the automatic one so that more meaningful conclusions can be made.

4.2 Human Evaluation

We asked the annotators to take notes during their analysis. In their reflections on four different outputs, all annotators were able to identify the source of the outputs (i.e., pre-trained MT, fine-tuned MT, human translation, and Google Translate).

The human translations demonstrated superior fluency and stylistic freedom, characterized by a richer and more idiosyncratic lexicon. Translation universals, particularly explicitation and implicitation, were frequently observed, reflecting the translator's active intervention in shaping cohesion, coherence, and sentence structure. Deliberate theme/rheme alterations and modifications to verb structures were also evident.

The fine-tuned model exhibited many features akin to human translation, albeit with certain differences. It demonstrated greater fluency and reduced literalness compared to other machine-generated outputs, alongside a similarly rich and idiosyncratic lexical profile. Explicitations and omissions were present. The model also incorporated theme/rheme changes and adapted verb structures, particularly in the use of modalities.

In contrast, the pre-trained model and Google Translate displayed more rudimentary characteristics. Both produced less fluent and more literal translations, often relying on repetitive lexical choices. They adhered closely to source text-based approaches for managing cohesion, coherence, sentence structure, and information flow, typically retaining default verb structures without significant modifications. Notably, these systems lacked the capacity to handle advanced translation features such as explicitation and implicitation, as indicated by the 'N/A' in the analysis. Table 5 summarizes the reflections of evaluators.

Human Translation	Fine-tuned Model	Pre-trained Model	Google Translate
most fluent and ‚free'	**more fluent**, **<u>less literal</u>**	less fluent, literal	less fluent, literal
richer, **<u>more idiosyncratic</u>** lexis	**richer**, **<u>more idiosyncratic</u>** lexis	repetitive lexis	repetitive lexis
explicitation, implicitation	**explicitation**, omissions	N/A	N/A
intervention to **cohesion**, **coherence**, and **sentence structure**	intervention to **cohesion**, **coherence**, and **sentence structure**	<u>ST-based</u> cohesion, coherence, and sentence structure	<u>ST-based</u> cohesion, coherence, and sentence structure
theme/rheme change	**theme/rheme change**	<u>ST-based</u> info flow	<u>ST-based</u> info flow
verb structure change	**verb structure change** (modalities)	default verb structure	default verb structure

Table 6: General characteristics of each output

As explained in the methodology section, inter-rater reliability is measured based on the simple match/no match scenarios. As an example, Table 6 shows the inter-rater reliability scores for two annotators who annotated the same section of *Ağ*. Although the results are mixed, partial category matches and literal or nonliteral matches seem to be more acceptable than any exact or annotation code matches.

	Fine-Tuned	Google Translate	Pre-Trained	Yeğinobalı
Exact Annotation Match	50%	7.7%	42.3%	38.5%
Partial Annotation Match	53.8%	38.5%	53.8%	46.2%
Exact Category Match	57.7%	30.8%	61.5%	42.3%
Partial Category Match	61.5%	69.2%	73.1%	61.5%
Literal or Nonliteral Match	38.5%	100%	50%	76.9%

Table 7: Inter-rater reliability scores

In terms of literal or nonliteral matches, a very visible trend is traceable in almost all annotations, as shown in the authors' key annotations in Tables 8 and 9, where the nonliteral translations are the most prevalent in human-translated texts by Yeğinobalı and Dişbudak, followed by the fine-tuned model for the latter and Google Translate for the former. A more detailed look into the key annotations can be found in Appendix B.

