# 2M-BELEBELE: Highly Multilingual Speech and American Sign Language Comprehension Dataset

**Anonymous ACL submission**

## Abstract

We introduce the first highly multilingual speech and American Sign Language (ASL) comprehension dataset by extending BELEBELE. Our dataset covers 74 spoken languages at the intersection of BELEBELE and FLEURS, and one sign language (ASL). We evaluate 2M-BELEBELE dataset for both 5-shot and zero-shot settings and across languages, the speech comprehension accuracy is $\approx 2\%$ average lower compared to reading comprehension.

## 1 Introduction

From an AI perspective, text understanding and generation services are used globally in more than a hundred languages, but the scarcity of labeled data poses a significant challenge to developing functional systems in most languages. Although natural language processing (NLP) datasets with extensive language coverage, such as FLORES-200 (NLLB-Team et al., 2022), are available, they mainly concentrate on machine translation (MT). Multilingual evaluation benchmarks such as those for multilingual question answering (Lewis et al., 2020; Clark et al., 2020), natural language inference (Conneau et al., 2018), summarization (Hasan et al., 2021; Ladhak et al., 2020), and reasoning datasets (Ponti et al., 2020; Lin et al., 2021) collectively cover only about 30 languages. Furthermore, the extension of such datasets to speech or American Sign Language (ASL) is lacking, with the exception of FLEURS (Conneau et al., 2022; Tanzer, 2024), which is based on FLORES-200.

The recent BELEBELE benchmark is the first corpus that addresses text reading comprehension for a large number of languages following a multi-way parallel approach (Bandarkar et al., 2023). The entire BELEBELE text statistics are summarized in Table 1. Currently, there are no highly multilingual evaluation datasets for natural language understanding that cover either both speech and text, and/or ASL.

The outstanding performance of some MT and text-to-speech (TTS) models has enabled a rise in the number of works using synthetically generated training data. Furthermore, some recent works propose to also use synthetic data for evaluation; e.g., (Üstün et al., 2024; Seamless-Communication et al., 2023; Nguyen et al., 2024; Nachmani et al., 2023). This strategy allows researchers to extend datasets to low-resource languages and to other modalities, such as speech. However, we prove that using synthetic data for evaluation does not provide comparable conclusions as relying on human speech for the particular task of automatic speech recognition (ASR) and the FLEURS domain (see Appendix D).

The evaluation dataset that is closest to the speech comprehension evaluation dataset presented in this paper is the generative QA dataset proposed in (Nachmani et al., 2023). The questions are taken from two sources: the WebQuestions dataset created by Berant et al. (2013) and a new test set called "LLama Questions." The dataset covers 300 questions in English. In this work, we extend the BELEBELE dataset to speech and sign (Section 2). By doing so, we create the first highly multilingual speech and sign comprehension dataset[1]: 2M-BELEBELE. Compared to spoken languages, sign languages are considered low-resource languages for natural language processing (Yin et al., 2021). Most popular datasets cover small domains of discourse; e.g., weather broadcasts (Camgoz et al., 2018), which has limited real world applications. There have been previous releases of large scale open domain sign language datasets; e.g., (Albanie et al., 2021; Shi et al., 2022; Uthus et al., 2024). However, the results and challenges on such datasets suggest that computational sign language research still requires additional datasets to reach the performance of their spoken language counter-

[1] Appendix A specifies language coverage.

parts (Müller et al., 2022, 2023). With the release of the ASL extension of the BELEBELE dataset, we aim to provide additional, high quality sign language data with gloss annotations to underpin further computational sign language research. Furthermore, due to the paragraph-level nature of the BELEBELE dataset, we enable paragraph-context sign language translation, which has been reported to improve translation performance (Sincan et al., 2023). 2M-BELEBELE is composed of human speech recordings covering 74 languages and human sign recordings for ASL.

As a by-product of 2M-BELEBELE, we also extend the FLEURS dataset (which is widely used to benchmark language identification and ASR) by providing recordings for more FLORES-200 sentences than were previously available and adding sign language, creating a new 2M-FLORES. This 2M-FLORES extends FLEURS by 20%.

Finally, we provide a very basic set of experiments that evaluate 2M-BELEBELE and provide some reference results on the dataset. We use direct and/or cascaded systems to evaluate 2M-BELEBELE dataset with direct and/or cascaded systems (Section 3). We also list several further experimentation that 2M-BELEBELE unblocks. Note that the main contribution of this paper is the creation of the first highly multilingual speech and sign comprehension dataset. The complete set of experiments is out of the scope of this paper (see Section on Limitations). By open-sourcing our dataset, we encourage the scientific community to pursue such experimentation.

## 2 2M-BELEBELE

| Passages | | Questions/Answers | |
|---|---|---|---|
| Distinct Passages | 488 | Distinct Q | 900 |
| Questions per passage | 1-2 | Multiple-choice A | 4 |
| Avg words (std) | 79.1 (26.2) | Avg words Q (std) | 12.9 (4.0) |
| Avg sentences (std) | 4.1 (1.4) | Avg words A (std) | 4.2 (2.9) |

Table 1: Statistics for 2M-BELEBELE, which covers 74 spoken languages plus ASL. Average words are computed for English.

