Apples to Apples? Towards Comparable Crosslingual Language Model Evaluation

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Abstract

Comparable evaluation of language models in different languages remains challenging. Existing studies adopt a variety of downstream tasks and intrinsic metrics with different theoretical justifications, yet there has been little empirical investigation of their validity. In this work, we examine possible approaches to crosslingual evaluation, including both intrinsic metrics and downstream tasks. We train monolingual language models on parallel data across 10 typologically diverse languages and 5 tokenizer vocabulary sizes to conduct a systematic analysis of commonly used intrinsic metrics. We discuss potential caveats in using downstream tasks for crosslingual comparison. Our results show that several widely used normalized metrics introduce crosslinguistic biases. In contrast, negative log-likelihood computed over semantically equivalent sequences provides more meaningful crosslingual comparisons.[1]

1 Introduction

A persistent challenge in multilingual NLP is that language models perform substantially better in English than in most other languages. This is changing, however. Chinese language performance is approaching parity with English, with the advent of models like DeepSeek R1 (Guo et al., 2025). There are also increasing efforts to create the best model for various languages, e.g., Finnish (`Poro`; Zosa et al., 2025), Sinhala (`SinLlama`; Aravinda et al., 2025), Portuguese (`Tucano`; Corrêa et al., 2024), among others. So, how will we know when we have achieved language equity?

For this, we need comparable evaluation. Evaluating language models across typologically diverse languages requires metrics that reliably reflect model performance rather than artifacts of the evaluation setup. Yet despite the centrality of this question to multilingual NLP, there has been relatively little systematic empirical investigation into which evaluation metrics are appropriate for crosslingual comparison.

In practice, the literature has adopted two broad evaluation strategies: downstream tasks and intrinsic metrics. Downstream evaluations often yield mixed results, with conclusions depending on the specific tasks used (Rust et al., 2021; Limisiewicz et al., 2023). Given this variability, intrinsic metrics offer a more controlled alternative for crosslingual comparison and remain widely used in practice.

Within intrinsic metrics, one line of work evaluates the probability assigned to sequences that express the same meaning across languages, typically using negative log-likelihood or surprisal (e.g., Mielke et al., 2019; Cotterell et al., 2018; Wan, 2022). Another common approach relies on unit-normalized variants such as perplexity (PPL; Shliazhko et al., 2024), bits-per-byte (BPB; Xue et al., 2022), or bits-per-character (BPC; Blevins et al., 2022), which normalize likelihood by tokens, bytes, or characters, respectively. Despite the intuitive justification for each of these metrics (e.g., tokenization agnostic for BPB (Gao et al., 2020)), empirical evidence examining these claims about which metric to use has remained limited. The use of intrinsic metrics is further challenged by Poelman and de Lhoneux (2026), who argue that current evaluation metrics may not be universally comparable. They show that (i) different metrics can produce different rankings across languages, and (ii) even within a single metric, paraphrases expressing the same meaning can lead to inconsistent crosslingual rankings.

Taken together, it remains unclear which metrics, if any, provide reliable crosslingual comparisons. Our work addresses this gap directly. We train monolingual language models on parallel corpora across 10 typologically diverse languages, varying the tokenizer vocabulary size across five settings. We conduct a systematic empirical comparison of

[1] Code provided upon publication.

intrinsic metrics and review the limitations of commonly used downstream evaluation setups. Our analysis identifies potential caveats in crosslingual downstream evaluation and shows that metrics normalized by tokens, bytes, or characters, such as perplexity, BPB, and BPC, introduce substantial biases. In contrast, sentence-level NLL provides more stable and meaningful comparisons, as it is less sensitive to tokenization and differences in linguistic encoding.

2 Background & Related Work

2.1 Tokenization & Representation Biases

For crosslinguistic evaluation to be meaningful, it is necessary to disentangle intrinsic linguistic complexity from technical artifacts introduced by representation and preprocessing choices (Shani et al., 2026). Prior work has identified several sources of such artifacts, particularly those arising from tokenization and orthographic encoding.

Tokenization Language models are trained to predict the next token in a sequence, from a vocabulary of discrete tokens. Consequently, how text is segmented into tokens directly affects how the model represents and learns linguistic structure. Semantically equivalent content across languages can be segmented into very different numbers of tokens, even when the same tokenization algorithm is used (Petrov et al., 2023; Arnett et al., 2025). This disparity is often quantified as *Corpus Token Count* (CTC; Schmidt et al. (2024)), which measures the total number of tokens required to encode a corpus under a given tokenizer.

Differences in token segmentation can influence both training dynamics and evaluation metrics. Even under identical tokenization settings, languages may be split into substantially different segments, which can affect model performance (Shani et al., 2026). As a result, different languages may benefit from different tokenization strategies (e.g., Fujii et al., 2023; Vemula et al., 2025; Reddy et al., 2025; Toraman et al., 2023). For instance, Toraman et al. (2023) show that morphologically-rich languages like Turkish require a larger vocab size.

Orthography and Encoding Representation disparities also arise from differences in orthographic encoding. The same semantic content written in different scripts may require different numbers of UTF bytes, a phenomenon known as the *byte premium* (Arnett et al., 2024). Similarly, different writing systems may encode equivalent content using substantially different numbers of characters, resulting in what has been termed the *length premium* (Arnett et al., 2024). These representational differences are independent of linguistic meaning but can systematically distort evaluation metrics that normalize by bytes or characters.