Ağ (*Under the Net*)	Literal/Nonliteral Ratios Across Evaluations	
	Literal (%)	Nonliteral (%)
Google Translate	54.2	45.8
Pre-trained Model	62.5	37.5
Fine-tuned Model	58.3	41.7
Yeğinobalı	12.5	87.5

Table 8: Literal vs. Nonliteral translation solutions
for *Ağ* (*Under the Net*) by Annotator 2

Floransa Kitapçısı (The Bookseller of Florence)	Literal/Nonliteral Ratios Across Evaluations	
	Literal (%)	Nonliteral (%)
Google Translate	48	52
Pre-trained Model	56	44
Fine-tuned Model	36	64
Dişbudak	10	90

Table 9: Literal vs. Nonliteral translation solutions
for *Floransa Kitapçısı* (*The Bookseller of Florence*) by Annotator 2

The percentage of nonliteral translation solutions in the fiction book was higher in the outputs generated by Google Translate and the pre-trained model than the output by the fine-tuned model in all annotators' evaluations except for the one by Annotator 2 as seen in Table 9.

5 Discussion

Our study investigated differences in the level of creativity of English–Turkish translations generated in four different ways: (a) a published human translation, (b) a pre-trained MT model, (c) a fine-tuned MT model, and (d) a freely available online MT system. We measured the level of creativity by looking at the number of creative solutions produced for translation units in a sample of outputs for fiction and nonfiction. Human translations belong to two renowned translators, Nihal Yeğinobalı and Belkıs Dişbudak. The pre-trained model was developed using OPUS-MT and the fine-tuned model using a general literary corpus as training data. We chose Google Translate as the online MT system.

Our style analysis suggests that the fine-tuned model, even though trained with a mix of translations that did not include the translator's other works, is the closest to the original translator's style. This finding provides further evidence that a translator's style can be replicated to a certain extent with the help of customized MT models. We operationalized creativity as non-literal translation solutions which are identifiable through comparing the translation units in the target text with their source. To this end, a set of translation strategies were adapted from a previous study that focused on plagiarism in translation (cf. Şahin et al. 2018).

For both fiction and nonfiction books, human translation reflects the highest degree of creativity, based on the percentage of nonliteral translation solutions, in line with previous findings by Guerberof-Arenas/Toral (2020, 2022) and Şahin/Gürses (2019). The higher number of nonliteral translation solutions observed in the outputs generated by the fine-tuned MT model for the nonfiction book can be interpreted as an indicator of creativity. This is due to the training datasets used in fine-tuning: human translations of literary texts. Our pre-trained MT model and Google Translate, on the other hand, opt mostly for literal solutions. In our sample analysis, human translations had almost no mistranslations.

On the other hand, based on the analyses of samples by four annotators, our fine-tuned model seems to have failed to produce more nonliteral solutions for the fiction book. Yet, the BLEU scores of the output generated by our fine-tuned model were the highest, indicating a higher level of accuracy.

This, in fact, is supported by the higher number of instances of mistranslations in the output by the pre-trained model. The total number of instances of mistranslations for the fiction book was equal in the outputs by the fine-tuned model and Google Translate and it was more than half of that in the pre-trained model's output.

Our study confirms that when the MT model is trained with literary texts, its translations become stylistically more distinguishable. However, as regards creativity, we were not able to obtain clear results. The number of nonliteral translation solutions in the 50-segment samples identified by four annotators was not always higher in the MT model fine-tuned with a dataset of Turkish literary translations. It is important to note that reflections by the annotators suggest that the outputs by the fine-tuned model showed more creativity but the statistical analysis of their codings for each output did not fully support this overall judgment.

Google Translate and other freely available MT systems work with anonymized, collective datasets. In our study, we focus on selected individual translators who have been known to have a distinct style and are also creative, where the latter does not necessarily follow from the former, as explained in our introduction and following definition of creativity used by Guerberof-Arenas/Toral (2020, 2022) and Şahin/Gürses (2019). Creativity is very closely related to stylistic competence and individualism, and the present findings suggest that it is possible to recreate style with models trained on texts within the same genre but such models are not always enough to boost creativity for all sub-genres.

6 Conclusions

The present study employed a set of pre-existing features to examine style and creativity in literary fiction and nonfiction translations produced by a human, a pre-trained MT model, a fine-tuned MT model, and a freely available online MT system. Findings suggest that a model fine-tuned on literary (same-genre) text data is more successful at replicating a translator's style and is also more creative relative to a pre-trained model (trained on generic text data) and a commercial MT system (i.e., Google Translate) in nonfiction translation. It is well worth underlining that none of the MT models' translations were as creative as the human translation.

