# Google Translate and DeepL: breaking taboos in translator training. Observational study and analysis

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## Abstract

The literature published in the last decades on the use of machine translation (MT) generally conveys the idea that it is not suitable for professional translation. Furthermore, translation students are usually warned that they should not use this tool in their assignments or exams and that doing so would be penalized. The reason behind such reluctance may be that MT produced poor results unless it was used on controlled language in pre-edited texts within a specific specialization field and the target texts were subsequently post-edited with appropriate tools. However, three main considerations lead us to propose a re-evaluation of the usefulness of MT in university translation courses: first, students employ MT despite warnings not to do so; second, current tools like Google Translate or DeepL have considerably improved outcomes; and third, MT is already being used as an assistant tool in computer-assisted translation (CAT) – although the results are usually monitored by a human translator. As translation teachers, we propose that post-editing MT-translated texts could be used for didactic purposes: the diagnosis of MT-errors could help improve students' translation skills and linguistic proficiency both in their mother tongue and their second language. In this article, we present the results of using MT plus post-editing in a university course on Spanish-German Specialized Translation. This type of translation poses considerable challenges for students and often requires them to review and deepen their knowledge of the target language grammar. Our aim was to contribute to the didactics of translation by training students in error prevention through the analysis of MT-errors, and to teach them to develop a critical attitude when post-editing.

**Keywords:** machine translation, post-editing, specialized translation, translation didactics, linguistic competence.

## Resumen

***Google Translate y DeepL: rompiendo tabúes en la formación de traductores. Estudio observacional y análisis***

Los estudios publicados en las últimas décadas sobre el uso de la traducción automática (TA) tienden a transmitir la idea de que esta no es adecuada para la traducción profesional. Además, se suele advertir a los estudiantes de traducción de que se verían penalizados si utilizaran dicha herramienta a la hora de realizar encargos o exámenes. El motivo de tales reticencias podría ser que la TA generaba resultados deficientes salvo cuando se aplicaba a lenguajes controlados en textos preeditados pertenecientes a campos de especialización concretos y cuando los textos meta se sometían a una posedición con herramientas apropiadas. No obstante, tres consideraciones nos condujeron a proponer una nueva valoración de la utilidad de la TA en la enseñanza universitaria de la traducción: en primer lugar, los estudiantes utilizan la TA a pesar de que se les advierta de que no deben hacerlo; en segundo lugar, los resultados de las herramientas actuales, como Google Translate o DeepL, han mejorado de forma considerable; y en tercer lugar, la TA ya funciona como una herramienta auxiliar en la traducción asistida por ordenador (TAO), aunque los resultados se revisen habitualmente por un traductor humano. Como profesoras de traducción planteamos que la posedición de los textos traducidos por TA se puede emplear como herramienta didáctica para mejorar la competencia lingüística y traductora de los estudiantes, tanto en su lengua materna como en su segunda lengua mediante el diagnóstico de los errores. En este artículo presentamos los resultados del uso de la TA junto con la posedición una asignatura de Traducción Especializada entre el español y el alemán. Este tipo de traducción, por un lado, supone un gran reto para los estudiantes y, por otro, a menudo requiere que en clase se repase la gramática de la lengua meta y se amplíen los conocimientos acerca de ella. Nuestro objetivo fue contribuir a la didáctica de la traducción, entrenando a los estudiantes a prevenir errores propios mediante el análisis de los errores producidos por la TA y una posedición con actitud crítica.


**Palabras clave:** traducción automática, posedición, traducción especializada, didáctica de la traducción, competencia lingüística.

## 1. Introduction

Until a few years ago, the use of machine translation (MT)[1] was considered inadequate for professional translation. Furthermore, students used to be systematically warned that they should not use this tool in their assignments or exams and that doing so would be penalized. The reason behind this reluctance may have been that MT produced poor results unless it was used on controlled language in pre-edited texts within a specific specialization field and the target texts were subsequently post-edited with appropriate tools. This situation led translators and teachers to avoid the use of MT. However, MT-systems applied to specialized texts and allowed a training period, have managed to produce quite acceptable results, and they are now used to speed up the translation process. Furthermore, recent developments in Neural Machine Translation (NMT) produce even better results. As translation teachers, we wondered whether MT post-editing could be applied to translation pedagogy, using MT-error diagnosis and therapy to improve students' command of their mother tongue or a second language. In a word, should we ignore the winds of change and close our eyes to reality? Or is it time to adapt to changes in the working environment?

