

GovAIEc: A Lexical Complexity Corpus for Spanish in Ecuadorian public documents

Anonymous ACL submission

Abstract

In this article, we present GovAIEc, a new annotated corpus of complex lexicon created with institutional texts in Ecuadorian Spanish, and we detail the process of compiling and annotating this corpus. With the aim of providing a valuable resource to the scientific community to advance research in the field of Lexical Simplification in the Spanish language, we carried out several complex word prediction experiments using this corpus. The complex word labeling process was carried out with a group of annotators with different levels of literacy, in order to ensure a comprehensive evaluation. We use Lexical Complexity metrics as units of analysis, and apply advanced multilingual language models such as XLM-RoBERTa-Base, RoBERTa-large-BNE, XLM-RoBERTa-Large and BERT to evaluate the corpus. This corpus is invaluable for identifying words that represent barriers in the reading comprehension of users who interact with bureaucratic procedures of various entities in Ecuador.

1 Introduction

In recent times, the use of artificial intelligence (AI) has seen a notable increase to address the governance challenges facing cities. Given its advanced capabilities, AI is expected to become a critical resource for local governments in their pursuit of smart and sustainable development (Son et al., 2023). Although the potential of Artificial Intelligence has been widely explored in the private sector, its usefulness in the public sphere is increasingly being recognized by governments themselves, who are adopting AI to strengthen their performance in various areas (Vélez et al., 2022), which includes an important challenge: improving communication between the government and citizens, an aspect that has represented a problem for a long time and is showing significant improvements in user satisfaction (Insapillo Fatama, 2023).

Many individuals encounter significant obstacles in understanding texts related to public administration (Yuan et al., 2023). These challenges may stem from struggles in deciphering lengthy sentences, technical jargon, uncommon terminology, or complex linguistic structures. Such hurdles directly impact individuals with intellectual disabilities or those with limited literacy skills. Even individuals with advanced education, such as university students specializing in various fields of study, may find themselves among those affected by reading difficulties (Alarcón et al., 2020). Public institutions are not exempt from this reality. Frequently, the content of texts directed towards citizens contains vocabulary that is challenging to comprehend, thereby complicating interpretation and the commencement of activities and administrative procedures by users (Roundy et al., 2023).

Reading comprehension is understanding a text in its entirety (Simanjuntak et al., 2024). For many people, the way a text is written can become an obstacle to understanding its content (Saggion et al., 2015). It is essential to note that complex words can present significant challenges, as their meaning is often intrinsically linked to context and cannot be easily deduced (Zaharia et al., 2021). The presence of infrequent or unknown words in the content of the texts significantly hinders the reader’s understanding (North et al., 2023).

Predicting which terms may be difficult to understand for a specific group of people is known as complex word identification (CWI) (Shardlow et al., 2020). The identification of complex words involves the detection of terms within documents that could present difficulties or be confusing to understand for individuals belonging to certain groups (Rico-Sulayes, 2020).

The main purpose of public companies is to provide high-quality services to citizens. In Ecuador, specifically in the city of Guayaquil, various state institutions such as such as: 1) *Illustrious Municipi-*

041
042
043
044
045
046
047
048
049
050
051
052
053
054
055
056
057
058
059
060
061
062
063
064
065
066
067
068
069
070
071
072
073
074
075
076
077
078
079
080
081

082 *pality of Guayaquil (GMO)*¹. 2) *The Internal Revenue Service (IRS)*². 3) *The National Telecommunications Corporation (NTC)*³. 4) *The National Electoral Council (NEC)*⁴. 5) *The Municipal Transit Authority (MTA)*⁵. These institutions have the responsibility of informing users about the available services and their improvements, as well as facilitating the necessary administrative procedures through various processes that must be completed by users. These institutions have a large number of users and are the ones in which we have carried out this research.

094 The objective of this research is to provide an essential resource to advance the study of Lexical Simplification, specifically in the identification of complex words in Spanish texts issued by various Ecuadorian public institutions. Our corpus has been annotated and evaluated by applying complexity metrics for Spanish. Additionally, we have conducted experiments using Transformers-based language models, evaluating their performance with common error metrics. The contributions of this research can be summarized as follows:

- 105 • A new corpus consists of 1,500 texts in Spanish which we have called *GovAIEc*. The texts that make up this corpus come from various sources of Ecuadorian public service institutions. A total of 7,813 complex words identified and a total of 12,095 annotations.
- 111 • The corpus has been evaluated by lexical complexity metrics for Spanish.

¹Illustrious Municipality of Guayaquil (GMO). The Municipal Palace of Guayaquil, also known as the Porteño town Council or simply as the Municipality, is the headquarters of the Very Illustrious Municipality of the city, that is, the Municipal Council and Mayor's Office of Guayaquil. - Available on <https://www.guayaquil.gob.ec/>

²Internal Revenue Service (IRS). The Internal Revenue Service is an autonomous body of the State of Ecuador, whose main function is the administration of taxes, based on a taxpayer database. Available on <https://www.sri.gob.ec/web/intersri/home>

³National Telecommunications Corporation (NTC). The National Telecommunications Corporation, is an Ecuadorian state telecommunications company, operating local, regional and international fixed telephone services, standard and high-speed internet access. Available on <https://www.cnt.com.ec/>

⁴National Electoral Council (NEC). The National Electoral Council of the Republic of Ecuador is the highest voting body in the country. - Available on <https://www.cne.gob.ec/>

⁵Municipal Transit Authority (MTA). The Municipal Public Company of Transit and Mobility of Guayaquil, better known simply as the Transit and Mobility Agency. - Available on <https://www.atm.gob.ec/>

- We calculated 23 linguistic features, which we combined with the encodings generated by the models based on the Transformers architecture: XLM-RoBERTa-Base, RoBERTa-large-BNE, XLM-RoBERTa-Large and BERT, with the purpose of evaluating the results obtained in our research and determining whether they support or contradict the statement formulated in our hypothesis.

