Evaluating Bias in Phoneme-Based Automatic Speech Recognition Systems: An Analysis of IPA Transcription Models

Anonymous ACL submission

Abstract

The popularization of automatic speech recognition (ASR) systems has increased exploration of the demographic biases related to race, age, gender, and accent, often formed from imbalanced training data. Most of these studies focused on standard grapheme-based ASR systems with comparatively little emphasis on phoneme-based systems, such as models that produce International Phonetic Alphabet (IPA) representations. As ASR systems shift toward multilingual support and low-resource language modeling, IPA-based layers serve as a critical, language-agnostic foundation. In this study, we evaluate the performance of two state-of-the-art open-source ASR systems, WhisperIPA and ZIPA, that generate IPA transcriptions across diverse accents and language sources. Our evaluation includes existing multilingual speech corpora and demographically annotated English-language corpora. We measure model performance by comparing model-generated IPA transcriptions against grapheme-to-phoneme (G2P) systems using both standard phoneme error rate (PER) and a proposed Soft PER metric that tolerates linguistically similar phoneme substitutions. Our analysis examines how performance varies across languages and demographic groups such as gender, accent, ethnicity, and age, revealing persistent disparities even after accounting for acceptable phonemic variation. These findings provide insight into potential sources of bias and inform the development of more inclusive and linguistically robust phoneme-based ASR systems. Our code and data will be made publicly available for the community.

1 Introduction

Automatic Speech Recognition (ASR) systems are a foundational component of modern agent-based technology. Current ASR systems typically rely on grapheme representations: graphemes are written units of language (e.g., letters or characters), while phonemes are units of sound that represent how words are pronounced. Existing research shows that grapheme-based ASR systems exhibit systematic disparities across demographic groups, including race, gender, age, accent, and language background (Tatman and Kasten, 2017; Tatman, 2017; DiChristofano et al., 2023; Jahan et al., 2025; El-Ghazaly et al., 2025; Scott et al., 2025; Serditova et al., 2025; Cunningham et al., 2025). ASR evaluation currently mostly focuses on word error rates (WER) (Feng et al., 2021). A majority of industry models are grapheme-based, but there has been a growing trend of integrating IPA layers with more multilingual capabilities. This new trend increases the importance of understanding the biases of phoneme models.

The International Phonetic Alphabet (IPA)[1] captures fine-grained phonetic details and cross-linguistic sound variations. Multilingual training on IPA tokens reduces phonetic token error rate by 60–70% in high-resource languages and 14–42% in low-resource languages (Żelasko et al., 2022). Including IPA layers in ASR models enables more effective generalization by providing a more direct mapping between the acoustic signal and its phonological categories. This makes recent work in phonetic (Bharadwaj et al., 2026; Goriely and Buttery, 2025) and IPA models (Fang et al., 2020a; Taguchi et al., 2023; Zhu et al., 2024; Lee et al., 2025; Zhu et al., 2025), integrated as standalone or intermediate layers, valuable for multilingual and low-resource ASR systems.

Bias in ASR systems has been extensively studied; prior work has focused on measuring WER. Comparatively little has been done on phoneme representations. If disparities are already present at the phoneme level, they may propagate through downstream components of integrated ASR systems. On the contrary, if phonetic representations are more

[1] https://en.wikipedia.org/wiki/International_Phonetic_Alphabet

robust, they may lead to more equitable speech recognition. Prior research suggests IPA-based systems can reduce error rates across diverse linguistic and demographic groups, but phonemic-level demographic bias remains largely underexplored.

Since pronunciation varies within a language, the same grapheme can correspond to different phonemes. As a result, phoneme error rate (PER) may penalize valid phoneme substitutions, making it a less reliable metric for evaluating demographic bias. In this work, we introduce a soft variant of PER that tolerates minor phonemic variation. This allows us to examine performance disparities across language, race, accent, gender, and age with less noise. We evaluate whether or not this PER variant changes our conclusions about phoneme ASR bias. Our main contributions include:

1. Introducing and evaluating a Soft PER that tolerates minor phonemic variation rather than strictly penalizing all substitutions. We compare Soft PER with standard PER to determine whether it yields a more robust metric for evaluating demographic bias.

2. Performing a bias analysis of IPA-based phoneme ASR models across race, accent, gender, age, and language. Our evaluation spans 11 languages (English, Hindi, Bangla, Panjabi, Tamil, Telugu, Arabic, French, Spanish, Turkish, and Shona). We also analyze different age groups, gender, four racial groups, and English accents of eight dialectal USA regions.

2 Related Work

End-to-end ASR systems have reached strong accuracy by scaling data and model size, especially with transformer-family architectures (Radford et al., 2023). Large models such as wav2vec 2.0 (Baevski et al., 2020), Whisper (Radford et al., 2023), and XLS-r (Babu et al., 2022) demonstrate that grapheme-based models can generalize to dozens of languages. Recent work focuses on even larger multilingual models that replace language-specific systems and target lower-resource languages (Meng et al., 2025; Omnilingual et al., 2025; Ramirez et al., 2024).

Despite these advances, ASR is concentrated in high-resource languages with standardized orthographic transcriptions (Gale et al., 2023; Gorisch and Schmidt, 2024). Grapheme-based models rely on widely adopted writing systems in paired speech-text data. For languages and conversation without a formal writing system, non-standardized orthography, limited textual resources, or code-switching, grapheme models are less reliable or unavailable. Most grapheme mappings do not consider phonetic variation (Fang et al., 2020b; Omnilingual et al., 2025; Ramirez et al., 2024).

By mapping acoustically similar sounds to shared phonetic symbols, these systems can transfer knowledge from high-resource to truly under-resourced languages (Daul et al., 2026). Currently, architectures introduce an explicit phonetic layer that improves robustness and data efficiency in low-resource settings (Lee et al., 2025). Incorporating phonemic supervision can reduce the ultimate WER (Fu et al., 2025; Scott et al., 2025).