So far, many professional translators have been strongly against MT because they considered that it threatened their jobs. The International Federation of Translators (FIT) even released several publications to calm the waters, in which they claimed that MT would not harm translators' activity (Läubli & Orrego-Carmona, 2017, p. 60). Conversely, results published by several researchers showed that some of the many translators dedicated to post-editing[2] were actually working on post-edition of MT-texts, and that they were not unhappy with it (Guerberof Arenas, 2013, pp. 92-93; Gaspari et al., 2015; Zaretskaya, 2017, p. 117; Scansani, 2020). Actually, reluctance to accept MT is rather surprising, since translators have long been working with translation memories (TM), which are based on the principles of MT, and must be followed by post-edition of the segments automatically proposed by the TM. A possible explanation for such generalized rejection of MT would be translators' concern about earning lower incomes from clients that usually ignore that MT-texts need correction and consequently intend to pay lower fees (as with TMs).

It is true, however, that until recently, MT required a huge post-editing effort, and that only a combination of pre-edited texts or texts written in controlled language, with trained MT-programs and a post-editing process could produce satisfactory results and be used in large texts. Initial MT developments were mainly rule-based (RBMT), i.e., based on linguistic knowledge. These systems mainly failed to translate correctly proper names, homonyms, prepositions and idioms. Nowadays, they are seldom used because this type of automatic translator is difficult to produce, it would only work in one language direction and any modification in a standard may conflict with other ones. More recently, Example-Based-Machine-Translation (EBMT) was developed. Hutchins (2005, p. 69) claimed that it "occupies an intermediary position between RBMT and SMT and it makes use of both statistical (SMT-like) and symbolic or linguistic (RBMT-like) methods", perhaps a 'true' hybrid MT approach. The next system was corpus-based and statistics-based (SMT: Statistical Machine Translation) and its weaknesses mainly affected negation, antonyms, conjugations and syntax; in addition, omissions and failure to adjust to the context are still frequent. SMT (actually, Phrase Based Statistical Machine Translation, PBSMT) represented a quality leap. It was based on aligned corpora of text in the two languages and worked bidirectionally using syntagms. However, there was the handicap that some languages were too complex in structure for this type of MT (e.g. German).

The processes of artificial intelligence (AI) are often obscure, and it is not easy to understand why an algorithm generates a particular result. In 2010, eXplainable artificial intelligence (XAI) was developed, and it was implemented as a new kind of neural network, more transparent in terms of information processing, in 2015. This new method was also known as "deep learning", which is where the name of the automatic translator DeepL comes from. As stated by Miller (2019, p. 3): "The running hypothesis behind the explainable artificial intelligence is that by designing and implementing intelligence agents that are transparent, users will be better equipped to understand and therefore trust the intelligent agents". Google, Yandex and Microsoft started using a Neural Machine Translation (NMT) system in 2015, i.e., OpenNMT, released by the Harvard NLP Group. In August 2017, the new NMT system DeepL was launched, showing a performance that exceeded expectations, and which was much discussed in social media.

In 2015, NMT brought about a change of paradigm, with learning algorithms re-using patterns stored in text corpora, and with an excellent performance in word-representation and word-prediction. It significantly improved translation fluency, because it performed better in keeping the word order, inserting function words correctly, improving morphological agreement, and making better lexical choices. As a consequence, neural network-based automatic translation is growing steadily with rising numbers of companies relying on it, e.g., e-Bay, Amazon and AliExpress (cf. Bares Sánchez, 2017)[3]. This latter fact demonstrates the importance of automatic translation in business and marketing, as it enables companies to advertise products in many languages thus increasing earnings.

In this context, it becomes important to question the quality of such translations. In our study, we compared DeepL translations with versus without post-editing by our students. In particular, we analyzed the types and frequencies of translation errors in MT-translated texts and compared them with those of post-edited ones, with the aim of identifying and classifying error tendencies and transferring this knowledge to students. The ultimate goal of this analysis was to gain insights into those features that need to be reinforced in the classroom, so as to reduce the number of errors in students' translations, improve their translation performance and enhance their academic results.

## 2. Hypothesis and objectives

Our hypothesis was that post-edition of machine translated texts by university translation students with poor command of the target language will produce better results than their translations without MT. The main objective of this study was to analyze the differences between MT-texts and MT-texts post-edited by students in terms of error diagnosis, to make students aware of their failures and introduce metacognitive error therapy.

## 3. Methods of the observational study

Some researchers in linguistics or translation claim that successful communication – instead of formal correctness – is the paramount goal. However, the quality of a translation is connected to professional performance and error prevention, and to ensuring that the translated text achieves its intended objective. A text containing grammar errors will hardly meet the readers' expectations and might be difficult or impossible to understand. We focused our research on the grammar errors found in students' German-Spanish translations. An essential question is to what extent MT differs from non-MT translation in terms of quality. In an earlier study published in 2006, we analyzed students' human translation with special focus on the errors that occurred in their translations from their mother tongue into a foreign language. In this study, we analyze whether the use of MT followed by post-edition could affect those results.