Our hypothesis “The implementation of Large-scale Language Models that combine features of diverse nature, such as linguistic features and encodings, leads to better model performance, resulting in higher accuracy in both prediction and identification of complex words”.

The rest of the article is organized as follows:

Section 2 describes the work related to lexical simplification focused on systems based on lexical complexity metrics for Spanish and on linguistic models. Section 3, introduce to *GovAIEc* corpus and the annotation process. Section 4, presents the experimentations and results and analysis on them. Section 5, summarizes main contributions and provides some insights on future work.

2 Related Works

Previous studies on Spanish corpora creation for complex word identification can be categorized into two sections. The first section encompasses works offering background, context, and theoretical foundations, underscoring the relevance and originality of our research. The second section focuses on studies applying Lexical Complexity Measures in Spanish.

2.1 Corpora for lexical complexity in Spanish

Pitkowski and Gamarra (2009) defines a *corpus* as an extensive collection of texts, whether written or oral, containing millions of words in electronic format. An annotated *corpus* is a fundamental resource for any Natural Language Processing (NLP) task (Quevedo-Marcos, 2020).

The development of effective Natural Language Processing (NLP) tools relies heavily on the existence of large annotated corpora of texts. Although annotated corpora in English are common, extensive corpora in Spanish are less frequent. Furthermore, corpora available in Spanish often lack the necessary annotations to facilitate the development of beneficial tools (Davidson et al., 2020). Creating an annotated corpus is a time-consuming process.

162 Furthermore, even with human annotation, discrep- 212
163 ancies can arise between annotators or within the 213
164 same annotator, which could compromise the qual- 214
165 ity of the corpus. Therefore, a lack of supervision 215
166 in the annotation process can result in a low-quality 216
167 corpus (García-Díaz et al., 2020). 217

168 Saggion et al. (2015) presented the results of the 218
169 Simplext project, focused on the automatic simplifi- 219
170 cation of texts in Spanish. This modular system fo- 220
171 cused on syntactic and lexical simplification, based 221
172 on the analysis of a manually simplified corpus 222
173 for people with special needs. They carried out an 223
174 evaluation using Spanish readability metrics, such 224
175 as the lexical and sentence complexity index pro- 225
176 posed by Anula (2008), as well as the readability 226
177 of Spanish according to Spaulding (1956). 227

178 In his research, Segura-Bedmar and Martínez 228
179 (2017) used the corpus *EasyDPL* (Easy Drug Pack- 229
180 age Leaflets), which consists of 306 leaflets written 230
181 in Spanish. These brochures are manually anno- 231
182 tated with 1,400 adverse effects of medications and 232
183 their simplest synonyms, since patients often have 233
184 problems understanding the sections that describe 234
185 the dosage (dosage amount and prescription), con- 235
186 traindications, and adverse reactions to the medica- 236
187 tion providing an automated approach that helped 237
188 pharmaceutical companies write drug package in- 238
189 serts in easy-to-understand language. 239

190 Ortiz-Zambrano and Montejo-Ráez (2017) de- 240
191 veloped the VYTEDU corpus (Videos and Tran- 241
192 scriptions for research in the Educational field) in 242
193 Spanish, obtained from the transcriptions of videos 243
194 recorded during university classes. For its construc- 244
195 tion, 55 videos were filmed during classes of dif- 245
196 ferent careers at the University of Guayaquil. The 246
197 system incorporates indicators selected by Saggion 247
198 et al. (2015) and applies the seven metrics of lex- 248
199 ical complexity for Spanish, which allowed them 249
200 to analyze the complexity of the text at different 250
201 levels, such as the lexical and sentence complexity 251
202 index. 252

203 The annotated corpus known as *VYTEDU-CW* 253
204 was introduced by Ortiz Zambrano et al. (2019). 254
205 This corpus arises from the process of identifying 255
206 and labeling complex words in the Spanish texts of 256
207 the VYTEDU corpus, carried out by students from 257
208 various disciplines at the University of Guayaquil. 258
209 This resource was offered to the participants of 259
210 the ALexS 2020 workshop (Lexical Analysis at 260
211 SEPLN 2020⁶) as part of the second edition of 261

⁶SEPLN 2020 - Available on <http://sepln2020.sepln>.

IberLEF 2020⁷

Zambrano and Montejo-Ráez (2021) introduces
*CLexIS*², a new annotated corpus in Spanish aimed
at researching complex words in computational
studies. Seven textual complexity metrics were
used to evaluate the complexity of the texts. Fur-
thermore, as a point of reference, two experiments
were carried out to predict word complexity: one
using a supervised learning approach and another
using an unsupervised approach based on word
frequency in a general corpus.

Ferrés and Saggion (2022) introduced ALEXSIS,
the initial dataset designed to assess lexical sim-
plification in Spanish. This data set incorporated
potentially valuable details for lexical simplicity
ranking and provided a higher average number of
unique synonyms. “ALEXISIS facilitated a com-
parison of several neural methods”, including their
adaptation of LSBert to Spanish, along with other
neural approaches that rely on pre-trained.