Phonemic models are particularly advantageous for orthographic limitations or linguistic variability. Phonemic/phonetic token models outperform orthographic baselines in both data-constrained and crosslingual domains (Daul et al., 2026). Shared phonetics allow easier cross-lingual transfer and generalize underrepresented languages (Goriely and Buttery, 2025; Zhu et al., 2025; Devi and Sarma, 2026). Phoneme-level modeling approaches directly capture acoustic distinctions, thus improving robustness to pronunciation variability (Lyu and Lyu, 2008; Solorio and Liu, 2008; Onda et al., 2026).

Rather than replacing grapheme-based systems, phonetic layers are often integrated within them. Multi-task learning frameworks jointly predict phonemes and graphemes. Hybrid approaches have demonstrated improved robustness in noisy, low-resource, and multilingual settings, suggesting that phonetic supervision can complement larger ASR architectures (Fang et al., 2020b).

Bias in ASR systems has been extensively studied in grapheme-based systems, with prior research showing significant disparities in WER across demographic groups — such as race, gender, dialect, and accent (Tatman and Kasten, 2017; DiChristofano et al., 2023; Jahan et al., 2025). An ASR system exhibits bias when its performance differs throughout user demographics (Zhang et al., 2023). Within grapheme-based models, commercial systems consistently have higher error rates for women compared to men (Ngueajio and Washington, 2022) (Aryal et al., 2023). Models often have higher error rates for children (Bhardwaj et al., 2022). Non-native and non-urban accents have been associ-

ated with higher error rates (Serditova et al., 2025; Torgbi et al., 2025; Wassink et al., 2022), with second-language speech accents showing higher error rates than speakers of non-standard or regional accents (Feng et al., 2021; Zhang et al., 2022). For example, commercial models produce nearly twice as many errors for African American speakers as for white speakers of English (Koenecke et al., 2020; Martin and Tang, 2020).

Standardized evaluation benchmarks and bias audits have been introduced to quantify these performance gaps and assess fairness in widely used ASR models. In contrast, investigations into phonetic or IPA-based ASR models remain limited. As phoneme-level systems become more common, either as full speech transcription models or as intermediate components within larger architectures, it is increasingly important to understand how they may contribute to or mitigate existing biases.

3 Methods

3.1 Datasets

We evaluate phoneme recognition models across two complementary dimensions: cross-lingual robustness and demographic variation.

Cross-lingual Datasets. To assess multilingual phoneme recognition performance, we use IPA-PACK (Zhu et al., 2024), MediaSpeech (Kolobov et al., 2021), and WAXAL (Diack et al., 2026). From these multilingual corpora, we select 11 languages for evaluation, including high-resource languages (English, Spanish, and French) and lower-resource languages (Hindi, Bangla, Panjabi, Tamil, Telugu, Arabic, Turkish, and Shona). Languages are selected based on support from both the G2P pipeline and the evaluated IPA models. Table 1 in Appendix A.1 provides more details about the language distributions of these datasets.

Demographic Datasets. To analyze demographic bias and variation in phoneme recognition, we use English speech datasets with speaker-level metadata: the Corpus of Regional African American Language (CORAAL) (Kendall and Farrington, 2018), the Edinburgh International Accents of English Corpus (EdAAC) (Sanabria et al., 2023), and the Sonos Voice Control Bias Assessment Dataset (SVC) (Sekkat et al., 2024). These datasets contain annotations for demographic attributes, including age, gender, ethnicity, accent, geographic region, and native-speaker status. Details about the demographic distributions of these datasets are presented in Table 2 in Appendix A.1.

3.2 Models

In this work, we evaluate two IPA-based ASR models which allows us to maximize coverage in cross-lingual evaluation, since they have the largest number of overlapping supported languages.

WhisperIPA. We evaluate WhisperIPA[2], a transformer-based encoder–decoder model built on the Whisper architecture (Radford et al., 2023). Whisper is originally pre-trained on 680,000 hours of weakly supervised multilingual speech data. The base-sized WhisperIPA variant, containing approximately 74M parameters, is further fine-tuned for direct speech-to-IPA transcription on 15,000 labeled synthetic IPA audio samples. The fine-tuning data is derived from the Common Voice 21 corpus and covers more than 70 languages with corresponding phonetic annotations.

ZIPA. We evaluate ZIPA (Zhu et al., 2025), a family of efficient multilingual phone recognition models built on the Zipformer architecture (Yao et al., 2024), and includes both transducer-based and CTC-based variants. In this work, we use the large consistency-regularized CTC model with noisy-student training. The ZIPA-CR-NS[3] large variant contains approximately 300M parameters and is trained on IPAPack++, a large-scale multilingual speech corpus containing 17,132 hours of normalized phone transcriptions across 88 languages. The noisy-student training stage further incorporates approximately 11,000 hours of pseudo-labeled multilingual speech from more than 4,000 languages, improving cross-linguistic phone recognition performance.

3.3 Experimental Setup

All models are evaluated in a zero-shot setting without additional fine-tuning on the evaluation datasets in order to measure out-of-the-box phoneme recognition performance. After both models generate IPA transcriptions for every audio sample, outputs are post-processed to remove special tokens, normalize whitespace, and ensure consistency with the reference phoneme format. Output post-processing details are described in Appendix A.2.

[2] https://huggingface.co/neurlang/ipa-whisper-base

[3] https://huggingface.co/anyspeech/zipa-large-crctc-ns-800k

Reference phoneme sequences are generated from orthographic transcripts using a multilingual grapheme-to-phoneme (G2P) pipeline. We use G2P+ (Goriely and Buttery, 2025) to generate IPA-based phonemic transcriptions across languages. Although automatically generated phonemic references introduce limitations due to possibly incorrect, oversimplified phoneme mappings, incomplete phonetic detail, and inconsistencies across languages, they provide a scalable framework for multilingual evaluation. These generated phoneme sequences serve as the ground-truth references for all experiments.

Soft PER We evaluate phoneme recognition accuracy using phoneme error rate (PER). However, because phoneme realizations can vary across accents, dialects, and languages without reflecting true recognition failures, we also introduce and evaluate a Soft PER metric that reduces penalties for linguistically similar substitutions. This evaluation uses a two-tier phoneme mapping to (1) establish broad interchangeable phonemic variation and (2) create language-specific pronunciation overlaps that are not global equivalents. A single equivalence tier is insufficient because many phonetic relationships are not identical between languages.