One explanation is that humans are determined by their biological and social conditions, and they are also capable of creating new things. When a machine or humanoid seems to be creative, this means that it is capable of creating complex syntheses or collages from its input. We believe that gifted people can create unexpected originals and this is also true for translations; we believe translators to be gifted people in the field of language and they have their own original ways of using language to create the target text, called styles. Because human styles are created by bio-social complexities we have to believe that they will always be better than their mechanical copies. The only problem is that mechanical copies can satisfy most needs; in daily life, people tend to work on a normal dosage of creativity. But MT models also help to develop their concept of 'normal.'

One of the limitations of our study is that the inter-rater reliability scores were not high in coding translation solutions, particularly in exact annotation matches. This can be partly due to the high number of codes used in the study. Moreover, the subjective nature of human evaluation may have contributed to this fact. A longer period of annotator training and a more focused quest for a set of translation strategies can help increase the inter-rater reliability scores. For the analysis of creativity, we used small samples from both books; increasing the volume of texts analyzed can provide more reliable results. Finally, future research could explore the relationship between style and creativity and aim at developing more objective quantifiable measures of both.

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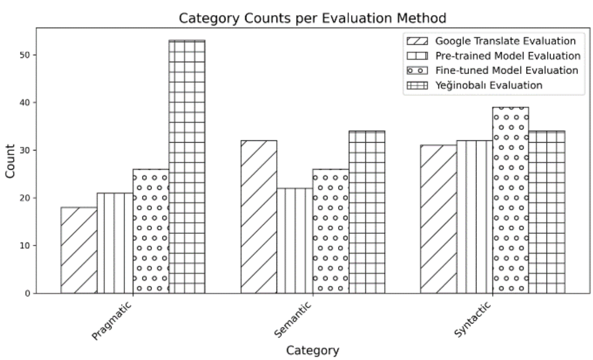
8 Appendices

8.1 Appendix A: List of codes for translation strategies

1. literal translation
2. addition
3. omission
4. unit shift
5. word choice
6. cohesion change
7. transposition
8. emphasis change
9. noun phrase structure
10. verb phrase structure
11. sentence structure change
12. paraphrase

13. free translation
14. theme/rheme change
15. discursive creation
16. coherence change
17. explicitation/implicitation
18. naturalization
19. loan
20. cultural adaptation
21. linguistic amplification
22. linguistic compression
23. variation
24. modulation
25. compensation
26. illocutionary change
27. other changes (e.g. word or syntactic transfer from the source language)
28. mistranslation

8.2 Categories of codes used in different evaluation sets by authors' key annotations



9 References

Baker, Mona (2000): "Towards a methodology for investigating the style of a literary translator." In: *Target. International Journal of Translation Studies* 12/2, pp. 241–266. DOI: <10.1075/target.12.2.04bak>.

Besacier, Laurent (2014): "Traduction automatisée d'une œuvre littéraire: une étude pilote." In: *21ème Traitement Automatique du Langage Naturel (TALN).* Marseille, France, pp. 389–394.

Besacier, Laurent / Schwartz, Lane (2015): "Automated Translation of a Literary Work: A Pilot Study." In: Feldman, Anna / Kazantseva, Anna / Szpakowicz, Stan / Koolen, Corina [eds.]: *Proceedings of the Fourth Workshop on Computational Linguistics for Literature.* Denver, Association for Computational Linguistics, pp. 114–122. DOI: <10.3115/v1/W15-0713>.

Boase-Beier, Jean (2011): *A Critical Introduction to Translation Studies.* Bloomsbury Publishing.

Boase-Beier, Jean (2019): *Translation and Style.* London / New York: Routledge.

Bosseaux, Charlotte (2001): "A Study of the Translator's Voice and Style in the French Translations of Virginia Woolf's *The Waves.*" In: Olohan, Maeve [ed.]: *CTIS occasional papers* 1. Manchester: St. Jerome Publishing, pp. 55–75.