Alarcon et al. (2023) introduced the EASIER cor-
pus, a valuable source that facilitates the construc-
tion of lexical simplification methods to process
texts in Spanish, regardless of their specific domain.
This corpus is composed of 260 documents, metic-
ulously annotated with 8,155 words identified as
complex and 5,130 words that have at least one
contextually suggested synonym. To guarantee the
reliability of the corpus, an agreement test between
annotators was carried out, yielding a Fleiss Kappa
coefficient of 0.641, indicating moderate consis-
tency.

Ortiz Zambrano et al. (2023) introduced *LegalEc*,
a novel corpus annotated with complex lexicon de-
rived from legal content in Ecuadorian Spanish.
They also outlined the compilation and annotation
process in detail. To establish baseline cases for
the scientific community, several experiments pre-
dicting complex words were conducted on this cor-
pus. They extracted 23 linguistic features, which
were combined with encodings generated by mod-
els like XLM-RoBERTa and RoBERTa-BNE from
the MarIA project. Evaluation results demonstrated
a significant enhancement in lexical complexity pre-

[org/index.php/iberlef/](http://index.php/iberlef/)

⁷IberLEF 2020: Iberian Language Evaluation Forum.
Available on <https://ceur-ws.org/Vol-2664/>.
Proceedings of the Iberian Languages Evaluation Forum (Iber-
LEF 2020) co-located with 36th Conference of the Spanish
Society for Natural Language Processing (SEPLN 2020) -
Available on <https://ceur-ws.org/Vol-2664/>.
Track 1: Lexical Analysis at SEPLN (ALexS). ALexS 2020:
Lexicon Analysis Task @ SEPLN (Ortiz-Zambrano and
Montejo-Ráez, 2020)

diction with the amalgamation of these linguistic features.

Sierra et al. (2024) presented a valuable resource in the form of an aligned parallel corpus consisting of Spanish Bible translations. This corpus comprises 11 translations of the Bible into Spanish, spanning different centuries and geographic regions, including Spain and Latin America, and representing various religious denominations, such as Protestants and Catholics. This corpus provides a valuable tool for various linguistic analyses, such as the detection of paraphrases, semantic clustering and the exploration of possible biases present in the texts specified for monolingual studies.

2.2 Measures of Lexical Complexity for Spanish

A strong indicator of writing quality lies in the use of a measure of lexical complexity, which encompasses the size, variety, and quality of vocabulary (Crossley et al., 2012). Another method to determine the lexical complexity of words in Spanish is based on the metrics proposed by Anula (2008) and Spaulding (1956). These metrics have been used in research on the simplification of texts in Spanish, such as the work carried out by Saggion et al. (2015), Ortiz-Zambrano and Montejo-Raéz (2017), Zambrano and Montejo-Raéz (2021), Ortiz Zambrano et al. (2023) among other notable examples. The formulas were proposed by Anula (2008) except the SSR formula corresponds to Spaulding (1956). For better understanding, the Table 1 shows the definition of the variables.

LC: The Lexical Complexity Index.

LDI: Lexical Distribution Index.

ILFW: Index of Low Frequency Words.

SSR: Spaulding’s Spanish Readability Index.

SCI: The Sentence Complex Index.

ASL: The Average Sentences Length.

CS: The Percentage of Complex Sentence.

We have added:

ARI: Automated Readability Index.

PM: Punctuation Mark.

$$LC = (LDI + ILFW)/2 \quad (1)$$

$$LDI = N_{dcw}/N_s \quad (2)$$

$$ILFW = N_{lfw}/N_{cw} * 100 \quad (3)$$

Variable	Total number of...
N_w	words
N_{cw}	content words
N_{dcw}	distinct content words
N_{rw}	rare words
N_{lfw}	frequent words
N_s	sentences
N_{cs}	complex sentences
	... per document

Table 1: Definition of the columns in Table 2.

$$SSR = 1.609N_w/N_s + 331.8N_{rw}/N_w + 22.0 \quad (4)$$

$$SCI = (ASL + CS)/2 \quad (5)$$

$$ASL = N_w/N_s \quad (6)$$

$$CS = N_{cs}/N_s \quad (7)$$

3 The GovAIEc corpus

GovAIEc provides a collection of 1,500 texts obtained mainly from two sources: notifications and instructions for administrative procedures that users receive through emails or find on the websites of public institutions. GovAIEc has a total of 7,813 complex words identified and a total of 12,095 annotations. The objective of GovAIEc is to contribute to research on the identification of complex words in state documents of Ecuador, specifically from public institutions with the largest number of users. This corpus is invaluable for two fundamental reasons. Firstly, it makes it possible to identify terms that hinder the understanding of readers who participate in administrative processes of various organizations. Secondly, it provides a valuable resource for the scientific community, allowing progress in research within the field of Lexical Simplification in the Spanish language.

For the construction of the data set, we followed the format of the data set provided by the SemEval-2021⁸ competition, for the proposal of the Task 1⁹: Lexical Complexity Prediction; and the efforts made in creating labeled corpora for research on complex word identification (Shardlow et al., 2020), (Zambrano and Montejo-Raéz, 2021),

⁸SemEval-2021 - The 15th International Workshop on Semantic Evaluation. Available on <https://semeval.github.io/SemEval2021/>

⁹SemEval 2021- Task 1: Lexical Complexity Prediction. Available on <https://semeval.github.io/SemEval2021/tasks>

