Evaluating Open-Source ASR Systems: Performance Across Diverse Audio Conditions and Error Correction Methods

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Abstract

Despite significant advances in automatic speech recognition (ASR) accuracy, challenges remain. Naturally occurring conversation often involves multiple overlapping speakers, of different ages, accents, and genders, as well as noisy environments and suboptimal audio recording equipment, all of which reduce ASR accuracy. In this study, we evaluate the accuracy of state of the art open source ASR systems across diverse conversational speech datasets, examining the impact of audio and speaker characteristics on WER. We then explore the potential of ASR ensembling and post-ASR correction methods to improve transcription accuracy. Our findings emphasize the need for robust error correction techniques and for continuing to address demographic biases to enhance ASR performance and inclusivity.

1 Introduction

Automatic Speech Recognition (ASR) technology has witnessed significant advancements in recent years, primarily due to the introduction of powerful transformer models trained on large datasets. These advancements have brought ASR systems close to human accuracy for conversational telephone speech (Stolcke and Droppo, 2017). However, ASR systems still face challenges in transcribing spontaneous human conversations (Szymański et al., 2020). In particular, naturally occurring conversation tends to involve multiple overlapping speakers, of different ages, accents, and genders, as well as noisy environments and suboptimal audio collection equipment. Transcription accuracy of state-of-the-art ASR systems varies significantly with audio characteristics such as accent, gender, overlapping speech, and background noise (Tatman and Kasten, 2017; Goldwater et al., 2008; Liesenfeld et al., 2023; Chen et al., 2022). Gaining a deeper understanding of how these factors influence ASR performance is essential for improving both accuracy and inclusivity.

To address these challenges, various ASR error correction methods have been explored. Traditional approaches like ROVER reflect the classic ASR pipeline comprising acoustic and language models (Fiscus, 1997). With the shift towards end-to-end (E2E) ASR systems, new transcription error correction methods have emerged (Chan et al., 2016). These methods often leverage large-scale pre-trained language models like BERT (Devlin et al., 2019) and T5 (Raffel et al., 2020) to enhance correction capabilities, especially in contexts with limited labeled speech data. However, previous studies have not extensively investigated error correction across ensembles of ASR systems.

In this study, we: (1) evaluate the accuracy of state-of-the-art open-source ASR systems across diverse conversational speech conditions, exploring the impact of speaker age, gender, accentedness, and background noise level; (2) examine the potential of ASR ensembling plus post-ASR correction methods to increase transcription accuracy; and (3) we release a dataset comprising the results from six different ASR systems across six datasets with varying audio characteristics, supporting reproducible research and encouraging further exploration of ASR ensembling strategies.[1]

2 Related Work

2.1 Disparities in ASR Performance

Previous research has highlighted disparities in ASR performance based on speaker attributes. Studies have demonstrated that gender, age, and accent can significantly influence WER. For instance, certain studies found female speech to be more accurately recognized than male speech, suggesting gender disparities in ASR performance (Adda-

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[1]https://github.com/sakimai/asr-evaluations

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Decker and Lamel, 2005; Goldwater et al., 2008; Feng et al., 2024). Conversely, (Garnerin et al., 2019; Tatman, 2017) observed a lower WER for male speech in specific contexts. Some studies reported no significant differences based on gender, highlighting the variability of ASR performance across different systems and datasets (Tatman and Kasten, 2017). Age-related differences in WER have also been documented, with findings indicating that child speech poses more challenges for ASR systems compared to adult speech due to physiological and behavioral differences (Jain et al., 2023). Accent presents another significant challenge, with systems often mis-recognizing the speech of speakers with accents divergent from the "standard" variant of the language used in training datasets (Tatman and Kasten, 2017; Koenecke et al., 2020; Dorn, 2019; DiChristofano et al., 2023; Tadimeti et al., 2022; del Río et al., 2023).

While the impact of individual audio characteristics on ASR performance has been extensively studied, less is known about how open-source ASRs with different architectures, such as Hidden Markov Models (HMM), self-supervised learning (SSL) models, speech foundation models, and E2E models perform across diverse datasets featuring various audio characteristics. In this study, we aim to fill this gap by comparing the transcription capabilities of six different open-source ASR systems across six conversational speech datasets.

2.2 Transcription Error Correction

Error correction models focus on detecting and correcting errors within ASR hypotheses. Traditional methods like ROVER use multiple hypothesis alignment and voting mechanisms to generate the best hypothesis (Fiscus, 1997). Other early error correction methods included statistical correction and statistical machine translation systems, and ontology learning (Cucu et al., 2013; D'Haro and Banchs, 2016; Anantaram et al., 2018). More recently, non-autoregressive correction models have shown promise (Leng et al., 2021b,a, 2023). Following the trend of E2E ASR systems, recent methods combine these components in an E2E manner (Guo et al., 2023; Hrinchuk et al., 2020; Guo et al., 2019). Pre-trained language models such as T5, BERT, and BART have also shown promise in correcting ASR transcription errors (Ma et al., 2023a; Li et al., 2024, 2021; Zhao et al., 2021; Ma et al., 2023b). Finally, generative large language models (LLMs) like GPT-3.5 and LLaMA have also been explored for this purpose (Ma et al., 2023c; Chen et al., 2023). Moreover, using multiple hypotheses—such as an n-best list—from a single ASR system can enhance the contextual framework for error correction models, allowing for improved correction capabilities (Zhu et al., 2021; Leng et al., 2021a). In this study, we compare different approaches to ASR error correction while combining hypotheses from multiple ASR systems.

