Replace, Paraphrase or Fine-tune? Evaluating Automatic Simplification for Medical Texts in Spanish

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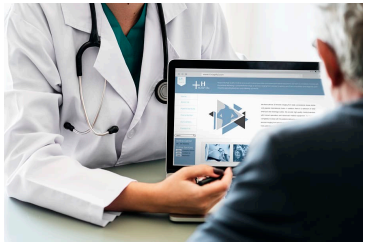
Introduction and Background

Introduction

- Medical records, medication leaflets or clinical trial announcements are written with **jargon** or **abbreviations/acronyms** that represent a communication barrier.

> Clinical trial to establish the effects of low-dose rtPA and the effects of intensive blood pressure lowering in patients with acute cerebrovascular accident

- Medical professionals need to **explain** details about conditions or procedures, but they often **lack the time** to give clear explanations.



→ **Automatic text simplification (ATS)** methods can alleviate the language gap and be a complement, provided that the content is transmitted rigurously.

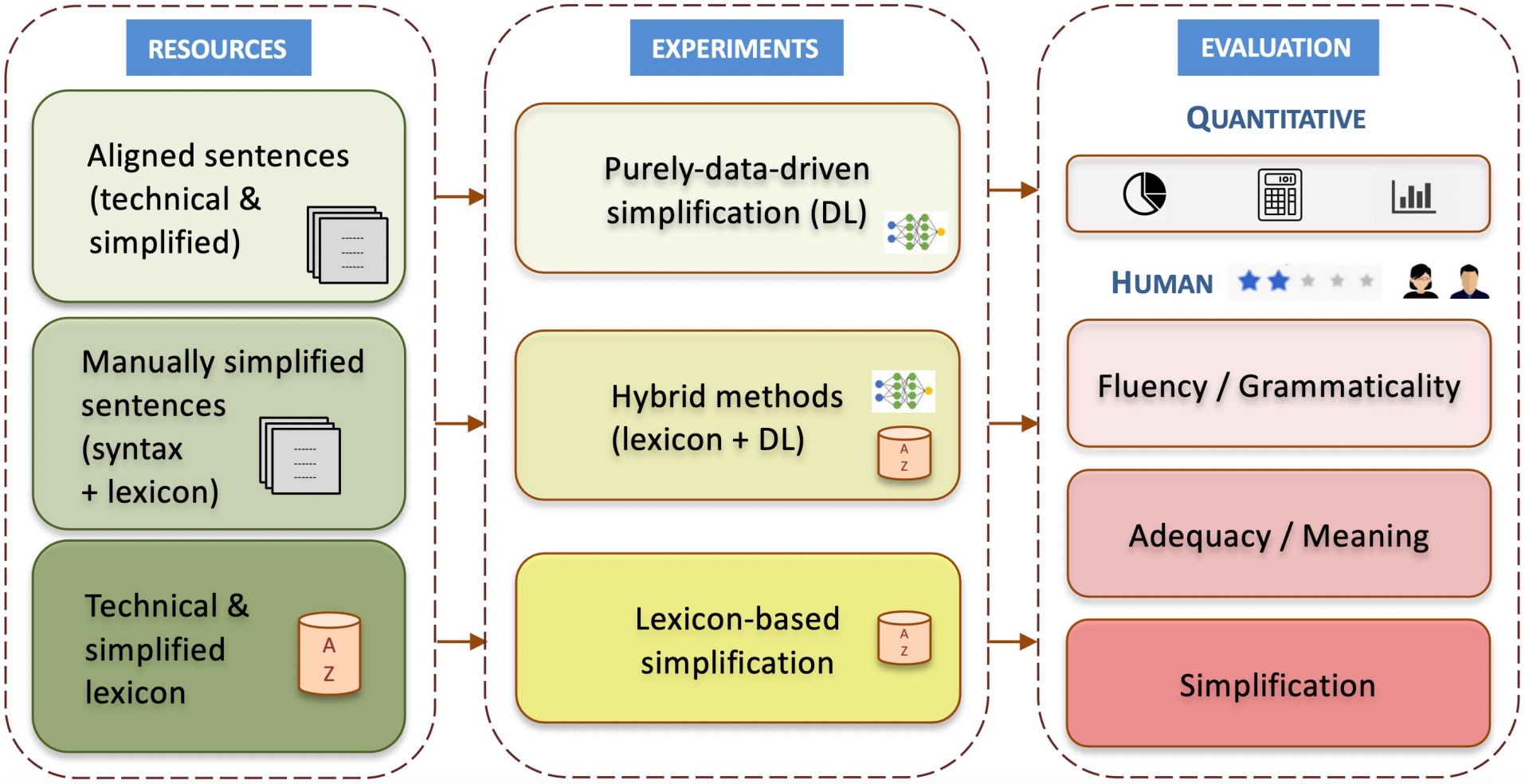
Background

- ATS methods rely on **lexicons, rules, machine learning/deep learning** or **prompt-based approaches** (Saggion, 2017; Shardlow & Nawaz, 2019; Wang et al., 2022)
- **Hybrid methods** (Bot et al. 2012; Cardon & Grabar 2020; Todirascu et al., 2022).
- Simplification applied at **all linguistic levels**: lexis, grammar, discourse...
- Resources and corpora are needed but scarce:
  - English: Newsela (Xu et al. 2015); medical corpora (Van den Bercken et al., 2019; Sakakini et al., 2020; Devaraj et al., 2021; Guo et al. 2022; Basu et al. 2023).
  - Spanish: EASIER (Alarcón et al. 2023), Saggion et al. (2011).
  - French (Grabar & Cardon, 2018; Gala et al. 2020).
  - German (Seiffe et al. 2020; Trienes et al. 2022).

Contributions: 1) First medical lexicon for simplification in Spanish
2) Experiments and human evaluation.
3) Trained models released on the Hugging Face hub

Methods

Methods


RESOURCES
Aligned sentences (technical & simplified)
Manually simplified sentences (syntax + lexicon)
Technical & simplified lexicon
EXPERIMENTS
Purely-data-driven simplification (DL)
Hybrid methods (lexicon + DL)
Lexicon-based simplification
EVALUATION