### 3.1. Sample and procedure

Six different texts (126-512 words each) were analyzed in this study. All texts were extracted either from articles published in the financial section of a non-specialized journal or from information articles in financial newspapers. It should be noted that they were controlled texts to some extent, since they belonged to well-defined areas that had been studied in class; thus, the number of errors was expected to be lower than in translations of unknown topics. The analyzed texts are listed in the Annex.

Participants were students from the fourth year (last year) of the Bachelor's degree in Translation and Interpreting of the University of Malaga, Spain. Since every text was translated in a different class session, the number of the participating students ranged from 31 to 34. They had to translate from their mother tongue, Spanish, into a foreign language, German, which they had officially learnt for 225 hours during the course of their studies. Translations had to be completed within 45 to 90 minutes depending on the extension of the text. Students were allowed to access the Internet and use their own materials (other translations, glossaries, etc.), as well as online resources like dictionaries or MT-tools. They were required to translate the original texts using the MT-tool DeepL and to subsequently post-edit the target text. Notice that corrections were required only when mandatory (thus stylistic errors were ignored). In this regard, we followed the International Organization for Standardization (ISO) 18587:2017 (2017) definition of "light post-editing", namely making corrections only "to obtain a merely comprehensible text without any attempt to produce a product comparable to a product obtained by human translation". As far as translation competence is concerned, post-editing has the advantage of bringing together two practice types: linguistic and instrumental (technological). The students' translated and post-edited texts were then analyzed, and the errors were quantified and classified.

### 3.2. Error classification

Translation errors can be classified in different ways and certain errors should always be taken into account in translations (cf. Varela Salinas, 2006). Although the diagnosis of individual errors is a complex issue, the asymmetry between source and target languages is a general difficulty. Usually, students are well aware of this when it comes to word choice (lexicon) and pronunciation (phonology), but not so much in sentence construction (syntax). In our experience, calques of grammatic patterns, especially syntactic ones, are rather frequent. Moreover, there is a difference between declarative and procedural knowledge: students can have quite a good knowledge of grammar theory but fail to apply the rules in specific exercises or in text productions such as translations.

In this research, we classified translation errors into the following categories:

pragmatics

grammar

equivalence (understanding the original text and choosing an equivalent expression or conveying the same idea/function in the target text)

spelling

lexicon/terminology

style

culture

Although different error classifications can be used, these categories were the most suitable ones for a comparison with the results of our above-mentioned study (Varela Salinas, 2006, pp. 189-203). Notice that any given error was counted once, regardless of the times it appeared in a text (i.e. repetitions were not counted as independent errors).

The results of MT and students' translations are described, for every single text, as: total number of errors, error rate (total errors over total number of words in the text), number of errors per category and error percentage per category (the proportion of errors in a certain category from the total errors in that text). In students' translations, the mean number of errors (mean error) is offered for comparison.

### 3.3. Choice of the MT-tool

In order to choose the MT-tool to be used in our study, we conducted an initial comparison between Google Translate and DeepL. Both MT-systems were used to analyze one of the texts of the study[4]; the results showed that DeepL performed better.

## 4. Results

In this section we discuss the main results of our observational study. The complete results are summarized in the tables in the Annex.

Tables 1 and 2 show the results of Google Translate vs. DeepL translation of one of the texts used in the study. Although the distribution of errors across the categories was similar for both, Google Translate showed a higher total number of errors and error rate (56 and 16.6, respectively) than DeepL (23 and 6.8, respectively). On this basis, we chose DeepL as the MT-tool to be used in this study.

**Google Translate**
Text 1: Los desempleados de más de 52 años recuperan el subsidio

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 7 | 17 | 8 | 1 | 19 | 3 | 1 | 16.6 | 56 |
| Percentage | 12.5% | 30.36% | 14.29% | 1.79% | 33.93% | 5.36% | 1.79% | | |

Table 1. MT translation with Google Translate.

**DeepL**
Text 1: Los desempleados de más de 52 años recuperan el subsidio

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 3 | 8 | 4 | | 7 | 1 | | 6.8 | 23 |
| Percentage | 13.04% | 34.78% | 17.39% | | 30.43% | 4.35% | | | |

Table 2. MT translation with DeepL.

**Students, n = 34**
Text 1: Los desempleados de más de 52 años recuperan el subsidio

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors | Mean error |
|---|---|---|---|---|---|---|---|---|---|---|
| Number | 33 | 475 | 10 | 35 | 232 | 9 | | 6.8 | 794 | 23 |
| Percentage | 4.16% | 59.8% | 1.26% | 4.4% | 29.1% | 1.13% | | | | |

Table 3. Students' light post-editing of MT translation with DeepL.