3 Data & Systems

Dataset selection. We chose datasets to ensure a comprehensive and accurate evaluation of conversational speech. Priority was given to datasets that are not commonly used in the training of ASR models. The datasets include child speech, different levels of noise, varying number of speakers, and multiple accents of English (Table 1).

On dataset complexity, we recognize that the multidimensional nature of complexity is difficult to capture in a 2-D table. For instance, child speech is challenging not only due to its pitch and acoustic features but also due to variability in linguistic and pronunciation characteristics (Lee et al., 1997, 1999). Two-speaker audio introduces multiple conversational dynamics and conditions, such as overlapped speech and acoustic variability related to changes in speaker characteristics like gender. In comparison, single-speaker accented speech lacks these dyadic conversational elements, making the former more complex (Takaaki et al., 2013). Our dataset selection reflects these nuances, ordered in decreasing order of complexity from top to bottom:

- *Sawyer* (Sawyer, 2013) – unstructured play sessions involving 20 children.
- *Cameron* (Starke, 2023) – structured interactions between an adult and a child in a controlled, quiet environment.
- *CHiME-5* (Barker et al., 2018) – multi-speaker conversations in noisy environments, such as dinner table recordings.
- *AMI* (Mccowan et al., 2005) – meetings involving multiple speakers.
- *Covid conversations* (Romero and Paxton, 2023) – two-speaker interactions from experimental psychology sessions.
- *SPGISpeech* (O'Neill et al., 2021) – earnings calls.

ASR system selection. We chose systems based on their performance, architecture diversity, and

Dataset	Data Split	Noisy audio?	# of speakers	Accented speech?	Child speech?	Total Length (Sample Length)
Sawyer	*All*		20		✓	24 h (23 min)
Cameron	*0wav*		2		✓	28 h (20 min)
CHiME-5	*dev*	✓	4	✓		4.5 h (22 min)
AMI	*IHM-test*	✓	4			100 h (16 min)
Covid Conversations	*All*		2			1.5 h (58 min)
SPGISpeech	*test*		1	✓		5,000 h (61 min)

Table 1: Characteristics of each dataset

representation of both traditional and modern approaches to speech recognition:

- *Kaldi (Librispeech)* (Povey et al., 2011) – A HMM system trained on 960 hours of Librispeech data.
- *Wav2Vec2 (Large-960h)* (Baevski et al., 2020) – A transformer-based SSL model pre-trained on unlabeled data and fine-tuned on 960 hours of labeled Librispeech data.
- *HuBERT (large-ls960-ft)* (Hsu et al., 2021) – Another transformer-based SSL model, also fine-tuned on 960 hours of Librispeech data.
- *Whisper (medium.en)* (Radford et al., 2023) – A transformer-based speech foundation model, multilingual, specifically fine-tuned for English language tasks.
- *Distil-Whisper (medium.en)* (Gandhi et al., 2023) [*DWhisper*] – A distilled version of the Whisper medium model.
- *NVIDIA (Conformer-Transducer X-Large)* (Gulati et al., 2020) – A conformer-based E2E model, trained on several thousand hours of English speech including Librispeech.

4 Metrics

4.1 Word Error Rate

Word error rate (WER) is a common metric used to evaluate the performance of ASRs. It quantifies the percentage of errors in the transcription generated by the ASR system compared to a reference transcription.

4.2 Stop Words Filtered WER (swf-WER)

Previous research has identified limitations in the utility of WER for accurately reflecting speech understanding (Wang et al., 2003). To address this, we also use Stop Words Filtered WER, *swf-WER*, which calculates WER excluding stop words (Garofolo et al., 1998). We used the part of speech tags provided by the spaCy NLP library to identify stop words in transcripts (Honnibal et al., 2020).

5 Methods

Figure 1 shows a visual presentation of our approach, which we describe below.

5.1 Dataset preprocessing

5.1.1 Generating turn-level audio files

ASR over long audio samples is more error-prone than ASR over short audio samples, so we constructed turn-level samples for our experiments. The SPGI and AMI datasets each contain a single utterance per audio file. However, for the other datasets, each recording contains an entire conversation. For the CHiME-5, Sawyer, and Cameron datasets, which include turn-level timestamps, we used ffmpeg (Tomar, 2006) to extract individual turns. The Psychology dataset came with non-timestamped turn-level transcripts, so we used the Montreal Forced Aligner (McAuliffe et al., 2017) to create time-aligned transcripts, from which we extracted turn-level timestamps.

