

Open Piper TTS Voices Ranked: Naturalness, Clarity, Speed and Licences of 1,683 Voices

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Technical report LA-RB-2026-003, version 1.0, 15 October 2026
<https://loudness.ai/research/piper-tts-voices-ranked/>

Abstract

Piper is a widely used neural text-to-speech engine for ordinary processors, with an official catalogue of 177 voice files in 53 languages and further community models. Choosing a voice is hard: the catalogue gives no comparative quality data, several models contain hundreds of speakers, and licences differ from file to file. We reviewed the licence of every official voice file and excluded 102: 76 fine-tuned from the Lessac voice, whose recordings are licensed for non-commercial use, and 26 with a non-commercial or research-only licence of their own. We then tested every speaker of the remaining 75 official files in 27 languages and of three community models trained from scratch: 1,683 voices in 32 language variants. Each voice read three sentences in its language and received a naturalness score from the UTMOS22 predictor and a clarity score from the character error rate of a Whisper large-v3 transcript, combined into an overall score and ranked within its language. The best voices are English: every one of the 793 voices that scored 90 or more out of 100. A community model, Clean 100, matched the best official voice (96.4 against 96.2) with a higher median speaker (93.2 against 90.8) while synthesising 6.2 times faster on a laptop CPU. Inside one model, speakers differed by up to 46.3 points, more than the gap between most models. We publish the scores, licences, checksums, pinned download links, listening samples and scripts, and an interactive explorer.

1 Introduction

Piper [1] synthesises speech with VITS [4] models small enough to run faster than real time on a few processor cores, which makes it a common choice for local assistants, accessibility tools and web services. Its official voice catalogue [2] holds 177 voice files in 53 languages, most trained by volunteers on public speech corpora, and community authors publish further models [3].

Three problems make choosing a voice harder than it should be. First, the catalogue describes each file by language, dataset and a coarse quality tier, but gives no measured quality, so users listen to voices one at a time. Second, multi-speaker models hide many voices behind one file: the LibriTTS model alone has 904 speakers, and the default speaker 0 is what most tools use. Third, licences vary. A voice card may list a permissive dataset licence while the model was fine-tuned from another voice whose recordings are licensed for non-commercial use only.

This report answers a practical question: *which Piper voices can a business use, and which of them sound best in each language?* Our contributions are:

1. A licence review of every official Piper voice file, including the fine-tuning lineage that the cards do not always state, and the list of excluded files with reasons.

Licence class	Voices	Licences
No conditions	51	CC0 1.0, Public domain
Credit required	1,613	CC BY 4.0, CC BY-SA 4.0, Apache 2.0, CC BY-SA 3.0 ES, Jenny (Dioco) licence
Copyleft	2	GPL-2.0, AGPL-3.0
Unclear	17	Not stated

Table 1: Voices tested, by licence class. Every class permits commercial use; “unclear” voices need a check of the source before such use.

2. Automatic naturalness and clarity scores, an overall score and within-language ranks for every speaker of every remaining official file and three community models: 1,683 voices.
3. Findings on community versus official models, speaker variation, quality tiers, gender and CPU speed.
4. Open data: per-voice scores, per-file licences, checksums and download links pinned to the tested revision, listening samples, scripts and an interactive explorer.

2 Voices and licences

Catalogue. We used revision `c10ece1` of the official voice repository [2], the revision current in October 2026, and recorded each file’s size and checksum. Every voice card was read in full, with its training data and licence.

Lineage. Piper voices are often trained by fine-tuning an existing voice rather than from scratch, which needs far less data. Fine-tuning starts from the parent model’s weights, so the new voice is in part derived from the parent’s recordings. Many official voices descend, directly or through another voice, from the Lessac voice, trained on recordings released for the Blizzard Challenge 2013 [5] under a non-commercial licence. Whether a fine-tuned model inherits its parent’s data licence is legally unsettled; as a precaution we excluded the 76 official files with Lessac lineage, even where their own dataset is permissive. We excluded a further 26 files whose own licence is non-commercial or research-only. Appendix B lists all 102 files. The remaining 75 official files cover 27 languages.

Community models. Bryce Beattie, author of several official voices, publishes further Piper models trained from scratch [3]. We added three: Clean 100 (245 speakers, trained on the clean-100 subset of LibriTTS-R [7], CC BY 4.0), ManyVoice (16 English speakers from public-domain LibriVox recordings), Jenny (Irish English; its licence permits commercial use but requires the voice to be called “Jenny” in software that generates audio). His Norman model is byte-identical to the official Norman file and is listed once; tested twice under the two names, it scored 89.6 and 89.5.