**FLEURS and BELEBELE passage alignment.** Since BELEBELE uses passages constructed from sentences in the FLORES-200 dataset, and FLEURS (Conneau et al., 2022) is a human speech version of FLORES-200 for a subset of its languages, we create a speech version of BELEBELE by aligning its passages with the speech segments available in FLEURS. This extension can be done without extra human annotation, just by computing the alignment between FLEURS and BELEBELE passages. However, such alignment does not cover the entire BELEBELE corpus because FLEURS does not cover the entirety of FLORES-200. There are 74 languages shared between FLEURS and BELEBELE. FLEURS does not cover the same passages as BELEBELE in all those 74 languages, which means that some languages have more speech passages than others. In general, we are able to match almost $\approx 80\%$ of the passages. Figure 1 shows the number of FLEURS paragraphs we can match, thus obtaining the number of paragraphs that must be recorded in order to cover all passages BELEBELE.

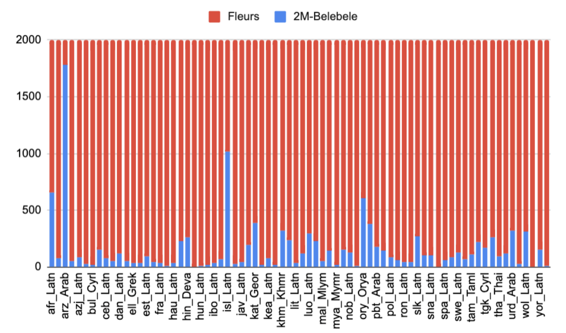


Figure 1: FLEURS vs New Recordings from 2M-BELEBELE for sentences in passages.

**Speech recordings.** We commission human recordings for the part of the BELEBELE dataset that is not covered by existing FLEURS recordings, as well as for elements of BELEBELE that do not exist in FLEURS (i.e. questions and answers). Recording participants must be native speakers of the languages they record. They must have an impeccable grasp of the conventions used in their respective languages for the narration of texts. The three tasks that participants are asked to perform are: (1) Read aloud and record the text passages provided (from FLORES-200); (2) Read aloud and record the provided written questions; (3) Read aloud and record the provided written answers. For the task, we provide the participants with (a) the text of the sentences to be recorded in TSV format (the number of passages may differ from language to language), (b) the written questions (900 per language, and (c) the written answer options (3,600 per language). Additional details on the recording guidelines provided to annotators are reported in the appendix B. We verify the quality of the recordings by randomly selecting 270 recordings (30% of sample size) and ensuring that the recordings do not contain background or ambient noise and that the voices of the participants are clearly audible.

**Sign recordings.** To obtain ASL sign recordings, we provide translators of ASL and native signers with the English text version of the sentences to be recorded. The interpreters are then asked to translate these sentences into ASL, create glosses for all sentences, and record their interpretations into ASL one sentence at a time. The glosses are subjected to an additional quality check by expert annotators to harmonize the glossing format. To harmonize the recording conditions and eliminate visual bias, the videos are recorded against plain monochrome backgrounds (e.g., white or green), and signers are requested to wear monochrome upper body clothing (e.g., black). All videos are captured in 1920x1080p resolution with all of the signing space covered in FOV. The recordings are done in 60 frames per second to address most of the motion blur that happens during signing.

**2M-BELEBELE Statistics.** The final dataset is composed of 75 languages (74 in speech, 1 in sign). Each of the languages' respective subsets includes 2,000 utterances organized in 488 distinct passages, 900 questions, and 4 multiple choice answers per question. For our recorded data (the red portion of Figure 1 plus questions and answers), we have one audio file or two per sentence, depending on the number of available participants (one participant only in 23 languages, and two participants in 51 languages). When two speakers are available, we request that one should represent a higher-pitch range, and the other a lower-pitch range for each passage. More details are available in Appendix A.

In addition, the data set includes video recordings in ASL for 2,000 FLORES sentences (not including the test partition) and is similarly organized in 488 distinct passages, as well as 900 questions and 4 multiple-choice answers for each question (see summary table 1). The ASL dataset was recorded by two interpreters, but, contrary to what was possible in other languages, each interpreter could only cover one-half of the dataset each.

## 3 Experiments

We evaluate 2M-BELEBELE, and compare performance across modalities. Our comparison is limited in number of systems and combination of modalities. 2M-BELEBELE offers the opportunity to check multimodal comprehension by combining speech/text/sign passages; questions and answers. In our case, we only provide results for entire text passages, questions and answers and speech passages, text questions and answers. A more comprehensive set of experiments is out of the scope of this paper, which aims at unblocking such experimentation by open-sourcing the dataset itself.

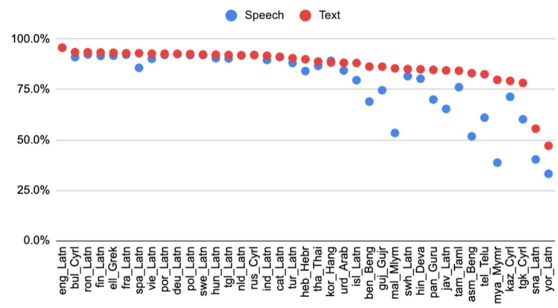


Figure 2: Speech and Text BELEBELE accuracy results in 39 languages. We compare text performance with LLAMA-3-CHAT (zero-shot) and speech performance with WHISPER +LLAMA-3-CHAT (asr+zero-shot).