QUANTITATIVE
HUMAN
Fluency / Grammaticality
Adequacy / Meaning
Simplification

Experimental data

5000 parallel (technical/simplified) sentences:

- **3800** (149 862 tokens):
  - Extracted from the CLARA-MeD corpus (Campillos-Llanos et al. 2022).
  - Aligned with Sentence Transformers (Reimers & Gurevych 2019) and revised.
  - Data sources: Medication leaflets/summaries of product characteristics, cancer-related information (NCI), and clinical trial announcements (EudraCT).

- **1200** (144 019 tokens):
  - Extracted from EudraCT and manually simplified (Campillos-Llanos et al. 2024)
  - Created simplification guidelines.
  - Used version with both syntactic and lexical simplification.

Experimental data

- Samples

Original	*Se considera mujer en edad fértil como aquellas mujeres que no hayan sido sometidas a procedimientos de infertilidad permanente o que sean amenorreicas desde hace menos de 12 meses.* (2019-004871-38) 'Women of childbearing age are considered to be those women who have not undergone permanent infertility procedures or who have been amenorrheic for less than 12 months'
Syntactic simplification	*Se consideran mujeres en edad fértil aquellas mujeres que no han sido sometidas a procedimientos de infertilidad permanente.* ***También*** *se consideran en edad fértil a quienes sean* ***amenorreicas*** *desde hace menos de 12 meses.* 'Women of childbearing age are considered to be those women who have not undergone permanent infertility procedures. Women are **also** considered of childbearing age if they have been **amenorrheic** for less than 12 months'
Lexical and syntactic simplification	*Se consideran mujeres en edad fértil aquellas que no han sido sometidas a procedimientos de infertilidad permanente.* ***También*** *se consideran en edad fértil a quienes* ***no tienen menstruación*** *desde hace menos de 12 meses*. 'Women of childbearing age are considered those who have not undergone permanent infertility procedures. Women are **also** considered of childbearing age if they have **not been menstruating** for less than 12 months.'