Licence classes. We group licences by what they ask of a commercial user (Table 1): *no conditions* (public domain, CC0), *credit required* (CC BY, CC BY-SA, Apache 2.0 and the Jenny licence; CC BY-SA also asks that adaptations of the voice keep the licence), *copyleft* (GPL and AGPL model licences) and *unclear* (the card states no licence or only points to a web page). This summary is not legal advice.

3 Method

Test sentences. Every voice of a language read the same three sentences: a short introduction of the voice, a sentence about a meeting on Monday morning and a question about the nearest train station, translated for each of the 27 language families. They contain no digits, abbreviations or symbols, so text normalization does not affect the result (we studied it separately [14]).

Synthesis. We used Piper 1.8.0 with each model’s own default settings (length, noise and noise-width scales from its configuration), one take per sentence, two intra-op threads, and converted every clip to 16 kHz mono for scoring. Multi-speaker models were run for every speaker identifier listed in their configuration.

Natural. The UTMOS22 “strong” predictor [9], through the SpeechMOS port [11], predicts the mean opinion score (1–5) that listeners would give a clip; it was among the best systems of the VoiceMOS Challenge 2022 [10]. We average it over the three sentences and rescale it to 0–100: $\text{Natural} = 100 (\text{MOS} - 1)/4$.

Clear. The three sentences are joined with 0.6 s of silence and transcribed in one pass by Whisper large-v3 [12] through faster-whisper 1.2.1 [13] (int8, greedy decoding, language forced, no voice-activity filter). Transcript and reference are NFKC-normalised, lower-cased and stripped of punctuation (and of spaces for Chinese), and $\text{Clear} = 100 (1 - \text{CER})$, where CER is the character error rate.

Overall. $\text{Overall} = \text{Natural}/2 + \text{Clear}/2 + 4 \cdot [22 \text{ kHz}]$. Medium and high quality Piper voices are recorded at 22.05 kHz and low and x_low voices at 16 kHz; both measures work on 16 kHz audio and cannot hear the extra bandwidth, which listeners do hear, so 22 kHz voices receive 4 points. Voices are ranked within their language variant only: UTMOS22 was trained mainly on English, and Whisper is much weaker in some languages, so scores are not comparable across languages.

Two rounds. Round one tested up to twelve speakers of each file on a cloud server (onnxruntime 1.31.0). Round two, on a laptop (onnxruntime 1.19.2), screened every speaker of the six largest multi-speaker sets and the community models with one sentence and then tested all 1,580 of them with all three; the one-sentence naturalness predicted the three-sentence mean with $r = 0.967$. Where a voice was tested twice we keep the round-two result. Sixty voices measured in both rounds agreed with $r = 0.948$ and a mean absolute difference of 3.4 points, which we take as the measurement noise: differences of a few points between two voices are not meaningful.

Gender. We report a voice’s gender only where its training dataset records the reader (the LibriTTS and LibriTTS-R speaker lists [6, 7] and the Jenny dataset); it is never inferred from the audio. The MLS speakers [8] and most single-speaker voices are therefore listed as not recorded. This gives 553 female, 597 male and 533 not recorded.

Speed. For each model held locally we timed the three sentences three times with two intra-op threads and report the median real-time factor (computing seconds per second of speech). Speed depends on the model’s size, not on the speaker.

4 Results

4.1 Best voices by language

Table 2 and Figure 1 give the best and median voice of each language variant. English leads by a wide margin: all 793 voices with an overall score of 90 or more are English, and 1,197 voices score 80 or more. Italian, Ukrainian, Swedish, Basque, Dutch, Icelandic, Urdu and Mexican Spanish each have a voice above 85. Most non-English variants have one to three voices. Telugu, Vietnamese, Nepali and Armenian score lowest, partly because the recogniser itself fails there (its Telugu transcripts drift into Kannada script); their ranks need a native listener’s check.

4.2 A community model matches the best official one

The best Clean 100 speaker scored 96.4 and the best speaker of the official high-quality LibriTTS model 96.2, a difference well inside the measurement noise. Clean 100 is more consistent: its median speaker scored 93.2 against 90.8, and its worst 87.1 against 78.6 (Table 3). It is a medium-quality model and synthesised speech in 0.091 of real time against 0.568 for LibriTTS high (Table 5), 6.2 times faster; on a cloud server with the same settings the ratio was 4.3. Both models derive from LibriTTS readers, but Clean 100 was trained on the restored LibriTTS-R audio with failed restorations removed, which may explain its narrower spread.

4.3 The speaker matters more than the model

Figure 2 shows every speaker of the eight models with ten or more speakers. Inside French MLS, speakers range from 24.4 to 70.7 (46.3 points); inside German MLS the range is 31.0 points. We did not study why individual speakers score low. Speaker 0, the default in most software, is rarely the best: users of multi-speaker models should choose a speaker deliberately.