The first tier groups phonemes into transitive equivalence classes using two allophonic resources. AlloVera (Mortensen et al., 2020) provides language-specific mappings between surface phones and canonical phonemes across 14 languages (e.g., aspirated /pʰ/→/p/ where a strongly breathed "p" sound is treated as a standard /p/, devoiced /b̥/→/b/ where a partially unvoiced "b" is mapped to its canonical form, etc.), with English given priority when a surface phone appears in multiple languages due to the larger proportion of English data in the demographic evaluation datasets. We then use articulatory feature representations from PHOIBLE (Moran and McCloy, 2019) to identify pairs of canonical phonemes that differ in only one of 34 articulatory features. These pairs are merged into shared equivalence classes. Together, these mappings create 62 equivalence classes spanning 254 phones. Table 4 in Appendix A.3 provides the full mapping for the first tier.

The second tier captures non-transitive cross-language similarities, also derived from AlloVera (Mortensen et al., 2020). When the same surface phone maps to different canonical phonemes across languages (e.g., the flap sound /ɾ/ is mapped to /t/ in English words such as "water," but to /r/ in Spanish words such as "pero"), those canonical phonemes are recorded as a direct pair without being merged into a shared equivalence class. This preserves the individual relations /t/≈/ɾ/ and /ɾ/≈/r/ without implying /t/≈/r/. A total of 90 such language-specific pairs are extracted from cross-language allophonic overlaps. Table 5 in Appendix A.3 provides the full mapping for the second tier.

During evaluation, Tier 1 equivalence classes are applied universally across all languages, while Tier 2 similarities are only applied when relevant to the target language. Substitutions within either similarity tier receive a zero penalty when computing Soft PER, allowing the metric to better distinguish genuine recognition errors from acceptable phonetic variation.

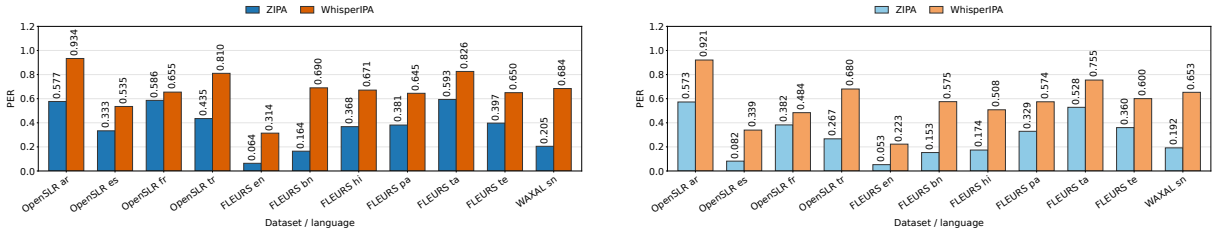
4 Results

4.1 Language Performance Evaluation

We first evaluate model performance across languages to understand how IPA-based ASR system accuracy varies in a multilingual setting. This analysis compares standard PER and Soft PER for both ZIPA and WhisperIPA across the available language datasets. Standard PER measures exact phoneme-level mismatch, while Soft PER applies the equivalence mappings described in Section 3.3 to reduce penalties for linguistically similar phoneme substitutions.

Figure 1 compares ZIPA and WhisperIPA across the evaluated languages using both standard PER and Soft PER. Across all languages, ZIPA achieves lower error rates than WhisperIPA, indicating stronger phoneme recognition performance in this multilingual evaluation. Under standard PER, both models show the lowest error rates for English and comparatively higher error rates for Arabic, Turkish, and Tamil, suggesting substantial variation in performance across languages. The same overall pattern remains under Soft PER, although error rates decrease for most languages.

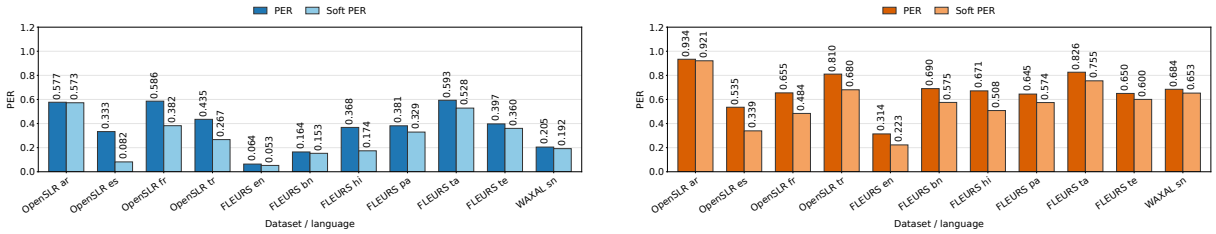
Figure 2 demonstrates the effect of applying Soft PER separately for each model. For ZIPA, Soft PER substantially reduces errors for several languages, particularly Spanish, French, Turkish, Hindi, Panjabi, Tamil, and Telugu, while yielding smaller reductions for Arabic, English, and Bangla. WhisperIPA shows a similar trend, with reduced error rates across most languages after soft matching. However, WhisperIPA continues to exhibit substan-



(a) Standard PER across languages for ZIPA and WhisperIPA.

(b) Soft PER across languages for ZIPA and WhisperIPA.

Figure 1: Comparison of standard PER and Soft PER across evaluated languages: (AR=Arabic, ES=Spanish, FR=French, TR=Turkish, en=English, bn=Bangla, hi=Hindi, pa=Panjabi, ta=Tamil, te=Telugu, and sn=Shona).



(a) Standard PER and Soft PER comparison for ZIPA.

(b) Standard PER and Soft PER comparison for WhisperIPA.

Figure 2: Effect of Soft PER on language-level evaluation for each model.