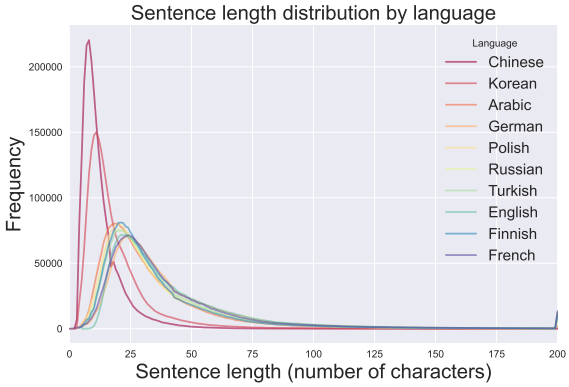

Figure 1: Length distribution (measured by characters) of each language in parallel-10 dataset

2.2 Crosslinguistic Evaluation

The most widely adopted approach relies on negative log-likelihood (NLL) computed over semantically equivalent sequences across languages. Within this framework, studies differ in how they normalize the raw NLL scores. Cotterell et al. (2018) and Mielke et al. (2019) normalize sentence-level surprisals by the number of characters of a specific language (usually English), using the resulting scores to rank languages by difficulty. Limisiewicz et al. (2024) adopts a similar approach but normalizes by the number of bytes instead. Wan (2022) simply aggregate sentence-level NLL over an entire development set without normalization. A more structured alternative is proposed by Tsvetkov and Kipnis (2024), who introduce Information Parity (IP), defined as the ratio of English NLL to the NLL of another language over parallel text.

Other work evaluates multilingual models using metrics that operate at different granularities. Shliazhko et al. (2024) report perplexity scores across languages, while Blevins et al. (2022) argue for bits per character (BPC) as a more language-neutral unit. Byte-level language models further shift toward bits per byte (BPB; Xue et al., 2022; Zhang and Xu, 2022), which Poelman and de Lhoneux (2026) suggest may yield fairer comparisons when scores are scaled to a shared unit. Despite the apparent justification for each of these metrics, Poelman

and de Lhoneux (2026) demonstrate that applying different metrics to the same model on the same data can produce conflicting language rankings—highlighting that metric choice is not merely a technical detail but a substantive decision with interpretive consequences. This work offers concrete empirical guidance for metric selection in crosslingual evaluation and contributes to ongoing efforts toward fair multilingual NLP.

3 Existing Intrinsic Metrics & Their Potential Confounds

In this section, we review mainstream probability-based metrics used in language modeling and evaluate their suitability for crosslinguistic and cross-model comparison. Let t_i be the ith token in sequence $\mathbf{s}$ which has b UTF8-bytes, c characters and can be tokenized into n tokens.

Bits per Byte BPB is proposed by Gao et al. (2020) because of "its invariance to different tokenization schemes and the ambiguity of measuring characters in Unicode."

$$\text{BPB}(\mathbf{s}) = -\frac{1}{b}\sum_{i=1}^{n}\log_2(P(t_i \mid \mathbf{t}_{<i})) \quad (1)$$

It has been used in cross-model evaluations (e.g., Rae et al., 2021) for the same language. However, we argue that BPB introduces bias when comparing across languages due to differences in orthographic encoding. The same semantic content written in different scripts may require different numbers of UTF bytes (i.e., different *byte premiums*). For example, Arnett et al. (2024) report that characters in scripts such as Khmer typically require three bytes per character (excluding diacritics), whereas Latin characters require only one byte. As a result, if two models assign similar probabilities to semantically equivalent sequences in two languages, the language with the higher byte premium will necessarily obtain a lower BPB score because the total surprisal $\sum_{i=1}^{n}\log_2(P(t_i \mid \mathbf{t}_{<i}))$ is normalized by a larger number of bytes, b.

Bits per Character Bits per Character (BPC) measures the average sequence NLL per character:

$$\text{BPC}(\mathbf{s}) = -\frac{1}{c}\sum_{i=1}^{n}\log_2(P(t_i \mid \mathbf{t}_{<i})) \quad (2)$$

It is mainly used in evaluations of character-level models (e.g., Al-Rfou et al., 2019). While it mitigates tokenization bias, it may still introduce orthographic bias like BPB. For example, Chinese translations are usually represented with fewer characters than English as shown in (Fig 1) and thus this metric has a lower length premium. Normalizing over the number of characters means that Chinese will almost always have a higher BPC than English, as c is smaller.

Mean Reciprocal Rank MRR (Limisiewicz et al., 2023) evaluates models on the rank of the next token rather than its probability, making it probability-agnostic. However, since ranking is computed over the entire vocabulary, a larger vocabulary raises the upper bound of possible ranks, such that models with larger vocabularies tend to achieve lower MRR regardless of actual performance.

$$\text{MRR}(\mathbf{s}) = \frac{1}{n}\sum_{t=1}^{n}\frac{1}{\text{rank}(t_i, P(\cdot \mid \mathbf{t}_{<i}))} \quad (3)$$

Perplexity Held-out perplexity measures the average number of nats (or bits) required to predict tokens in a corpus. It has been the default metric for evaluating language models, with lower values typically indicating better performance (e.g., Brown et al., 2020):

$$\text{PPL}(\mathbf{s}) = \exp(-\frac{1}{n}\sum_{i=1}^{n}\ln(P(t_i \mid \mathbf{t}_{<i}))) \quad (4)$$

Some previous studies reported perplexity as the measure to compare models with different tokenizers and training data (Hu et al., 2020; Blevins et al., 2024), but they caution that perplexity is not directly comparable across datasets. Because perplexity is averaged over the number of tokens, it is highly sensitive to how the input is tokenized. A model with a smaller vocabulary achieves lower perplexity through two compounding effects: each token has a higher marginal probability, and the same sentence is split into more tokens, increasing the denominator. Neither reflects better language modeling quality. In crosslinguistic comparison, training tokenizers in a comparable way may still result in a wide range of number of tokens across languages (Arnett et al., 2025). Consequently, the language that is split into more tokens (higher corpus token counts; CTC) is more likely to have a lower perplexity.