4.4 Quality tiers, gender and the two measures

Piper’s quality tiers describe model size and sample rate. The high tier has the highest median (Table 4), but tiers are confounded with language and dataset: most high-quality voices are English LibriTTS speakers and many medium-quality voices are MLS speakers of other languages. Within English, the best medium voices equal the best high ones. Female and male voices scored alike: among LibriTTS readers, women averaged 90.8 and men 90.1; in Clean 100, 93.6 and 92.5. Natural and Clear correlate across all voices ($r = 0.80$), but not tightly enough to replace each other: a voice can be easy to understand yet sound unnatural, or the reverse.

4.5 Speed

Table 5 gives the real-time factor of each model we hold locally, on an Apple M4 laptop with two threads. Medium and x_low models synthesise speech 10 to 18 times faster than real time; LibriTTS high about twice as fast. On a cloud server with 12 AMD EPYC virtual cores and the same two threads, medium voices measured 0.17–0.19 and LibriTTS high 0.83, between 1.5 and 2 times slower than the laptop.

Language	Voices	Best voice	Best	Median
English (United States)	1,158	Clean 100 · speaker 118	96.4	91.3
English (US/UK mix)	16	ManyVoice · speaker 2	95.0	89.2
English (Ireland)	1	Jenny	93.5	93.5
English (Great Britain)	4	Cori (medium)	92.4	90.1
Italian (Italy)	3	Serena (high)	89.6	86.3
Ukrainian (Ukraine)	7	Tetiana	88.1	84.8
Swedish (Sweden)	2	NST	86.4	86.3
Basque (Spain)	2	Maider	85.6	82.3
Dutch (Netherlands)	55	Alex	85.6	61.3
Icelandic (Iceland)	4	Steinn	85.3	83.2
Urdu (Pakistan)	1	Aegis Female	85.2	85.2
Spanish (Mexico)	2	Claude	85.0	79.5
Slovenian (Slovenia)	1	Artur	84.6	84.6
Farsi (Iran)	1	Gyro	84.2	84.2
Latvian (Latvia)	1	Aivars	82.8	82.8
Norwegian (Norway)	10	NVCC · speaker 6	82.0	77.8
German (Germany)	241	Karlsson	81.8	70.0
Chinese (China)	1	Huayan	79.6	79.6
Dutch (Belgium)	3	Nathalie	79.5	76.8
Czech (Czech Republic)	1	Kasandra	78.1	78.1
Greek (Greece)	2	Rapunzelina (medium)	77.0	72.2
Kazakh (Kazakhstan)	8	ISSAI · speaker 4	77.0	71.1
Finnish (Finland)	1	Harri	76.8	76.8
French (France)	129	Gilles	76.8	61.8
Catalan (Spain)	2	UPC Ona	76.6	76.2
Spanish (Spain)	3	MLS 9972	75.8	75.1
Portuguese (Brazil)	1	Edresson	74.1	74.1
Polish (Poland)	1	MLS 6892	68.8	68.8
Armenian (Armenia)	1	Gor	64.3	64.3
Telugu (India)	2	Padmavathi	56.8	54.1
Vietnamese (Vietnam)	1	25hours single	56.4	56.4
Nepali (Nepal)	18	Google · speaker 1	55.5	48.0

Table 2: Best and median overall score per language variant, with the number of voices tested.

Best and median voice in each language

Overall score (0-100) of the voices that allow commercial use. Compare within a language.