341	(Ortiz Zambrano et al., 2023).		
342			
343	Each sample of the GovAIEc data set contains		
344	the following fields:		
345	• Id: The identification number of each record.		
346	• Source: The description of the source where		
347	the text comes from, that is, of the public in-		
348	stitution.		
349	• Sentence: The set of words for which com-		
350	plexity was needed to be measured.		
351	• Token: The word identified as complex for		
352	the annotator to understand. The only word		
353	needed to measure complexity.		
354	• Complexity: It is the level of complexity of		
355	the word whose value is within the range [0,		
356	1].		
357	• Features: To strengthen the data set, a set of		
358	23 linguistic features was included and com-		
359	puted for each sentence. Zeng et al. (2024)		
360	refers to linguistic features as indicators used		
361	to describe the linguistic properties of texts.		
362	The linguistic features that we have calcu-		
363	lated correspond to the works presented by		
364	(Shiroyama, 2022), (Ronzano et al., 2016),		
365	(Shardlow et al., 2020), (Paetzold, 2021), Mos-		
366	quera (2021), (Desai et al., 2021), (Shiroyama,		
367	2022)		
368	1. The absolute frequency .	15. The number of hyperonyms.	387
369	2. The number of characters of the token.	16. The number of nouns, singular or mas-	388
370	3. The relative frequency of the word before	sive.	389
371	the token.	17. The number of auxiliaries verbs.	390
372	4. The relative frequency of the word after	18. The number of adverbs.	391
373	the token.	19. The number of symbols.	392
374	5. The relative frequency of the token.	20. The number of numeric expressions.	393
375	6. The number of syllables.	21. The number of verbs.	394
376	7. The position of the target word in the	22. The number of nouns.	395
377	sentence.	23. The number of pronouns.	396
378	8. Number of words in sentence.		
379	9. The number of characters in the word		
380	before the token.		
381	10. The number of characters in the word		
382	after the token.		
383	11. The Part Of Speech category.		
384	12. Lexical diversity.		
385	13. The number of synonyms.		
386	14. The number of hyponyms.		
		3.1 Annotation Process	397
		3.1.1 Description of the annotation system	398
		A graphical user interface (GUI) was created using	399
		the Tkinter library, designed to offer an intuitive	400
		and easy-to-use experience to users of the annota-	401
		tion system. The user had to select the words that	402
		were difficult to understand and assign them a level	403
		of complexity, which could be neutral, difficult	404
		or very difficult. This interface provided various	405
		functionalities related to the research processes,	406
		including user registration, complex word identi-	407
		fication, linguistic feature extraction, and data set	408
		generation.	409
		3.1.2 Labelers selection criteria	410
		For the selection process of users in charge of tag-	411
		ging complex words in public texts, a total of 30	412
		users who had carried out processes in the institu-	413
		tions mentioned in the 1 section were chosen.	414
		A selection criterion was established based on	415
		the academic level of the users made up of young	416
		people, adults, and older adults: 10 users were	417
		selected, equally distributed between men and	418
		women, that is, 5 men were chosen and 5 women.	419
		In this way, the representation of users with a ba-	420
		sic or lower academic level was guaranteed, these	421
		being people who only finished school or dropped	422
		out, made up of young people, adults, and older	423
		adults. Likewise, another 10 users with a medium	424
		academic level were selected, we refer to those	425
		users who finished secondary school as high school	426
		graduates; and 10 additional users with a university	427
		academic level or higher.	428
		4 Results	429
		Several experiments were carried out for the eval-	430
		uation of the GovAIEc corpus to demonstrate its	431
		relevance and usefulness. Details the order of exe-	432
		cutions:	433

434 *Firstly:* We apply the Lexical Complexity met- 483
435 rics for Spanish to the GovAIEc corpus. 484

436 *Second:* The application of the Fleiss-Kappa 485
437 Coefficient as a measure of agreement to evaluate 486
438 the consistency of annotations. 487

439 *Third:* Evaluation applying LLMs, specif- 488
440 ically: XLM-RoBERTa-Base, RoBERTa-large- 489
441 BNE, XLM-RoBERTa-Large and BERT. 490

442 **4.1 Lexical Complexity Variables for Spanish**

443 It was necessary to calculate the lexical complex- 493
444 ity variables for Spanish in order to subsequently 494
445 obtain the corpus statistics. 495

446 Some statistics on the corpus texts are presented 496
447 in Table 2, while the definition of the variables is 497
448 shown in table 1. It is notable that the number of 498
449 rare words (N_{rw}) is considerably greater than that 499
450 of less frequent words (N_{lfw}). 500

451 Table 3 presents several examples of the words 501
452 identified and annotated as complex in the corpus 502
453 during the GovAIEc tagging process. 503

454 **4.2 Inter-annotator Agreement**

455 A total of 7,813 complex words identified and a 504
456 total of 12,095 annotations in the 1,500 texts that 505
457 make up the GovAIEc corpus were labeled by the 506
458 annotators when reviewing the public texts of the 507
459 GovAIEc corpus. 508

460 Below are some examples of the complex words 509
461 noted by three taggers: *jurisdiction, hierarchiza-* 510
462 *tion, climatological, apprehended, aquaplaning.* 511

463 Some examples of the words noted by 2 taggers 512
464 were: *sporadic, scheduling, certification, homolo-* 513
465 *gation, stirrups, therapeutic.* 514

466 Other examples of the words selected by 1 anno- 515
467 tator: *emanated, regulations, regulations, legaliza-* 516
468 *tion, will establish, preservation.* 517

469 We applied the Fleiss-Kappa coefficient as a 518
470 measure of agreement to evaluate the consistency 519
471 of annotations made by multiple taggers. We ob- 520
472 tained a value of 0.165, which, according to the ref- 521
473 erence table, indicates a slight level of agreement. 522
474 It is important to highlight that the annotators were 523
475 users of the mentioned public institutions and came 524
476 from various academic levels. This means that for 525
477 some, ignorance of certain terminology may have 526
478 complicated the understanding of the notifications 527
479 or the understanding according to the instructions 528
480 of the steps necessary to carry out a certain bu- 529
481 reaucratic procedure in certain state institutions in 530
482 Ecuador. 531