Token-level Negative log-likelihood Token-level NLL (Token NLL) measures the NLL of the sequence normalized by the number of tokens:

$$\text{Token NLL}(\mathbf{s}) = -\frac{1}{n}\sum_{i=1}^{n}\log_2(P(t_i \mid \mathbf{t}_{<i})) \quad (5)$$

Token NLL shares the same tokenization sensitivity as perplexity, as discussed above.

Sentence-level Negative log-likelihood Sentence-level NLL (Sent-NLL) is the sum of the NLL or surprisal per token (See 6).

$$\text{Sent-NLL}(\mathbf{s}) = -\sum_{i=1}^{n}\log_2(P(t_i \mid \mathbf{t}_{<i})) \quad (6)$$

Because Sent-NLL sums over the entire sequence without dividing by token count, it is not directly affected by how the sequence is segmented, making it less sensitive to vocabulary size than perplexity, Token NLL, BPB, or BPC. For this reason, Sent-NLL of parallel sentences has been more widely adopted in crosslinguistic comparisons (Lin et al., 2024; Costa-Jussà et al., 2022; Chang et al., 2024), and we argue that it provides the most meaningful basis for crosslingual evaluation among the metrics considered here.

Other metrics There are other metrics such as Information Parity (IP; Tsvetkov and Kipnis, 2024) and Bits per English Character (BPEC; Cotterell et al., 2018). As they are transformations of sent-NLL covered here, they should align with the results of sent-NLL.

Summary Normalization over tokens, characters, or bytes can introduce biases that depend on tokenization and script differences. We argue that BPB and BPC are appropriate for comparing models within the same language, but not across languages, because different writing systems lead to different byte and character counts (i.e., byte and length premiums). Perplexity is not suitable for crosslinguistic comparison because different tokenizers segment languages into different numbers of tokens. MRR is suitable when tokenizer is fixed with vocab sizes. In contrast, NLL over semantically equivalent content is suitable for both cross-model and crosslinguistic comparison because it does not normalize by representation units but by units of comparable meaning.

4 Method

To test the potential confounds discussed, we train monolingual models on parallel data and evaluate them on each of the metrics described in Section 3. We then test whether we find correlations between the confounds we identified and the metric values in order to determine to what extent these confounds impact these evaluation metrics.

4.1 Data

We train equal size monolingual models on multi-parallel data for 10 languages from 6 language families: Arabic, Chinese, English, French, German, Italian, Polish, Portuguese, Russian, and Turkish. The data come from OPUS12 (Yang et al., 2025) and were extended with sentences sampled from OPUS (Tiedemann, 2012). The base dataset has approximately 20M words per language. Constructing multi-parallel corpora for multilingual research typically necessitates a trade-off between linguistic diversity and data volume. Our ten-language sample prioritizes broad crosslinguistic coverage. Detailed procedures for corpus construction are provided in Section A.

4.2 Models

We train `GPT2-small` models (Radford et al., 2019) from scratch for each experimental setting. Following Yang et al. (2026), we use this model size as it has been shown to outperform smaller architectures in comparable setups.

To examine potential evaluation biases introduced by tokenization, we train separate models for each language using a BPE tokenizer with varying vocabulary sizes. Specifically, we evaluate five vocabulary sizes: 8192, 32768, 49152, 65536, 81920. Each model is trained for 10 epochs. All other hyperparameters follow Chang et al. (2024). Additional training details are provided in Appendix B.

4.3 Evaluation

We evaluate our models on three parallel data sources in the corresponding languages: FLORES-200 (NLLB Team et al., 2022), a multi-parallel machine translation benchmark covering more than 200 languages; the parallel-10 test split, which corresponds to the test portion of our training corpus (40k sentences, see Table 4); and 1,000 sentences from the Parallel Universal Dependencies treebanks (PUD; Zeman et al., 2017).

5 All metrics except for Sent-NLL are biased in different ways

We report crosslingual rankings across different metrics for FLORES-200 in Figure 2.[2] It is clear that different metrics produce different crosslingual rankings, suggesting that metric choice itself is a significant source of variance in crosslingual evaluation. While Poelman and de Lhoneux (2026) attribute this inconsistency to the unreliability/incomparability of probability-based metrics in general, we argue that the inconsistency can be traced to specific, identifiable biases in each metric, specifically, their normalization units (i.e., number of tokens, bytes and characters).

We conduct Spearman's rank correlation tests between each metric and the corresponding potential bias factors discussed in Section 3. For BPC and BPB, the number of characters and bytes for a given language remains constant regardless of tokenization, so we average model performance across tokenizers before computing correlations. In contrast, CTC varies across tokenization settings because different tokenizers produce different numbers of tokens for the same language. We therefore compute correlations between each model's metric value and its corresponding CTC directly, without averaging across tokenizers. For Sent-NLL, which is not affected by normalization over tokens, characters, or bytes, we compute correlations with all three factors.

Both the correlation coefficient ρ and p-value p of the correlation analysis are reported in Table 1. We find that the potential confounds are strongly and significantly correlated with language rankings for all metrics (ρ>0.8, p<0.01) except Sent-NLL, where metric performance is not correlated with any potential bias factors. This suggests that these metrics capture evaluation artifacts rather than differences in model performance.

Metric	Potential Confounds	ρ	p
BPC	#characters	-0.81	0.0082
BPB	#bits	-0.94	<0.001
PPL	CTC	-0.93	<0.001
MRR	CTC	0.89	0.001
Token NLL	CTC	-0.93	<0.001
Sent NLL	#characters	-0.38	0.28
Sent NLL	#bits	0.14	0.71
Sent NLL	CTC	-0.19	0.19

Table 1: Correlation Analysis between metrics and potential confounds. PPL is scaled by log10.