**Systems.** We use the speech section of the 2M-BELEBELE dataset to evaluate the speech comprehension task with a cascaded system consisting of first speech recognition (ASR) using the WHISPER-LARGE-V3 model (Radford et al., 2022) (hereinafter, WHISPER) and SEAMLESSM4T (corresponding to SEAMLESSM4T-LARGE V2) model (Seamless-Communication et al., 2023) feeding into LLAMA-3[2]. We also provide results with a unified system SPIRITLM (Nguyen et al., 2024), which is a multimodal language model that freely mixes text and speech. Since the size of this model is 7B and is based on LLAMA-2, we also add a comparison to the LLAMA-2 model. We compare these results with LLAMA-3 and LLAMA-3-CHAT using the BELEBELE text passage as input. For these systems, we report the results in 5-shot in-context learning and zero-shot on 39 languages at the intersection of WHISPER, SEAMLESSM4T and 2M-BELEBELE (see Appendix A).

**Zero-shot Evaluation.** We use the same evaluation strategy as in (Bandarkar et al., 2023). SPIRITLM is not available in chat mode.

[2] https://ai.meta.com/blog/meta-llama-3/

| Dataset | Model | Size | Vocab | AVG | % ≥ 50 | % ≥ 70 | Eng | non-Eng |
|---|---|---|---|---|---|---|---|---|
| *5-Shot In-Context Learning (examples in English)* | | | | | | | | |
| BELEBELE | LLAMA-3 | 70B | 128K | - | - | - | 94.8 | - |
| 2M-BELEBELE | WHISPER + LLAMA-3 | 70B | 128K | 77.1 | 89.7 | 71.8 | 94.4 | 76.6 |
| 2M-BELEBELE | SEAMLESSM4T + LLAMA-3 | 70B | 128K | 81.7 | 94.9 | 92.7 | 93.5 | 81.4 |
| 2M-BELEBELE | WHISPER + LLAMA-2 | 7B | 32K | - | - | - | 49.9 | - |
| 2M-BELEBELE | SPIRITLM | 7B | 37K | - | - | - | 25.9 | - |
| *Zero-Shot* | | | | | | | | |
| BELEBELE | LLAMA-3-CHAT | 70B | 128K | 87.0 | 97.4 | 94.9 | 95.8 | 86.7 |
| 2M-BELEBELE | WHISPER + LLAMA-3-CHAT | 70B | 128K | 79.1 | 92.3 | 76.9 | 95.7 | 78.7 |
| 2M-BELEBELE | SEAMLESSM4T + LLAMA-3-CHAT | 70B | 128K | 84.8 | 94.9 | 94.9 | 95.5 | 84.5 |

Table 2: Summary of accuracy results on 2M-BELEBELE compared to BELEBELE across models and evaluation settings. % ≥ 50/70 refers to the proportion of languages for which a given model performs above 50/70% for question and answer in text and passage in speech. (*At the time of submission, we were missing LLAMA-3 5-shot results)

**5-shot In-Context Learning.** The few-shot examples are taken randomly from the English training set and they are prompted as *text* format to the model. Different from (Bandarkar et al., 2023), we do not pick the answer with the highest probability but directly assess the predicted letter of the answer.

For 5-shot and zero-shot settings, our instruction prompt is as follows *"Given the following passage, query, and answer choices, output the letter corresponding to the correct answer. Do not write any explanation. Only output the letter within A, B, C, or D that corresponds to the correct answer."* and we report the averaged accuracy over 3 runs[3].

**Results.** 2M-BELEBELE accuracy results per language compared to BELEBELE are shown in Figure 2. Differences in speech and text vary slightly depending on the languages. Low-resource languages have a greater variation between text and speech BELEBELE. The ten languages with the largest gap are: Burmese, Maltese, Assamese, Telugu, Javanese, Tajik, Bengali, Shona, Eastern Panjabi, Yoruba, Gujarati. Table 2 reports the summary of the results. The English drop from direct text to speech task does not vary much between 5-shot and zero-shot strategies, being slightly higher in the zero-shot setting (coherently with previous LLAMA-3 results that show better performance in zero-shot in other tasks[4]). When comparing speech and text comprehension in zero-shot setting, we observe that speech decreases performance in about 2% average across languages. Table 2 reports English results for SPIRITLM, a direct multimodal model. One of the reasons SPIRITLM may be performing worse is that 5-shot examples are in text, while the passage on the asked question is in speech.

**ASL** We know from previous large-scale translation attempts (Albanie et al., 2021; Müller et al., 2022) that models struggle to generalize over both individuals/appearance and large domain of discourse. Compared to speech and text models, sign language models suffer from having to learn generalized representations from high-dimensional inputs, i.e. videos, without overfitting to limited training dataset. Previous attempts have been made to create a more generalizable abstraction layer in the form of subunits (Camgoz et al., 2020), similar to phonemes for speech, which achieved promising results on a translation task with a small discourse domain. However, this work is yet to be applied to large discourse domain translation tasks. The best results in the FLORES domain have been achieved with close models that are not available (Zhang et al., 2024). Trying (Rust et al., 2024) as an open model did not perform above chance in the final reading comprehension dataset. However, we believe that the release of this new dataset with the additional gloss annotation will help in training models that generalize over individuals better and improve large-scale sign language translation.