5.1.2 Removing paralinguistic transcriptions

Transcriptions of the CHiME-5, Cameron, and Sawyer datasets included paralinguistic annotations such as "laugh" or "xxx" for unintelligible utterances. To focus on the linguistic content, we excluded these annotations from our analysis. However, the audio was retained as it provided more context information, and exposed the systems to real-world conditions and various speaker conditions (Shriberg, 2005; Schuller and Batliner, 2013). The Cameron dataset, in particular, offers both phonetic and semantic transcriptions. We chose to use the semantic transcriptions to align with modern ASR systems that use language models to generate hypotheses. For instance, phonetic transcriptions like "ah a gobritha [: gorilla]" were converted

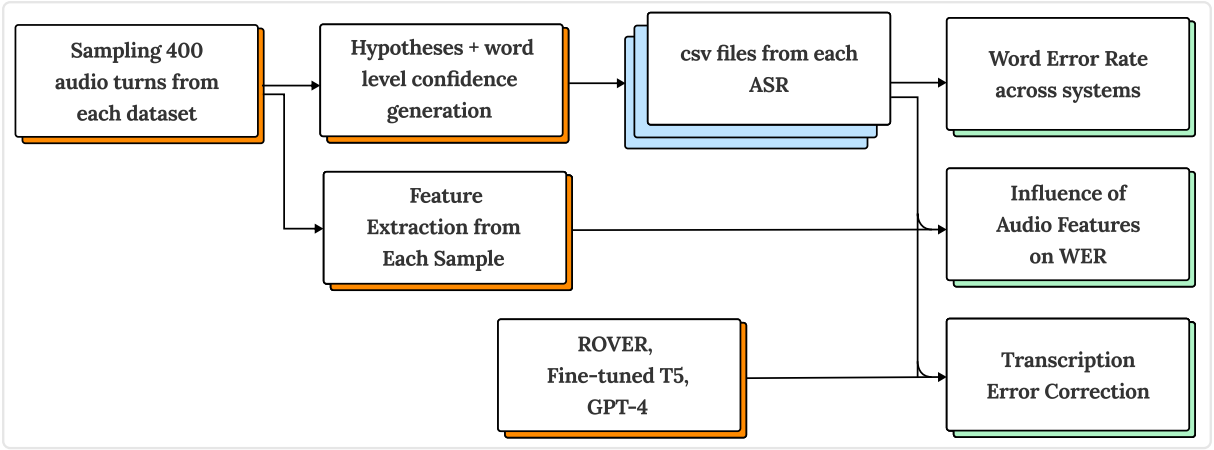

Figure 1: Method diagram

to their semantic equivalents, "ah a gorilla." It is important to note that this method might not be advantageous for ASR systems like Kaldi, which predominantly rely on acoustic models to produce transcriptions.

5.2 Random Sampling of Dataset

We randomly sampled 400 audio turns from each dataset. All audio files were then resampled to a mono channel at 16 kHz to meet the sample rate requirements of the ASR systems. The total audio duration for these 400 turns from each dataset is summarized in Table 1.

5.3 Feature Extraction from Each Sample

With limited speaker metadata available for our datasets, we used machine learning based models to estimate gender, age, and accent (Zuluaga-Gomez et al., 2023; Burkhardt et al., 2023; Ferreira, 2023). We measured noise levels using Power Spectral Density (PSD) estimates via Welch's method from scipy, and computed both audio duration and syllables per second (PyPI, 2024).

6 Analysis of ASR Performance

In this section, we analyze the effects of various speaker and audio characteristics on WER. In subsection 6.1, we look at the overall accuracy of each recognizer. In subsection 6.2, we analyze differences in WER due to continuous features (duration, speaking rate, noise level, age). In subsection 6.3, we analyze differences in WER due to categorical features (accentedness and speaker gender).

6.1 Comparative WER across different ASR systems

A comparative analysis of WER across different ASR systems is shown in Figure 2. We plot WER on a logarithmic scale due to its wide range and order datasets from the most to the least complex from left to right (see Table 1 for the features we consider as contributing to dataset complexity), with the rightmost column representing the results for all six datasets combined.

Performance Trends. As expected, we observe a decrease in WER as we move from the more complex datasets to the simpler ones. Speech Foundation models, such as DWhisper and Whisper, generally exhibit lower WER, suggesting a higher robustness to diverse audio characteristics. The E2E NVIDIA ASR has a slightly higher WER on simpler datasets, but a lower WER on the most complex dataset.

Variability in Performance. The error bars, representing standard deviations, indicate variability in WER for each system across the datasets. Systems exhibit higher variability (larger error bars) for more complex datasets like Sawyer and CHiME-5, implying fluctuating performance in challenging conditions. Whisper, in particular, shows extended error bars in these datasets, which is indicative of issues including hallucination.