Experimental data

- Samples

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SimpMedLexSp

- First patient-oriented Spanish lexicon of medical terms and simplified forms

```
CUI|TECHNICAL_TERM|PATIENT_TERM
C0004057|ácido acetilsalicílico|aspirina
C0006736|cálculo urinario|piedra en la orina
C0007137|ca epidermoide|carcinoma epidermoide
C0007137|cec|carcinoma escamocelular
C0040423|amigdalectomía|operación de anginas
C0231221|asintomático|sin síntomas
C0277797|apirético|sin fiebre
C0522523|percutáneo|a través de la piel
```

```
p.a.|presión arterial
peg|polietilenglicol
per os|por la boca
percutánea|a través de la piel
percutáneas|a través de la piel
percutáneo|a través de la piel
percutáneos|a través de la piel
peribucales|alrededor de la boca
peribucal|alrededor de la boca
```

- Subset mapped to Unified Medical Language System Concept Unique Identifiers
- 12 605 term pairs in the experiments (but >14000 variant forms to date)
- Available at: https://digital.csic.es/handle/10261/349662

SimpMedLexSp

- Data sources:
  - Terms with colloquial equivalents from the Dictionary of Medical Terms (RANME)
  - Eugloss glossary (https://users.ugent.be/~rvdstich/eugloss/welcome.html)
  - Abbreviations and acronyms from the MedLexSp lexicon
  - Paraphrase patterns and definitions extracted from the CLARA-MeD corpus

    Ej. *amenorrea (es decir, problemas con la regla)*

    'amenorrhea (that is to say, problems with menstruation)'

- Frequency-based filter (frequency > 100) to discard widely-used medical terms (Leroy and Endicott, 2012; Chen et al., 2018)

Lexicon-based simplification

- The lexicon was split into two files to conduct:
  - **Lexical substitution** → simpler synonyms

    `cephalea → headache`

    Technical: cephalea might occur

  - **Paraphrase, explanation or definition** → preserve term and append paraphrase

    `clomipramine → medical drug to treat depression`

    Technical: patients that were prescribed clomipramine

Lexicon-based simplification

- The lexicon was split in two files to conduct:
  - **Lexical substitution** → simpler synonyms

    `cephalea → headache`

    Simplified: headache might occur

  - **Paraphrase, explanation or definition** → preserve term and append paraphrase

    `clomipramine → medical drug to treat depression`

    Simplified: patients taking clomipramine (medical drug to treat depression)

Deep learning-based methods

- **Fine-tuned models:**
  - multilingual BART (mBART; Liu et al. 2020)
  - multilingual T5 (mT5; Xue et al. 2021)
  - NASES (BART model trained on news summarization dataset; Ahuir et al. 2021)
  - MariMari (RoBERTa model trained on the MLSUM dataset; Fandiño et al. 2022)
  - Pegasus XSUM (Zhang et al., 2020)
  - OpenNMT (Klein et al. 2017; results below the expected, finally not applied)
- **Prompt-based learning:**
  - BERTIN Alpaca (zero-shot prompting) (BERTIN-project 2023)*
  - BERTIN Alpaca (few-shot prompting)
  - BERTIN Alpaca fine-tuned with training set + lexicon (zero-shot prompting)

*https://huggingface.co/bertin-project/bertin-gpt-j-6B-alpaca

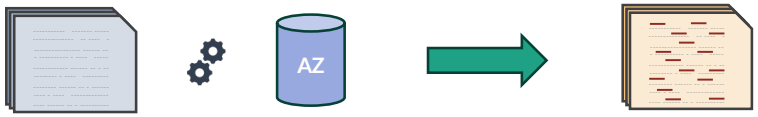
Deep learning-based methods

Zero-shot prompting
Below is an instruction that describes a task. Write a response that appropriately completes the request. ### Instruction: Write as easy-to-read text the following text: {asymptomatic} ### Response:
Few-shot prompting
Below there are some examples to simplify medical text. Write a response following the examples: ### Complex text: {asymptomatic} ### Simple text: {no symptoms} ### Complex text: {apyretic} ### Simple text:

Table 10: Samples of prompts used to train the BERTIN model

Experiments

- **Method A**: only use the lexicon (lexical substitution or append paraphrases)

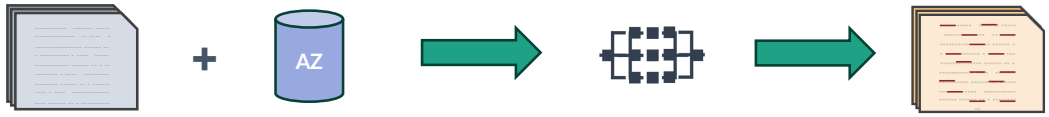


- **Method B**: only zero-shot or few-shot prompting (BERTIN Alpaca)

- **Method C**: fine-tuning without the lexicon

Experiments

- **Method D**: use the lexicon and sentences for training



- **Method E**: use the lexicon and sentences for training and append paraphrases

- **Method F**: use the lexicon for lexical substitution of terms in training data

- **Method G**: lexicon for lexical substitution in training data and for paraphrasing in predictions

Distribution of trained models

https://huggingface.co/CLARA-MeD

CLARA-MeD Community

https://clara-nlp.uned.es/home/med/ lcampillos · Upgrade to Enterprise

+ New | Activity Feed | Organization settings | Watch repos

AI & ML interests

Natural language processing for automatic text simplification of medical texts

Team members 2

Organization Card Edit org card

The CLARA-MeD project applies automatic natural language processing methods to enhance the accessibility of health information.

One of the approaches is term simplification; i.e. substituting a difficult-to-read word (e.g. *amigdalectomía*) with an easier or more explicative paraphrase (e.g. *operación de anginas*).

The CLARA-MeD repository includes the following work:

- A parallel corpus of technical-patient aligned sentences, extracted from the CLARA-MeD comparable corpus of technical and laymen documents.
- Models used in experiments to compare simplification approaches based on state-of-the-art neural-network algorithms.

Models 8 ↑↓ Sort: Recently updated

CLARA-MeD/flan-t5-large
Text2Text Generation • Updated 27 days ago • ↓ 10 • ♡ 1

CLARA-MeD/bertin-gpt
Updated Oct 11, 2023

CLARA-MeD/mbart-large-50
Text2Text Generation • Updated Mar 28, 2023 • ↓ 3

CLARA-MeD/pegasus-xsum
Text2Text Generation • Updated Feb 5, 2023 • ↓ 3

CLARA-MeD/flan-t5-base
Text2Text Generation • Updated Jan 31, 2023 • ↓ 5

CLARA-MeD/mt5-simplification-spanish
Text2Text Generation • Updated Jan 29, 2023 • ↓ 73 • ♡ 1

Evaluation

- 5-fold cross-validation:
  - From the 3800 subset: 80% (3040 sentences) train / 20% (760) test
  - From the 1200 subset: 80% (960 sentences) train / 20% (240) test
- Quantitative evaluation:
  - BLEU (Papineni et al., 2002)
  - ROUGE-1, ROUGE-2, ROUGE-L (Lin, 2004)
  - SARI (Xu et al. 2016)

Human evaluation

- **11 evaluators** (documentalists and linguists)
- **500 sentences** evaluated in two rounds:
  - **250** sentences from the 3800 subset (50 random sentences x 5 simplifications)
  - **250** from the 1200 subset (idem)
- Only evaluated models without high rate of severe hallucinations:
  - Lexicon approach (replace + paraphrase, method A)
  - Prompt—based (BERTIN Alpaca, method B)
  - mBART (method C)
  - mBART + fine-tuning with lexicon (method D)
  - mBART + fine-tuning with lexicon + post-processing with lexicon (method E)