Table 3 shows the results of students' MT + light post-editing. Like in our 2006 study, most errors fell into category Grammar; followed by much less errors in Lexicon/terminology, Spelling and Equivalence. A similar distribution pattern with grammar at the top of difficulties was observed in all the students' texts. As in our previous article, we propose that an insufficient amount of German language class hours could account for this finding. Pragmatics errors were scarce and stylistic errors were even scarcer, which was not surprising since only light post-editing was required. However, this result could be due to such errors being subsumed into other categories like Lexicon, Grammar or Equivalence, or to the type of text chosen. Culture errors were not recorded because the source texts did not contain cultural words.

A comparison between the results of DeepL vs. students' DeepL+light post-editing translations (Tables 2 and 3) shows that the total number of errors with DeepL was equivalent to the student's error mean (23); and that the total error rate of DeepL was equivalent to the students' one (6.8). An analysis of every individual translation showed that 44% of students made a similar number of errors in this text. Regarding the other texts, students showed slightly higher error numbers and rates than DeepL in two of them and slightly lower values in another two, while in the longest text, students performed much worse than DeepL. However, understanding these differences in the students' MT performance would require further research.

Since Grammar errors were by far the most frequent ones, we classified them into the following subcategories for further analysis:

declension

syntax

conjugation

passive voice

pronouns

determined/undetermined articles

gender

punctuation

conjunctions

subject omission

tenses

prepositions

subjunctive

Errors within category Grammar can help identifying error tendencies and, more important, provide knowledge about the specific features that need to be emphasized in the didactic use of MT. The tables in the annex about text 1 show the results of DeepL vs. students in terms of the distribution of grammar errors in the text[6].

The remarkably high number of errors made by students in Grammar subcategories Syntax, Declension and Prepositions is in agreement with our results published in 2006. The differences between DeepL and students can be observed at once; although the MT-system struggled with prepositions at the same level as students, its use of tenses was – at least in this text – markedly poorer, and so were the correct use of (un)determined articles and gender.

In translation didactics, it is important to consider potential problems that students might find during the post-editing process. The fact that students made more mistakes in Syntax, Declension and Prepositions suggests that they did not rely on DeepL to solve those problems. On the other hand, the high number of errors made by DeepL in the use of tenses is remarkable.

According to Silva (2014, p. 33), MT performance is better with shorter text segments. In our study, the translation of the text "Inflación subyacente", which was considerably shorter and syntactically less complex than the rest, showed similar error tendencies for both DeepL and students in the main general categories (Tables 4 and 5). Thus, Grammar and Lexicon were the most problematic areas for both; otherwise, students experienced more difficulties with Spelling and DeepL, with Pragmatics.

**DeepL**
Text 3: Inflación subyacente

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 2 | 4 | | | 4 | 2 | | 6.25 | 12 |
| Percentage | 16.7% | 33.4% | | | 33.4% | 16.7% | | | |

Table 4. MT translation with DeepL.

**Students, n = 31**
Text 3: Inflación subyacente

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors | Mean error |
|---|---|---|---|---|---|---|---|---|---|---|
| Number | 0 | 136 | 7 | 25 | 58 | 56 | 0 | 4.69 | 282 | 9 |
| Percentage | | 48.2% | 2.5% | 8.9% | 20.6% | 19.9% | | | | |

Table 5. Students' MT translation with DeepL followed by light post-editing.

The fact that the students' error mean was slightly lower than the total errors with DeepL may be surprising. A possible reason for this finding could be that students were more confident with using DeepL because this text was the last assignment and they had gained experience throughout the term.

When the Grammar error subcategories were considered, DeepL again showed difficulties with Prepositions, while students struggled with the same subcategories as before, i.e., Syntax, Declension and Prepositions. Interestingly, the figures clearly show that students tended to introduce errors into the MT-text, usually in the categories that are most difficult for them.

The analysis of the remaining four texts in our study[7] yielded similar results in students' Grammar errors in the three main subcategories, a finding that could be accounted for by their insufficient command of the target language. In this regard, MT and post-editing have limitations, although a slight improvement in students' use of MT-tools was noticed in the last text.

## 5. Discussion

Our results indicate that post-editing the outcome of MT can be helpful provided that the translator masters the target language; thus, the use of MT can significantly enhance the quality and consistency of a translation in that case. In this regard, our findings support "research findings that translators are more productive when post-editing" (Cadwell et al., 2018, p. 318). However, if the translator has a poor command of the target language, MT post-edition does not help, and may even lead to impaired results. Our students showed a tendency to "correct" assumed MT-errors, eventually producing worse versions.

The nature of students' errors indicates the grammatical aspects that should be reinforced with the aim of enhancing their linguistic knowledge, with Syntax and Declension appearing as the most frequent error types. However, it should be considered that some errors may have been included into different categories (e.g., an incorrect irregular verb may be due to a poor grammar knowledge or may be a spelling error). It should be noted that the assessment of translation quality errors should be weighed according to the extent they distort communication. Thus, spelling errors that could be caused by typing mistakes would be less important than grammar or terminology errors. The latter ones should be penalized more strictly since they hinder, to a greater extent, the accurate comprehension and/or functional achievement of the text.