● Best voice ● Median voice

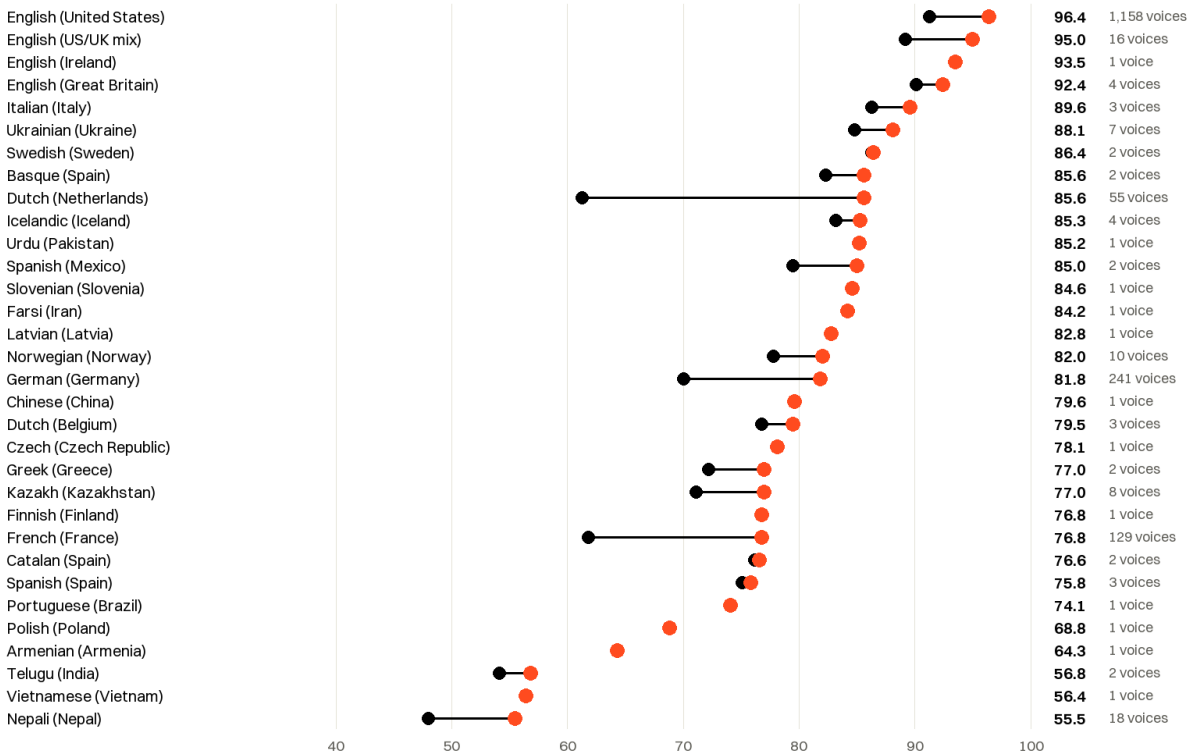


Figure 1: Best (orange) and median (black) overall score per language variant.

Model	Speakers	Best	Median	Worst	Spread
Clean 100 (community)	245	96.4	93.2	87.1	9.3
LibriTTS (English, high)	904	96.2	90.8	78.6	17.6
ManyVoice (community)	16	95.0	89.2	76.1	18.9
NVCC (Norwegian, medium)	10	82.0	77.8	73.0	9.0
MLS (German, medium)	236	81.2	69.9	50.2	31.0
MLS (French, medium)	125	70.7	61.8	24.4	46.3
MLS (Dutch, medium)	52	69.7	61.2	30.9	38.8
Google (Nepali, x_low)	18	55.5	48.0	43.8	11.7

Table 3: Overall score of every speaker in the models with ten or more speakers.

Quality	Voices	Median	Best
high	917	90.7	96.2
medium	715	72.6	96.4
low	21	75.8	92.2
x_low	30	52.0	79.6

Table 4: Overall score by Piper quality tier.

5 Using the results

The report’s web page includes an explorer that filters all 1,683 voices by language, gender, licence class, quality, source and minimum score, plays a sample of each and links its model and configuration files. Official files link to the repository at the tested revision, so the files match their published checksums; community files link to their author’s hosting with SHA-256 checksums. Each voice shows its licence, training data, a credit line where one is needed and the Piper command for its speaker. Appendix A lists the top three voices of each language variant.

Practical advice follows from the results. For English, Clean 100 offers many strong speakers at medium-model speed. For multi-speaker models, pick a speaker by listening to the top of the ranking rather than using speaker 0. For low-resource languages, treat our ranks as a starting point and ask a native speaker. Check the licence class: most voices need a visible credit line.

6 Limitations

All scores are automatic; no human listening test was run. UTMOS22 was trained mainly on English ratings, and its values in other languages are less reliable than its ordering within one language. The three sentences per language were written for this benchmark and translated, not composed by native speakers, and each was synthesised once; Piper’s output varies slightly between takes. Rounds one and two ran on different machines and runtime versions. Gender coverage is limited to what datasets record. Licence summaries reflect the cards at the tested revision and are not legal advice.

7 Data availability

The study package (scores, per-file licences, checksums and links, the test sentences, 1,683 listening samples and the scripts for synthesis, scoring, ranking and speed) is available from the report’s

The speaker you pick matters more than the model

Overall score of every speaker in each model with ten or more speakers; the grey shape shows how many voices score at each level.