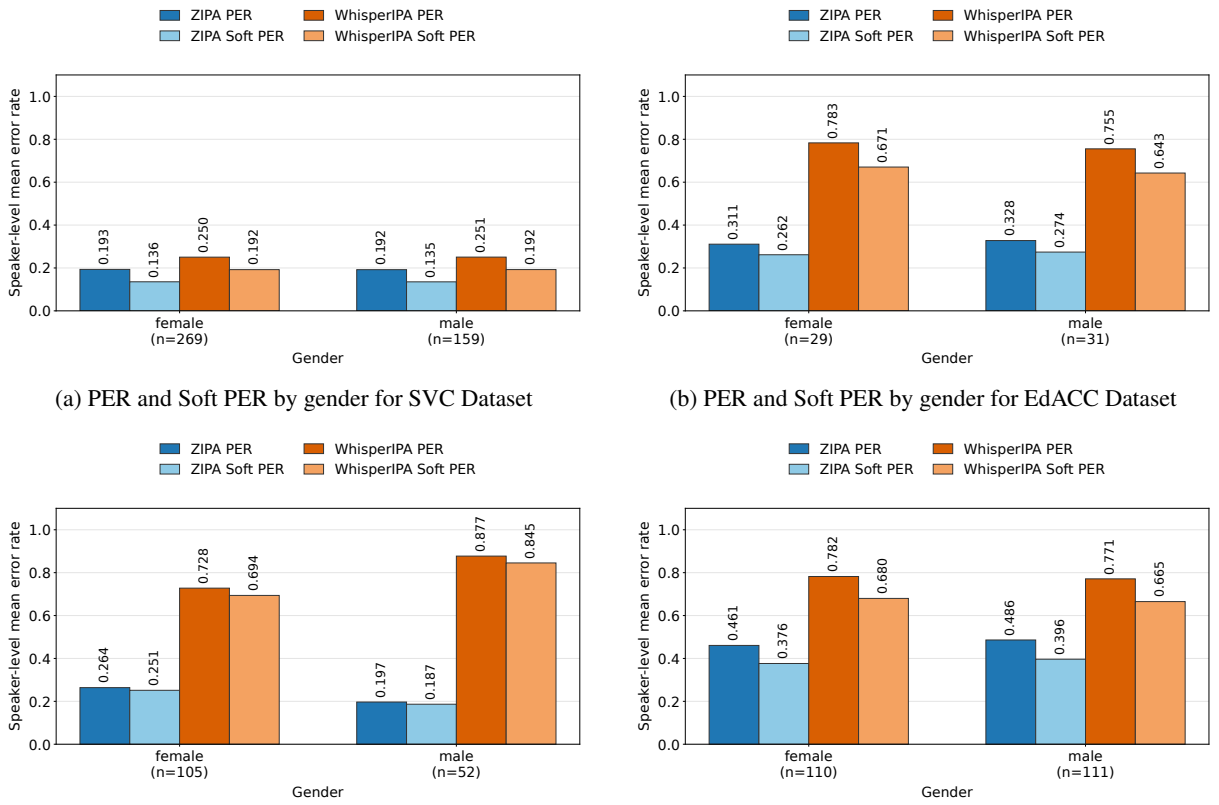
tially higher error rates than ZIPA, particularly for Arabic, Turkish, Bangla, Hindi, and Tamil.

Key Takeaways: Overall, the language-level evaluation shows that ZIPA consistently outperforms WhisperIPA across all evaluated languages. Exact PER averages 0.373 for ZIPA and 0.674 for WhisperIPA, corresponding to a 0.301 absolute reduction. Under Soft PER, the averages decrease to 0.281 for ZIPA and 0.574 for WhisperIPA, preserving the same ranking while reducing the absolute gap to 0.293. Considering English, Spanish, and French as high-resource languages and Hindi, Bangla, Panjabi, Tamil, Telugu, Arabic, Turkish, and Shona as low-resource languages, performance is consistently worse on the low-resource set. Averaged across both systems, exact PER is 0.565 for low-resource languages versus 0.415 for high-resource languages, a 36.2% increase. The gap is larger under Soft PER: low-resource languages have an average of 0.49 Soft PER compared to 0.261 for high-resource languages, resulting in an absolute difference of 0.23. This gap may reflect differences in model architecture, training objectives, and multilingual training data. Soft PER reduces absolute error rates for both models, suggesting that some standard PER errors arise from phonemically similar substitutions rather than entirely incorrect recognitions. Soft PER does not substantially alter model rankings or cross-lingual performance, showing that these language-specific differences exist after accounting for acceptable phonemic variation.

4.2 Demographic Performance Evaluation

We next analyze how phoneme recognition performance varies across demographic groups using CORAAL, EdAAC, SVC, and WAXAL, focusing on gender, age, ethnicity, and accent/dialect. We note that dataset characteristics may contribute more strongly to performance variation than the demographic attributes themselves. We interpret demographic patterns within each dataset rather than treating absolute error rates across datasets to account for this.

Gender: Figure 3 presents PER and Soft PER across gender groups for SVC, EdACC, WAXAL, and CORAAL datasets. Across all datasets, we observe limited evidence of systematic gender-based disparities. Male and female speakers exhibit highly similar PER and Soft PER values for both ZIPA and WhisperIPA. Though Soft PER reduces absolute error rates, it preserves the same ranking, indicating that apparent differences are not driven by minor phonemic variation. Overall, these results do not indicate a systematic gender-based disparity; instead, model choice and dataset characteristics appear to have a larger impact.



(a) PER and Soft PER by gender for SVC Dataset

(b) PER and Soft PER by gender for EdACC Dataset

(c) PER and Soft PER by gender for WAXAL Dataset

(d) PER and Soft PER by gender for CORAAL Dataset

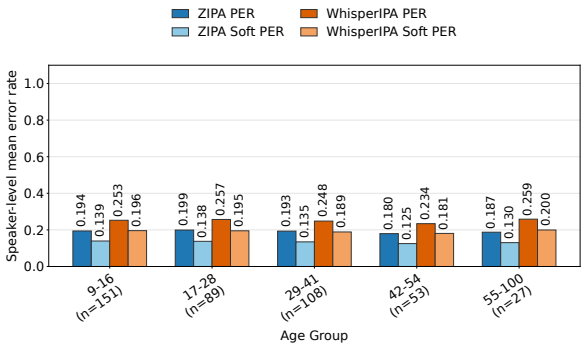
Figure 3: PER and Soft PER comparison by gender across demographic datasets.