ASR Recommendation. The NVIDIA ASR consistently achieves the lowest mean WER across all datasets, followed by DWhisper. For highly complex and noisy conditions, the E2E NVIDIA ASR offers reliable performance with the least variability. In contrast, DWhisper may be more suitable for environments with less complex settings.

In Table 2, we analyze swf-WER:

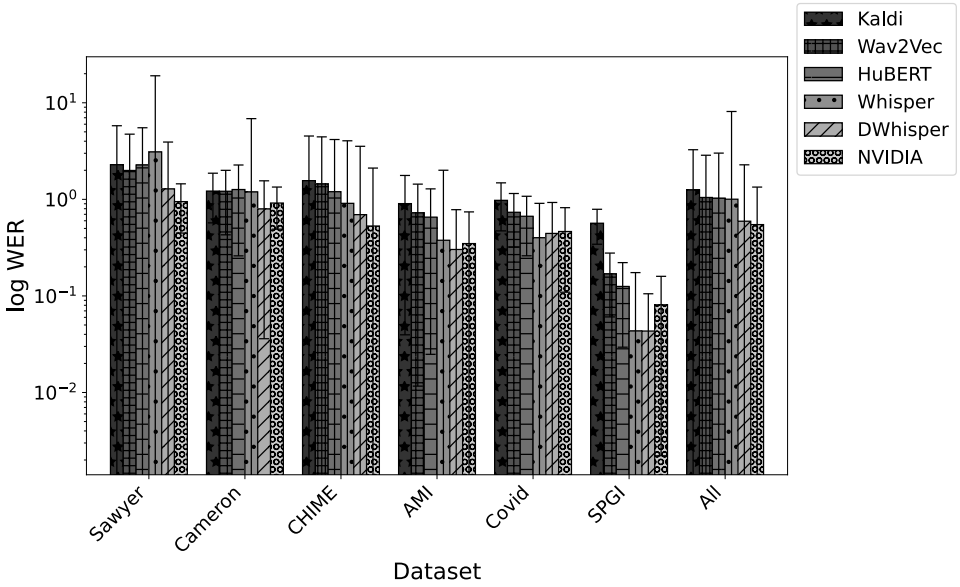

Figure 2: Mean and SD of WER by System and Dataset

Dataset	Mean		Standard Deviation		Minimum		Maximum	
	WER	swf-WER	WER	swf-WER	WER	swf-WER	WER	swf-WER
Sawyer	1.98	1.83	1.50	1.36	0.65	0.64	4.44	4.06
Cameron	1.10	1.15	0.56	0.60	0.59	0.61	1.94	2.07
CHiME-5	1.06	0.96	0.64	0.57	0.39	0.39	1.96	1.77
AMI	0.55	0.57	0.39	0.36	0.16	0.21	1.08	1.05
Covid	0.61	0.66	0.30	0.31	0.31	0.35	1.05	1.10
SPGI	0.17	0.21	0.21	0.24	0.02	0.05	0.57	0.66

Table 2: Comparison of WER by dataset

Lower swf-WER for Complex Datasets. In complex environments represented by Sawyer, Cameron, and CHiME-5, swf-WER is consistently lower than WER. This suggests that errors involving stop words, which are typically less acoustically distinct, are more prevalent in noisy settings, thus disproportionately affecting the perceived accuracy of ASR systems. Removing these words from the error calculation refocuses the metric on content that significantly impacts comprehension.

Consistent Performance for Simpler Datasets. Datasets like AMI, Covid, and SPGI, which exhibit lower and more stable WERs, reflect consistent ASR performance. For these acoustically simpler datasets, swf-WER is slightly higher than WER, possibly indicating greater linguistic complexity such as a greater variety of named entities in these datasets.

6.2 Impact of Continuous Features on WER

We analyzed the impact of continuous audio features including speaking rate (syllables per second), speaker age, noise level, and audio duration by fitting regression models. After visualizing the data, we used cubic regression functions to model these relationships. However, the results for noise level and duration were not statistically significant, likely due to data clustering within a narrow value range and limited variability. Despite attempts to rescale noise level using normalization, log transformation, and standardization, the regression remained statistically insignificant. This is likely due to data clustering within a narrow value range, a similar issue was observed with audio duration, where limited variability was present due to the uniform sampling of audio lengths. Therefore, this section focuses on the impact of speaking rate and speaker age on WER. Full regression equations, R^2 values, and p-values are provided in the appendix (Section A.1).