Human evaluation

Score	Grammaticality / Fluency
	Is the simplified sentence grammatically correct or sufficiently readable? Does it have errors in syntax, agreement or too many words that make it difficult to read?
5	The sentence is fluent (native speaker level) and grammatically correct.
4	The sentence is nearly fluent (non-native speaker level) and grammatically correct.
3	The sentence is less fluent, with some ungrammatical but understandable parts.
2	The sentence is less fluent and with fewer grammatical parts, but is partially understandable.
1	The sentence is completely unintelligible.
Score	Semantic adequacy / Meaning preservation
	Does the simplified sentence adequately preserve the original meaning, and is it meaningless or inadequate in relation to the original?
5	The sentence adequately conveys the core meaning of the original sentence.
4	The sentence mostly conveys the essential meaning of the original sentence.
3	The central meaning of the original text is not conveyed, but some information from the original text is partially preserved.
2	The meaning of the sentence is markedly different from the original sentence, even contrary.
1	It is impossible to evaluate the meaning of the target sentence due to its unintelligibility.
Score	Simplification
	Is the resulting text simpler than the original? Is the simplification of good quality?
5	The target sentence is much simpler than the original and no information is lost.
4	The target sentence is simpler than the original and not much (or any) information is lost.
3	The target sentence is as simple/difficult as the original.
2	The target sentence is slightly more difficult than the original and/or the resulting sentence loses some relevant information.
1	The target sentence is more difficult and/or loses important information compared to the original; or it is impossible to evaluate the simplicity of the target sentence due to its unintelligibility.

Instructions for human evaluation, translated to English and adapted from (Yamaguchi et al., 2023)

Results

Results – Quantitative evaluation

Method		Rouge1	Rouge2	RougeL	SARI	BLEU
(A) Only lexicon	Replacements	**46.69 (±1.06)**	**28.64 (±0.82)**	**41.79 (±1.00)**	45.85 (±0.5)	**19.67 (±0.74)**
	Replacements + *par./def.*	46.24 (±0.8)	27.49 (±0.65)	40.29 (±0.79)	**47.41 (±0.53)**	14.49 (±0.53)

Table 1: Results of the quantitative evaluation with the 3800 aligned sentences pairs (Method A)

Method		Rouge1	Rouge2	RougeL	SARI	BLEU
(B) Only prompts	BERTIN (zero-shot prompting)	**41.89 (±0.62)**	**23.19 (±0.66)**	**35.60 (±0.72)**	43.07 (±0.27)	**15.75 (±0.78)**
	BERTIN (few-shot prompting)	39.27 (±0.59)	21.43 (±0.55)	34.08 (±0.60)	**43.29 (±0.52)**	12.01 (±0.41)

Table 2: Results of the quantitative evaluation with the 3800 aligned sentences pairs (Method B)

Results – Quantitative evaluation

Method		Rouge1	Rouge2	RougeL	SARI	BLEU
(C) Fine-tuning without lexicon	BERTIN	46.90	29.17	41.73	47.00	22.03
		(±1.95)	(±1.54)	(±1.79)	(±2.74)	(±0.74)
	MariMari	42.47	24.28	36.78	47.08	17.89
		(±0.66)	(±0.78)	(±0.67)	(±0.72)	(±0.94)
	mBART	**48.82**	**31.04**	**43.96**	**50.93**	**22.90**
		(±1.02)	**(±1.01)**	**(±1.02)**	**(±0.62)**	**(±0.98)**
	mT5	34.20	19.85	31.56	40.46	6.58
		(±0.79)	(±0.61)	(±0.66)	(±0.45)	(±0.39)
	NASES	44.33	26.51	38.54	48.68	20.47
		(±1.18)	(±1.25)	(±1.23)	(±0.64)	(±1.16)
	Pegasus	43.78	25.86	39.74	41.65	14.62
	XSUM	(±0.7)	(±0.85)	(±0.76)	(±0.23)	(±0.43)

