Sonos Voice Control Bias Assessment Dataset: A Methodology for Demographic Bias Assessment in Voice Assistants

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Abstract

Recent works demonstrate that voice assistants do not perform equally well for everyone, but research on demographic robustness of speech technologies is still scarce. This is mainly due to the rarity of large datasets with controlled demographic tags. This paper introduces the Sonos Voice Control Bias Assessment Dataset, an open dataset composed of voice assistant requests for North American English in the music domain ($1,038$ speakers, 166 hours, 170k audio samples, with $9,040$ unique labelled transcripts) with a controlled demographic diversity (gender, age, dialectal region and ethnicity). We also release a statistical demographic bias assessment methodology, at the univariate and multivariate levels, tailored to this specific use case and leveraging spoken language understanding metrics rather than transcription accuracy, which we believe is a better proxy for user experience. To demonstrate the capabilities of this dataset and statistical method to detect demographic bias, we consider a pair of state-of-the-art Automatic Speech Recognition and Spoken Language Understanding models. Results show statistically significant differences in performance across age, dialectal region and ethnicity. Multivariate tests are crucial to shed light on mixed effects between dialectal region, gender and age.

Keywords: speech corpus, automatic speech recognition, spoken language understanding, demographic bias, bias detection

1. Introduction

One of the main applications of Automatic Speech Recognition (ASR) is Spoken Language Understanding (SLU). SLU combines speech and natural language processing techniques and is used in voice interfaces such as domestic voice assistants in smart speakers. It typically combines several tasks like intent classification and slot filling Tur (2011). Such a field of application raises many challenges, especially around footprint and privacy (always-on setting, edge processing like in He et al. (2018); Saade et al. (2019)), proper nouns and rare words recognition (e.g. for music entities recognition, in Liao et al. (2023); Sainath et al. (2021)) and acoustic robustness (far-field noisy settings typical of the home environment, like in Braithwaite and Kleijn (2019); Défossez et al. (2020)).

However less research is directed on what we could call *demographic robustness* of voice assistants. There is some evidence though that ASR systems do not perform equally well for everyone (see Section 2). In particular, performance degradation stemming from demographic factors – gender, age, accent, race – can be observed, leading to our definition of demographic bias: when the performance of a speech recognition system depends on the group of people it is evaluated upon. Such research is nonetheless mostly focused on conversational use cases of the general domain for dictation and the underlying metric to optimize is transcription accuracy or Word Error Rate (WER). We believe these are not representative of voice assistant usage that focuses on the recognition of short action-oriented commands and that SLU metrics are likely to be a better proxy for voice assistant user experience. The correct execution of voice assistant requests indeed strongly depends on the recognition of isolated and sometimes complex entities, rather than on the exact transcription of the entire utterance.

In this work, we propose an open dataset, the Sonos Voice Control Bias Assessment Dataset ($1,038$ speakers, 166 hours, 170k audio samples, with $9,040$ unique labelled transcripts), composed of voice assistant requests in the music domain with a controlled demographic diversity (gender, age, dialectal region and race). The dataset is accompanied by a statistical bias assessment methodology tailored to this use case, leveraging intent and entity tagging through the Exact Match (EM) metric rather than WER. The statistical tests include a standard univariate approach, but also multivariate models to identify possible mixed ef-

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fects. The proposed approach is illustrated on state-of-the-art End-to-End (E2E) ASR and SLU models. The code to reproduce our results is available on GitHub[1].

2. Related Work

2.1. Bias Assessment

Existence of biases. A number of works investigate the disparities in performance of commercial and open source ASR systems across a variety of speaker characteristics, most of them focusing on variations of English. Among the most studied demographic variables are native vs. non-native accents (dialectal region), gender, age, and race.

Evidence is mixed regarding gender: some studies found that ASR systems favor female speakers Koenecke et al. (2020); Goldwater et al. (2010); Adda-Decker and Lamel (2005); Sawalha and Abu Shariah (2013); Feng et al. (2024) while others found that male speakers have a better recognition rate Tatman (2017); Garnerin et al. (2019, 2021), or no significant bias at all (Meyer et al., 2020).

ASR systems tend to better recognize native speakers vs. non-native ones Koenecke et al. (2020); Palanica et al. (2019); Wu et al. (2020); Tatman and Kasten (2017); Tatman (2020); Feng et al. (2021, 2024) due chiefly to language variability (regional and/or socio-linguistic), accents, articulation and speech rates. Evidence of commercial ASR systems exhibiting racial biases can be found in Koenecke et al. (2020); Tatman (2017) between Black and White speakers. Finally, several studies point out that younger speakers ($18 - 30$) are better understood than children and seniors Sawalha and Abu Shariah (2013); Feng et al. (2021). This can be explained by the challenge represented by child speech due to their shorter vocal tracts, more variable speaking rate and inaccurate articulation Qian et al. (2017).