## 4 Conclusions

The 2M-BELEBELE dataset[5] allows to evaluate natural language comprehension in a large number of languages, including ASL. 2M-BELEBELE is purely human-made and covers the BELEBELE passages, questions, and answers for 75 languages: 74 in the speech modality and 1 in the sign modality.

[3]Random seeds: 0, 1, 2.

[4]https://ai.meta.com/blog/meta-llama-3-1/ and https://ai.meta.com/blog/meta-llama-3/

[5]Scripts to build the 2M-BELEBELE dataset are available in Github BLIND

## Limitations and ethical considerations

Our speech annotations do not have the entire set completed with two annotators. Due to the high volume of the dataset, not every recording has been thoroughly verified. Some of the languages in 2M-BELEBELE are low-resource languages, which pose a challenge in sourcing professionals to record. Therefore, some of the audios were recorded in home settings and may contain minor background noise, static noise, echoes, and, occasionally, the speech could be slightly muffled or soft. All annotators are native speakers of the target language, but they may have regional accents in their speech, and their personal speech styles may be present in the audio as well. However, the mentioned imperfections should not affect intelligibility; all the recordings can be clearly understood by human standards. Note that we are planning to release more languages as reported in Appendix C.

We can group the ASL limitations under two categories, namely visual and linguistic. For visual limitations, ASL sequences are recorded in what can be considered laboratory environments with few signer variance. This makes it harder for models trained on them to generalize to unseen environments and signers. For linguistic limitations, ASL sequences are collected one sentence at a time. Although this enables pairwise training and evaluation, such as classical text-based NMT, the generated sequences may not be fully realistic in terms of real-world signing. An example would be the use of placement. In sentence-per-sentence sequence generation, a signer would refer to an entity with their sign each sentence, whereas in long-form conversation, a signer would place the entity in their signing space after first reference and refer them in via use of placement in the following sentences.

Our benchmarking is limited compared to the potential capabilities of the dataset. For example, since we have spoken questions, passages and responses, instead of just using a fix modality (spoken passages, text questions and responses), we could explore the performance when using all combinations among modalities (e.g., question in speech, answer in speech, passage in speech; or question in speech, answer in text, passage in speech; or question in speech, answer in speech and passage in text.)

In terms of compute budget, we estimate it as 47K Nvidia A100 hours by taking into account the product of following factors: number of languages (39), number of random seeds (3), number of GPUs required by model (8), number of experiment setups (5) and estimated number of hours per experiment (10).

Speakers and signers were paid a fair rate. Our recorded data reports self-identified gender by participant. Each of the speakers and signers signed a consent form agreeing on the dataset and its usage that they were participating in.

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## A Languages

Table 3 reports details on languages covered by FLEURS, TTS and ASR.

## B Annotation Guidelines

**Recording process.** Find a quiet place free from distractions and noises, and choose a headphone that is comfortable to wear and a good quality microphone that will not distort or break your voice. Read aloud and record the scripts in a pleasant tone and at a constant and even pace, as if you were reading a formal document. Try not to speak too quickly or slowly and aim for a natural pace that is easy to follow. The audio files below provide examples of paces that are expected, too fast, or too slow, for the sentence. The hearing also marks the date for the suspect's right to a rapid trial.

To achieve the best sound quality when recording, position the microphone close to your mouth so that the voice will sound clear and present, but not too close that it sounds muddy or you can hear a puff of air. Clearly enunciate the words and avoid mumbling. Be sure to provide a 2-second pause between sentences to add clarity and keep the overall pace down. When dealing with long, complicated sentences that contain multiple clauses or phrases, there are several approaches to ensure clarity and a natural flow as follows. Break it down: Separate the sentence into smaller parts or clauses. Practice reading aloud several times before starting the recording. This can help you get a feel for the rhythm and pacing of the sentence. Pace yourself: Try to maintain a steady, even pace. If the sentence is particularly long, it is possible to take a brief pause at a natural breakpoint to catch your breath. You should read the provided passages aloud without repairs (a repair is the repetition of a word that was incorrectly pronounced to correct its pronunciation).