Age: Figure 4 presents PER and Soft PER across age groups for SVC, EdACC, and CORAAL datasets. In SVC, both ZIPA and WhisperIPA show relatively small differences across all age groups, as shown in Figure 4a. In EdACC and CORAAL, overall error rates are substantially higher than in SVC, and WhisperIPA shows a clearer increase in error for older speakers, with the 45–59 age group (EdACC) and 51+ age group (CORAAL) producing the highest PER and Soft PER, as shown in Figures 4b and 4c. Although the 45–59 age group has a small sample size and should be interpreted cautiously. Soft PER lowers absolute errors but maintains the relative ordering of groups, suggesting that age differences also arise from broader recognition challenges rather than phonemic substitutions.

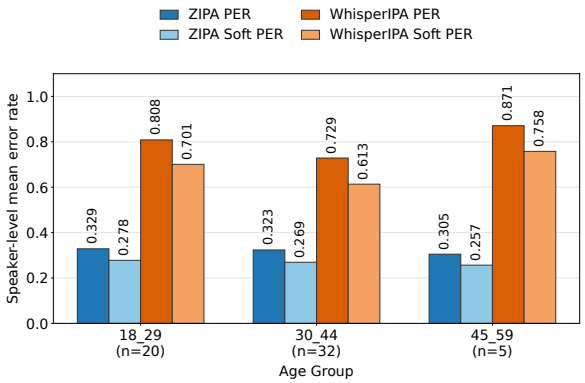
Ethnicity: Figure 5 presents PER and Soft PER across ethnicities for the EdACC dataset. Note that, in the EdACC dataset, "White", "Asian", "Black", and "South Asian" are possible self-selected ethnicity descriptors[4]. As shown in Figure 5a, WhisperIPA produces substantially higher error rates than ZIPA across all ethnicity groups, consistent with the model-level differences observed in the broader demographic evaluation. The disparity heatmap in Figure 5b shows that Black speakers have the largest positive disparity from the overall mean with disparities of $+0.050$ (ZIPA PER), $+0.035$ (ZIPA Soft PER), $+0.058$ (WhisperIPA PER), and $+0.046$ (WhisperIPA Soft PER). Asian speakers also consistently show above-average error rates, with disparities of $+0.012$ and $+0.013$ for ZIPA PER and Soft PER, and noticeably larger deviations of $+0.048$ and $+0.051$ for WhisperIPA PER and Soft PER. In contrast, White and South Asian speakers are generally below the overall mean. Although the South Asian group has the smallest sample size and should be interpreted cautiously.

Accent: Figure 6 presents PER and Soft PER across accent and dialect groups in the SVC dataset. Note that, in the SVC dataset, six regional groups (USA Southern, USA Western, USA Mid-Atlantic, USA Midland, USA Inland-North, and USA New England) represent native speakers of American English, and the last two groups (Asian and Latino)

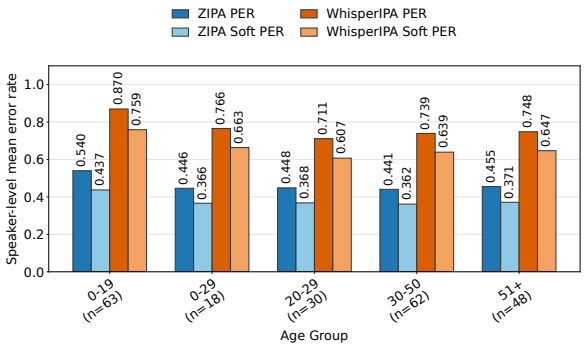
[4]https://groups.inf.ed.ac.uk/edacc/EDACC_statement.pdf



(a) PER and Soft PER by age group for the SVC dataset.



(b) PER and Soft PER by age group for the EdACC dataset.



(c) PER and Soft PER by age group for the CORAAL dataset.

Figure 4: PER and Soft PER comparison by age group across datasets.

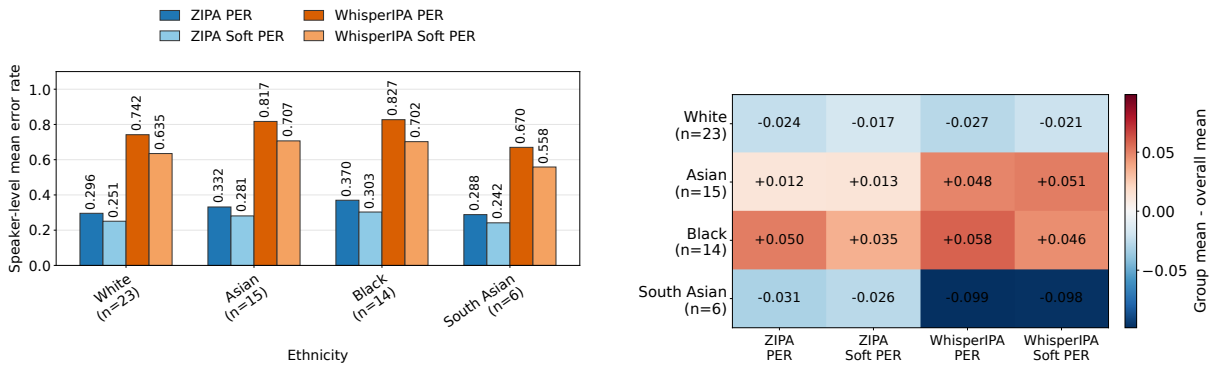
represent non-native speakers residing in the USA and natives of Asia and Latin America. As shown in Figure 6a, most USA regional accent groups have similar or slightly below-average error rates across both ZIPA and WhisperIPA. In contrast, Latino and Asian speaker groups show the highest error rates, particularly for WhisperIPA, suggesting that non-regional accent variation may be associated with larger phoneme recognition errors. The disparity heatmap in Figure 6b further supports this pattern: Latino speakers have the largest positive disparity from the overall mean, with disparities of $+0.057$ and $+0.032$ for ZIPA PER and Soft PER, and $+0.063$ and $+0.033$ for WhisperIPA PER and Soft PER respectively, followed by Asian speakers. In contrast, USA Mid-Atlantic, New England, Inland-North, Western, Midland, and Southern groups are generally at or below the overall mean. Although Soft PER reduces the magnitude of these disparities, the same relative pattern remains, indicating that the differences are not fully explained by minor phonemic variation captured by the soft equivalence mapping.