On the other hand, it is essential to know the error tendencies of the MT-system used, to better anticipate such errors and compensate for them during the post-editing process. Finally, the context is crucial for a correct translation, and if this is not provided, no current MT can translate accurately. Machine translation is not able "to think outside the box". This also happens with cultural words, intertextual references, degrees of politeness and implicit knowledge. After all, MT is a mechanical process, while human translation is a mental process. We propose that, to acquire knowledge and train the necessary skills, the user should begin by learning to use MT-systems adequately, something easy to do since there are several free online MT-systems available. Once the weaknesses of an MT-system for a given language pair are known, it becomes easier to detect errors and enhance the quality of the target text through a post-editing process.

Several authors have published studies on MT and post-editing (cf. Balling et al., 2014), specially focusing on productivity (words/hour, words/day). However, although important in professional practice, time pressure may be an additional error factor when training students with a poor command of the target language. In our study, students simply had to meet the previously established deadlines. Nevertheless, authors point out that there is "an average time saving of 25% from post-editing machine translation over translation from scratch" (Elming et al., 2014, p. 147). It is our opinion that students, in their expectations about professional practice, should regard MT as a part of the new translation flow, where translators may work as language experts, in tasks like post-editing and correcting human or machine translations. This should not be seen as a complete automation of the translation process, but rather as the use of a helpful tool, bearing in mind that the results will still need revision.

Using MT also has a negative side that should be considered. Svoboda (2017, p. 95); for example, stated:

> Assuming that future MT solutions (including neural MT), to some extent, will be reusing existing language material to become trained, they run the risk of producing and consolidating superficial language. By this we mean a flattened language consisting of a limited number of the most commonly used words and phrases, without the true richness and diversity found in human expressions.

The FIT Europe (2015) expressed similar ideas:

> The translator has to read the warnings and must never use online MT (and even API) with sensitive data, because they are all transferred to the translation memory in order to train it and improve its results; hence the need to warn students on using it in a thoughtless way.

Moreover, it should be pointed out that there is an ethical dimension to the use of MT-systems: it is a translator's/vendor's/buyer's choice whether to use MT or not, and whether to contribute to training a third-party's system with his/her own renderings (Svoboda, 2017, p. 105).

## 6. Conclusions and prospects

ICT-tools are currently a part of the translator's working environment, and they are here to stay. Therefore, we postulate that post-editing machine translated texts should also be a part of translators' training programs (Sánchez-Gijón, 2016, p. 161; Aranberri, 2017, p. 89).

It is essential that future translators learn to use MT with a critical mind, especially when translating into a foreign language. Error counting, description and classification allow teachers to identify those features that require practical or theoretical reinforcement in class. This is especially important when teaching students with a low level of the target language.

Proper use of technological tools may improve the quality of translation. In this context, it seems safe to assume that improvements in MT-technology will eventually lead to the disappearance of the translator profession as it is today (cf. Svoboda 2017, p. 101 ff.). Translation is currently undergoing deep changes, and the professional profiles required by future employers will most probably shift from translators capable of transferring texts from one language to another while conveying the content, intention and cultural elements, to language experts skilled in different tasks such as post-edition, reviewing, layout, re-writing (transcreation), and other possible novel tasks like training translation engines, supervising post-edition quality, working in computational linguistics, etc. Thus, in our opinion, translators do not need to worry about the disappearance of their profession, but instead they should learn to use machine translation to increase their productivity. After all, we walk towards an integration of human and artificial intelligence. We are witnessing the beginning of an artificial intelligence revolution that will influence many areas, including machine translation. To successfully navigate this change and to train competitive translators, we teachers need to adopt a didactic approach that integrates MT and human translation.

In agreement with other authors, like Doherty and Kenny (2014) or Pym (2014), we postulate that better integration of MT and post-editing into translation studies is needed. In our opinion, besides learning to use Computer Assisted Translation (CAT) tools, applications for automatic translation and post-edition of CAT-texts, translators should learn the basics of different MT types and post-edition of MT-texts. In this connection, it should be borne in mind that reviewing someone else's translations and correcting MT errors, peers' errors or one's own errors help translators become aware of translation decisions and gain command of foreign languages.

Because of our reduced sample size, the results and conclusions of this study cannot be extrapolated to the general population. However, they are illustrative of important aspects to be considered in teaching translation students and may serve as a basis for future research. Currently, a new observational study is underway in our research group, aimed at comparing the quality of translation MT with and without post-edition into the translator's mother tongue.

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## NOTES

[1] According to ISO 18587:2017 (2017), MT is defined as "automatic translation of text from one natural language to another using a computer application".

[2] Defined by ISO 18587:2017 (2017) as to "edit and correct machine translation output".

[3] For a better understanding of NMT, see Nitzke & Hansen-Schirra (2021).