● Best voice | Median voice

Clean 100 · English (US), community

245 speakers · 87.1–96.4

LibriTTS · English (US), high

904 speakers · 78.6–96.2

ManyVoice · English, community

16 speakers · 76.1–95.0

NVCC · Norwegian

10 speakers · 73.0–82.0

MLS · German

236 speakers · 50.2–81.2

MLS · French

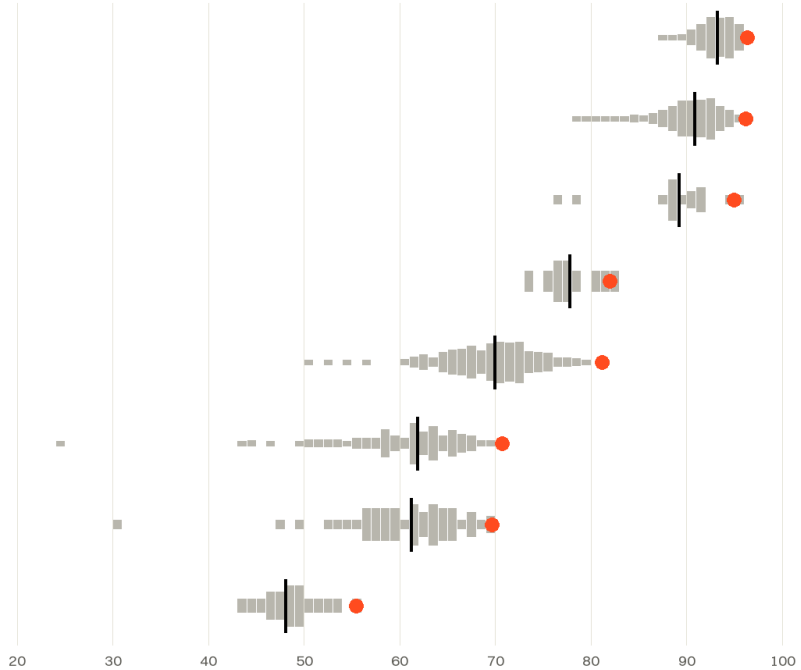
125 speakers · 24.4–70.7

MLS · Dutch

52 speakers · 30.9–69.7

Google · Nepali, x_low

18 speakers · 43.8–55.5



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Figure 2: Every speaker of each model with ten or more speakers: distribution (grey), median (black) and best (orange).

web page. Data and text are released under CC BY 4.0 and scripts under the Apache License 2.0; samples keep their model’s licence.

Competing interests and funding. The author develops Loudness.ai, whose text-to-speech tool offers a selection of these voices chosen with the same scores. No external funding was received.

References

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Model	Quality	Rate (Hz)	RTF
LibriTTS (English, high)	high	22,050	0.568
MLS (German, medium)	medium	22,050	0.083
MLS (French, medium)	medium	22,050	0.086
MLS (Dutch, medium)	medium	22,050	0.089
Google (Nepali, x_low)	x_low	16,000	0.055
Clean 100 (community)	medium	22,050	0.091
ManyVoice (community)	medium	22,050	0.095
Jenny (community)	medium	22,050	0.084

Table 5: Real-time factor (RTF, lower is faster): computing seconds per second of speech, median of three passes.

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A Top three voices per language variant

Language	#	Voice	Natural	Clear	Overall	Licence
Armenian (Armenia)	1	Gor	56.5	64.2	64.3	GPL-2.0
Basque (Spain)	1	Maidier	71.8	91.4	85.6	CC BY 4.0