To achieve this, familiarize yourself beforehand with the correct pronunciation of difficult words, proper nouns, and transliterated words, as well as signs and symbols, dates and times, numbers, abbreviations, and punctuation marks. Some elements may have more than one correct pronunciation. In this case, use the one that comes the more naturally to you, as long as it is an accepted pronunciation (i.e., it is acknowledged in your language's dictionaries). Practice reading the passages aloud several times to become more comfortable with the material. Please pay particular attention to the following items:

**Numbers.** Number formats can vary from language to language; it is important to follow the pronunciation rules in your language. Here are

| Language | Code | Script | Family | FLEURS | ASR | 2M-BELEBELE |
|---|---|---|---|---|---|---|
| Mesopotamian Arabic | acm_Arab | Arab | Afro-Asiatic | | | |
| Afrikaans | afr_Latn | Latn | Indo-European | ✓ | | ✓(1) |
| Tosk Albanian | als_Latn | Latn | Indo-European | | | |
| Amharic | amh_Ethi | Ethi | Afro-Asiatic | ✓ | | ✓(2) |
| North Levantine Arabic | apc_Arab | Arab | Afro-Asiatic | | | |
| Modern Standard Arabic | arb_Arab | Arab | Afro-Asiatic | | | |
| Modern Standard Arabic | arb_Latn | Latn | Afro-Asiatic | | | |
| Najdi Arabic | ars_Arab | Arab | Afro-Asiatic | | | |
| Moroccan Arabic | ary_Arab | Arab | Afro-Asiatic | | | |
| Egyptian Arabic | arz_Arab | Arab | Afro-Asiatic | ✓ | | ✓(2) |
| Assamese | asm_Beng | Beng | Indo-European | ✓ | ✓ | ✓(2) |
| North Azerbaijani | azj_Latn | Latn | Turkic | ✓ | | ✓(1) |
| Bambara | bam_Latn | Latn | Niger-Congo | | | |
| Bengali | ben_Beng | Beng | Indo-European | ✓ | ✓ | ✓(2) |
| Bengali | ben_Latn | Latn | Indo-European | | | |
| Standard Tibetan | bod_Tibt | Tibt | Sino-Tibetan | | | |
| Bulgarian | bul_Cyrl | Cyrl | Indo-European | ✓ | ✓ | ✓(2) |
| Catalan | cat_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Cebuano | ceb_Latn | Latn | Austronesian | ✓ | | ✓(1) |
| Czech | ces_Latn | Latn | Indo-European | ✓ | | ✓(2) |
| Central Kurdish | ckb_Arab | Arab | Indo-European | ✓ | | |
| Danish | dan_Latn | Latn | Indo-European | ✓ | | ✓(2) |
| German | deu_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Greek | ell_Grek | Grek | Indo-European | ✓ | ✓ | ✓(2) |
| English | eng_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Estonian | est_Latn | Latn | Uralic | ✓ | | ✓(1) |
| Basque | eus_Latn | Latn | Basque | | | |
| Finnish | fin_Latn | Latn | Uralic | ✓ | ✓ | ✓(2) |
| French | fra_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Fulfulde (Nigerian) | fuv_Latn | Latn | Atlantic-Congo | | | |
| Oromo (West Central) | gaz_Latn | Latn | Afro-Asiatic | (✓) | | |
| Guarani | grn_Latn | Latn | Tupian | | | |
| Gujarati | guj_Gujr | Gujr | Indo-European | ✓ | ✓ | ✓(1) |
| Haitian Creole | hat_Latn | Latn | Indo-European | | | |
| Hausa | hau_Latn | Latn | Afro-Asiatic | ✓ | (✓) | ✓(2) |
| Hebrew | heb_Hebr | Hebr | Afro-Asiatic | ✓ | ✓ | ✓(2) |
| Hindi | hin_Deva | Deva | Indo-European | ✓ | ✓ | ✓(2) |
| Hindi | hin_Latn | Latn | Indo-European | | | |
| Croatian | hrv_Latn | Latn | Indo-European | ✓ | | ✓(2) |
| Hungarian | hun_Latn | Latn | Uralic | ✓ | ✓ | ✓(2) |
| Armenian | hye_Armn | Armn | Indo-European | ✓ | | ✓(1) |
| Igbo | ibo_Latn | Latn | Atlantic-Congo | ✓ | | ✓(1) |
| Ilocano | ilo_Latn | Latn | Austronesian | | | |
| Indonesian | ind_Latn | Latn | Austronesian | ✓ | ✓ | ✓(2) |
| Icelandic | isl_Latn | Latn | Indo-European | ✓ | ✓ | ✓(1) |
| Italian | ita_Latn | Latn | Indo-European | ✓ | | ✓(2) |
| Javanese | jav_Latn | Latn | Austronesian | ✓ | ✓ | ✓(1) |
| Japanese | jpn_Jpan | Jpan | Japonic | ✓ | | ✓(2) |
| Jingpho | kac_Latn | Latn | Sino-Tibetan | | | |
| Kannada | kan_Knda | Knda | Dravidian | ✓ | | |
| Georgian | kat_Geor | Geor | Kartvelian | ✓ | | ✓(2) |
| Kazakh | kaz_Cyrl | Cyrl | Turkic | ✓ | ✓ | ✓(1) |
| Kabuverdianu | kea_Latn | Latn | Indo-European | ✓ | | ✓(1) |