Bias assessment methodology. Most of previous work focus on the average relative degradation of the transcription accuracy (through word, character or phoneme error rates) across speaker groups (e.g. male vs. female, native vs. non-native, White vs. African-American). To the best of our knowledge, no previous work aims at quantifying demographic bias through SLU metrics.

Only a handful of prior studies propose univariate statistical tests or models to find out whether these mean variations are statistically significant. Statistical tests such as Wilcoxon Rank Sum, Kruskall-Wallis Garnerin et al. (2021, 2019) and one-way analyses of variance (ANOVA) Feng et al. (2024); Meyer et al. (2020) are used. Even fewer studies consider second order effects with, for instance, linear mixed-effects regressions Tatman (2017); DiChristofano et al. (2022) (with speaker and year as random effects) and mixed-effects Poisson regressions Liu et al. (2021) (with speaker as random effect and demographic tag of interest as fixed effect).

2.2. Available datasets

There is a lack of standard benchmarks in the literature for demographic bias assessment in voice assistants Ngueajio and Washington (2022). Though previous studies are extremely valuable, the datasets used are often small in terms of number of audio samples, speakers and transcripts variability. For instance, the one used in Tatman (2017) is made of 62 words read in isolation by 80 speakers. Other studies use internal datasets such as *VoiceCommand* in Liu et al. (2021). It was collected through a crowd-sourcing campaign where a limited number of 95 participants were instructed to utter voice commands. When not limited by the number of speakers, the datasets are not representative of the voice assistant use-case but instead comprise books or stories Panayotov et al. (2015); Bradlow et al. (2010), broadcast news (Kalluri et al., 2021), conversational speech Oostdijk (2000); Kendall and Farrington; Pitt et al. (2005), human-machine interaction speech Cucchiarini et al. (2006), interviews Hazirbas et al. (2021), random paragraphs Weinberger and Kunath (2011), and improvised speech Wang et al. (2021); Bradlow et al. (2010).

One of the most recent attempts to publish an open source (under the Creative Commons CC-0 license) dataset for demographic bias assessment is the Artie Bias Corpus introduced in Meyer et al. (2020), a manually annotated subset of the Common Voice (Ardila et al., 2019) test set comprising $1,712$ audio clips (≈ 2.4 hours), $1,903$ utterances, 3 gender classes, 8 age ranges and 17 English accent classes. However, the metadata is self reported and sometimes incomplete (the accent label is missing for around 33% of the data). This dataset is also very imbalanced towards younger, male, US English speakers. As pointed out by the authors, one of the main limitations of this dataset is its small size which has a direct impact on the statistical power of the tests.

3. Sonos Voice Control Bias Assessment Dataset

The Sonos Voice Control Bias Assessment dataset addresses the usage of a voice assistant for music control, which is reported as the most

[1] https://github.com/sonos/svc-demographic-bias-assessment

common use case[2], and includes $170,413$ audio samples in North American English (≈ 166 hours) along with their transcripts, labels, and demographic metadata about the speaker. The dataset was designed mostly for evaluation purposes, but splits for training and development are also made available. Audio samples were obtained following a directed process (read speech) described in the following sections, based on transcript and label production on the one hand, and on speaker specification and selection on the other hand. The dataset is available for download and can be used for academic and/or research purposes[3].

3.1. Transcripts and labels

Transcripts of this dataset are divided into a set of 32 *intents*, each standing for a class of actions which can typically be requested within the music domain, related to playing music, controlling the music stream, requesting information, switching, grouping and ungrouping devices, and managing the user's library. Intents can further specify optional or required *entities*, in the form of slots, to make their semantic interpretation, in terms of action, complete and coherent. In the case of `PlayMusic` or `VolumeUp`, such entities can be names and titles from the music domain, or level quantifiers, identified as e.g. `artist` or `volume_level`, which fill up the action of content playing with an actual, quantifiable or identifiable value. The music entities (`artist`, `song`, `album`) contain much more distinct values than the rest of the entities, with respectively $1,715$ artists, $2,643$ songs and $1,626$ albums values found in all the transcripts. There are 32 unique entities in the dataset, distributed among all intents. Transcripts and their labels (intents and slots) are generated through a semi-automated process that is beyond the scope of the present paper.

Two assistant interaction contexts are usually considered. On one hand, the `PlayMusic` intent (e.g. *play the song Abbey Road*) which is the only one related to content initiation, with music entities and arguably the most complex intent: a third of the `PlayMusic` queries have 3 slots or more. On the other hand, the rest of the 31 intents are denoted `Transport Control` intents, e.g. `Forward` (*fast forward a little*), `Again` (*once more*), or `VolumeUp` (*play louder*). They are typically short queries, 80% of them have either 1 or no slot, and the number of possible phrasings is limited. There is a total of $9,040$ unique transcripts in the dataset, $8,114$ for the `PlayMusic` intent and 926 for `Transport Control` intents. Appendix A.2 provides provides more insights on the ontology coverage.