Language	#	Voice	Natural	Clear	Overall	Licence
Catalan (Spain)	2	Antton	57.8	92.3	79.0	CC BY 4.0
	1	UPC Ona	55.5	97.8	76.6	CC BY-SA 3.0 ES
	2	UPC Pau	59.8	91.8	75.7	CC BY-SA 3.0 ES
Chinese (China)	1	Huayan	67.5	91.7	79.6	Not stated
Czech (Czech Republic)	1	Kasandra	49.3	99.0	78.1	CC BY 4.0
Dutch (Belgium)	1	Nathalie	63.5	95.6	79.5	CC0 1.0
	2	RDH (medium)	46.0	99.6	76.8	CC0 1.0
	3	RDH (x_low)	54.8	97.2	75.9	CC0 1.0
Dutch (Netherlands)	1	Alex	63.7	99.6	85.6	CC0 1.0
	2	MLS · speaker 51	52.8	78.5	69.7	CC BY 4.0
	3	MLS · speaker 37	49.9	80.6	69.2	CC BY 4.0
English (Great Britain)	1	Cori (medium)	76.8	100.0	92.4	Public domain
	2	Cori (high)	78.8	97.2	92.0	Public domain
	3	Alan	77.2	99.1	88.2	Not stated
English (Ireland)	1	Jenny	78.9	100.0	93.5	Jenny (Dioco) licence
English (US/UK mix)	1	ManyVoice · speaker 2	82.0	100.0	95.0	Public domain
	2	ManyVoice · speaker 9	80.2	100.0	94.1	Public domain
	3	ManyVoice · speaker 10	76.8	99.1	91.9	Public domain
English (United States)	1	Clean 100 · speaker 118	84.7	100.0	96.4	CC BY 4.0
	2	Clean 100 · speaker 25	84.8	100.0	96.4	CC BY 4.0
	3	Clean 100 · speaker 108	84.3	100.0	96.2	CC BY 4.0
Farsi (Iran)	1	Gyro	72.5	87.9	84.2	Not stated
Finnish (Finland)	1	Harri	60.0	93.6	76.8	CC0 1.0
French (France)	1	Gilles	59.0	94.7	76.8	CC0 1.0
	2	Tom	46.0	99.6	76.8	AGPL-3.0
	3	Siwis	51.5	98.4	74.9	CC BY 4.0
German (Germany)	1	Karlsson	66.2	97.4	81.8	Not stated
	2	MLS · speaker 162	62.3	92.2	81.2	CC BY 4.0
	3	Kerstin	60.2	100.0	80.2	CC0 1.0
Greek (Greece)	1	Rapunzelina (medium)	55.8	90.1	77.0	CC0 1.0
	2	Rapunzelina (low)	51.5	83.4	67.5	CC0 1.0
Icelandic (Iceland)	1	Steinn	69.8	93.0	85.3	Not stated
	2	Salka	65.2	94.7	84.0	Not stated
	3	Ugla	64.0	93.0	82.5	Not stated
Italian (Italy)	1	Serena (high)	71.2	100.0	89.6	CC BY 4.0
	2	Serena (medium)	65.5	99.2	86.3	CC BY 4.0
	3	Riccardo	44.0	97.5	70.7	Not stated
Kazakh (Kazakhstan)	1	ISSAI · speaker 4	55.8	90.2	77.0	CC BY 4.0
	2	ISSAI · speaker 1	51.0	89.4	74.2	CC BY 4.0
	3	ISSAI · speaker 0	53.2	86.0	73.6	CC BY 4.0
Latvian (Latvia)	1	Aivars	68.8	88.9	82.8	CC0 1.0
Nepali (Nepal)	1	Google · speaker 1	41.3	69.7	55.5	CC BY-SA 4.0
	2	Google · speaker 5	37.2	70.1	53.6	CC BY-SA 4.0
	3	Google · speaker 8	37.9	66.8	52.4	CC BY-SA 4.0
Norwegian (Norway)	1	NVCC · speaker 6	58.2	97.7	82.0	CC0 1.0
	2	NVCC · speaker 8	60.5	94.5	81.5	CC0 1.0
	3	NVCC · speaker 0	62.3	90.9	80.5	CC0 1.0

Language	#	Voice	Natural	Clear	Overall	Licence
Polish (Poland)	1	MLS 6892	43.5	94.2	68.8	CC BY 4.0
Portuguese (Brazil)	1	Edresson	49.8	98.4	74.1	CC BY 4.0
Slovenian (Slovenia)	1	Artur	61.5	99.6	84.6	CC BY 4.0
Spanish (Mexico)	1	Claude	62.3	99.6	85.0	Apache 2.0
	2	Ald	49.0	99.2	74.0	Not stated
Spanish (Spain)	1	MLS 9972	57.0	94.6	75.8	CC BY 4.0
	2	CarlFM	53.0	97.1	75.1	Public domain
	3	MLS 10246	17.2	90.0	53.6	CC BY 4.0
Swedish (Sweden)	1	NST	66.2	98.5	86.4	CC0 1.0
	2	Alma	66.8	97.5	86.2	Not stated
Telugu (India)	1	Padmavathi	67.8	37.9	56.8	CC BY 4.0
	2	Venkatesh	59.5	35.2	51.4	CC BY 4.0
Ukrainian (Ukraine)	1	Tetiana	69.5	98.7	88.1	Apache 2.0
	2	Oleksa	67.2	99.6	87.4	Apache 2.0
	3	Ukrainian TTS speaker 2	67.5	95.2	85.3	CC0 1.0
Urdu (Pakistan)	1	Aegis Female	65.0	97.4	85.2	Not stated
Vietnamese (Vietnam)	1	25hours single	25.0	87.8	56.4	Not stated