6.2.1 Effect of Speaking Rate on WER

Table 3 shows the local minimizer, R^2 value, and Bonferroni corrected p-value for the cubic coefficient for each ASR system. The local minimizer represents the number of syllables per second that achieves the local minimum WER according to the

System	Local Minimizer	R^2	Corrected p-value
Kaldi	6.851	0.128	<0.01
Wav2Vec	6.832	0.176	<0.01
HuBERT	6.668	0.178	<0.01
Whisper	6.810	0.013	0.085
DWhisper	6.276	0.077	<0.01
NVIDIA	6.430	0.103	<0.01

Table 3: Impact of syllables per second on WER

System	Local Minimizer	R^2	Corrected p-value
Kaldi	24.208	0.031	0.011
Wav2Vec	22.810	0.052	<0.01
HuBERT	28.148	0.070	<0.01
Whisper	32.274	0.012	1.000
DWhisper	31.898	0.036	0.035
NVIDIA	24.428	0.122	<0.01

Table 4: Effect of age on WER across systems

System	Mean Difference	Corrected p-value
Kaldi	-0.632	<0.01
Wav2Vec	-0.620	<0.01
HuBERT	-0.707	<0.01
Whisper	-0.334	1.00
DWhisper	-0.240	1.00
NVIDIA	-0.065	1.00

Table 5: Effect of speaker overlap on WER

System	Mean Difference	Corrected p-value
Kaldi	0.636	<0.01
Wav2Vec	0.691	<0.01
HuBERT	0.725	<0.01
Whisper	1.040	0.04
DWhisper	0.417	<0.01
NVIDIA	0.291	<0.01

Table 6: Gender-related differences in WER

regression equation. We observe that most systems achieve the minimum WER when the speaking rate is between 6.4 and 6.8 syllables per second, indicating optimal ASR performance around this range.

6.2.2 Effect of Speaker Age on WER

Speaker age significantly impacts ASR system performance (Table 4). The local minimizer represents the age at which the ASR system achieves the lowest WER according to the regression equation. Most systems achieve optimal performance with speakers in their 20s, aligning with previous studies indicating lower WER for young to middle-aged adults (Werner et al., 2019). However, we did not obtain statistically significant results for DWhisper, Whisper, or Kaldi, suggesting that these systems are less sensitive to speaker age.

6.3 Impact of Discrete Features on WER

We analyzed the impact of discrete audio features using the student's t-test. To control for any false discovery rate arising from multiple tests, we applied Holm's sequential Bonferroni procedure (Benjamini and Hochberg, 1995).

6.3.1 Speaker Overlap and WER Variability

The data in Table 5 highlights the impact of speaker overlap on ASR accuracy. The recent transformer-based ASR systems, such as Whisper and DWhisper, as well as the conformer-based NVIDIA system, did not show a significant mean difference under speaker overlap, indicating their robustness in challenging conditions. In contrast, Kaldi, Wav2Vec, and HuBERT exhibited significant mean differences, suggesting lower performance when dealing with overlapping speech.

6.3.2 Gender-Related Differences in WER

The analysis of gender-related differences in WER demonstrates a bias in ASR system performance against male speakers (coded as 1), with all ASR systems showing higher WER for male voices compared to female voices (coded as 0). There are positive mean differences across the board in Table 6, which are statistically significant, except for the Whisper model, suggesting that Whisper is more robust to both male and female speakers.

6.3.3 Accent-Related WER Discrepancies

One would expect non-general American accents (coded as 1) to be associated with higher WER compared to the general American accent (coded as 0). However, our results did not show this trend. None of the ASRs showed statistical significance in the mean WER between non-general American and general American accents. This lack of significance could be due to the subtle nature of accent differences or to the machine learning methods used to classify these accents.

System	Mean Difference	Corrected p-value
Kaldi	0.0165	1.00
Wav2Vec	-0.088	1.00
HuBERT	-0.075	1.00
Whisper	0.279	1.00
DWhisper	0.012	1.00
NVIDIA	-0.014	1.00

Table 7: Effect of accent on WER

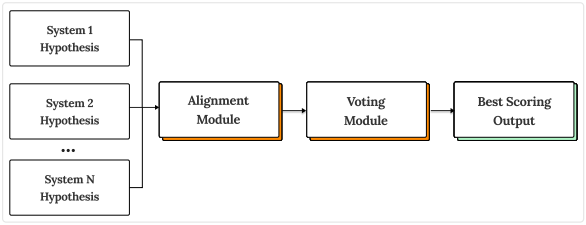

Figure 3: ROVER

7 Transcription Error Correction

In this section, we evaluate three ASR error correction methods described in the literature (see Section 2). For each method, we provide the one-best hypothesis from each of the ASR systems described in Section 3.

7.1 Recognizer Output Voting Error Reduction (ROVER)

ROVER combines multiple ASR outputs into a single word transition network (Fiscus, 1997). This network is then processed through a voting mechanism that identifies the most reliable output sequence based on the lowest aggregate score (Figure 3). The "voting" or rescoring process reconciles differences in ASR system outputs.