3.2. Speaker demographic metadata

A total of $1,038$ speakers were selected following three dimensions of demographic characteristics: **gender** (male and female here, though we recognize that gender cannot be captured by a binary variable), **age range** (5 age ranges starting at 9 years old) and **dialectal region**. The latter dimension accounts for dialectal variation, e.g. pronunciation and intonation contrasts and fluctuations inside the United States. Six regional groups represent native speakers of American English and two groups represent non-native speakers residing in the USA, native of Asia (Asian) and Latin America (LatinX), with internal variations being expected within each region or group. More details on the choice and definition of these groups can be found in Appendix A.1.

Ethnicity was unreported in the initial version of the dataset. Though we made sure that regions (and more specifically cities) where ethnic diversity is prominent were represented in the data collection, this lack of information made it impossible to quantify bias between different racial groups. Some context can be found in Appendix A.4. We therefore launched an additional campaign targeting specifically Caucasians (50 speakers) and African Americans (48 speakers), present only in the test split. The gender distribution for these speakers is balanced ($49\%-51\%$) and the regional distribution is roughly similar to that of the rest of the dataset. However, recruiting children under 16 proved difficult, therefore constraints imposed on that age group were relaxed.

3.3. Audio samples

Each of the $1,038$ speakers have recorded 193 distinct transcripts on average, except for 9 to 16 year old children (328 speakers) who recorded only 96 transcripts on average and for speakers with ethnicity information (98 speakers) who recorded 150 transcripts on average. This disparity is explained by the difficulties encountered when hiring speakers from these specific demographic groups. Recording conditions are uniformly clean and close-field.

The total number of audio samples is $170,413$ over $9,040$ unique transcripts, (≈ 166 hours): $77,515$ (92.88 hours) for the `PlayMusic` intent and $92,898$ (72.66 hours) for the `Transport Control` intents. Train, dev and test splits are finally created by splitting speakers among 10 speaker groups, each balanced in terms of demographic characteristics. Speaker groups 1 to 5 are used for the train (428 speakers, $69,206$ samples)

[2] Adobe Digital insights 2018

[3] https://github.com/sonos/svc-demographic-bias-assessment

Split	Samples	Speakers	Duration
Train	69,206	428	68:49
Dev	6,703	38	6:26
Test	94,504	572	90:30

Table 1: Description of the dataset across splits in terms of number of samples, number of speakers and duration (h:min).

and dev (38 speakers, $6,703$ samples) splits and speaker groups 6 to 10 for the test split (572 speakers, $94,504$ samples). A description of the splits can be found in Table 1.

Fig. 1 displays the audio sample distribution in the test split of the dataset for each demographic group. We see that the dataset is skewed towards female and younger speakers. We also note that the LatinX and Asian groups are slightly less populated than the other dialectal regions.

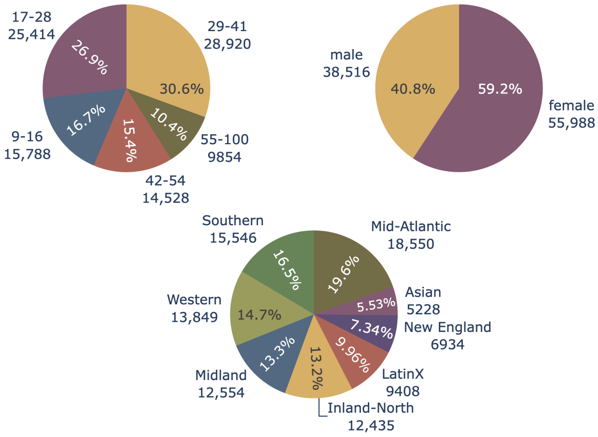


Figure 1: Audio sample distribution in the test split of the dataset in terms of age, gender, and dialectal region. The number of samples in each group is displayed under the group label.

The 3 demographic dimensions included in this dataset (gender, age, dialectal region) amount to 80 different demographic groups (not considering the smaller subset with ethnicity labels), that we tried to keep reasonably balanced by a minimum speaker distribution in each of them. As an illustration, Table 2 displays the age and gender distribution for each dialectal region in the test split. We believe that the coverage in terms of speakers and audio samples in the Sonos Voice Control dataset should allow to assess potential biases of a voice assistant related to demographic characteristics of speakers. Further descriptive statistics can be found in Appendix A and B.