B Excluded official voice files

Voice file	Language	Reason	Stated licence
ar_J0-kareem-low	Arabic (Jordan)	Lessac lineage	See source
ar_J0-kareem-medium	Arabic (Jordan)	Lessac lineage	See source
bg_BG-dimitar-medium	Bulgarian (Bulgaria)	Lessac lineage	CC0
bn_BD-google-medium	Bengali (Bangladesh)	Lessac lineage	Not stated
ca_ES-upc_ona-medium	Catalan (Spain)	Lessac lineage	CC BY-SA 3.0 ES
cs_CZ-jirka-low	Czech (Czech Republic)	Lessac lineage	CC0
cs_CZ-jirka-medium	Czech (Czech Republic)	Lessac lineage	CC0
cy_GB-bu_tts-medium	Welsh (Great Britain)	Lessac lineage	CC BY 4.0
cy_GB-gwryw_gogleddol-medium	Welsh (Great Britain)	Lessac lineage	See source
da_DK-talesyntese-medium	Danish (Denmark)	Lessac lineage	CC0
de_DE-pavoque-low	German (Germany)	Non-commercial	CC BY-NC-SA 4.0
de_DE-thorsten-high	German (Germany)	Lessac lineage	CC0
de_DE-thorsten-medium	German (Germany)	Lessac lineage	CC0
de_DE-thorsten_emotional-medium	German (Germany)	Lessac lineage	CC0
el_GR-joy-medium	Greek (Greece)	Non-commercial	CC BY-NC 4.0
en_GB-alan-medium	English (Great Britain)	Lessac lineage	See source
en_GB-alba-medium	English (Great Britain)	Lessac lineage	CC BY 4.0
en_GB-arun-medium	English (Great Britain)	Lessac lineage	CC BY 4.0
en_GB-jenny_dioco-medium	English (Great Britain)	Lessac lineage	See source
en_GB-northern_english_male-medium	English (Great Britain)	Lessac lineage	CC BY-SA 4.0
en_GB-semaine-medium	English (Great Britain)	Non-commercial	CC BY-NC-SA 4.0
en_GB-vctk-medium	English (Great Britain)	Lessac lineage	CC BY 4.0
en_US-amy-medium	English (United States)	Lessac lineage	See source
en_US-arctic-medium	English (United States)	Lessac lineage	See source
en_US-hfc_female-medium	English (United States)	Non-commercial	CC BY-NC-SA 4.0
en_US-hfc_male-medium	English (United States)	Non-commercial	CC BY-NC-SA 4.0
en_US-joe-medium	English (United States)	Lessac lineage	CC0
en_US-kusal-medium	English (United States)	Lessac lineage	See source
en_US-l2arctic-medium	English (United States)	Non-commercial	CC BY-NC 4.0