Cercel, Larisa / Agnetta, Marco / Amido Lozano, María Teresa [eds.] (2017): *Kreativität und Hermeneutik in der Translation* [*Creativity and Hermeneutic in Translation*] (= *Translationswissenschaft*, Bd. 12). Tübingen: Narr Francke Attempto Verlag.

Chesterman, Andrew (1997): *Memes of Translation. The Spread of Ideas in Translation Theory.* Amsterdam: John Benjamins.

Dalli, Harun / Dursun, Olgun / Yirmibeşoğlu, Zeynep / Hodzik, Ena / Gürses, Sabri / Güngör, Tunga / Şahin, Mehmet (2024): "Giving a Translator's Touch to the Machine: Reproducing Translator Style in Literary Machine Translation." In: *Palimpsestes. Revue de traduction* 38, n.p. DOI : <10.4000/12sp6>.

Delisle, Jean (1993): *La traduction raisonnée. Manuel d'initation à la traduction professionnelle de l'anglais vers le français.* Ottawa: Presses de l'Université d'Ottawa.

Dorst, Aletta G. (2024): "Metaphor in Literary Machine Translation: Style, Creativity and Literariness." In: Rothwell, Andrew / Way, Andy /

YOUDALE, Roy [eds.]: *Computer-Assisted Literary Translation*. Abingdon: Routledge, pp. 173–186.

FRANKENBERG-GARCIA, Ana (2022): "Can a Corpus-Driven Lexical Analysis of Human and Machine Translation Unveil Discourse Features that set them Apart?" In: *Target* 34/2, pp. 278–308. DOI: <10.1075/target.20065.fra>.

GUERBEROF-ARENAS, Ana / TORAL, Antonio (2020): "The Impact of Post-editing and Machine Translation on Creativity and Reading Experience." In: *Translation Spaces* 9/2, pp. 255–282.

GUERBEROF-ARENAS, Ana / TORAL, Antonio (2022): "Creativity in Translation: Machine Translation as a Constraint for Literary Texts." In: *Translation Spaces* 11/2, pp. 184–212.

GÜRSES, Sabri (2007): "İntihal Kültürü" ["Culture of Plagiarism"]. In: *Varlık* 1194, pp. 9–16.

GÜRSES, Sabri / ŞAHIN, Mehmet / HODZIK, Ena / GÜNGÖR, Tunga / DALLI, Harun / DURSUN, Olgun (2024): "Çeviribilim Çalışmalarında Çevirmenin Üslubu ve Makinenin Üslubu." ["The Style of the Translator and the Style of the Machine in Translation Studies."] In : *Çeviribilim ve Uygulamaları Dergisi* 36, pp. 100–124. DOI : <10.37599/ceviri.1468718>.

HANSEN, Damien (2024): "Évaluation experte d'un prototype d'aide à la traduction créative. La traduction littéraire automatique individualisée au regard de ses enjeux traductologiques, éthiques et sociétaux." In: ProQuest Dissertations & Theses Global, Universite de Liege (Belgium). Publicly Available Content Database, URL : <https://www.proquest.com/dissertations-theses/évaluation-experte-dun-prototype-daide-à-la/docview/3122662807/se-2> (25.07.2025).

HERMANS, Theo (2019): "Hermeneutics." In: BAKER, Mona / SALDANHA, Gabriela [eds.]: *Routledge Encyclopedia of Translation Studies*. London / New York: Routledge, pp. 227–232.

KENNY, Dorothy / WINTERS, Marion (2020): "Machine Translation, Ethics and the Literary Translator's Voice." In: *Translation Spaces* 9/1, pp. 123–149. DOI: <10.1075/ts.00024.ken>.

KUSSMAUL, Paul (2000): *Kreatives Übersetzen*. Tübingen: Stauffenburg.

LEFEVERE, André (1992): *Translation, Rewriting and the Manipulation of Literary Fame*. London / New York: Routledge.