6 Sent-NLL is more robust for translation alternatives

One potential objection to Sent-NLL is that different translations of the same text may yield different probability distributions, leading to inconsistent crosslingual rankings (Poelman and de Lhoneux, 2026). However, Poelman and de Lhoneux (2026) demonstrate this instability using both translations and paraphrases within the same language rather than translations only. Because paraphrases allow more flexible wording as long as the gist of the meaning is kept (Neusner, 1986; Bhagat and Hovy, 2013), and thus they are more likely to encode different amounts of information. In this case, their findings speak to within-language variation rather than the validity of crosslingual comparison over parallel translations. We provide additional discussion about this assumption in Section 8.2

Here, we replicate their experiment using translations only and additionally evaluate Sentence NLL. Specifically, we use the English-German translation pairs from WMT2019 (Barrault et al., 2019) with an additional translation reference source from Freitag et al. (2020), denoted as DE1 and DE2 separately. Following Poelman and de Lhoneux (2026), for these two alternative German translations, we construct two derived datasets: DE_{lowest} and $\text{DE}_{highest}$, consisting of sentences that receive the lower or higher metric value in each pairwise comparison, respectively. We compare each metric for English and German across the five data sources: EN (English source text), DE1 (German translation), DE2 (German alternative translation), DE_{lowest}, and $\text{DE}_{highest}$.

The results are shown in Figure 3 (last row) and reveal three major findings. First, metrics including MRR, PPL, and Token NLL vary monotonically by vocabulary size, which is consistent with our findings in Section 5. Second, for these metrics, even with the same vocab size setting, using different translations in German yields different language rankings between English and German. This pattern is especially salient when vocab size $\geq$ 33k. Finally, we find that Sentence NLL produces consistent language rankings across translation variants (i.e., English scores lower than all four German datasets). The same applies to BPB and BPC, but as we show in Section 5, if we consider more typologically diverse language with different scripts,

[2] Since the findings are similar for the other two datasets, their results are reported in Appendix C.

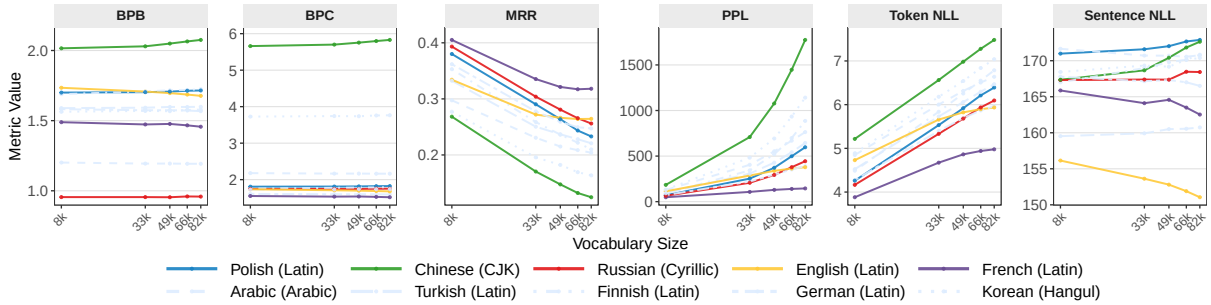

Figure 2: Language rankings across different intrinsic metrics. Some languages are highlighted in light blue with distinct line types for readability. Except for MRR, lower values indicate better performance for all other metrics. The complete rankings with individual colors are shown in Appendix Figure 4.

the results will change.

A possible objection is that even for semantically equivalent translations, sentence-level rankings may not align across languages, potentially affecting aggregated language rankings. We argue that such sentence-level mismatches introduce noise, and that their impact diminishes when averaged over a sufficiently large number of parallel sentences. To test this, we conduct a follow-up experiment under the same setting while varying the number of samples from 1 to the full dataset. For each sample size, we repeat the experiment with 15 random seeds. The results are shown in Figure 3. When the sample size is small (1–100), the rankings are indeed unstable. However, they become stable once the sample size reaches around 500.[3]

7 Downstream Tasks

While we have focused primarily on intrinsic evaluation, here we briefly introduce considerations for comparable evaluation on downstream tasks.

Translated Benchmarks. Some translated tasks may enable comparable evaluation across languages. For example, a math benchmark translated into another language may allow a researcher to make an inference about the relative performance on math tasks in two languages. Math and reasoning benchmarks are less likely to be influenced by translation quality and are more language-agnostic (Wu et al., 2025). This relies on sufficiently high translation quality, however. Machine translated benchmarks without human validation may contain translation artifacts and introduce noise into the evaluation (Singh et al., 2025). High-quality benchmarks created through professional human translation, e.g. MMMLU (OpenAI, 2024) or FLORES (NLLB Team et al., 2022) and derivatives like Belebele (Bandarkar et al., 2024) or SIB-200 (Adelani et al., 2024), are less likely to suffer from these issues.

Culture-specific tasks. Another consideration is cultural specificity. Even when translated faithfully, some benchmarks may not be appropriate for comparable evaluation if their content is specific to a particular linguistic or cultural context. Localized benchmarks, e.g. IndoMMLU (Indonesian; Koto et al., 2023), CMMLU (Chinese; Li et al., 2024), Turkish MMLU (Yüksel et al., 2024), Arabic MMLU (Koto et al., 2024), and KMMLU (Korean; Son et al., 2025) are evaluate not only target-language performance but also cultural knowledge. Localized benchmarks such as these correlate more strongly with human preferences than simply translated benchmarks (Wu et al., 2025). But achieving the same score on two localized MMLU-style benchmarks does not signal comparable performance, as the questions are not difficulty-matched or otherwise controlled.

Language-specific tasks. Language-specific tasks, such as linguistic knowledge benchmarks like BLiMP (Warstadt et al., 2020) and MultiBLiMP (Jumelet et al., 2026), may not be comparable across languages for other reasons. First, even benchmarks which evaluate the same relatively narrow tasks, such as subject-verb agreement in MultiBLiMP (Jumelet et al., 2025), are based on non-parallel data. The items for each language differ in quantity and quality. The number of items in MultiBLiMP per language ranges from 7 (Gujarati) to 4615 (Old Russian). For languages with very few items, like Gujarati, MultiBLiMP scores may be less reliable than those with much

[3]Note that all other experiments in this paper use sample sizes greater than 500.