Voice file	Language	Reason	Stated licence
en_US-lessac-high	English (United States)	Non-commercial	Lessac (Blizzard 2013)
en_US-lessac-low	English (United States)	Non-commercial	Lessac (Blizzard 2013)
en_US-lessac-medium	English (United States)	Non-commercial	Lessac (Blizzard 2013)
en_US-libritts_r-medium	English (United States)	Lessac lineage	CC BY 4.0
en_US-mike-medium	English (United States)	Lessac lineage	CC0
en_US-reza_ibrahim-medium	English (United States)	Lessac lineage	CC0
en_US-ryan-high	English (United States)	Non-commercial	CC BY-NC-SA 4.0
en_US-ryan-low	English (United States)	Non-commercial	CC BY-NC-SA 4.0
en_US-ryan-medium	English (United States)	Non-commercial	CC BY-NC-SA 4.0
en_US-sam-medium	English (United States)	Lessac lineage	Apache 2.0
es_AR-daniela-high	Spanish (Argentina)	Lessac lineage	CC BY-SA 4.0
es_ES-davefx-medium	Spanish (Spain)	Lessac lineage	CC0
es_ES-sharvard-medium	Spanish (Spain)	Lessac lineage	CC BY 3.0
es_MX-ald-medium	Spanish (Mexico)	Lessac lineage	Unlicense
et_EE-news-medium	Estonian (Estonia)	Lessac lineage	CC BY 4.0
fa_IR-amir-medium	Farsi (Iran)	Lessac lineage	CC0
fa_IR-ganji-medium	Farsi (Iran)	Lessac lineage	CC0
fa_IR-ganji_adabi-medium	Farsi (Iran)	Lessac lineage	CC0
fa_IR-reza_ibrahim-medium	Farsi (Iran)	Lessac lineage	CC0
fi_FI-harri-medium	Finnish (Finland)	Lessac lineage	CC0
fr_FR-siwis-medium	French (France)	Lessac lineage	CC BY 4.0
fr_FR-upmc-medium	French (France)	Lessac lineage	CC BY-SA 4.0
he_IL-saspeech-medium	Hebrew (Israel)	Non-commercial	See source
hi_IN-pratham-medium	Hindi (India)	Non-commercial	CC BY-NC-SA 4.0
hi_IN-priyamvada-medium	Hindi (India)	Non-commercial	CC BY-NC-SA 4.0
hi_IN-rohan-medium	Hindi (India)	Lessac lineage	IndicTTS licence
hu_HU-anna-medium	Hungarian (Hungary)	Lessac lineage	CC0
hu_HU-berta-medium	Hungarian (Hungary)	Lessac lineage	CC0
hu_HU-imre-medium	Hungarian (Hungary)	Lessac lineage	CC0
id_ID-news_tts-medium	Indonesian (Indonesia)	Lessac lineage	See source
it_IT-paola-medium	Italian (Italy)	Lessac lineage	See source
ja_JP-hi-fi_captain-medium	Japanese (Japan)	Non-commercial	CC BY-NC-SA 4.0
ka_GE-natia-medium	Georgian (Georgia)	Lessac lineage	See source
ko_KR-kss-medium	Korean (South Korea)	Non-commercial	CC BY-NC-SA 4.0
ku_TR-berfin_renas-medium	Kurmanji Kurdish (Turkey)	Non-commercial	Not stated
lb_LU-marylux-medium	Luxembourgish (Luxembourg)	Non-commercial	CC BY-NC-SA 4.0
lt_LT-reginute1-medium	Lithuanian (Lithuania)	Lessac lineage	CC BY 4.0
ml_IN-arjun-medium	Malayalam (India)	Lessac lineage	See source
ml_IN-meera-medium	Malayalam (India)	Lessac lineage	See source
mr_IN-google-medium	Marathi (India)	Lessac lineage	CC BY-SA 4.0
ne_NP-chitwan-medium	Nepali (Nepal)	Lessac lineage	CC0
ne_NP-google-medium	Nepali (Nepal)	Lessac lineage	CC BY-SA 4.0
nl_BE-nathalie-medium	Dutch (Belgium)	Lessac lineage	CC0
nl_NL-pim-medium	Dutch (Netherlands)	Lessac lineage	CC0
nl_NL-ronnie-medium	Dutch (Netherlands)	Lessac lineage	CC0
no_NO-talesyntese-medium	Norwegian (Norway)	Lessac lineage	CC0
pl_PL-bass-high	Polish (Poland)	Lessac lineage	Not stated
pl_PL-darkman-medium	Polish (Poland)	Lessac lineage	CC0
pl_PL-gosia-medium	Polish (Poland)	Lessac lineage	CC0
pl_PL-mc_speech-medium	Polish (Poland)	Lessac lineage	CC0
pt_BR-cadu-medium	Portuguese (Brazil)	Lessac lineage	CC0
pt_BR-faber-medium	Portuguese (Brazil)	Lessac lineage	CC0

Voice file	Language	Reason	Stated licence
pt_BR-jeff-medium	Portuguese (Brazil)	Lessac lineage	CC0
pt_PT-tugão-medium	Portuguese (Portugal)	Lessac lineage	CC0
ro_RO-mihai-medium	Romanian (Romania)	Lessac lineage	CC0
ru_RU-denis-medium	Russian (Russia)	Lessac lineage	CC0
ru_RU-dmitri-medium	Russian (Russia)	Lessac lineage	CC0
ru_RU-irina-medium	Russian (Russia)	Lessac lineage	Not stated
ru_RU-ruslan-medium	Russian (Russia)	Non-commercial	CC BY-NC-SA 4.0
sk_SK-lili-medium	Slovak (Slovakia)	Lessac lineage	CC0
sq_AL-edon-medium	Albanian (Albania)	Lessac lineage	CC0
sr_RS-serbski_institut-medium	Serbian (Serbia)	Non-commercial	CC BY-NC-SA 4.0
sv_SE-lisa-medium	Swedish (Sweden)	Lessac lineage	Not stated
sw_CD-lanfrica-medium	Swahili (Democratic Republic of the Congo)	Non-commercial	See source
te_IN-maya-medium	Telugu (India)	Lessac lineage	IndicTTS licence
th_TH-tsync2-medium	Thai (Thailand)	Non-commercial	CC BY-NC-SA 3.0
tr_TR-dfki-medium	Turkish (Turkey)	Non-commercial	CC BY-NC-SA 4.0
ur_PK-fasih-medium	Urdu (Pakistan)	Lessac lineage	Not stated
vi_VN-vais1000-medium	Vietnamese (Vietnam)	Lessac lineage	CC BY 4.0
vi_VN-vivos-x_low	Vietnamese (Vietnam)	Non-commercial	CC BY-NC-SA 4.0
zh_CN-chaowen-medium	Chinese (China)	Lessac lineage	CC0
zh_CN-huayan-medium	Chinese (China)	Lessac lineage	Not stated
zh_CN-xiao_ya-medium	Chinese (China)	Non-commercial	DataBaker, non-commercial