Key Takeaways: Overall, the demographic analysis shows limited evidence of systematic gender-based disparity, while larger differences exist for accent, ethnicity, and age depending on the dataset and model. In SVC, Latino and Asian accent/dialect groups show large positive disparities from the overall mean, whereas most USA regional groups remain near or below average. In EdACC, ethnicity and age differences are more visible, particularly for WhisperIPA, although several groups have small sample sizes and should be interpreted with caution.

PER vs. Soft PER: Soft PER reduces absolute error rates but generally preserves the same relative group patterns, indicating that most disparities are not driven by minor phonemic variation alone. If the errors were primarily due to phonologically similar substitutions—such as accent or dialect-related shifts—Soft PER would noticeably reduce the gaps among various demographic groups. Instead, the stable rankings across both metrics suggest that the underlying differences stem from broader recognition errors that persist even after accounting for phonologically reasonable substitutions. This suggests that standard PER, despite producing higher absolute error rates, may still be sufficient for identifying systematic biases while providing greater comparability across studies for now.

5 Conclusion

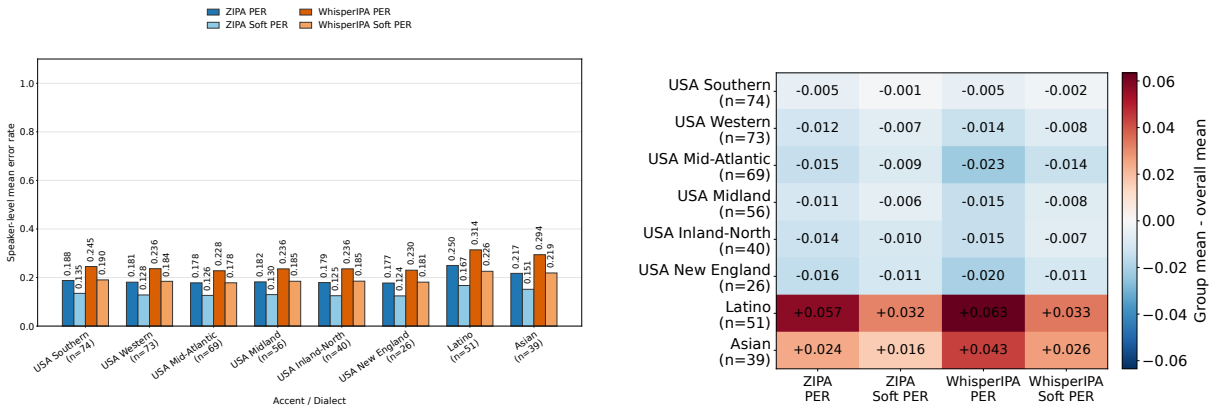
In this work, we evaluate bias and performance variation in IPA-based phoneme recognition models across languages and speaker demographics. We compare two open-source IPA transcription systems, ZIPA and WhisperIPA, using both standard PER and a proposed Soft PER metric that reduces penalties for linguistically similar phoneme substitutions. Across the multilingual evaluation, ZIPA consistently achieves lower error rates than WhisperIPA, while both models show substantial variation across languages. This performance gap



(a) PER and Soft PER by ethnicity group for the EdACC dataset.

(b) Ethnicity disparity from the overall mean for the EdACC dataset.

Figure 5: PER, Soft PER, and group-level disparity by ethnicity for the EdACC dataset.



(a) PER and Soft PER by accent/dialect group for the SVC dataset.

(b) Accent/dialect disparity from the overall mean for the SVC dataset.

Figure 6: PER, Soft PER, and group-level disparity by accent/dialect for the SVC dataset.

may be partly attributable to differences in model architecture, training objective, and training data scale. Although Soft PER reduces absolute error rates for most languages, it does not remove cross-lingual performance disparities or change the overall model ranking. This indicates that some standard PER errors reflect acceptable phonemic variation, but that meaningful language-level differences remain even under relaxed matching.

The demographic evaluation also shows that the performance variation is not uniform across speaker identity characteristics. Gender-based differences are small and inconsistent across datasets and models, suggesting limited evidence of systematic gender disparity in this evaluation. In contrast, large differences emerge for accent, ethnicity, and age. In the SVC dataset, "Latino" and "Asian" accent/dialect groups show large positive disparities from the overall mean, while most U.S. regional groups remain near or below average. In EdACC, speech from "Black" and "Asian" participants experienced higher PER from both WhisperIPA and ZIPA. Age differences are noticeable for WhisperIPA, though some age ranges have small sample sizes and should be interpreted with caution. Across demographic attributes, Soft PER lowers absolute error rates but generally preserves relative group-level patterns, suggesting that observed disparities are not fully explained by minor phonemic variation alone.

Overall, our findings show that IPA-based ASR systems are not free from demographic or language-level disparities. Although phoneme-based representations provide a promising foundation for low-resource and multilingual speech technologies, their performance can still vary substantially between languages, accents, and demographic groups. These results highlight the need for more careful evaluation of phoneme-level ASR systems, richer demographic and sociophonetic benchmarks, and evaluation metrics that distinguish genuine recognition errors from acceptable pronunciation variation.

Limitations

The key limitation of phoneme-level evaluation is the reliance on auto-generated IPA ground truth, because of the high costs of specialized manual phonemic annotation. Unlike orthographic transcriptions, phonemic annotations depend on G2P conversion and forced alignment, which can introduce systematic noise and model bias in the ground truth. Because our pipeline converts written transcripts into IPA representations, the resulting "ground truth" often reflects standardized pronunciation, which can encode biases of what constitutes "correct" speech into our analysis (Vythelingum et al., 2017; MacKenzie and Turton, 2020). This issue will naturally increase the error rates for accented speech, dialectal variation, and non-canonical pronunciations, where no single canonical phonemic form may exist (Fatema et al., 2024). Even with a softened PER, it may reflect annotation artifacts rather than true model error. Addressing this limitation may require future evaluation frameworks that utilize expert-validated phonemic annotations.

Our Soft PER hopes to partially mitigate sensitivity to annotation noise. While this acts as a necessary smoothing, it introduces a tradeoff between linguistic fidelity and metric standardization. Our definition of Soft PER may not be directly comparable to standard PER or WER, limiting cross-study comparability. Additionally, the equivalence mapping rely on English-prioritized relations when a surface phone appears across multiple languages. Although this provides a consistent normalization strategy, it may bias the metric toward English phonological interpretations and over-normalize distinctions that remain contrastive in other languages. Future work should explore language-adaptive mappings that better preserve cross-lingual phonological variation.