LI, Defeng / ZHANG, Chunling / KANGLONG, Liu (2011): "Translation Style and Ideology: A Corpus-Assisted Analysis of two English Translations of Hongloumeng." In: *Literary and Linguistic Computing* 26/2, pp. 153–166. DOI: <10.1093/llc/fqr001>.

MALMKJÆR, Kirsten (2003): "What happened to God and the angels: An exercise in translational stylistics." In: *Target. International Journal of Translation Studies* 15/1, pp. 37–58. DOI: <10.1075/target.15.1.03mal>.

MALMKJÆR, Kirsten (2020): *Translation and Creativity*. London / New York: Routledge.

MARGOT, Jean-Claude (1979): *Traduire sans trahir. La théorie de la traduction et son application aux textes bibliques*. Lausanne: L'Age d'Homme.

MASTROPIERRO, Lorenzo (2018): "Key Clusters as Indicators of Translator Style." In: *Target* 30/2, pp. 240–259. DOI: <10.1075/target.17040.mas>.

MIKHAILOV, Mikhail (2021): "Corpus-Based Analysis of Russian Translations of *Animal Farm* by George Orwell." In: JI, Meng / OAKES, Michael P. [eds.]: *Corpus Exploration of Lexis and Discourse in Translation*. London / New York: Routledge, pp. 56–82.

MOLINA, Lucia / HURTADO ALBIR, Amparo (2002): "Translation Techniques Revisited: A Dynamic and Functionalist Approach." In: *Meta* 47/4, pp. 498–512.

MUNDAY, Jeremy (2008): "The Relations of Style and Ideology in Translation: A Case Study of Harriet de Onís." In: PEGENAUTE, Luis / DE CESARIS, Janet Ann / TRICÁS PRECKLER, Mercedes / BERNAL, Elisenda [eds.]: *La traducción del futuro: mediación lingüística y cultural en el siglo XXI. Actas del III Congreso Internacional de la Asociación Ibérica de Estudios de Traducción e Interpretación.* Barcelona: Promociones y Publicaciones Universitarias, pp. 22–24.

NEWMARK, Peter (1988): *A Textbook of Translation*. London: Prentice Hall International.

NIDA, Eugene (1964): *Toward a Science of Translating with Special Reference to Principles and Procedures Involved in Bible Translating*. Leiden: E. J. Brill.

OLOHAN, Maeve (2004): *Introducing Corpora in Translation Studies*. London / New York: Routledge.

RISKU, Hanna / MILOŠEVIĆ, Jelena / ROGL, Regina (2017): "Creativity in the Translation Workplace." In: Cercel, Larisa / AGNETTA, Marco / AMIDO LOZANO, María Teresa [eds.]: *Kreativität und Hermeneutik in der Translation*. Tübingen: Narr Francke Attempto Verlag, pp. 455–469.

ROTHWELL, Andrew / WAY, Andy / YOUDALE, Roy [eds.] (2024): *Computer-Assisted Literary Translation*. Abingdon: Routledge.

ŞAHIN, Mehmet / DUMAN, Derya / GÜRSES, Sabri (2015): "Big Business of Plagiarism under the Guise of (Re)translation: The Case of Turkey." In: *Babel* 61/2, pp. 193–218.

ŞAHIN, Mehmet / DUMAN, Derya / GÜRSES, Sabri / KALEŞ, Damla / WOOLLS, David (2018): "Toward an Empirical Methodology for Identifying Plagiarism in Retranslation." In: BERK ALBACHTEN, Özlem / TAHIR GÜRÇAĞLAR, Şehnaz [eds.]: *Perspectives on Retranslation*. London / New York: Routledge, pp. 166–191.

ŞAHIN, Mehmet / DUNGAN, Nilgün (2014): "Translation Testing and Evaluation: A Study on Methods and Needs." In: *The International Journal for Translation & Interpreting Research* 6/2, pp. 67–90.