Dialectal region	Samples	Speakers	Age distribution	Gender distribution
Southern	15546	97	$9-16: 17\%$ $17-28: 23\%$ $29-41: 34\%$ $42-54: 15\%$ $55-100: 11\%$	Female: 55% Male: 45%
Western	13849	87	$9-16: 19\%$ $17-28: 28\%$ $29-41: 24\%$ $42-54: 20\%$ **55-100: 9%**	Female: 61% Male: 39%
Inland North	12435	73	$9-16: 10\%$ $17-28: 24\%$ $29-41: 34\%$ $42-54: 18\%$ $55-100: 14\%$	Female: 52% Male: 48%
New England	6934	43	$9-16: 20\%$ $17-28: 32\%$ $29-41: 31\%$ **42-54: 9%** **55-100: 8%**	Female: 67% Male: 33%
Mid Atlantic	18550	111	$9-16: 17\%$ $17-28: 23\%$ $29-41: 26\%$ $42-54: 19\%$ $55-100: 15\%$	Female: 57% Male: 43%
Midland	12554	73	$9-16: 16\%$ $17-28: 26\%$ $29-41: 31\%$ $42-54: 16\%$ $55-100: 11\%$	Female: 63% Male: 37%
LatinX	9408	56	$9-16: 16\%$ $17-28: 36\%$ $29-41: 36\%$ **42-54: 8%** **55-100: 4%**	Female: 66% Male: 34%
Asian	5228	32	$9-16: 23\%$ $17-28: 36\%$ $29-41: 35\%$ **42-54: 4%** **55-100: 2%**	Female: 62% Male: 38%

Table 2: Statistical distribution of audio samples for each dialectal region in terms of age and gender in the test split. In bold are the categories for which we have less than 10% of data points.

3.4. Ethical considerations on the audio collection

To perform the audio collection, we commissioned a third-party data collection company to hire $1,080$ American English speakers (initially, later reduced to $1,039$ for quality reasons) who met the set of criteria we defined on ethnicity, age, gender, and dialectal regions, based on self declaration. These criteria amount to 80 distinct demographic groups (not considering the smaller subset with known ethnicity), such as the 9-16 year old LatinX female speakers group. We further imposed a minimum number of speakers in each of these groups and a minimum amount of audio recording per speaker to guarantee a balanced distribution and enough power for the statistical tests. We provided recording scripts, as defined in 3.1.

The demographic category for a speaker was based on self declaration and no other personal information was collected apart from gender, age, dialectal region and ethnicity. We also explicitly collected consent from the speakers to re-distribute audio recordings of their voice for non-commercial academic and research purposes. The way the data was collected and will be distributed is fully compliant with the GDPR.

The third-party data collection company informed us that all participants were paid well above minimum wage. Hourly rate ranges from $\$15$ to $\$40$ per hour depending on the task requirements, such as the task duration. The estimated time of completion was tracked and adjusted based on previous collections and internal testing of each task to reflect the median time of completion.

All participant recruitment for child recordings is targeted towards parents who worked with their child(ren) to complete the recordings. The privacy policy of the third-party data collection company specifies that they do not process any personal data of children under 16 years of age without consent given or authorized by the holder of parental responsibility over the child. The payment is done directly to the parent of the child.

4. Bias Assessment Methodology

4.1. Approach

In this section, we present the proposed methodology to assess the demographic biases of any given ASR system in the specific context of a music voice assistant. The SLU metric we choose as proxy for user experience is **Exact Match** (EM, also called utterance-level accuracy in some works Kashiwagi et al. (2023)). An utterance i is said to be exactly parsed ($EM_i = 1$) if both the correct intent and all the correct slots are retrieved (else $EM_i = 0$). In the case of a music voice assistant, EM is particularly relevant due to the intrinsic complexity of the slots values, especially artists or songs names that may be cross-lingual (e.g. Spanish songs or artists in an English request) and might be harder to pronounce for some demographic groups.

We propose to conduct statistical tests with logistic regressions McCullagh and Nelder (1989) in order to assess the presence of demographic bias within the SLU system, i.e. to show whether the observed performance disparities are significant. EM serves as **binary response variable** for the tests. The subpopulations of interest are described by **categorical explanatory variables**: gender, age, dialectal region, and ethnicity.

Statistical testing with logistic regression helps to identify the effect of a single variable (e.g. singling out the effect of gender), via **univariate** models (Section 4.2.1) on the one hand. It also allows for identification of mixed effects (e.g. dialectal region *and* gender) through **multivariate** approaches (Section 4.2.2) on the other hand, as there could be demographic correlation between variables. In any case, a descriptive analysis of the data is always needed for the interpretation of such tests.

The proposed methodology is valid under several conditions. First, we assume that each observation is independent, i.e. we do not take into account the speaker-level effect. We may therefore operate at the utterance-level for clarity of the interpretation and results. Second, we suppose that the speakers in our dataset are representative of their sub-group. Third, we expect the response variable (EM) to be a function of a linear combination of the considered explanatory variables (age, gender, dialectal region, ethnicity). Finally, we presume that the transcripts' difficulty is uniformly distributed among speakers (i.e. there are no speakers who have more complicated utterances to pronounce than others).