7.2 Fine Tuned T5 (Ft-T5)

We finetuned the T5 transformer model to perform ASR error correction over transcripts from an ensemble of ASR models, inspired by the approach described in (Ma et al., 2023a). As described in Section 5, we processed 400 audio turns from each of the 6 datasets through each of the 6 ASR systems, leading to 6 ASR transcripts for a total of 2400 audio files. We split these ASR transcripts into ten folds. In round-robin fashion, we then selected each fold for testing, finetuning T5 on the rest. T5 was finetuned using concatenated ASR transcripts and their corresponding word-level confidence scores, with the accurate transcription serving as the target output, as shown in Figure 4.

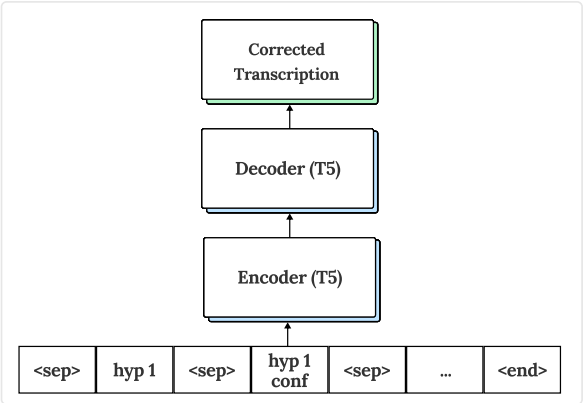

Figure 4: T5 fine-tuning

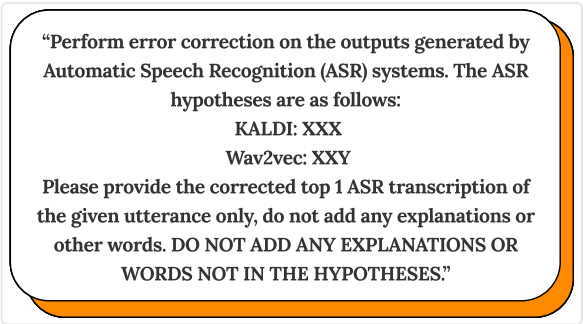

Figure 5: Zero-shot error correction using GPT-4

7.3 GPT-4

Following the work by (Ma et al., 2023c), we used GPT-4 zero-shot to perform ASR error correction over transcripts from an ensemble of ASR models. Following limited experimentation, we used the prompt shown in Figure 5. The capitalization in the prompt is important for best results.

7.4 Error Correction Results

The results of the three transcription error correction methods are shown in Tables 8 and 9. We present the results in two separate tables because subsets of the datasets were used during the fine-tuning process for the T5 model, as described in Section 7.2. Table 8 compares WER across different datasets, illustrating the effectiveness of each method per dataset. Table 9 provides an aggregated view of WER across all methods, highlighting the overall performance trends. These results include: (1) Oracle performance: the lowest possible WER achievable using all tokens from transcripts output by the six ASRs; (2) Baseline performance: the WER of the top-performing ASR for each audio file; and (3) Mean: the average WER of the six ASR systems. The baseline and mean values are equivalent to the minimum and mean values in Ta-

	Oracle		Baseline		Mean		ROVER		GPT-4	
Dataset	WER	swf-WER	WER	swf-WER	WER	swf-WER	WER	swf-WER	WER	swf-WER
Sawyer	0.49	0.53	0.65	0.64	1.98	1.83	0.99	0.97	6.60	4.79
Cameron	0.48	0.53	0.59	0.61	1.10	1.15	0.81	0.81	0.97	1.01
CHiME-5	0.24	0.28	0.39	0.39	1.06	0.96	0.66	0.64	0.97	0.80
AMI	0.13	0.19	0.16	0.21	0.55	0.57	0.33	0.34	0.48	0.48
Covid	0.22	0.27	0.31	0.35	0.61	0.66	0.40	0.41	0.81	0.55
SPGI	0.01	0.05	0.02	0.05	0.17	0.21	0.05	0.07	0.04	0.07

Table 8: Comparison of WER across error correction methods by dataset

Metric	**Oracle**	**Baseline**	**Mean**	**ROVER**	**GPT-4**	**Ft-T5**
WER	0.26	0.36	0.91	0.54	1.64	7.21
swf-WER	0.31	0.37	0.90	0.54	1.28	7.22

Table 9: Comparison of WER across error correction methods

ble 2.

ROVER Outperforms. Table 8 shows that ROVER outperforms the mean WER across different datasets. This indicates ROVER's effectiveness in leveraging multiple ASR outputs to improve transcription accuracy. Conversely, GPT-4 exhibits a higher WER, particularly for more complex datasets like Sawyer, where it even underperforms compared to the mean WER. This suggests that while GPT-4 shows promise for transcription error correction of clean speech (as the literature suggests with clean speech such as LibriSpeech), it struggles with more complex audio scenarios.

Hallucinations in Fine-Tuned T5. Despite its potential, the performance of Ft-T5 is significantly worse than that of the other methods. Also, we observed hallucinations in the output from the Ft-T5 model, where the same word was repeated multiple times. This issue may be due to the limited amount of data available for fine-tuning.