| Language | Code | Script | Family | FLEURS | ASR | 2M-BELEBELE |
|---|---|---|---|---|---|---|
| Mongolian | khk_Cyrl | Cyrl | Mongolic | (✓) | | ✓(2) |
| Khmer | khm_Khmr | Khmr | Austroasiatic | ✓ | | ✓(1) |
| Kinyarwanda | kin_Latn | Latn | Atlantic-Congo | | | |
| Kyrgyz | kir_Cyrl | Cyrl | Turkic | ✓ | | |
| Korean | kor_Hang | Hang | Koreanic | ✓ | ✓ | ✓(1) |
| Lao | lao_Laoo | Laoo | Kra-Dai | ✓ | | |
| Lingala | lin_Latn | Latn | Niger-Congo | ✓ | | |
| Lithuanian | lit_Latn | Latn | Indo-European | ✓ | | ✓(2) |
| Ganda | lug_Latn | Latn | Atlantic-Congo | ✓ | | ✓(1) |
| Luo | luo_Latn | Latn | Atlantic-Congo | ✓ | | ✓(2) |
| Standard Latvian | lvs_Latn | Latn | Indo-European | (✓) | | ✓(2) |
| Malayam | mal_Mlym | Mlym | Dravidian | ✓ | ✓ | ✓(2) |
| Marathi | mar_Deva | Deva | Indo-European | ✓ | | |
| Macedonian | mkd_Cyrl | Cyrl | Indo-European | ✓ | | ✓(2) |
| Maltese | mlt_Latn | Latn | Afro-Asiatic | ✓ | | |
| Maori | mri_Latn | Latn | Austronesian | ✓ | | |
| Burmese | mya_Mymr | Mymr | Sino-Tibetan | ✓ | ✓ | ✓(2) |
| Dutch | nld_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Norwegian Bokmål | nob_Latn | Latn | Indo-European | ✓ | | ✓(2) |
| Nepali | npi_Deva | Deva | Indo-European | ✓ | | ✓(2) |
| Nepali | npi_Latn | Latn | Indo-European | | | |
| Northern Sotho | nso_Latn | Latn | Atlantic-Congo | ✓ | | |
| Nyanja | nya_Latn | Latn | Afro-Asiatic | ✓ | | |
| Odia | ory_Orya | Orya | Indo-European | ✓ | | ✓(1) |
| Eastern Panjabi | pan_Guru | Guru | Indo-European | ✓ | ✓ | ✓(2) |
| Southern Pashto | pbt_Arab | Arab | Indo-European | (✓) | | ✓(1) |
| Western Persian | pes_Arab | Arab | Indo-European | (✓) | | ✓(1) |
| Plateau Malagasy | plt_Latn | Latn | Austronesian | | | |
| Polish | pol_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Portuguese | por_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Romanian | ron_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Russian | rus_Cyrl | Cyrl | Indo-European | ✓ | ✓ | ✓(2) |
| Shan | shn_Mymr | Mymr | Tai-Kadai | | | |
| Sinhala | sin_Latn | Latn | Indo-European | | | |
| Sinhala | sin_Sinh | Sinh | Indo-European | | | |
| Slovak | slk_Latn | Latn | Indo-European | ✓ | | ✓(1) |
| Slovenian | slv_Latn | Latn | Indo-European | ✓ | | ✓(2) |
| Shona | sna_Latn | Latn | Atlantic-Congo | ✓ | ✓ | ✓(2) |
| Sindhi | snd_Arab | Arab | Indo-European | ✓ | | ✓(2) |
| Somali | som_Latn | Latn | Afro-Asiatic | ✓ | | |
| Southern Sotho | sot_Latn | Latn | Atlantic-Congo | | | |
| Spanish | spa_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Serbian | srp_Cyrl | Cyrl | Indo-European | ✓ | | ✓(2) |
| Swati | ssw_Latn | Latn | Atlantic-Congo | | | |
| Sundanese | sun_Latn | Latn | Austronesian | | | |
| Swedish | swe_Latn | Latn | Indo-European | ✓ | ✓ | ✓(2) |
| Swahili | swh_Latn | Latn | Atlantic-Congo | ✓ | ✓ | ✓(1) |
| Tamil | tam_Taml | Taml | Dravidian | ✓ | ✓ | ✓(2) |
| Telugu | tel_Telu | Telu | Dravidian | ✓ | ✓ | ✓(2) |
| Tajik | tgk_Cyrl | Cyrl | Indo-European | ✓ | ✓ | ✓(1) |
| Tagalog | tgl_Latn | Latn | Austronesian | (✓) | ✓ | ✓(2) |
| Thai | tha_Thai | Thai | Tai-Kadai | ✓ | ✓ | ✓(2) |
| Tigrinya | tir_Ethi | Ethi | Afro-Asiatic | | | |
| Tswana | tsn_Latn | Latn | Atlantic-Congo | | | |