ŞAHIN, Mehmet / GÜRSES, Sabri (2019): "Would MT Kill Creativity in Literary Retranslation?" In: HADLEY, James / POPOVIĆ, Maja / AFLI, Haithem / WAY, Andy [eds.]: *Proceedings of the Qualities of Literary Machine Translation*. Dublin: European Association for Machine Translation, pp. 26–34. URL: <https://aclanthology.org/W19-7304/>.

ŞAHIN, Mehmet / GÜRSES, Sabri (2021): "English–Turkish Literary Translation through Human-Machine Interaction." In: *Tradumàtica* 19, pp. 171–203. DOI: <10.5565/rev/tradumatica.284>.

ŞAHIN, Mehmet / GÜRSES, Sabri (2023): "A Call for a Fair Translatiosphere in the Post-Digital Era." In: *Parallèles* 34/2, pp. 1–17. DOI: <10.17462/para.2022.02.01>.

SALDANHA, Gabriela (2011): "Translator Style: Methodological Considerations." In: *The Translator* 17/1, pp. 25–50. DOI: <10.1080/13556509.2011.10799478>.

SCHREIBER, Michael (2017): "Kreativität in Translation und Translationswissenschaft: Zwei Fallbeispiele und ein Vorschlag." In: CERCEL, Larisa / AGNETTA, Marco / AMIDO LOZANO, María Teresa [eds.]: *Kreativität und Hermeneutik in der Translation*. Tübingen: Narr Francke Attempto Verlag, pp. 349–358.

SLUYTER-GÄTHJE, Henny / BARTELD, Fabian / ZINSMEISTER, Heike (2018): "Neural Machine Translation for Literary Texts [Poster presentation]." At: *40th Annual Conference of the German Linguistic Society*. University of Stuttgart, Germany.

ŠPLÍCHALOVÁ, Tereza (2024): „(Re)creating Equivalence of Stylistic Effect: A Corpus-Aided Methodology." In: ROTHWELL, Andrew / WAY, Andy / YOUDALE, Roy [eds.]: *Computer-Assisted Literary Translation*. Abingdon: Routledge, pp. 219–233.

TAIVALKOSKI-SHILOV, Kristiina (2019): "Ethical Issues Regarding Machine (-assisted) Translation of Literary Texts." In: *Perspectives* 27/5, pp. 689–703.

TIEDEMANN, Jörg / THOTTINGAL, Santhosh (2020): "OPUS-MT–Building Open Translation Services for the World." In: MARTINS, André et al. [eds.]: *Proceedings of the 22nd annual conference of the European Association for Machine Translation*. Lisboa: European Association for Machine Translation, pp. 479–480. URL: <https://aclanthology.org/2020.eamt-1.61/> (24.06.2025).

TORAL, Antonio / WAY, Andy (2018): "What Level of Quality Can Neural Machine Translation Attain on Literary Text?" In: MOORKENS, Joss / CASTILHO, Sheila / GASPARI, Federico / DOHERTY, Stephen [eds.]: *Translation Quality Assessment: From Principles to Practice*. Cham: Springer International Publishing, pp. 263–287.

TURELL, M. Teresa (2004): "Textual Kidnapping Revisited: The Case of Plagiarism in Literary Translation." In: *International Journal of Speech, Language and the Law* 11/1, pp. 1–26.

VAJN, Dominik (2009): *Two-Dimensional Theory of Style in Translations: An Investigation into the Style of Literary Translations*. Unpublished Master's Thesis, University of Birmingham.

VÁZQUEZ-AYORA, Gerardo (1977): *Introducción a la traductología*. Washington: Georgetown University Press.

VINAY, Jean Paul / DARBELNET, Jean (1958/1977): *Stylistique comparée du français et de l'anglais*. Paris: Didier.

WINTERS, Marion (2007): "F. Scott Fitzgerald's *Die Schönen und Verdammten*: A Corpus-Based Study of Speech-Act Report Verbs as a Feature of Translators' Style." In: *META* 52/3, pp. 412–425.