Table 3: Results of the quantitative evaluation with the 3800 aligned sentences pairs (Method C)

Results – Quantitative evaluation

Method		Rouge1	Rouge2	RougeL	SARI	BLEU
(D) Fine-tuning with lexicon	*BERTIN (zero-shot)*	48.34 (±0.83)	29.27 (±0.85)	42.95 (±0.98)	49.09 (±0.52)	21.08 (±0.90)
	MariMari	43.35 (±0.92)	25.95 (±2.4)	37.75 (±1.06)	47.35 (±0.75)	18.30 (±1.07)
	mBART	**50.50 (±0.98)**	**32.65 (±1.00)**	**45.33 (±1.03)**	**51.20 (±0.63)**	**24.71 (±1.34)**
	NASES	30.10 (±16.07)	14.74 (±12.63)	25.52 (±13.97)	42.67 (±7.57)	11.16 (±9.31)

Table 4: Results of the quantitative evaluation with the 3800 aligned sentences pairs (Method D)

Method		Rouge1	Rouge2	RougeL	SARI	BLEU
(E) Fine-tuning with lexicon + post-processing (par./def.)	MariMari	41.88 (±0.99)	23.8 (±1.19)	35.83 (±1.04)	47.7 (±0.62)	14.27 (±1.16)
	mBART	**48.07 (±0.82)**	**30.07 (±0.83)**	**42.42 (±0.82)**	**51.11 (±0.43)**	**18.26 (±0.83)**
	NASES	39.74 (±1.66)	22.2 (±1.84)	33.37 (±1.74)	48.17 (±0.44)	13.14 (±1.08)

Table 5: Results of the quantitative evaluation with the 3800 aligned sentences pairs (Method E)

Results – Quantitative evaluation

Method		Rouge1	Rouge2	RougeL	SARI	BLEU
(F) Lexical substitution with lexicon + fine-tuning	MariMari	42.73 (±0.94)	24.41 (±1.00)	36,99 (±1.11)	47.44 (±0.72)	17.63 (±0.97)
	mBART	**48.83 (±1.16)**	**30.69 (±1.27)**	**43.75 (±1.14)**	**50.28 (±0.79)**	**22.90 (±0.98)**
	NASES	44.19 (±0.70)	22.26 (±0.85)	38.31 (±0.74)	48.16 (±0.50)	19.15 (±1.28)

Table 6: Results of the quantitative evaluation with the 3800 aligned sentences pairs (Method F)

Method		Rouge1	Rouge2	RougeL	SARI	BLEU
(G) Lexical substitution with lexicon + fine-tuning + post-processing	MariMari	44.0 (±0.82)	25.57 (±0.80)	38.28 (±1.03)	47.29 (±0.48)	17.9 (±1.00)
	mBART	**49.5 (±2.34)**	**31.42 (±2.34)**	**44.48 (±2.42)**	**50.12 (±1.01)**	**23.25 (±1.96)**
	NASES	45.32 (±1.02)	27.12 (±1.22)	39.2 (±1.12)	47.63 (±0.55)	19.73 (±0.89)

Table 7: Results of the quantitative evaluation with the 3800 aligned sentences pairs (Method G)

Results – Quantitative evaluation

Method		Rouge1	Rouge2	RougeL	SARI	BLEU
(A) Only lexicon	Replacements	73.95 (±0.86)	59.72 (±1.32)	68.77 (±0.98)	50.81 (±0.75)	41.11 (±1.13)
	Replacements + par./def.	69.29 (±1.0)	53.66 (±1.28)	62.71 (±0.94)	49.55 (±0.90)	36.41 (±1.98)
(C) Fine-tuning without lexicon	*BERTIN*	70.43 (±1.63)	54.21 (±1.71)	63.31 (±1.59)	51.87 (±1.73)	43.40 (±2.26)
	mBART	**76.96 (±0.82)**	**63.57 (±0.97)**	**71.37 (±0.77)**	**61.04 (±0.86)**	**52.49 (±1.06)**
(D) Fine-tuning with lexicon	*BERTIN (zero-shot)*	72.92 (±0.42)	59.77 (±0.70)	68.12 (±0.22)	55.66 (±0.41)	44.5 (±1.08)
	mBART	74.78 (±0.84)	61.21 (±1.21)	69.36 (±0.97)	57.81 (±0.87)	48.95 (±1.48)
(E) Fine-tuning with lexicon + post-processing (par./def.)	*mBART*	70.55 (±0.64)	55.75 (±1.1)	64.00 (±0.75)	55.71 (±0.47)	40.68 (±1.86)