8 Conclusions and Future Work

In this study, we have provided a comprehensive evaluation of the accuracy of state of the art open-source ASR systems on naturally occurring human conversations covering a range of acoustic and speaker characteristics. In contrast to its benchmark performances on various datasets, Whisper's performance on challenging audio conditions was ineffective and exhibited hallucination issues.

Our analysis indicates a gender bias in ASR performance for most systems, with male speakers experiencing higher WER compared to female speakers. Additionally, speaker age significantly impacts ASR performance, with younger adult speakers generally achieving lower WER. These findings emphasize the need for ASR systems to account for demographic factors to improve accuracy.

Among the error correction methods evaluated, ROVER consistently outperformed others, demonstrating its effectiveness in leveraging ensembles of ASR systems to enhance transcription accuracy. Another advantage of ROVER is that the graph it generates can be used to identify regions of speech that likely need human editing, and potentially even to prioritize which regions to focus on when one has a limited budget or time for human editing. We leave this idea for future work.

Furthermore, while our study focused on the computational efficiency of a 1-best approach, we acknowledge that an n-best approach could provide richer context. Future work could investigate the benefits of incorporating n-best hypotheses to further improve error correction strategies.

Our findings provide insights into the performance of various ASR systems under complex audio conditions and the challenges of error correction compared to ideal scenarios. Moreover, by releasing 14,400 audio-hypothesis-transcription pairs (2400 pairs per ASR, totaling 200 minutes of audio) on less commonly used datasets, we aim to foster open collaboration in the field.

9 Ethical Discussion and Limitations

We used ML models to detect age, accent, and gender when demographic information was unavailable. For example, age was provided in the Sawyer and Cameron datasets, and gender was specified in the AMI dataset. This raises ethical questions regarding the potential for misclassification. Relying solely on automated methods for sensitive attribute detection can perpetuate stereotypes, further em-

bedding bias within ASR systems. Ethical practices in this context necessitate transparency about the limitations of these models and the incorporation of human oversight to correct misclassifications.

In this paper, we focused on English speech primarily from Western countries; our evaluation data and most of the models we evaluated were English-only. However, there are more than 7000 languages spoken worldwide and many of these languages have no language technology at all (Hou et al., 2020; Conneau et al., 2023). There are compelling social justice reasons to do much more research on non-English ASR. Furthermore, the datasets we used do not encompass all possible characteristics of speakers of English language. The collection of more varied datasets, especially including underrepresented dialects of English, would be necessary to fully understand the scope of English ASR performance disparities.

Another limitation is the focus on open-source ASR systems may not fully represent the capabilities of proprietary ASR technologies used in commercial applications. The performance and biases of these open-source systems may differ from those of their commercial counterparts, potentially limiting the generalizability of our findings.

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A Regression Plots

A.1 Regression Table

Table 10 on the next page presents the regression table, including the regression equation, R^2 value, and Bonferroni-corrected p-values for the cubic coefficients analyzed in Section 6.2. This includes each continuous feature: duration, syllables per second, noise level and age.