4.2. Statistical Analysis

4.2.1. Univariate models

Logistic regression is a powerful statistical tool to measure demographic bias: it can shed light on the magnitude of the bias on the response variable through the estimated coefficients (fitted via maximum likelihood) and odds ratios (ORs). The probability that the Exact Match for observation i is 1: $\pi_i = \mathbb{P}(EM_i = 1)$ can be estimated by taking a monotonic real function $g(.) : [0, 1] \to \mathbb{R}$ such that $g(\pi_i) = \beta_0 + \beta_1 x_i$, for instance the `logit` function:

$$g(\pi_i) = \ln \frac{\pi_i}{1-\pi_i} \text{ with } g^{-1}(y) = \frac{e^y}{1+e^y}, \quad (1)$$

and x_i the value of the explanatory variable for observation i, β_1 its associated coefficient and β_0 a constant. The corresponding odds is:

$$\Omega_i(x_i) = \frac{\mathbb{P}(EM_i = 1)}{\mathbb{P}(EM_i = 0)} = \frac{\pi_i}{1-\pi_i} = \exp(\beta_0 + \beta_1 x_i), \quad (2)$$

i.e. given x_i, it is the relative chance of having $\mathbb{P}(EM_i = 1)$ compared to $\mathbb{P}(EM_i = 0)$.

Illustrating this on the binary explanatory variable *gender*, with $x_i = \mathbb{1}_{\text{male}}$, the OR is defined as:

$$OR = \frac{\Omega_i(\mathbb{1}_{x_i})}{\Omega_i(\mathbb{1}_{1-x_i})} = \frac{\exp(\beta_0 + \beta_1)}{\exp \beta_0} = \exp \beta_1, \quad (3)$$

i.e. $\exp \beta_1$ represents the odds of a male speaker to be exactly parsed compared to a female one, all other things being equal. If $OR = 1$, then *gender* has no impact on $\mathbb{P}(EM_i = 1)$ (independence).

Additionally, we perform hypothesis testing (Wald test Wald (1943)) on the estimated parameter β_1 where the null is $H_0 : \beta_1 = 0$. The latter is rejected at the α-level if the corresponding p-value is lower than α. This can be easily extended to non-binary categorical variables by following the method described in 4.2.2. It is used to test if all coefficients but the constant are null. Rejecting this null hypothesis means that at least one estimated coefficient is not null, but it does not inform us on which one it is. To get a better grasp at which modality impacts the *EM* with respect to the reference modality, one must look at the individual p-values of each coefficient (or, equivalently, at the confidence intervals of the ORs). Note that every coefficient must be interpreted with respect to the reference group (e.g. *female* in the above example).

4.2.2. Multivariate models

As mentioned previously, there might be confounding variables that could lead to spurious correlations and impact the statistical validity of our analysis. Gender is often described as such in the literature Tatman (2017) and age can be another one. To uncover such potential issues, we perform adjustment tests by augmenting the previous univariate models. For the sake of simplicity, let's illustrate the approach with two discrete variables: gender ($g = \mathbb{1}_{\text{male}}$) and dialectal region ($d_j = \mathbb{1}_{\text{j}}$, with $J = 6$ modalities, leaving out the reference group). For the observation i, the multivariate model writes:

$$g(\pi_i) = \beta_0 + \sum_{j=1}^{J} \beta_{1j} d_{ij} + \beta_2 g_i. \tag{4}$$

To assert whether gender could be a potential confusion variable with respect to the dialectal region (i.e. are observed differences in EMs between dialectal regions due to gender imbalance?), we compare model (4) to the univariate one:

$$g(\pi_i) = \beta_0' + \sum_{j=1}^{J} \beta_{1j}' d_i. \tag{5}$$

Our proposed procedure to assess whether adding gender to the model adds significance, i.e. $H_0 : \beta_2 = 0$, is as follows:

- Maximum Likelihood Estimation (MLE) of (4) and (5).
- Log-likelihood ratio test (LLR). L_u is the log-likelihood (natural logarithm of the MLE function) of (5) and L_m the one of (4). Under H_0, the test statistic $T = 2(L_m - L_u) \sim \chi^2_r$ where r is the difference between the number of parameters of the two models. Similarly as before, H_0 can be rejected at the α-level when $T > q_{r,1-\alpha}$, where T is the test statistic and $q_{r,1-\alpha}$ the $1 - \alpha$ quantile of a χ^2 distribution with r degrees of freedom.

Rejecting H_0 implies that gender adds information to the model. To further assess whether it confounds the effect of the dialectal region, we compare the p-values of the coefficients associated to the dialectal regions in (4) and (5). If the conclusions of the Wald tests in (5) are changed (i.e. p-values becoming lower or greater than the α level), we can say that gender is a confounding factor for dialectal region, else there is no statistical evidence supporting this claim.

5. Bias Assessment Experiments

In the following we propose an illustration of the proposed statistical method for bias assessment on the SLU task. To do so, we take an off-the-shelf ASR model (**wav2vec2.0** from Baevski et al. (2020)) that we fine-tune on part of the train split of Sonos Voice Control bias assessment dataset to get audio transcription. Intent Classification (IC), Slot Filling (SF) and computation of the EM metric are done by using a **JointBERT** SLU model Chen et al. (2019). The goal of this Section is to demonstrate the capabilities of our proposed dataset and methodology to quantify demographic bias in voice assistants. Consequently, the ASR and SLU models have not been particularly optimized for bias mitigation.