WINTERS, Marion / KENNY, Dorothy (2024): "Mark my Keywords: A Translator-Specific Exploration of Style in Literary Machine Translation." In: ROTHWELL, Andrew / WAY, Andy / YOUDALE, Roy [eds.]: *Computer-Assisted Literary Translation*. Abingdon: Routledge, pp. 69–88.

YIRMIBEŞOĞLU, Zeynep / DURSUN, Olgun / DALLI, Harun / ŞAHIN, Mehmet / HODZIK, Ena / GÜRSES, Sabri / GÜNGÖR, Tunga (2023): "Incorporating Human Translator Style into English–Turkish Literary Machine Translation." In: NURMINEN, Mary et al. [eds.]: *Proceedings of the 24th Annual Conference of the European Association for Machine Translation*. Tampere: European Association for Machine Translation, pp. 419–428.

YOUDALE, Roy (2020): *Using Computers in the Translation of Literary Style: Challenges and Opportunities*. London / New York: Routledge.

About the Authors:

Mehmet Şahin is professor in the Department of Translation and Interpreting Studies at Boğaziçi University in Istanbul. He completed his undergraduate studies in Translation and Interpretation at Bilkent University in Ankara, Turkey, where he also received a master's degree in Teacher Education. He holds a PhD in Curriculum and Instruction with a concentration in Applied Linguistics/TESOL from Iowa State University. His doctoral research focused on computer-assisted language learning and educational technology. His current research interests include translation studies, translation and interpreting technologies, machine translation, and translator and interpreter education.

Ena Hodzik is Research Fellow (Marie Skłodowska Curie COFUND Action) at Université de Mons, Belgium. She is working on a project investigating Predictive processes in sight translation from English into French. Previously, she worked as Assistant Professor at the Department of Translation and Interpreting Studies at Boğaziçi University, where she was researcher on a project investigating literary machine translation. She completed her PhD at the University of Cambridge, focusing on predictive processes during simultaneous conference interpreting from German into English. She is interested in interdisciplinary research areas that intersect with the study of translation and interpreting as cultural and social phenomena.

Sabri Gürses is a writer, literary translator, and assistant professor in the Department of English Translation and Interpreting at Üsküdar University in Istanbul. After graduating from Russian Studies, he obtained his MA in Translation Studies and a PhD in Russian Studies. His research interests include translation history, plagiarism and creativity in literature and translation, and the effects of artificial intelligence on creativity. He has several awards in writing and translation and has worked as the president of the Translation Society in Turkey.

Tunga Güngör is a professor at the Department of Computer Engineering at Boğaziçi University. He obtained his MS and PhD degrees from the same department. His research interests include artificial intelligence, natural language processing, machine translation, and machine learning. He is a member of the Artificial Intelligent Lab and the Text Analytics and Bioinformatics Lab at the department. He teaches undergraduate and graduate level courses on the topics of artificial intelligence, natural language processing, machine translation, and algorithm analysis.

Zeynep Yirmibeşoğlu is a Ph.D. student at the Department of Computer Engineering at Boğaziçi University. She completed her Bachelor's degree in Computer Engineering at Istanbul Technical University and obtained her Master's degree in Computer Engineering at Boğaziçi University. She conducts research in natural language processing, deep learning, and machine translation, and is a member of the Artificial Intelligence Lab and the Text Analytics and Bioinformatics Lab at the department.

Olgun Dursun is an NLP developer working on speech recognition and natural language understanding. He holds a master's degree in Cognitive Science and a bachelor's degree in Translation Studies from Boğaziçi University. He is a contributor to the Text Analytics and Bioinformatics Lab in the Department of Computer Engineering at Boğaziçi University.

Harun Dallı is a PhD fellow at the Department of Applied Linguistics, Translation and Interpreting Studies at the University of Antwerp. He holds a master's degree in Translation Studies from Boğaziçi University and a bachelor's degree in English Language and Literature from Hacettepe University. His research focuses on audiovisual translation, corpus linguistics, media accessibility, and the translation process. In addition to his research, he works as a professional subtitler.

Contact: mehmet.sahin5@bogazici.edu.tr