[4] Text: «Los desempleados de más de 52 años recuperan el subsidio».

[5] Prag: pragmatics, Gr: grammar, Eq: equivalence, Spell: spelling, Lex/Term: lexicon/terminology, Sty: style, Cult: culture.

[6] «Los desempleados de más de 52 años recuperan el subsidio».

[7] See Annex for the figures and percentages corresponding to all the analyzed texts, including the ones that are not shown in the manuscript: "La inflación baja dos décimas en octubre hasta el 1,6% por los carburantes", "El desempleo en Reino Unido", "La inflación (sin alimentos ni energía) recula una décima en Alemania y da un respiro a Draghi" y "La inflación de Alemania sube en junio hasta el 1,6%".

# APPENDIX

**Text 1: Los desempleados de más de 52 años recuperan el subsidio**

Source: *El Economista*. Economía. October 18, 2017.
https://www.eleconomista.es/economia/noticias/8682005/10/17/Los-desempleados-de-mas-de-52-anos-recuperan-el-subsidio.html

**Google Translate**
Text 1: Los desempleados de más de 52 años recuperan el subsidio

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 7 | 17 | 8 | 1 | 19 | 3 | 1 | 16.6 | 56 |
| Percentage | 12.5% | 30.36% | 14.29% | 1.79% | 33.93% | 5.36% | 1.79% | | |

**Google Translate**
Text 1: Los desempleados de más de 52 años recuperan el subsidio

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | | |
| Syntax | 1 | 5.88% |
| Conjugation | 2 | 11.76% |
| Passive voice | | |
| Pronouns | | |
| Determined/Undetermined articles | 2 | 11.76% |
| Gender | | |
| Punctuation | 3 | 17.65% |
| Conjunctions | 2 | 11.76% |
| Subject omission | 1 | 5.88% |
| Use of tenses | 3 | 17.65% |
| Prepositions | 2 | 11.76% |
| Subjunctive | 1 | 5.88% |

**DeepL**
Text 1: Los desempleados de más de 52 años recuperan el subsidio

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 3 | 8 | 4 | | 7 | 1 | | 6.8 | 23 |
| Percentage | 13.04% | 34.78% | 17.39% | | 30.43% | 4.35% | | | |

**DeepL**
Text 1: Los desempleados de más de 52 años recuperan el subsidio

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | 1 | 12.5% |
| Syntax | 1 | 12.5% |
| Conjugation | | |
| Passive voice | | |
| Pronouns | | |
| Determined/Undetermined articles | 1 | 12.5% |
| Gender | 1 | 12.5% |
| Punctuation | | |

| | | |
|---|---|---|
| Conjunctions | | |
| Subject omission | | |
| Use of tenses | 2 | 25% |
| Prepositions | 2 | 25% |
| Subjunctive | | |

| Students, n = 34<br>Text 1: Los desempleados de más de 52 años recuperan el subsidio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors | Mean error |
| Number | 33 | 475 | 10 | 35 | 232 | 9 | | 6.8 | 794 | 23 |
| Percentage | 4.16% | 59.8% | 1.26% | 4.4% | 29.1% | 1.13% | | | | |

| Students, n = 34<br>Text 1: Los desempleados de más de 52 años recuperan el subsidio | | |
|---|---|---|
| Grammar error subcategory | Number | Percentage |
| Declension | 104 | 21.8% |
| Syntax | 121 | 25.5% |
| Conjugation | 45 | 9.5% |
| Passive voice | 8 | 1.7% |
| Pronouns | 15 | 3.2% |
| Determined/Undetermined articles | 5 | 1.1% |
| Gender | 35 | 7.4% |
| Punctuation | 49 | 10.3% |
| Conjunctions | 10 | 2.1% |
| Subject omission | 2 | 0.4% |
| Use of tenses | 4 | 0.8% |
| Prepositions | 73 | 15.4% |
| Subjunctive | 4 | 0.8% |

**Text 2: La inflación baja dos décimas en octubre hasta el 1,6 % por los carburantes**

Source: *La Vanguardia*. Sociedad. November 14, 2017. https://www.lavanguardia.com/vida/20171114/432880754106/la-inflacion-baja-dos-decimas-en-octubre-hasta-el-16—por-los-carburantes.html

| DeepL<br>Text 2: La inflación baja dos décimas en octubre hasta el 1,6 % por los carburantes | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
| Number | 3 | 2 | | | 1 | | | 4.76 | 6 |
| Percentage | 50% | 33.33% | | | 16.66% | | | | |

**DeepL**
Text 2: La inflación baja dos décimas en octubre hasta el 1,6 % por los carburantes

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | | |
| Syntax | 1 | 50% |
| Conjugation | | |
| Passive voice | | |
| Pronouns | | |
| Determined/Undetermined articles | | |
| Gender | | |
| Punctuation | | |
| Conjunctions | | |
| Subject omission | | |
| Use of tenses | | |
| Prepositions | 1 | 50% |
| Subjunctive | | |