5.1. Models

ASR model description. The chosen ASR is an E2E Wav2Vec2-Large-960h model, developed by Meta and pre-trained using self-supervised learning (SSL) on 960 hours of English speech data from the Librispeech dataset introduced by Panayotov et al. (2015) and fine-tuned on a subset of the train split of the Sonos Voice Control bias assessment dataset: audio samples from speaker groups 2 and 3 (192 speakers). It represents $30,602$ audio samples which amounts to 30.4 hours of data. The entire dev split is used for validation.

In addition to the large wav2vec2.0 model, we incorporate an extra layer with 1024 neurons and LeakyReLU as the activation function followed by a fully-connected layer and a final 40-dimensional softmax layer, each dimension corresponding to a character. This neural network architecture comprises a total of 316.5M trainable parameters. The weights of the two added layers were randomly initialized, while the weights of the wav2vec2.0 were initialized using the pre-trained weights.

This SSL model is then fine-tuned with the additional layers, with a batch size of 12, distributed across 4 NVIDIA V100 32GB GPU cards. Two optimizers are used: Adadelta Zeiler (2012) for updating the additional layers' weights and Adam Kingma and Ba (2014) for fine-tuning the SSL model, with initial learning rates of 1.0 and $1\mathrm{e}{-4}$ respectively. The maximum number of epochs is set to 80: the best model on the validation is obtained at epoch 72, with a word error rate of 4.45% on the dev split of the Sonos Voice Control bias assessment dataset. Processing an entire epoch takes around 52 minutes. During the fine-tuning process, a SpecAugment data augmentation technique was applied to the audio signal Park et al. (2019). The ASR system has been implemented by using the open source Speechbrain toolkit Ravanelli et al. (2021).

SLU model description. The SLU model is the `bert-base-uncased` version of the JointBERT Chen et al. (2019) model, pre-trained on BookCorpus (800M words) Zhu et al. (2015) and English Wikipedia ($2,500$M words). One linear layer is added on top of BERT and the IC weight in the cross-entropy loss is set to 0.01. The batch size is 128 and the transcripts are sorted by length and grouped into length buckets of size 10 in order to ensure that batches are not padded too much. The whole network (109M parameters) is fine-tuned on the transcripts and labels of the full train split of the Sonos Voice Control dataset. During training, each transcript has been augmented once by replacing slot values by randomly drawing from all possible values in the train split. We use the Adam optimizer with a learning rate of $5\mathrm{e}{-5}$; no dropout is applied. We train the model for 20 epochs and select the checkpoint achieving the smallest weighted cross-entropy loss on the dev set as final model.

5.2. Results

We compute the Exact Match Ratio (EMR, the fraction of exactly parsed audio samples) on the test split, using the fine-tuned E2E model for audio transcription and the fine-tuned SLU model to retrieve intents and slots. We find an EMR of 89% (76% for `PlayMusic` and 99% for `TransportControl`) and a WER of 2.5%. The variation of EMR per demographic group can be found in Figure 2. Some individual speakers (outlier points) are much less well understood than others in the same demographic group. This is consistent with the literature (Tatman and Kasten, 2017; Tatman, 2020; Feng et al., 2024). Consideration on speaker variability and more details on WER can be found in Appendix C.

Applying the method described in Section 4, we find statistically significant evidence of bias for all considered explanatory variables in the **univariate** setting at the 5% level. Regarding **gender**, men are significantly better recognized than women ($OR = 1.05$, $p = 0.017$). However, the OR is very close to 1 and we see in panel (c) of Figure 2 that the difference is slim.