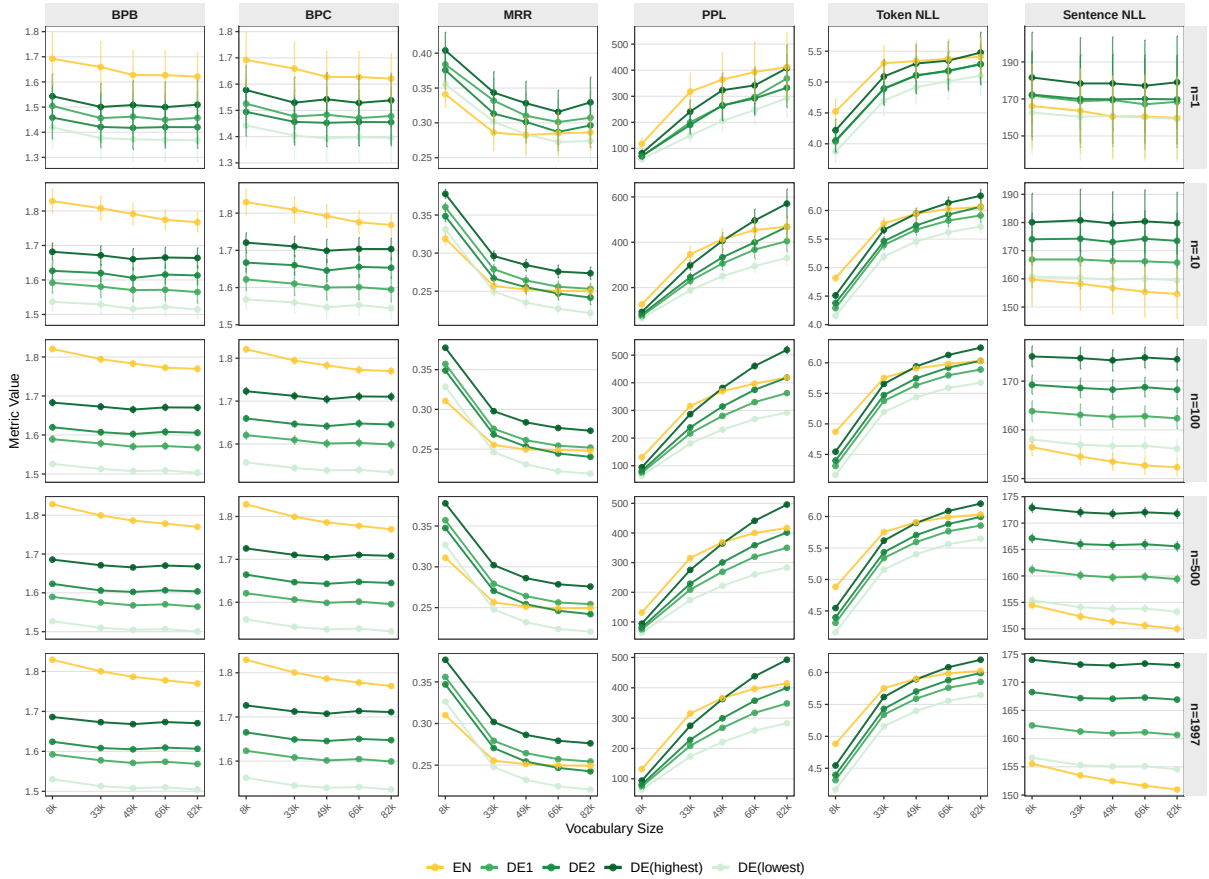

Figure 3: Each row shows results for a different sample size. Error bars represent 95% CI across 15 random seeds.

larger numbers of samples. Additionally, as MultiBLiMP is based on UD Treebanks (de Marneffe et al., 2021; Nivre et al., 2020), which vary in their annotation schema. These inconsistencies may lead to different conclusions about relative linguistic complexity, for example (Rodríguez and López, 2025). Both of these issues can be addressed through the use of balanced parallel data with consistent annotation schema.

These benchmarks are also sensitive to crosslinguistic differences. In the development of CLAMS (Mueller et al., 2020), the authors discuss how differences in pronoun dropping, grammatical person distinction, and distribution of negative polarity items shaped the types of tests they could use in the comparison of agreement across languages.

Subject-verb agreement is inherently different across languages. For some languages, the task is trivial as there is no agreement and the verb form is always the same (e.g. Chinese and Tagalog; Chao, 1968; Reyes, 1969). Other languages have more complex agreement patterns due to higher number of distinctions between number (singular, dual, and plural number, e.g. Arabic; Bettega and D'Anna, 2022), gender/noun class (about 10 noun classes in Swahili; Moxley, 1998), verb class (at least 4 verb classes in Georgian; Makharoblidze, 2012), gender (Tamil; Venkatesan, 2024). It remains an open question how to fairly compare linguistic performance across languages, when the complexity of the phenomenon differs.

8 Discussion

It is important to note that Sent-NLL is not entirely free from confounds. However, we argue that the potential confounds are more linguistically inherent than technical artifacts.

8.1 The linguistic equi-complexity hypothesis

Our proposal implicitly assumes that all languages encode roughly comparable amounts of information. Evidence in the literature both supports and challenges this assumption (Koplenig et al., 2017; Crystal, 2010; Joseph and Newmeyer, 2012; Fenk-Oczlon and Fenk, 2014; Bentz et al., 2023).