483 The table 4 shows the number of annotations 484
485 made by the annotators in each category. It is ob- 486
487 served that the annotators of the low academic level 487
488 have made more annotations compared to those of 488
489 the medium level. On the other hand, scorers at 489
490 the middle level have made fewer annotations in 490
491 relation to those at the previous level. Furthermore, 491
492 the annotators of the high level have recorded a 492
493 smaller number of complex words compared to the 493
494 annotators of the previous groups. 494

495 **4.3 Application of complexity measures for** 493 496 **Spanish** 494

495 In the second phase of results, we evaluate the 495
496 GovAIEc corpus using seven complexity measures 496
497 for Spanish detailed in detail in the section 2.2. See 497
498 Table 5. 498

499 The application of the LC metric has been fun- 499
500 damental to evaluate the quality of the texts by 500
501 analyzing their level of lexical complexity within 501
502 the GovAIEc corpus. We have obtained an average 502
503 value of 28.87, which indicates considerable com- 503
504 plexity in the evaluated texts, which corresponds 504
505 to various aspects, such as lexical diversity, the 505
506 length of the words and the breadth of the vocabu- 506
507 lary present in each text. Another relevant result to 507
508 highlight is the average obtained through the ASL 508
509 (Average Sentence length) metric, which reveals 509
510 the complexity of the texts based on the average 510
511 length of the sentences. The value of 40.43 is the 511
512 average value referring to the number of words 512
513 per sentence, indicating greater complexity and dif- 513
514 ficulty in understanding the texts, especially for 514
515 those readers with limited linguistic skills. 515

516 **4.4 Evaluation applying LLMs**

517 In this study, to meet our ultimate goal of evaluat- 517
518 ing the GovAIEc corpus, models known for their 518
519 robustness and effectiveness in investigating lexi- 519
520 cal complexity in Spanish texts were used, such 520
521 as XLM-RoBERTa-Base, RoBERTa-large-BNE, 521
522 XLM-RoBERTa-Large and BERT. these models 522
523 have been widely used to create state-of-the-art so- 523
524 lutions for numerous tasks (Paetzold, 2021). These 524
525 models were trained and evaluated using the Go- 525
526 vAIEc corpus in Spanish. 526

527 Executions were carried out with each of the 527
528 models, applying 30, 50, 70 and 100 epochs. These 528
529 experiments are part of a series aimed at explor- 529
530 ing different approaches. Our strategy focuses on 530
531 integrating the 23 linguistic features of the corpus 531
532 with the encodings generated by previously trained 532

The Statistics of GovAIEc

	N_{chrs}	N_w	N_{dcw}	N_{cw}	N_{lfw}	N_{rw}	N_s	N_{cs}
Mode	197.00	38.00	29.00	19.00	5.00	20.00	1.00	0.00
Median	250.00	44.00	34.00	24.00	6.00	23.00	1.00	1.00
Mean	278.00	49.37	36.94	26.75	6.97	25.18	1.31	0.55
Std.Dev	118.17	21.66	12.48	11.14	3.57	10.79	0.59	0.59
Min	93.00	15.00	12.00	9.00	0.00	7.00	1.00	0.00
Max	1024.00	192.00	105.00	96.00	26.00	84.00	5.00	3.00

Table 2: Descriptive Statistics of different counters over documents in GovAIEc.

Words tagged by the annotators in the texts of the corpus GovAIEc

ID	Sentence	Complexity
CNE-3432	La Secretaría General del Consejo Nacional Electoral - CNE [...] remitir a la Dirección Nacional de Organizaciones Políticas, que será la encargada de emitir el informe correspondiente, [...]	0.33
CNT-4334	La CNT EP, no cobrará ningún valor por las reparaciones de los daños producidos entre la central y la caja de dispersión inclusive si el daño se localiza entre la caja de dispersión y el aparato [...]	1.00
ATM-0097	De no haberse efectuado la aprehensión del o los vehículos [...] [...] el agente fiscal podrá solicitar al Juez de Tránsito disponga las [...] cautelares pertinentes para la práctica de las mencionadas [...].	1.00
SRI-7274	De acuerdo a lo señalado en el Código Tributario Artículo 153 (Plazos para el pago), el porcentaje para el pago de la primera cuota siempre será del 20% de la obligación tributaria, por lo que este [...]	0.33
6613	Retiro Temporal, con el que debe acudir a la Ventanilla # 38 [...]	

Table 3: Examples of words tagged by the annotators in the texts of the GovAIEc corpus.

Agreement between labelers

PI	Low Academic level		Middel Academic level		University Academic level	
	women taggers	men taggers	women taggers	men taggers	women taggers	men taggers
MTA	467	598	457	346	420	317
NEC	551	963	511	452	290	387
NTC	547	541	363	484	246	451
GMO	562	653	442	318	164	295
IRS	348	209	188	189	163	173
# tagged words	2475	2964	1961	1789	1283	1623

Table 4: Analysis of the degree of agreement between the annotators in relation to the academic level.

models. The objective is to evaluate whether this combination provides satisfactory answers to our research hypothesis.

We have carried out experiments without tuning the encoders, using only pre-trained models. Runs were performed to determine whether combining linguistic features (LF) represents an improvement over full end-to-end approaches. Integrating lin-

guistic features involves concatenating them, after applying min-max scaling, with the embeddings resulting from the last encoding layer, and before reaching the classification header. See Figure 1.