The analysis is further constrained by the demographic metadata available in the evaluated datasets. These categories do not capture finer sociophonetic variation such as code-switching, intra-speaker variability, or regional micro-dialects. In addition, certain demographic groups are underrepresented, which may limit the statistical robustness and generalizability of the results. Future work could address this by incorporating or creating a dataset with richer sociolinguistic annotations optimized for multilingual analysis to better understand the relationship among different dimensions.

Finally, while IPA provides a more fine-grained representation of speech than grapheme-based transcription, it is an abstract acoustic representation. There is ongoing debate in linguistics regarding the extent to which phonemic representations can fully capture gradient phonetic variation (Mallaband, 2024; Mitterer et al., 2018). Dialectal variation and allophonic realizations may not be fully represented within standardized IPA inventories, which may further influence both the accuracy of the ground truth and evaluation results (Fatema et al., 2024). Hybrid evaluation frameworks in the future that jointly leverage phonemic representations and acoustic similarity measures could potentially provide a more accurate representation of ASR performance across diverse demographics.

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A Appendix

A.1 Dataset Details

Table 1 summarizes the multilingual speech datasets used for cross-lingual evaluation, including the languages represented in each dataset and the dataset split used for analysis. Together, these datasets support evaluation across both high-resource and lower-resource languages.

Table 2 provides a detailed summary of the English-language datasets and the speaker-level demographic metadata available in each dataset. These metadata fields, including age, gender, ethnicity, accent, and dialectal region, are used to evaluate whether IPA-based ASR models exhibit systematic performance variation across demographic groups.

A.2 IPA Transcription Post-Processing

To ensure that the evaluation focused on phonemic correspondence rather than superficial transcription differences, we apply the same normalization procedure to both the G2P-generated ground-truth IPA transcriptions and the model-generated outputs before computing PER and Soft PER as described in Table 3. The normalization rules are designed to reduce variation caused by stress notation, IPA symbol variants, tokenization conventions, and formatting artifacts, while preserving the underlying phone sequence as much as possible.

After applying these transformations, the normalized phone strings were re-tokenized into whitespace-separated phone sequences. This produced a consistent representation across reference and generated outputs, reducing the impact of orthographic IPA variants and tokenization artifacts on downstream evaluation.

A.3 Soft PER Details

Table 4 lists the transitive phonetic equivalence classes used in the first tier of Soft PER. These classes group phones that are treated as interchangeable during evaluation, allowing the metric to avoid penalizing substitutions that correspond to linguistically similar or allophonic variants. The Tier 1 mapping is applied universally across languages and is intended to capture broad phonemic variation that should not necessarily be counted as a recognition error.

The Tier 1 equivalence classes are constructed from two sources of phonetic similarity. First, language-specific allophonic mappings are derived from AlloVera, which links surface phones to canonical phonemes across multiple languages. Second, articulatory feature representations from PHOIBLE are used to identify canonical phonemes that differ by only one articulatory feature. These phones are merged into shared transitive classes, producing a mapping that spans 62 equivalence classes and 254 phones. During Soft PER computation, substitutions within the same Tier 1 class receive zero penalty, allowing the metric to better distinguish substantial recognition errors from acceptable phonetic variation.

Table 5 lists the language-specific non-transitive similarity pairs used in the second tier of Soft PER. Unlike the Tier 1 classes, these pairs are not merged into broader equivalence classes. Instead, they capture cases where the same surface phone corresponds to different canonical phonemes across languages. This allows Soft PER to recognize language-specific pronunciation overlap without incorrectly making all connected phonemes globally interchangeable.

The Tier 2 mapping is also derived from AlloVera. When a surface phone maps to different canonical phonemes in different languages, the corresponding canonical phonemes are recorded as a direct similarity pair. During evaluation, these pairs are applied only when relevant to the target language. Substitutions covered by Tier 2 receive zero penalty, but the relation remains non-transitive; for example, if two separate language-specific mappings relate one phone to two different phones, Soft PER does not automatically treat those two phones as equivalent to each other. This design preserves language-specific phonological distinctions while still reducing penalties for acceptable cross-lingual or allophonic variation.

Table 1: Dataset Metadata and Speech Characteristics

Dataset	Languages / Varieties	Subset†	Collection Period	Speech Style	Recording Environment
Fleurs_IPA	English, Hindi, Bangla, Punjabi, Tamil, Telugu	Test	2020–2022	Read speech (utterance-level)	Unedited original recordings
MediaSpeech	Arabic, French, Spanish, Turkish	N/A	2020	Read and spontaneous speech	YouTube broadcasts/channels
Waxal	Shona	Train	Jan. 2021–Mar. 2024	Natural, spontaneous speech	Natural environments
EdAcc	English	Test	2023	Naturalistic, spontaneous interactions	Zoom recordings
SVC	English	Train	2024	Read speech	Clean, close-field environments
CORAAL	African American English	Train	2023	Sociolinguistic interviews	Unedited original recordings

† Dataset partition used for bias evaluation.

Table 2: Dataset Languages and Demographic Attributes

Dataset	Language(s)	Demographic Attributes
WAXAL	Shona	gender
EdACC	English	gender, year_of_birth, ethnicity, education, l1, l2, accent, english_since, countries_lived, lang_home, lang_friends
SVC Bias Assessment	English	age_group, gender, dialectal_region
CORAAL	African American English	city, se_group, age_group, gender

Table 3: Normalization rules applied to both ground-truth IPA transcriptions and model-generated outputs prior to evaluation.