However, even if languages systematically differ in the amount of information required to express the same semantic content, such differences reflect

intrinsic linguistic properties rather than artifacts introduced by evaluation metrics. In this sense, Sent-NLL may reflect both how well a model has learned a language and the intrinsic information density of that language. In contrast, metrics such as perplexity and BPB are directly affected by tokenization decisions and script choice[4], which vary across technical choices and are independent of linguistic content. Therefore, even if the linguistic equi-complexity hypothesis is falsified, Sent-NLL may not be a perfect measure of model performance in isolation, but it remains the least biased option among commonly used intrinsic metrics for crosslingual comparison. Any remaining confound due to linguistic complexity should be viewed as a limitation shared by all crosslingual evaluation rather than a systematic bias of the metric itself.

8.2 Paraphrases encode different amounts of information

Another concern may arise from our exclusion of paraphrases in Section 6. Including paraphrases from Freitag et al. (2020) could indeed change the results. For instance, DE_{lowest} might obtain lower values and potentially rank below English , based on the results from Poelman and de Lhoneux (2026). This doubt, however, relies on a common, but flawed, assumption that paraphrases within the same language should receive similar probabilities from a language model because they express the *same meaning*, i.e., they are assumed to be semantically identical (Barzilay and McKeown, 2001; Boonthum, 2004; Madnani and Dorr, 2010) and therefore language models should assign similar probabilities to paraphrases of the same text (Poelman and de Lhoneux, 2026).[5]

We argue that this assumption does not necessarily hold. Paraphrases are often semantically similar but not strictly identical, and they encode different amounts of information. Consequently, there is no theoretical reason to expect that language models should assign more similar probabilities to two paraphrases than to translations of either sentence.

To illustrate this point, we use two paraphrases of a sentence from Poelman and de Lhoneux (2026) as an example:

(1) a. Do you know how to play chess?
b. Can you play chess?

'Know how to play chess' entails possessing the procedural knowledge about the rules of chess. 'Can play chess' only implies knowledge of the rules, and is more sensitive to context. It could refer to possession of a chessboard or whether it is socially acceptable to play.

While in many contexts these differences may not be important, paraphrases are rarely semantically equivalent. Even grammatical alternations, e.g. dative alternation (c.f. 'I threw the box to John' and 'I threw John the box.'; Levin, 1993), may not be considered semantically equivalent (Bresnan and Nikitina, 2009). It may be more precise to label the sentences in Ex. (1) as *quasi-paraphrases* (Bhagat and Hovy, 2013) or *near-equivalence* (Santos and Barreiro, 2025), which may encompass a "broader, approximate, equivalence".

Admittedly, both translations and paraphrases may encode different amounts of information for the same source. However, paraphrases typically permit substantially greater variation because they are not constrained by crosslinguistic correspondence (e.g., Neusner, 1986). As a result, inconsistencies observed with paraphrases do not necessarily undermine crosslingual evaluation. Instead, they introduce an additional and less controlled source of variation.

9 Conclusion

As the development of language models expands beyond English to an increasing number of languages, fair crosslingual evaluation becomes essential. How we evaluate language models determines how we intepreted the results. In this work, we discuss potential caveats in downstream task evaluation and provide a systematic empirical analysis of widely-used intrinsic metrics. We show that normalized metrics such as perplexity, BPB, and BPC introduce crosslinguistic biases driven by tokenization and orthographic differences, while sentence-level NLL computed over semantically equivalent content provides more stable and meaningful comparisons. This work offers concrete empirical guidance for metric selection in crosslingual evaluation and contributes to ongoing efforts toward fair multilingual NLP.

[4] For example, modern standard Serbian has two official scripts.

[5] For example, Poelman and de Lhoneux (2026) assume that paraphrases have the same information content and therefore language models should assign "roughly the same [Token NLL or BPC] values for paraphrases within a single language".

Limitations

Our evaluation only covers 10 languages due to limited parallel data. A broader language sample would strengthen generalizability, although the significant correlations observed for all other metrics under the same sample size suggest that statistical power is sufficient to detect meaningful relationships.

In the paraphrase experiments, only English and German translation pairs are tested due to the limited translation resources. Extending this analysis to additional bilingual pairs with multiple translation references would further strengthen the conclusions.

More broadly, our approach relies on high-quality parallel sentences. Although datasets such as FLORES provide relatively broad coverage, many languages still lack reliable parallel data, which limits the applicability of this evaluation framework.

AI assistance

We used GPT-5 to assist with polishing the writing. All code was written by the authors and subsequently reviewed with the help of GPT-5.

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A Parallel Multilingual Corpus

The training data sources and split can be found in Table 3 and Table 4. All the sources follow the data license from OPUS (Tiedemann, 2012).

B Model Training Details

The training hyperparameters are reported in Table 2.

Training	
train_size	10M
num_epoch	10
train_amount	19M
batch_size	128
context_length	128
grad_acc_steps	1
weight_decay	0.1
warmup_steps	10%
lr	5e-4
lr_scheduler	linear

Table 2: Training Hyperparameters

C Evaluation Dataset-specific results

The crosslingual rankings for FLORES, Parallel-10 test split, and PUD are shown in Figures 4, 5, 6 separately. The correlation test are visualized in Figures 7, 8, 9 separately. We observe similar patterns as discussed in the main text. In the correlation test, we find significant correlation between each metric and their potential confounds across three datasets, but this is not the case for Sent-NLL.

Source	Description	Parallel-10	
		Words	Sents
OpenSubtitles (Lison and Tiedemann, 2016)	Movie/TV show subtitles	17.0M	2.0M
Bible (Christodouloupoulos and Steedman, 2015)	Bible text	1.5M	57K
WikiTitle	Titles of Wikipedia articles	167K	42K
Neulab-Ted	Ted talks	356K	19K
KDE4	KDE4 localization files	117K	13K
Ted2020 (Reimers and Gurevych, 2020)	Ted talks	347K	19K
QED	Subtitles for educational videos	10K	0.6K
Ubuntu	Ubuntu localization files	<1K	<100
Tatoeba	Translated sentences from Tatoeba	<1K	<100
GNOME	GNOME localization files	<1K	<100
Overall		19.5M	2.4M

Table 3: Sources of the Parallel-10.