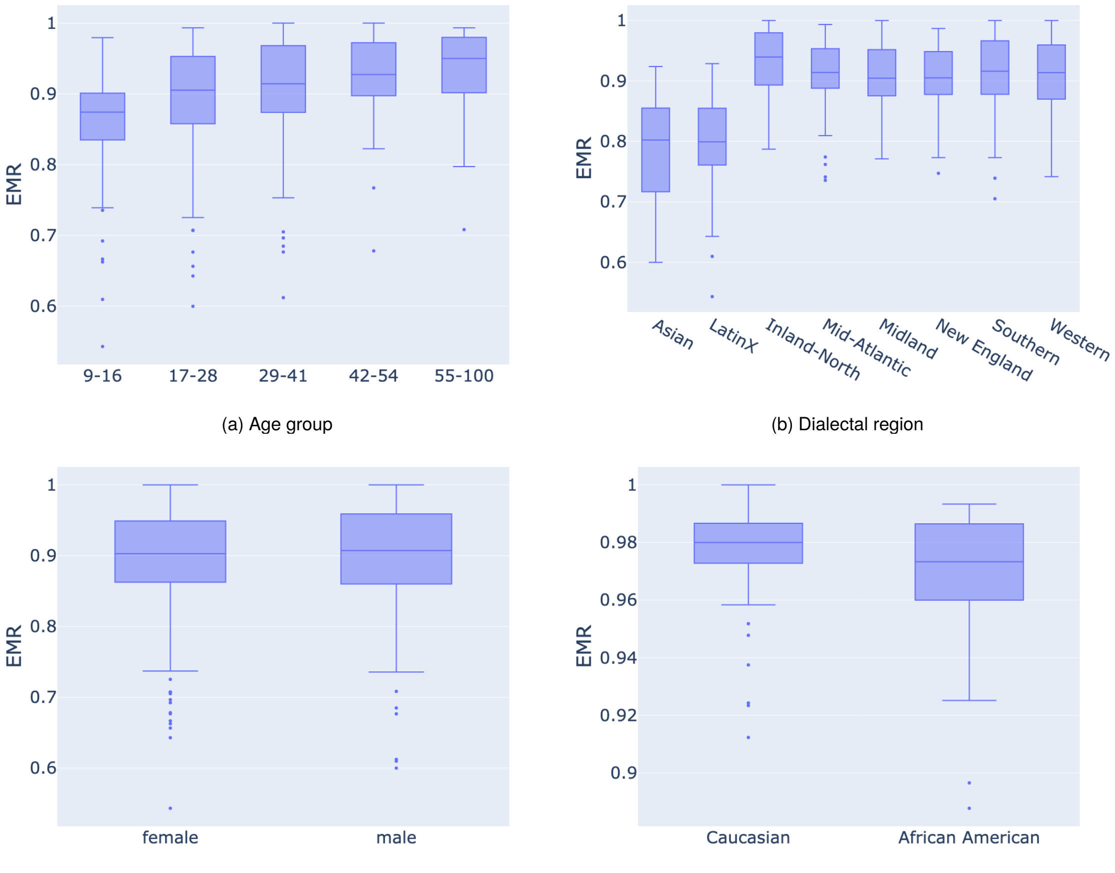
Tests on the **age** variable show that children are not recognized as well ($OR = 0.85$, $p = 4.145\mathrm{e}{-8}$ for the 9-16 group) as younger adults (17-28yo, reference group), while older groups are increasingly better recognized (ORs are 1.11, 1.48, and 1.70 for 29-41, 42-54, and 55-100 respectively, all p-values are $< 1\mathrm{e}{-4}$). Interestingly, we note that when isolating `Transport Control` requests only (simpler patterns, without music entities; see Section 3.1 for the exact definition), the disparities observed between children and younger adults are not statistically significant anymore ($p = 0.070$).

For **dialectal region**, every group is better recognized than the Asian reference group. However, while requests from all American regional groups have around 3 times more chance to be exactly parsed than Asians' (ORs are around 3, all p-values are $< 1\mathrm{e}{-89}$), this is only just slightly the case for the LatinX group ($OR = 1.15$). This is clearly visible in panel (b) of Figure 2. On the smaller **ethnicity** dataset, we found that Caucasian speakers are better understood than African Americans ($OR = 1.59$, $p = 5.5\mathrm{e}{-5}$). Additional univariate tests were performed; results can be found in Appendix C.1.

The **multivariate** analysis introduced in Section 4.2.2 is key to shine light on possible mixed effects. We detect several confusion variables. On one hand, **dialect is a confounding factor for gender**: the LLR test is statistically significant ($T = 1748 > q_{7,0.05} = 14.07$) and the coefficient associated to *male* is no longer significant ($p = 0.8 > 0.05$). The difference observed in the univariate case for gender was actually due to the dialectal region. This hypothesis is confirmed by the gender distribution of the Asian group found in Table 2 (and to a lesser extent of the LatinX group): it is more skewed towards female speakers, while being also less well recognized than the other groups.

On the other hand, combining dialectal region and age brings more significance to the model as in both cases (adjustments of dialectal region on age and of age on dialectal region), H_0 is rejected (respectively, $T = 193 > q_{4,0.05} = 9.49$ and $T = 1559 > q_{7,0.05} = 14.07$). The conclusions of the respective univariate tests are not changed (Wald p-values are still lower than 0.05). However a **cross-effect of age and dialectal region** is brought to light since the corresponding ORs decrease from the univariate to the multivariate case (for instance, from 3.12 to 2.91 for the Mid-Atlantic group). This means that some of the difference observed between dialectal regions is actually due to the age disparity (and vice versa). This effect can be seen in Figure 3. Interestingly, younger Asian and LatinX speakers are better understood while it is the opposite for American regional groups.

By restricting our multivariate analysis to the subset of observations for which we have the ethnicity label, we did not find evidence of any confusion bias between ethnicity and the 3 other de-



(a) Age group

(b) Dialectal region

(c) Gender

(d) Ethnicity

Figure 2: Exact Match Ratio (EMR) per speaker's demographic group. Points indicate individual speakers.

mographic groups. Appendix C.2 displays the exhaustive and systematic analysis of all multivariate tests.