Category	Normalization behavior
Stress marks	Primary and secondary stress marks, such as ˈ and ˌ, were removed.
Length marks	Length markers, including ː, ˑ, and the ASCII colon :, were removed.
Rhotics	Rhotic consonants such as ɹ, r, ʁ, and ʀ were mapped to r. Rhotic vowels such as ɚ and ɝ were expanded to ə r and ɛr, respectively. Rhoticity marks, such as ə^{r}, were also normalized to a vowel followed by r.
Diphthongs	Joined diphthong symbols were tokenized as separate phone sequences. For example, eɪ was normalized to e ɪ.
Affricates	Joined and tie-barred affricates were tokenized as separate phones. For example, tʃ, t͡ʃ, and ʧ were normalized to t ʃ.
Token separators	Whitespace, SentencePiece markers such as ▁, hyphens, slashes, and similar separators were collapsed into phone-token boundaries.
Combining marks	Separated combining marks were attached to the preceding phone. For example, ɑ ˜ was normalized to ɑ̃.
Symbol choices	Common spelling variants were standardized. For example, ASCII g was normalized to IPA ɡ, and dark-*l* variants such as l^{ɣ}, l^{ɣ}, and separated l ˠ were normalized to ɫ.

Table 4: Phonetic Transitive Equivalence Classes (Tier 1).

Index	Representations
0	ŋ, n, ŋ
1	ɪ, a, aː, a, i, a, ɒ, ɒ, a
2	by, bjj
3	bw, pw
4	tʃ, tʃ
5	d, d
6	dʒ, dʒ
7	e, eː, e, ɤa
8	f, fː, v, vː, v, ʔ, v
9	fj, vj, vj, vj
10	fw, vw
11	gj, gjj
12	h, h
13	hj, ɕj
14	i, iː, i
15	dʒ, i, j, zj, z, j
16	c, g, gj, gː, k, kx, k^h, kj, kː, k, kp, ɟ, g, gː, g, ɣ
17	kj, kjj
18	kj, gj
19	kw’, k’w
20	l, lː, l, l
21	m, mː, ɸ
22	mj, mjj
23	n, nː, n, n
24	nj, nj
25	o, oː, o, o
26	b, bː, b, b, p, p^h, pː, b, β, β
27	pj, pjj
28	bj, pj
29	b’, p’
30	pf, pf
31	d, p, q, t
32	ɾ, ɾː, ɾ, ɾ, ɾ, ɾ, χ
33	rj, rj
34	rj, rj
35	s, sː, s, z, z
36	sj, zj
37	s’, t’, ts’
38	d, dː, d, d, t, t^h, tː, t, t, d
39	dj, tj
40	tw’, t’w
41	dz, ts, ts
42	ts^h, ts^h
43	$tʃ^h$, $tʃ^h$
44	tʃj, tʃj
45	tʃ, tʃ
46	u, uə, uː, uw, ɱ, ɱ
47	x, ː
48	xj, xj, ɣj
49	y, ʏ
50	ð, θ
51	ŋ, ŋ, ŋm
52	ɑ, ɑ, ɔ
53	ɕ, ɕː
54	ə, ə
55	gw, kw, gw
56	ɾ, ɻ
57	ʃj, ʃjː
58	ʃ, ʃx, ʒ, ʒ, ʒx
59	d, d, t
60	ts, ts
61	ts^h, ts^h

Table 5: Language Specific Non-Transitive Pairs (Tier 2).

Phoneme 1	**Phoneme 2**	**Language**	**Phoneme 1**	**Phoneme 2**	**Language**
ŋ	m	eng, jpn	ŋ	n	eng, jpn, kaz
ŋ	ŋ	eng, jpn	ŋ	ɲ	fra, jpn
a	aː	jpn, tur	a	æ	deu, eng
a	ɑ	cmn, eng	a	ɔ	eng, jav
a	ə	eng, rus	a	ɛ	cmn, eng
a	ʊ	eng, rus	aː	ɑ	deu, eng
b	b^j	jpn, rus	b	p	amh, eng, kaz, rus, spa
b	v	spa, tur	b^j	p^j	rus
tʃ	k	jpn, vie	d	dʒ	ita, tgl
d	t	eng, kaz, rus, vie	d	ð	eng, spa
d	ɽ	spa, tgl	d^j	t^j	rus
dʒ	ts	ita, tgl	dʒ	ʒ	amh, eng, ita, tgl
e	eː	deu, eng, jpn, tur	e	i	eng, tgl
e	æ	eng, tur	e	ɛ	deu, eng
e	ɪ	eng, tgl	e	ʊ	cmn, eng
h	r	fra, kaz	h	x	deu, tur
h	ɕ	deu, jpn	i	iː	deu, eng, jpn, tur
i	ɛ	eng, tgl	i	ɪ	deu, eng
j	y	eng, jpn	j	ɕ	deu, rus, spa
j	ɦ	cmn, fra	j	ɪ	eng
j	ʎ	deu, spa	k	q	eng, jav
k	x	deu, tgl	k	g	amh, deu, eng, kaz, rus
k	g^j	rus	m	m^j	jpn, rus
m	n	eng, ita	m	ŋ	eng, ita, tgl
m	ɲ	eng, fra, ita	n	ŋ	eng, spa, tgl
n	ɲ	eng, fra, ita	o	oː	deu, eng
o	u	eng, tgl	o	ɔ	eng
o	ʊ	eng, tgl	p	p^j	jpn, rus
p	q	jpn, vie	q	r	fra, kaz
q	s	eng, jpn	r	x	deu, fra, kaz, spa
r	r	eng, spa	r	ɽ	jpn, spa, tgl
r	ʃ	eng, kaz	r	ʒ	eng, kaz
s	z	amh, deu, eng, kaz	s	ʃ	eng, tgl
s	θ	eng, spa	ʃ	ʃ	cmn, jpn
t	tʃ	spa, tgl	ts	tʃ	spa, tgl
ts	z	ita, jpn	u	uː	deu, eng, jpn, tur
u	w	eng, ita	u	ɨ	jpn, rus
u	ʊ	deu, eng	w	ʊ	eng
x	ɣ	rus, spa	y	yː	deu, fra
ʌ	ʌː	deu, fra	ʌ	ɵ	deu, fra
ŋ	ɲ	eng, ita	ɔ	ə	amh, eng
ə	ɛ	amh, eng	ɣ	ɲ	tgl, tur
ɨ	ɪ	amh, eng	ɨ	ɲ	rus, vie
ɨ	ʊ	amh, eng	ɪ	ɽ	eng, tgl
ʃ	ʒ	eng, kaz	ʎ	ʒ	eng, spa