Language	Train		Dev		Test	
	#sent	#word	#sent	#word	#sent	#word
English	2,338,286	19,089,154	10,000	82,457	40,000	327,724
Arabic	2,338,286	14,426,353	10,000	61,982	40,000	246,954
Chinese	2,338,286	30,129,452	10,000	130,205	40,000	516,401
Turkish	2,338,286	12,540,711	10,000	54,238	40,000	215,345
German	2,338,286	16,544,740	10,000	71,464	40,000	283,997
Korean	2,338,286	11,857,382	10,000	51,292	40,000	203,336
Polish	2,338,286	13,458,472	10,000	57,932	40,000	231,262
French	2,338,286	17,603,323	10,000	76,087	40,000	302,056
Russian	2,338,286	14,613,449	10,000	62,951	40,000	251,018
Finnish	2,338,286	11,975,617	10,000	51,698	40,000	205,766

Table 4: Data splits for three experimental settings across ten languages. Word counts are computed using whitespace-separated tokens for all languages except Chinese, for which each character is treated as a word.

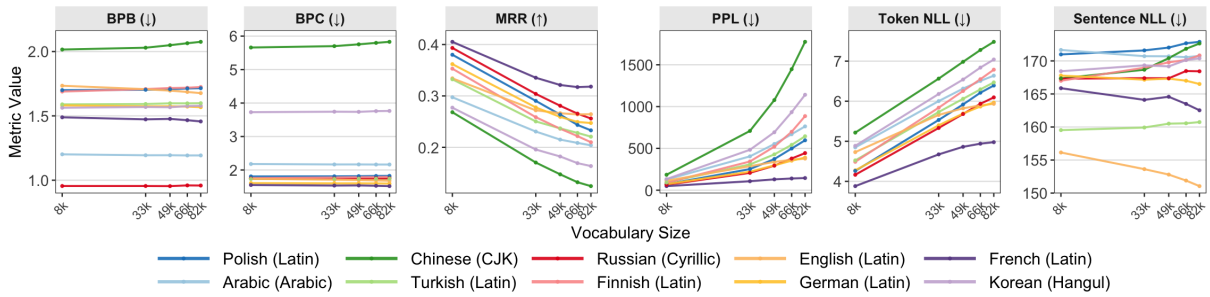

Figure 4: Language rankings across different intrinsic metrics

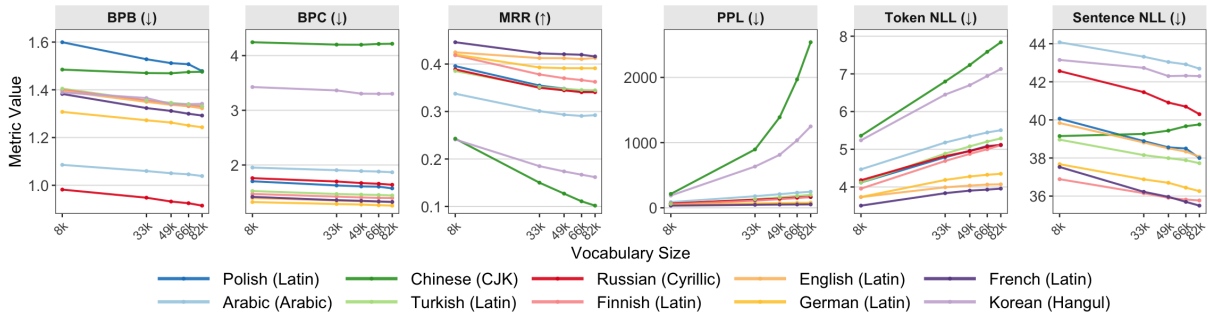

Figure 5: Language rankings across different intrinsic metrics for Parallel-10 test split