**Students, n = 34**
Text 2: La inflación baja dos décimas en octubre hasta el 1,6 % por los carburantes

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors | Mean error |
|---|---|---|---|---|---|---|---|---|---|---|
| Number | 23 | 106 | 5 | 5 | 15 | | | 3.57 | 154 | 4.5 |
| Percentage | 14.93 % | 68.83 % | 3.25 % | 3.25 % | 9.74 % | | | | | |

**Students, n = 34**
Text 2: La inflación baja dos décimas en octubre hasta el 1,6 % por los carburantes

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | 39 | 37% |
| Syntax | 27 | 25% |
| Conjugation | 7 | 7% |
| Passive voice | 1 | 1% |
| Pronouns | 4 | 4% |
| Determined/Undetermined articles | | |
| Gender | | |
| Punctuation | 5 | 5% |
| Conjunctions | 5 | 5% |
| Subject omission | | |
| Use of tenses | 1 | 1% |
| Prepositions | 17 | 16% |
| Subjunctive | | |

### Text 3: Inflación subyacente

Source: *Expansión*. Economía. July 13, 2017. Second part.
https://www.expansion.com/economia/2017/07/13/59672874268e3eea408b45e6.html

**DeepL**
Text 3: Inflación subyacente

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 2 | 4 | | | 4 | 2 | | 6.25 | 12 |
| Percentage | 16.7% | 33.4% | | | 33.4% | 16.7% | | | |

**DeepL**
Text 3: Inflación subyacente

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | | |
| Syntax | | |
| Conjugation | | |
| Passive voice | | |
| Pronouns | | |
| Determined/Undetermined articles | | |
| Gender | 1 | 25% |
| Punctuation | | |
| Conjunctions | | |
| Subject omission | 1 | 25% |
| Use of tenses | | |
| Prepositions | 2 | 50% |
| Subjunctive | | |

**Students, n = 31**
Text 3: Inflación subyacente

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors | Mean error |
|---|---|---|---|---|---|---|---|---|---|---|
| Number | 0 | 136 | 7 | 25 | 58 | 56 | 0 | 4.69 | 282 | 9 |
| Percentage | | 48.2% | 2.5% | 8.9% | 20.6% | 19.9% | | | | |

**Students, n = 31**
Text 3: Inflación subyacente

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | 30 | 22.1% |
| Syntax | 48 | 35.3% |
| Conjugation | 10 | 7.3% |
| Passive voice | | |
| Pronouns | 8 | 5.9% |
| Determined/Undetermined articles | 4 | 2.9% |
| Gender | 1 | 0.7% |
| Punctuation | 5 | 3.7% |
| Conjunctions | 14 | 10.3% |
| Subject omission | 1 | 0.7% |
| Use of tenses | | |
| Prepositions | 15 | 11.0% |
| Subjunctive | | |

**Text 4: El desempleo en Reino Unido**

Source: *El Economista*. Economía._October 18, 2017. https://www.eleconomista.es/economia/noticias/8682338/10/17/El-desempleo-britanico-se-situa-en-el-43-y-alcanza-nivel-minimo-en-12-anos.html

**DeepL**
Text 4: El desempleo en Reino Unido

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 3 | 6 | 4 | 0 | 3 | 2 | 0 | 4.68 | 18 |
| Percentage | 16.67% | 33.33% | 22.22% | | 16.67% | 11.11% | | | 100% |

**DeepL**
Text 4: El desempleo en Reino Unido

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | 2 | 33.33% |
| Syntax | | |
| Conjugation | | |
| Passive voice | | |
| Pronouns | | |
| Determined/Undetermined articles | | |
| Gender | | |
| Punctuation | | |
| Conjunctions | | |
| Subject omission | | |
| Use of tenses | 3 | 50% |
| Prepositions | | |
| Subjunctive | 1 | 16.67% |

**Students, n = 34**
Text 4: El desempleo en Reino Unido

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors | Mean error |
|---|---|---|---|---|---|---|---|---|---|---|
| Number | 3 | 518 | 6 | 31 | 144 | 15 | | 5.45 | 717 | 21 |
| Percentage | 0.4% | 72.2% | 0.8% | 4.3% | 20.0% | 2.1% | | | 100% | |

**Students, n = 34**
Text 4: El desempleo en Reino Unido

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | 77 | 14.9% |
| Syntax | 132 | 25.5% |
| Conjugation | 18 | 3.5% |
| Passive voice | 1 | 0.2% |
| Pronouns | 71 | 13.7% |
| Determined/Undetermined articles | 29 | 5.6% |
| Gender | 24 | 4.6% |
| Punctuation | 37 | 7.1% |
| Conjunctions | 33 | 6.4% |
| Subject omission | 2 | 0.4% |
| Use of tenses | 13 | 2.5% |
| Prepositions | 50 | 9.7% |
| Subjunctive | 31 | 6.0% |