Table 8: Results of the quantitative evaluation with the 1200 manually simplified sentences pairs (average score ± standard deviation of 5 experimental rounds); *par.*: 'paraphrase'; *def.*: 'definition'; the name of the methods that the human evaluators assessed qualitatively appears in italics; best results in bold

Results – Human evaluation

Method	Manually-aligned sentences (n=3800)				Manually-simplified sentences (n=1200)			
	G	M	S	Avg	G	M	S	Avg
Lexicon (replace + paraphrase/definition)	4.1	**4.3**	3.3	3.9	4.2	**4.5**	**3.3**	4.0
mBART	4.2	3.3	2.7	3.4	4.2	3.9	3.0	3.7
mBART + fine-tune with lexicon	4.3	3.7	3.1	3.7	4.2	3.9	3.0	3.7
mBART + fine-tune lexicon + post-proc.	4.0	3.7	3.1	3.6	3.9	3.9	3.0	3.6
Prompt learning fine-tuned with lexicon	**4.7**	**4.3**	**3.4**	**4.1**	**4.7**	**4.5**	3.1	**4.1**

Table 9: Results (average of 5-point Likert scale) of the human evaluation (n=11) of simplifying the 3800 sentence pairs (left) and 1200 sentences pairs (right) for Grammaticality / Fluency (G), Semantic adequacy / Meaning preservation (M), and Simplification (S); and average (Avg) of scores for the three aspects

Simplification samples

Original	*Disección radical de ganglios linfáticos.* 'Radical dissection of lymph nodes'
Only lexicon	*Disección radical de ganglios linfáticos (nódulos que forman parte del sistema inmunitario).* 'Radical dissection of lymph nodes (nodes that are part of the immune system)'
mBART	*Dificultad para abrir los ganglios linfáticos.* 'Difficulty opening the lymph nodes'
mBART + lexicon	*A veces se administran ganglios linfáticos a través de la piel.* 'Sometimes, lymph nodes are administered through the skin.'
mBART + lexicon + postproces.	*A veces se administran ganglios linfáticos (nódulos que forman parte del sistema inmunitario) a través de la piel.* 'Sometimes, lymph nodes (nodes that are part of the immune system) are administered through the skin.'
BERTIN + lexicon	*Disección radical de ganglios linfáticos (extirpación de todos los ganglios linfáticos de una zona del cuerpo)* 'Radical dissection of lymph nodes (removal of all lymph nodes from a body part)'

Discussion and Conclusions

Discussion

- **Findings:**
  - Using the **lexicon** tended to obtain **higher results**.
  - **BLEU**, **ROUGE** or **SARI** metrics did **not match human evaluation** scores
  - The **only-lexicon approach** and the **prompt-method** rated in **first position** wrt **semantic adequacy** and **simplification** → **a lexicon is preferred for correctedness**
  - The prompt-based method showed balanced scores across all rated aspects

- **Limitations:**
  - We did **not** apply any method for **candidate selection** before lexicon substitution
  - The **coverage of the lexicon** still needs to be **improved**

Conclusions

- **Experiments combining a patient-oriented medical lexicon and deep learning**
- **Quantitative evaluations and human assessments** (n = 11 subjects)
- Findings show that **using a lexicon increased results** wrt methods without it
- **New resource distributed and trained models released publicly**
- Results might be **similar** in **other languages** → **still to be confirmed**

Thanks for your attention!

Questions?

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https://clara-nlp.uned.es/home/med/

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