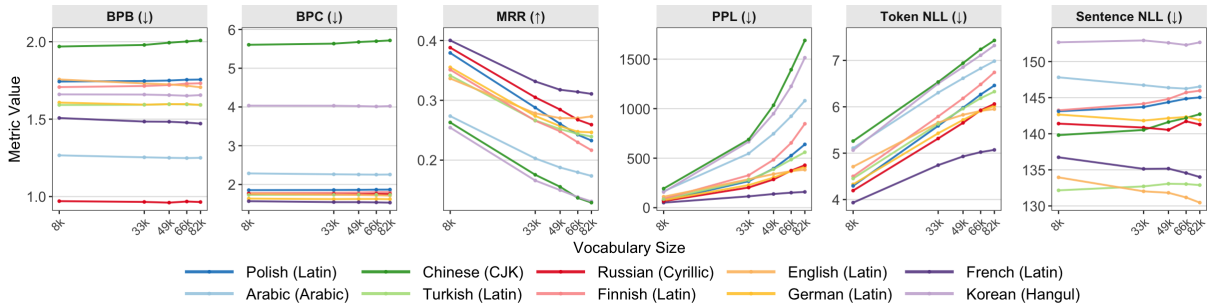

Figure 6: Language rankings across different intrinsic metrics for PUD

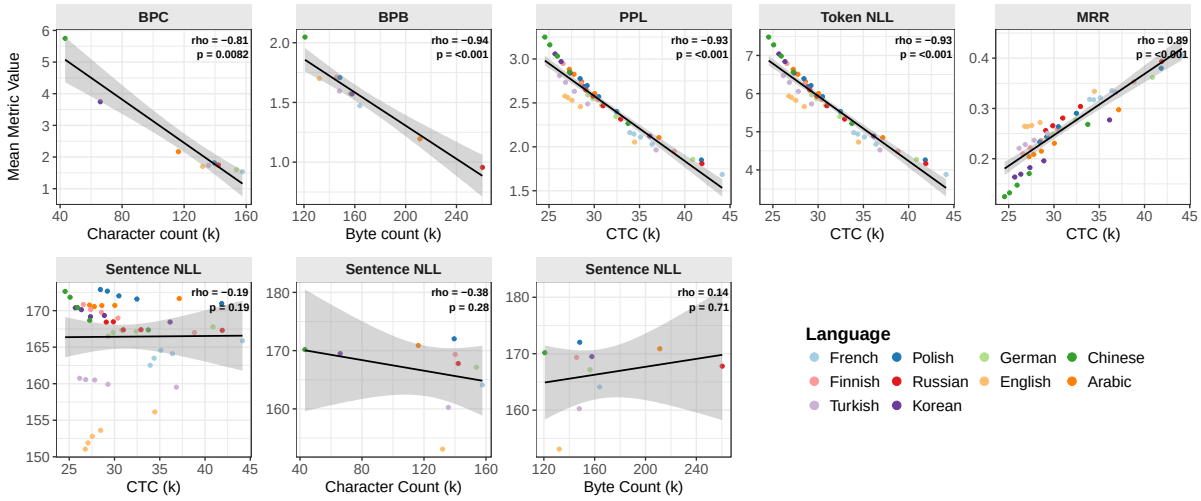

Figure 7: Spearman's Rank Correlation between the intrinsic metrics and their potential confounding factors in FLORES (perplexity is scaled by log10).

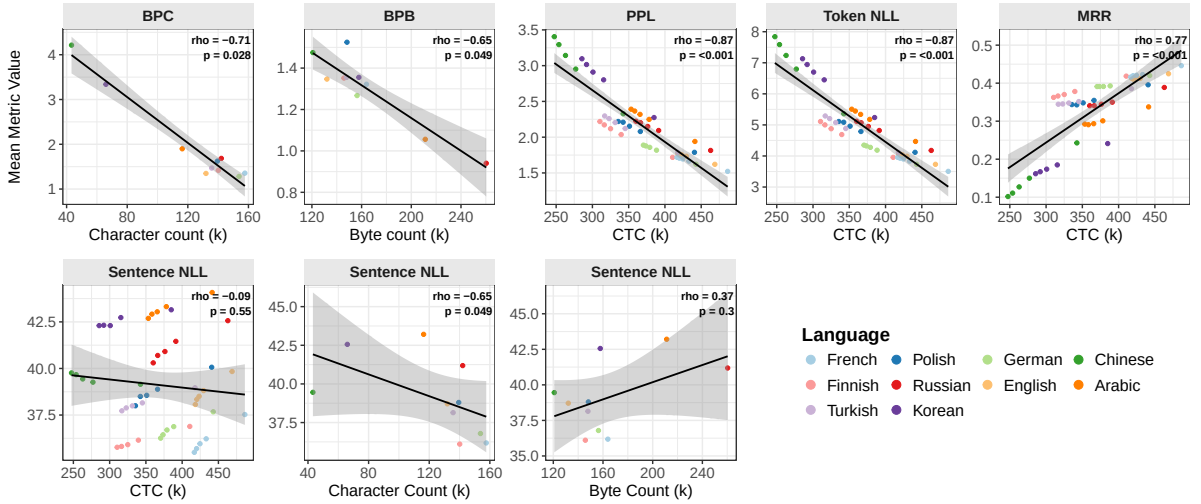

Figure 8: Spearman's Rank Correlation between the intrinsic metrics and their potential confounding factors in Parallel10 (perplexity is scaled by log10).

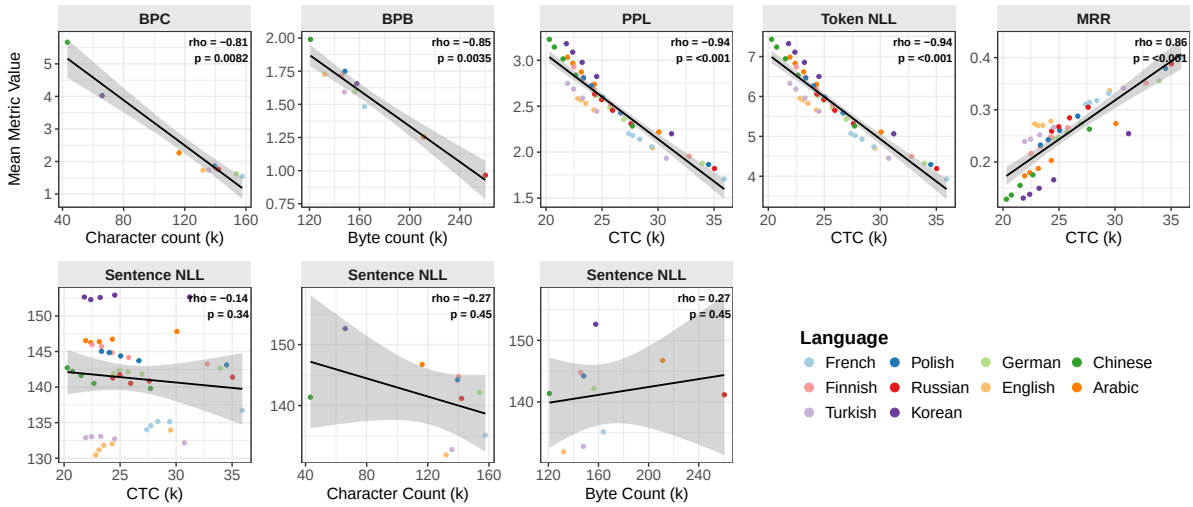

Figure 9: Spearman's Rank Correlation between the intrinsic metrics and their potential confounding factors in PUD (perplexity is scaled by log10).