The table 6 shows the results of the executions with the different models. We have evaluated the results based on the mean absolute error (MAE). We observe that the BERT model, particu-

Lexical Complexity Metrics for Spanish in GovAIEc

	LDI	ILFW	LC	SSR	ASL	CS	SCI	ARI	PM
Mode	29.00	33.33	27.00	244.80	38.00	0.00	19.00	19.16	3.00
Median	29.00	27.07	28.51	256.65	38.00	0.29	19.00	24.22	4.00
Mean	30.67	27.07	28.87	258.17	40.43	0.44	0.43	25.53	4.46
Std.Dev	11.04	11.00	7.25	33.47	16.83	0.46	8.46	8.44	2.83
Min	6.00	0.00	7.5	148.28	8.67	0.00	4.5	6.63	1.00
Max	96.00	76.92	58.41	464.25	177.00	1.00	89.00	94.31	23.00

Table 5: Results of the application of lexical complexity metrics for Spanish in corpus GovAIEc.

Spanish Language Model pre-trained with GovAIEc

with 50 epochs				
Model	MAE	MSE	RMSE	R2
XLM-RoBERTa-Large	0.20618	0.05533	0.23521	-0.00692
XML-RoBERTa-Large \oplus LF	0.19824	0.06221	0.24943	-0.11003
RoBERTa-Large-BNE	0.21077	0.05623	0.23712	-0.00321
RoBERTa-Large-BNE \oplus LF	0.20399	0.05112	0.22610	0.02651
XML-RoBERTa-BASE	0.16807	0.06074	0.24645	-0.09903
XML-RoBERTa-BASE \oplus LF	0.19492	0.04825	0.21966	0.09482
BERT	0.14641	0.05374	0.23181	0.01266
BERT \oplus LF	0.14777	0.05151	0.22697	0.01875

Table 6: Results of the pre-trained models applying 50 epochs.

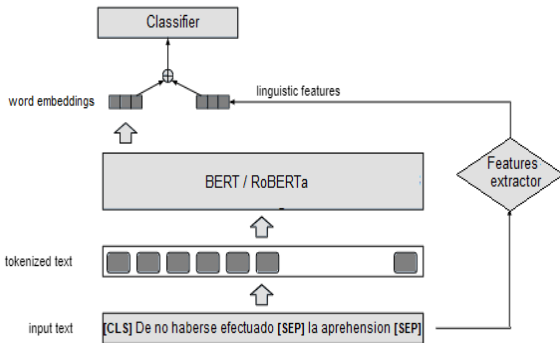


Figure 1: Process flow methodology integrating linguistic features.

larly its Spanish-adapted variant known as BERT BASE Spanish wwm uncased, offers superior performance compared to other models. This optimal performance was achieved with 50 execution epochs. It should be noted that the wholeword masking technique applied in this model contributes to its effectiveness. An interesting finding is that by incorporating the 23 additional linguistic features into the data set, even better results are obtained with the same BERT model.

5 Conclusions and Recommendations

To ensure the quality and reliability of the corpus, we carried out a comprehensive evaluation. We

used measures of complexity and readability, as well as the Fleiss-Kappa coefficient to assess agreement between annotators. In addition, we perform performance tests on models based on the Transformers architecture, trained with the corpus, to validate their effectiveness in identifying complex words in Ecuadorian public documents.

The lexical complexity metrics for Spanish demonstrated that the terminology used in texts addressed to users, both in notifications and in bureaucratic processes, becomes a difficulty for recipients to understand state documents and their implications.

The experiments revealed a significant improvement in the performance of the models when integrating linguistic features obtained from the texts. Furthermore, the evaluation results indicated that the combination of these features contributes to improving the prediction of lexical complexity.

Based on the findings of this research, we recommend promoting more agile, open and innovative governments through the use of emerging technologies such as artificial intelligence and accessible websites. These technologies can improve the efficiency of government processes by facilitating the understanding of the content of public documents, which in turn guarantees the quality of services offered to citizens.

6 Limitations

The restrictions and challenges that result from the applicability of our work are:

Corpus timing:

The corpus is constructed from texts from a specific time period, which may not reflect changes in language and terminology over time. The evolution of institutional language and the emergence of new terminologies may not be represented.

Diversity of Sources:

The sources of the texts focus on a specific context, which is the government sphere. The corpus is limited to documents from certain Ecuadorian public institutions, the results could vary in other contexts.

Annotation Quality:

The annotation process for complex words may be subject to human error or tagger bias. Of course, annotators could have different criteria for identifying complex words, which could affect the consistency of the corpus.

Complexity Criteria:

The criteria used according to other research carried out to define and measure the complexity of words may not capture all dimensions of lexical complexity due to contextual, cultural or context- and language-specific factors, in our case although the language is Spanish and the public study institutions are Ecuadorian, these factors could influence the perception of complexity and not be fully considered.

Data Access and Use:

Access to certain documents sent to users through notifications by public institutions could be restricted for reasons of privacy or confidentiality, which would limit the inclusion of certain types of texts in the corpus.

Applicability of Results:

The results derived from this study may not be easily generalizable and applicable to other languages or dialects of Spanish. Regional linguistic variability could limit the generalizability of the conclusions.