**Text 5: La inflación (sin alimentos ni energía) recula una décima en Alemania y da un respiro a Draghi**

Source: *Blog de Economía y Finanzas Bankinter*. October 13, 2017. https://www.bankinter.com/blog/lo-ultimo/inflacion-sin-alimentos-energia-recula-una-decima-alemania-respiro-draghi

**DeepL**

Text 5: La inflación (sin alimentos ni energía) recula una décima en Alemania y da un respiro a Draghi

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 2 | 3 | 0 | 0 | 3 | 0 | 0 | 2.09 | 8 |
| Percentage | 25% | 37.5% | | | 37.5% | | | | 100% |

**DeepL**

Text 5: La inflación (sin alimentos ni energía) recula una décima en Alemania y da un respiro a Draghi

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | | |
| Syntax | | |
| Conjugation | | |
| Passive voice | | |
| Pronouns | | |
| Determined/Undetermined articles | | |
| Gender | | |
| Punctuation | | |
| Conjunctions | | |
| Subject omission | | |
| Use of tenses | | |
| Prepositions | 2 | 66.67% |
| Subjunctive | 1 | 33.33% |

**Students, n = 34**

Text 5: La inflación (sin alimentos ni energía) recula una décima en Alemania y da un respiro a Draghi

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors | Mean error |
|---|---|---|---|---|---|---|---|---|---|---|
| Number | | 560 | 44 | 104 | 328 | 16 | | 274.67 | 1052 | 31 |
| Percentage | | 53.23% | 4.18% | 9.89% | 31.18% | 1.52% | | | 100% | |

**Students, n = 34**

Text 5: La inflación (sin alimentos ni energía) recula una décima en Alemania y da un respiro a Draghi

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | 49 | 8.75% |
| Syntax | 118 | 21.07% |
| Conjugation | 48 | 8.57% |
| Passive voice | 19 | 3.39% |
| Pronouns | 11 | 1.96% |
| Determined/Undetermined articles | 16 | 2.86% |
| Gender | 42 | 7.5% |
| Punctuation | 57 | 10.18% |

| | | |
|---|---|---|
| Conjunctions | 43 | 7.68% |
| Subject omission | 12 | 2.14% |
| Use of tenses | 5 | 0.89% |
| Prepositions | 42 | 7.5% |
| Subjunctive | 98 | 17.5% |

**Text 6: La inflación de Alemania sube en junio hasta el 1,6%**

Source: *Expansión*. Economía. July 13, 2017.
https://www.expansion.com/economia/2017/07/13/59672874268e3eea408b45e6.html

**DeepL**
Text 6: La inflación de Alemania sube en junio hasta el 1,6%

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors |
|---|---|---|---|---|---|---|---|---|---|
| Number | 1 | 1 | 2 | | 8 | | | 3.8% | 12 |
| Percentage | 8.3% | 8.3% | 16.7% | | 66.7% | | | | |

**DeepL**
Text 6: La inflación de Alemania sube en junio hasta el 1,6%

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | | |
| Syntax | | |
| Conjugation | | |
| Passive voice | | |
| Pronouns | | |
| Determined/Undetermined articles | | |
| Gender | | |
| Punctuation | | |
| Conjunctions | | |
| Subject omission | | |
| Use of tenses | 1 | 100% |
| Prepositions | | |
| Subjunctive | | |

**Students, n = 34**
Text 6: La inflación de Alemania sube en junio hasta el 1,6%

| Error category[5] | Prag | Gr | Eq | Spell | Lex/Term | Sty | Cult | Error rate | Total errors | Mean error |
|---|---|---|---|---|---|---|---|---|---|---|
| Number | | 237 | 52 | 44 | 162 | 14 | | 4.5 | 509 | 15 |
| Percentage | | 46.56% | 10.22% | 8.64% | 31.83% | 2.75% | | | 100% | |

**Students, n = 34**
Text 6: La inflación de Alemania sube en junio hasta el 1,6%

| Grammar error subcategory | Number | Percentage |
|---|---|---|
| Declension | 17 | 7.17% |
| Syntax | 76 | 32.07% |
| Conjugation | 27 | 11.39% |
| Passive voice | | |

| | | |
|---|---|---|
| Pronouns | 18 | 7.59% |
| Determined/Undetermined articles | 10 | 4.22% |
| Gender | 7 | 2.95% |
| Punctuation | 35 | 14.77% |
| Conjunctions | 16 | 6.75% |
| Subject omission | 4 | 1.69% |
| Use of tenses | 5 | 2.11% |
| Prepositions | 22 | 9.28% |
| Subjunctive | | |