| **Language** | **Code** | **Script** | **Family** | FLEURS | ASR | 2M-BELEBELE |
|---|---|---|---|---|---|---|
| Tsonga | tso_Latn | Latn | Afro-Asiatic | | | |
| Turkish | tur_Latn | Latn | Turkic | ✓ | ✓ | ✓(1) |
| Ukranian | ukr_Cyrl | Cyrl | Indo-European | ✓ | | |
| Urdu | urd_Arab | Arab | Indo-European | ✓ | ✓ | ✓(2) |
| Urdu | urd_Latn | Latn | Indo-European | | | |
| Northen Uzbek | uzn_Latn | Latn | Turkic | ✓ | | |
| Vietnamese | vie_Latn | Latn | Austroasiatic | ✓ | ✓ | ✓(2) |
| Waray | war_Latn | Latn | Austronesian | | | |
| Wolof | wol_Latn | Latn | Atlantic-Congo | ✓ | | ✓(1) |
| Xhosa | xho_Latn | Latn | Atlantic-Congo | ✓ | | ✓(1) |
| Yoruba | yor_Latn | Latn | Atlantic-Congo | ✓ | ✓ | ✓(2) |
| Chinese | zho_Hans | Hans | Sino-Tibetan | ✓ | | ✓(2) |
| Chinese | zho_Hant | Hant | Sino-Tibetan | (✓) | | |
| Standard Malay | zsm_Latn | Latn | Austronesian | (✓) | | |
| Zulu | zul_Latn | Latn | Atlantic-Congo | ✓ | | |
| American Sign Language | ase | - | Sign Language | | | ✓(2) |

Table 3: Languages details. Column FLEURS reports the languages covered by Speech BELEBELE v1. Column ASR shows the languages reported in the experiment section, note that Hausa is covered by WHISPER-LARGE-V3 but not for SEAMLESSM4T. The number in brackets shows the number of annotations per language.

some general guidelines and examples: Decimal numbers: Read the whole part of the number as a whole number and then individually read every number after the decimal point. For example, in English, the decimal number 3.14 should be read as ”three point one four.” Different languages may have different rules, and you should follow the rules that are appropriate for your language. Cardinal numbers represent quantities or amounts. Ordinal numbers represent positions or ranks in sequential order and should be read with the appropriate suffix. For example, in English, the ordinal number 1st is read ”first” (not ”onest”) and 5th is read ”fifth” (not ”fiveth”). Different languages may have different rules, and you should follow the rule that is appropriate for your language.

Roman numerals are a collection of seven symbols that each represent a value: I = 1, V = 5, X = 10, L = 50, C = 100, D = 500, and M = 1,000. The can be pronounced in slightly different ways depending on the context, but they are never pronounced as individual letters. For example, in English, VIII in Henry VIII is pronounced ”Henry the eighth”, while Superbowl LVIII is pronounced ”Superbowl fifty-eight”, but they are never pronounced ”Henry v i i i” or ”Superbowl l v i i i”. Different languages may have different rules, and you should follow the rules that are appropriate for your language. Punctuation marks: As a general rule, punctuation marks should not be pronounced, except quotation marks.

For example, in English, punctuation marks such as periods, commas, colons, semicolons, question marks, and exclamation points are typically not pronounced. For example, the sentence. As a result of this, a big scandal arose. will be pronounced ”As a result of this a big scandal arose” - not ”As a result of this comma a big scandal arose period”. However, in formal-register English (in the news, for example), a difference is made between content created by the news team and content that should be attributed to someone else by explicitly pronouncing quotation marks. For example, the news transcript The fighter said: ”I am here to try to win this.” will be pronounced: ”The fighter said, quote, I am here to try to win this. End of quote.” In this case, different languages may have different rules, and you should follow the rules that are appropriate for your language. Signs and symbols. Signs and symbols need to be pronounced as they would be heard in a speech-only setting. Attention should be paid: (a) to potential number or gender agreement (for example, in English, ”40%” should be read as ”forty percent” — not ”forty percents”) (b) to potential differences between the place of the sign or symbol in writing and in speech (for example, in English, the ”$” sign should be read as ”dollar” and should be read after the number it precedes; i.e. ”$22” should be read as ”twenty-two dollars” — not ”dollars twenty-two”) (c) to the way the sign or symbol gets expanded in speech (for example, in English, ”Platform 9 ¾” should be read ”platform nine and three quarters” — not ”platform nine three quarters”). Similarly, 50 km/h would be pronounced ”fifty kilometers per hour” — not ”fifty kilometers hour”). Different languages may have different rules, and you should follow the rules that are appropriate for your language.

**Proper nouns and foreign expressions.** Even the same language may have at least 2 different ways to pronounce foreign expressions of proper nouns: (a) one way is to try to approach the way they would sound in the foreign language from which they come (for example, in English, Louis in Louis XIV is pronounced ”lewee” as it would be in French); (b) the other way is to pronounce them according to the rules of the adopting language (for example, in English, Louis in the City of St Louis is pronounced as in the English proper noun ”Lewis”)

**Abbreviations.** Abbreviations should be expanded as much as possible. However, it is suggested to refrain from expanding them if their expansion results in unnatural speech. For example, in English, abbreviations such as Dr. or etc. are pronounced ”doctor” and ”et cetera”, respectively (not ”d r” nor ”e t c”). However, abbreviations such as AM or PhD are pronounced as a sequence of letters without being expanded (”a m” and ”p h d”, respectively - not ”ante meridiem” nor ”philosophy doctorate”). Different languages may have different conventions, and you should follow the conventions that are appropriate for your language.

# C Extra languages pending for collection

We plan to collect in total 91 languages with both high-pitched and low-pitched. This is the list of all the languages in planning.