References

- Rodrigo Alarcón, Lourdes Moreno, and Paloma Martínez. 2020. Hulat-alex's cwi task-cwi for language and learning disabilities applied to university educational texts. In *IberLEF@ SEPLN*, pages 24–30. 641–647–643–644–645
- Rodrigo Alarcon, Lourdes Moreno, and Paloma Martínez. 2023. Easier corpus: A lexical simplification resource for people with cognitive impairments. *Plos one*, 18(4):e0283622. 646–647–648–649
- Alberto Anula. 2008. Lecturas adaptadas a la enseñanza del español como l2: variables lingüísticas para la determinación del nivel de legibilidad. *La evaluación en el aprendizaje y la enseñanza del español como LE L*, 2:162–170. 650–651–652–653–654
- Scott A. Crossley, Tom Salsbury, and Danielle S. McNamara. 2012. Predicting the proficiency level of language learners using lexical indices. *Language Testing*, 29(2):243–263. 655–656–657–658
- Sam Davidson, Aaron Yamada, Paloma Fernandez Mira, Agustina Carando, Claudia H Sanchez Gutierrez, and Kenji Sagae. 2020. Developing nlp tools with a new corpus of learner spanish. In *Proceedings of the 12th language resources and evaluation conference*, pages 7238–7243. 659–660–661–662–663–664
- Abhinandan Tejalkumar Desai, Kai North, Marcos Zampieri, and Christopher Homan. 2021. [LCP-RIT at SemEval-2021 task 1: Exploring linguistic features for lexical complexity prediction](#). In *Proceedings of the 15th International Workshop on Semantic Evaluation (SemEval-2021)*, pages 548–553, Online. Association for Computational Linguistics. 665–666–667–668–669–670–671
- Daniel Ferrés and Horacio Saggion. 2022. [ALEXIS: A dataset for lexical simplification in Spanish](#). In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 3582–3594, Marseille, France. European Language Resources Association. 672–673–674–675–676
- José Antonio García-Díaz, Ángela Almela, Gema Alcaraz-Mármol, and Rafael Valencia-García. 2020. Umucorpusclassifier: Compilation and evaluation of linguistic corpus for natural language processing tasks. *Procesamiento del Lenguaje Natural*, 65:139–142. 677–678–679–680–681–682
- Milagros del Pilar Insapillo Fatama. 2023. Implementación de chatbot con inteligencia artificial para el mejoramiento del sistema helpdesk en el gobierno regional loreto, iquitos 2023. 683–684–685–686
- Alejandro Mosquera. 2021. Alejandro mosquera at semeval-2021 task 1: Exploring sentence and word features for lexical complexity prediction. In *Proceedings of the 15th International Workshop on Semantic Evaluation (SemEval-2021)*, pages 554–559. 687–688–689–690–691
- Kai North, Marcos Zampieri, and Matthew Shardlow. 2023. Lexical complexity prediction: An overview. *ACM Computing Surveys*, 55(9):1–42. 692–693–694