A.2 Effect of speech rate on WER: syllables per second

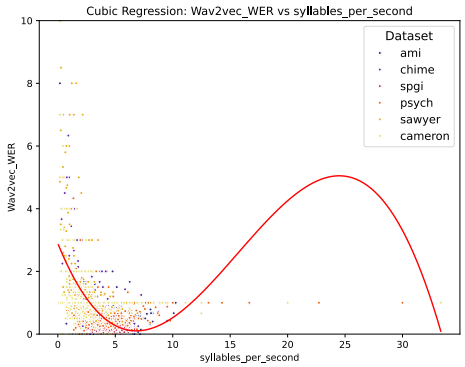

Figure 6: Syllables per second vs. Wav2Vec WER

A.3 Effect of speaker age on WER

Figure 7: Age vs. NVIDIA WER

Feature	System	Equation	R-squared	Cubic p-value corrected
duration	Hubert_WER	$1.143847 - 0.050390x + 0.003325x^2 - 0.00004419553x^3$	0.002007	1.000
duration	Nemo_WER	$0.742504 - 0.06105213x + 0.002466x^2 - 0.00002652036x^3$	0.029774	0.054
duration	Whisper_WER	$1.254405 - 0.1138149x + 0.007652x^2 - 0.000102221x^3$	0.000810	1.000
duration	DWhisper_WER	$0.696095 - 0.05223893x + 0.003812x^2 - 0.00005063922x^3$	0.003690	0.162
duration	Wav2vec_WER	$1.280726 - 0.09236164x + 0.005366x^2 - 0.00006851686x^3$	0.007801	0.016
duration	Kaldi_WER	$1.316008 - 0.04138082x + 0.003508x^2 - 0.00004977125x^3$	0.002428	0.623
syllables_per_second	Hubert_WER	$3.062961 - 1.003102x + 0.095750x^2 - 0.002054537x^3$	0.177675	<0.01
syllables_per_second	Nemo_WER	$1.164577 - 0.310183x + 0.030336x^2 - 0.0006422186x^3$	0.103088	<0.01
syllables_per_second	Whisper_WER	$3.005466 - 0.9785362x + 0.091793x^2 - 0.001950684x^3$	0.013453	0.085
syllables_per_second	DWhisper_WER	$1.717833 - 0.5726267x + 0.056937x^2 - 0.001197455x^3$	0.077001	<0.01
syllables_per_second	Wav2vec_WER	$2.890523 - 0.9004172x + 0.084326x^2 - 0.001794931x^3$	0.175698	<0.01
syllables_per_second	Kaldi_WER	$2.996386 - 0.850825x + 0.079613x^2 - 0.001700960x^3$	0.128006	<0.01
noise_level	Hubert_WER	$1.006434 + 8.550411 \times 10^6 x + 0.941321x^2 + 0.0000001434107x^3$	0.002240	0.490
noise_level	Nemo_WER	$0.538853 + 3.193943 \times 10^6 x + 0.351624x^2 + 0.00000005357002x^3$	0.001956	0.726
noise_level	Whisper_WER	$0.988826 + 5.316402 \times 10^6 x + 0.585287x^2 + 0.0000000891687x^3$	0.000067	1.000
noise_level	DWhisper_WER	$0.576200 + 6.258136 \times 10^6 x + 0.688963x^2 + 0.0000001049638x^3$	0.001660	1.000
noise_level	Wav2vec_WER	$1.033201 + 4.608494 \times 10^6 x + 0.507353x^2 + 0.00000007729541x^3$	0.000774	1.000
noise_level	Kaldi_WER	$1.229745 + 7.710911 \times 10^6 x + 0.848900x^2 + 0.0000001293303x^3$	0.001764	0.951
age	Hubert_WER	$2.278215 - 0.1313002x + 0.003599x^2 - 0.00003150352x^3$	0.069813	<0.01
age	Nemo_WER	$1.189794 - 0.06417423x + 0.001680x^2 - 0.00001438768x^3$	0.122077	<0.01
age	Whisper_WER	$2.919885 - 0.1956161x + 0.004967x^2 - 0.00004003803x^3$	0.012023	1.000
age	DWhisper_WER	$1.340553 - 0.07641958x + 0.002053x^2 - 0.00001787210x^3$	0.035992	0.035
age	Wav2vec_WER	$1.985948 - 0.1013680x + 0.002950x^2 - 0.00002734097x^3$	0.052151	<0.01
age	Kaldi_WER	$2.093572 - 0.09149935x + 0.002616x^2 - 0.00002364298x^3$	0.031291	0.011

Table 10: Regression analysis of continuous features on WER with cubic coefficients

B Violin Plots from Variance Analysis

B.1 Speaker overlap and WER variability

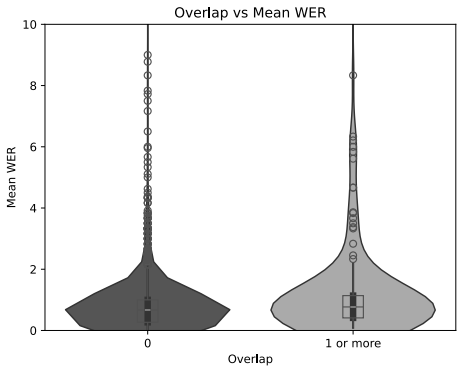

Figure 8: Overlapping speech

B.2 Gender-related WER differences

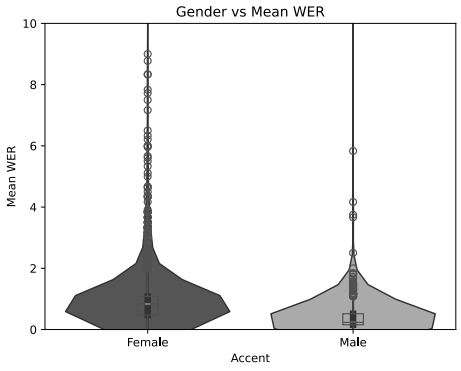

Figure 9: Gender

B.3 Accent-related WER discrepancies

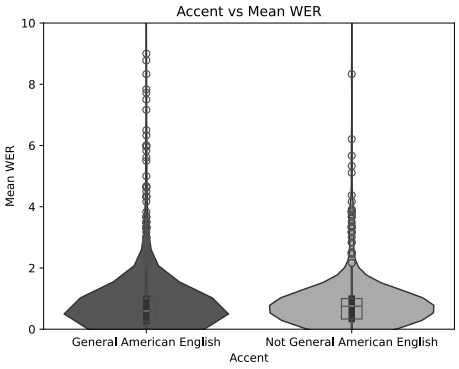

Figure 10: Accent