- Central Kurdish
- Nigerian Fulfulde
- West Central Oromo
- Kannada
- Kyrgyz
- Lao
- Lingala
- Marathi
- Maltese
- Maori
- Northern Sotho
- Chewa
- Somali
- Ukrainian
- Northern Uzbek
- Malay
- Zulu

# D Ablation study: Synthetic extension in speech evaluation datasets

In this part of our work, we aim to analyze the feasibility of synthetically extending text benchmarks to speech using TTS systems, thereby creating multimodal datasets. Our goal is to understand if it would have been feasible to obtain the speech version of BELEBELE by using state of the art TTS systems, instead of human recordings.

For this study we use FLEURS dataset, that contains ASR data in the same domain as BELEBELE. We chose to perform this study in the ASR task because it is simpler compared to other speech tasks, due to its monotonic alignment process and minimal need for reasoning. This ensures that the overall model performance and the complexity of the task are less likely to influence the results.

For our experiments, we generate a synthetic copy of the FLEURS dataset using the MMS TTS (Pratap et al., 2024) system on the FLEURS transcripts. Then, we benchmark state-of-the-art models (WHISPER, SEAMLESSM4T and MMS ASR) on both the original and synthetic datasets and analyze whether the conclusions remain consistent across both datasets. [6]

It is important to note that a decrease in system performance is expected when using synthetic data. However, if this decrease occurs proportionally across all models, the synthetic data could still be useful to benchmark models. Conversely, if the model performance ranking changes, we can conclude that synthetic data is not reliable when benchmarking models.

To measure the variability in model rankings between the original and the synthetic data, we track the inversions that occur in the order of the models in the two settings. We define an inversion as a

[6] Note that we perform the study on the FLEURS languages that are covered by all MMS, WHISPER and SEAMLESSM4T.

swap between two models that appear in adjacent positions on the list. We count how many swaps are needed in the ranking obtained using synthetic data to match the ranking from the original dataset.

| | SEAMLESSM4T | | WHISPER | | MMS | | |
|---|---|---|---|---|---|---|---|
| | **Hum** | **Syn** | **Hum** | **Syn** | **Hum** | **Syn** | **Inv** |
| Bengali | 14.1 | 21.1 | 114.7 | 105.8 | 14.6 | 25.0 | |
| Catalan | 8.2 | 13.2 | 6.7 | 16.4 | 10.3 | 21.8 | ✓ |
| Dutch | 9.9 | 20.0 | 8.5 | 19.7 | 12.4 | 28.3 | |
| English | 6.0 | 11.7 | 4.5 | 9.8 | 12.3 | 19.2 | |
| Finnish | 20.1 | 20.8 | 12.5 | 18.9 | 13.1 | 18.4 | ✓ |
| French | 9.5 | 10.8 | 6.7 | 11.3 | 12.4 | 16.6 | ✓ |
| German | 8.5 | 13.9 | 5.2 | 12.3 | 10.5 | 20.8 | |
| Hindi | 11.9 | 13.4 | 33.5 | 28.7 | 11.1 | 18.3 | ✓ |
| Indonesian | 12.1 | 12.8 | 8.7 | 14.2 | 13.2 | 21.9 | ✓ |
| Korean | 25.7 | 40.3 | 15.4 | 29.9 | 47.8 | 61.2 | |
| Polish | 13.0 | 14.7 | 8.1 | 13.3 | 11.6 | 18.1 | ✓ |
| Portuguese | 9.0 | 8.0 | 4.1 | 6.9 | 8.7 | 10.4 | ✓ |
| Romanian | 12.6 | 11.7 | 13.5 | 25.4 | 12.0 | 15.4 | ✓ |
| Russian | 10.2 | 18.6 | 5.6 | 17.4 | 18.8 | 34.3 | |
| Spanish | 6.3 | 9.1 | 3.4 | 10.0 | 6.4 | 10.8 | ✓ |
| Swahili | 19.5 | 19.0 | 64.2 | 58.4 | 14.2 | 19.0 | ✓ |
| Swedish | 15.4 | 20.1 | 11.3 | 19.1 | 21.0 | 27.8 | |
| Telugu | 27.4 | 28.0 | 132.2 | 133.9 | 24.2 | 27.8 | |
| Thai | 127.8 | 135.5 | 104.0 | 121.3 | 99.8 | 99.9 | |
| Turkish | 18.6 | 23.0 | 8.4 | 16.5 | 19.2 | 30.3 | |
| Ukrainian | 15.0 | 23.5 | 9.8 | 21.8 | 18.1 | 34.7 | |
| Vietnamese | 16.0 | 20.1 | 10.2 | 14.2 | 25.8 | 25.3 | |

Table 4: WER(↓) results on the ASR task. Last column marks if the language has at least 1 inversion in ASR performance ranking comparing human vs TTS inputs.

In Table 4 we see that in the ASR setting, conclusions regarding model performance can vary depending on whether human or synthetic data is used. Although these conclusions are specific to the evaluated tasks and datasets, we demonstrate that even with the outstanding performance of current TTS methods, this does not guarantee the reliability of the data they generate when it comes to evaluation purposes. This is true not only for low-resource languages, but also for high-resource languages such as French or Spanish. These findings show that speech benchmarks might not be reliable if synthetically generated even in widely researched areas, further supporting the creation of evaluation datasets by humans.