695	Jenny Ortiz-Zambrano and Arturo Montejó-Ráez. 2017.	Isabel Segura-Bedmar and Paloma Martínez. 2017. Sim-	749
696	Vytedu: Un corpus de vídeos y sus transcripciones	plifying drug package leaflets written in spanish by	750
697	para investigación en el ámbito educativo.	using word embedding. <i>Journal of biomedical se-</i>	751
		<i>mantics</i> , 8(1):1–9.	752
698	Jenny Ortiz-Zambrano and Arturo Montejó-Ráez. 2020.	Matthew Shardlow, Michael Cooper, and Marcos	753
699	Overview of alexs 2020: First workshop on lexical	Zampieri. 2020. CompLex — a new corpus for lex-	754
700	analysis at sepln. In <i>Proceedings of the Iberian Lan-</i>	ical complexity prediction from Likert Scale data .	755
701	<i>guages Evaluation Forum (IberLEF 2020)</i> , volume	In <i>Proceedings of the 1st Workshop on Tools and</i>	756
702	2664, pages 1–6.	<i>Resources to Empower People with REAding Dif-</i>	757
703	Jenny Ortiz Zambrano, Arturo MontejóRáez,	<i>ficulties (READI)</i> , pages 57–62, Marseille, France.	758
704	Katty Nancy Lino Castillo, Otto Rodrigo	European Language Resources Association.	759
705	Gonzalez Mendoza, and Belkis Chiquinquirá		
706	Cañizales Perdomo. 2019. Vytedu-cw: Difficult	Tomotaka Shiroyama. 2022. Comparing lexical com-	760
707	words as a barrier in the reading comprehension of	plexity using two different ve modes: a pilot study.	761
708	university students. In <i>The International Conference</i>	<i>Intelligent CALL, granular systems and learner data:</i>	762
709	<i>on Advances in Emerging Trends and Technologies</i> ,	<i>short papers from EUROCALL 2022</i> , page 358.	763
710	pages 167–176. Springer.		
711	Jenny Alexandra Ortiz Zambrano, César Espin-Riofrio,	Gerardo Sierra, Gemma Bel-Enguix, Ameyali Díaz-	764
712	and Arturo Montejó Ráez. 2023. Legalec: A new	Velasco, Natalia Guerrero-Cerón, and Núria Bel.	765
713	corpus for complex word identification research in	2024. An aligned corpus of spanish bibles. <i>Lang-</i>	766
714	law studies in ecuatorian spanish.	<i>guage Resources and Evaluation</i> , pages 1–31.	767
715	Gustavo Paetzold. 2021. Utfpr at semeval-2021 task 1:	Syahdani Azhara Simanjuntak, Dian Fajrina, Nurul In-	768
716	Complexity prediction by combining bert vectors and	ayah, and Saiful Marhaban. 2024. The correlation	769
717	classic features. In <i>Proceedings of the 15th Interna-</i>	between students’ vocabulary knowledge and reading	770
718	<i>tional Workshop on Semantic Evaluation (SemEval-</i>	comprehension outcome. <i>Research in English and</i>	771
719	<i>2021)</i> , pages 617–622.	<i>Education Journal</i> , 9(1):10–17.	772
720	Elena Fabiana Pitkowski and Javier Vásquez Gamarra.	Tim Heinrich Son, Zack Weedon, Tan Yigitcanlar,	773
721	2009. El uso de los corpus lingüísticos como her-	Thomas Sanchez, Juan M. Corchado, and Rashid	774
722	ramienta pedagógica para la enseñanza y aprendizaje	Mehmood. 2023. Algorithmic urban planning for	775
723	de ele. <i>Tinkuy: boletín de investigación y debate</i> ,	smart and sustainable development: Systematic re-	776
724	(11):31–51.	view of the literature . <i>Sustainable Cities and Society</i> ,	777
725	Borja Quevedo-Marcos. 2020. Análisis de las her-	94:104562.	778
726	ramientas de procesamiento de lenguaje natural para	Seth Spaulding. 1956. A spanish readability formula.	779
727	estructurar textos médicos.	<i>The Modern Language Journal</i> , 40(8):433–441.	780
728	Antonio Rico-Sulayes. 2020. General lexicon-based	María Isabel Vélez, Cristina Gómez Santamaría, and	781
729	complex word identification extended with stem n-	Mariutsi Alexandra Osorio Sanabria. 2022. Concep-	782
730	grams and morphological engines. In <i>Proceedings of</i>	tos fundamentales y uso responsable de la intelligen-	783
731	<i>the Iberian Languages Evaluation Forum (IberLEF</i>	cia artificial en el sector público. informe 2.	784
732	<i>2020)</i> , CEUR-WS, Malaga, Spain, volume 23.		
733	Francesco Ronzano, Luis Espinosa Anke, Horacio Sag-	Yun-Peng Yuan, Yogesh K. Dwivedi, Garry Wei-Han	785
734	gion, et al. 2016. Taln at semeval-2016 task 11: Mod-	Tan, Tat-Huei Cham, Keng-Boon Ooi, Eugene Cheng-	786
735	elling complex words by contextual, lexical and se-	Xi Aw, and Wendy Currie. 2023. Government digital	787
736	matic features. In <i>Proceedings of the 10th Interna-</i>	transformation: Understanding the role of govern-	788
737	<i>tional Workshop on Semantic Evaluation (SemEval-</i>	ment social media . <i>Government Information Quar-</i>	789
738	<i>2016)</i> , pages 1011–1016.	<i>terly</i> , 40(1):101775.	790
739	Philip T Roundy, John M Trussel, and Stephan A Dav-	George-Eduard Zaharia, Dumitru-Clementin Cercel,	791
740	enport. 2023. The text complexity of local govern-	and Mihai Dascalu. 2021. Upb at semeval-2021	792
741	ment annual reports. <i>Local Government Studies</i> ,	task 1: Combining deep learning and hand-crafted	793
742	49(5):1135–1156.	features for lexical complexity prediction. <i>arXiv</i>	794
743	Horacio Saggion, Sanja Štajner, Stefan Bott, Simon	<i>preprint arXiv:2104.06983</i> .	795
744	Mille, Luz Rello, and Biljana Drndarevic. 2015.	Jenny A Ortiz Zambrano and Arturo Montejó-Raéz.	796
745	Making it simplext: Implementation and evaluation	2021. Clexis2: A new corpus for complex word	797
746	of a text simplification system for spanish. <i>ACM</i>	identification research in computing studies. In <i>Pro-</i>	798
747	<i>Transactions on Accessible Computing (TACCESS)</i> ,	<i>ceedings of the International Conference on Recent</i>	799
748	6(4):1–36.	<i>Advances in Natural Language Processing (RANLP</i>	800
		<i>2021)</i> , pages 1075–1083.	801

802 Jinshan Zeng, Xianchao Tong, Xianglong Yu, Wenyan
803 Xiao, and Qing Huang. 2024. Interpretara: Enhanc-
804 ing hybrid automatic readability assessment with lin-
805 guistic feature interpreter and contrastive learning.
806 In *Proceedings of the AAAI Conference on Artificial*
807 *Intelligence*, volume 38, pages 19497–19505.

808 **A Anexo 1: The files that correspond to**
809 **the GovAIEc corpus**

810 The link is shared where the material corresponding
811 to the GovAIEc corpus is stored. You can also
812 contact the authors.

813 [https://ugye-my.sharepoint.com/:f:](https://ugye-my.sharepoint.com/:f:/g/personal/jenny_ortizz_ug_edu_ec/EjBB5s1CzjNMty6GRXUhAIsBzIM3DzHD310PzyVB06p9xA?e=7XEvaC)
814 [/g/personal/jenny_ortizz_ug_edu_ec/](https://ugye-my.sharepoint.com/:f:/g/personal/jenny_ortizz_ug_edu_ec/EjBB5s1CzjNMty6GRXUhAIsBzIM3DzHD310PzyVB06p9xA?e=7XEvaC)
815 [EjBB5s1CzjNMty6GRXUhAIsBzIM3DzHD310PzyVB06p9xA?](https://ugye-my.sharepoint.com/:f:/g/personal/jenny_ortizz_ug_edu_ec/EjBB5s1CzjNMty6GRXUhAIsBzIM3DzHD310PzyVB06p9xA?e=7XEvaC)
816 [e=7XEvaC](https://ugye-my.sharepoint.com/:f:/g/personal/jenny_ortizz_ug_edu_ec/EjBB5s1CzjNMty6GRXUhAIsBzIM3DzHD310PzyVB06p9xA?e=7XEvaC)