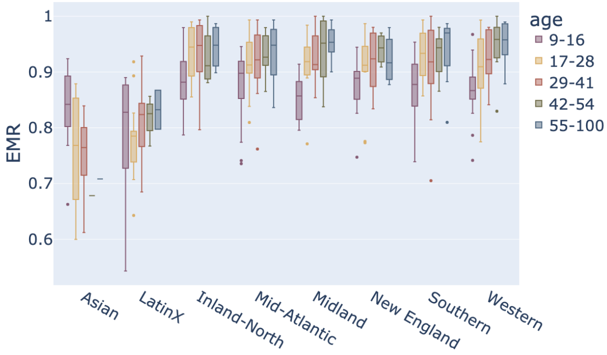


Figure 3: Interaction effect on the Exact Match Ratio (EMR) of age and dialectal region. By splitting across dialectal regions, the differences in EMR between age groups are getting wider compared to Figure 2(a).

6. Conclusion and Discussion

This paper introduces the Sonos Voice Control bias assessment dataset, an open corpus made of $170,737$ audio samples (166 hours) from $1,039$ different speakers with their transcripts, labels and demographic tags (age, gender, dialectal region and ethnicity). We also propose a statistical bias assessment methodology (open sourcing its implementation), at the univariate and multivariate levels, tailored to the specific context of voice assistants. We consider Spoken Language Understanding (SLU) metrics measuring the interpretability of a user's request, rather than the standard transcription accuracy, as we believe it is more representative of end-to-end user experience. After describing the dataset (Section 3) and the statistical methodology (Section 4), their capabilities are illustrated with state-of-the-art ASR and SLU models (Section 5). Results on this example show statistically significant disparities in terms of SLU metrics across age, dialectal region and ethnicity. Second-order considerations allow to unveil mixed effects between dialectal region, gender and age. We hope that releasing this dataset and statistical methodology will foster research on demographic bias for voice assistants.

We identify several limitations in this study. Descriptive analysis of the dataset shows that the empirical distribution of a demographic variable of interest is not the same for the different modalities of another demographic variable of interest (e.g. distribution of gender across dialectal regions; Table 2). These differences are statistically significant (unveiled by non-parametric independence tests; results are not presented here). Therefore there is a selection bias in our dataset leading to a confusion bias when analyzing data. It has to be taken into account for results' interpretation and motivates the need to perform multivariate analysis in addition to univariate tests (as seen with gender in Section 5.2).

A side effect of controlling the request distribution in the dataset, so that they are representative of a voice assistant in the music domain, is that the recorded samples are not spontaneous, but must follow an imposed transcript. This setting creates two main limitations in the dataset that might amplify bias against some demographic groups. First, evidence shows that the performance of ASR systems degrades in spontaneous speech conditions Nakamura et al. (2008) and this degradation may not be uniform across all groups. Second, imposing the transcript necessarily erases possible lexical and grammatical particularities of each population, which might also amplify bias.

However, recent research seems to suggest that observed disparities in speech recognition accuracy rather stem from the acoustic model rather than the language model Koenecke et al. (2020). Moreover, the music voice assistant use case is constrained to a small number of possible phrasings (think about how one can ask about a song, an artist or a volume set). This dampens the effects of variability in wording. Moreover, while reading is not a perfect simulation for speech that is directed at voice assistants, it allows for controlled collection and is the only feasible option for large-scale data collection such as ours.

We also want to emphasize that the demographic description of the speakers in the dataset has evidently strong limitations in terms of linguistic, social and geopolitical representation, and is only acceptable in terms of the linguistic approximations required for the use case at hand. In addition, any regional split over dialectal variation can be considered as arbitrary, since it generalises over partial demographic estimations and since dialectal variation can be viewed as a linguistic continuum rather than a set of contiguous spaces. We also only consider a binary view of gender while there are more fluid experiences. Other factors such as literacy, level of education, social, cultural and economical background DiChristofano et al. (2022); Chan et al. (2022) could be taken into account, as well as possible speech impairments (e.g. dysarthria in Tu et al. (2016); Moro-Velazquez et al. (2019) or cleft lip and palate Schuster et al. (2006)).

Moreover, modeling explicitly the speaker effect in the statistical analysis is possible (as a random effect for instance as in Liu et al. (2021)) but would increase the complexity of our approach without bringing massive improvements. We argue that the main goal of this paper is to propose a simple yet effective statistical methodology to assess the demographic bias of any given SLU system and provide clear interpretation of the results.

Future work includes considering narrower age ranges to study the effects of younger children without reading capabilities, or elderly adults whose speech patterns may deviate significantly from standard speech. On another topic, it will be extremely interesting to generate far-field and noisy versions of the dataset by simulating realistic acoustic conditions (through room impulse response and reverberation simulation for instance): the performance of ASR systems is indeed particularly degraded in these conditions, while they are typical of domestic voice assistant usage.

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A. Appendix A: Sonos Voice Control Bias Assessment Dataset, additional descriptive statistics

A.1. Dialectal regions definition

Dialectal regions in America are defined based on phonemic/phonetic, lexical, and syntactic features. Speakers from a certain region may use certain vocabulary or lexical items that are specific to their region (for example ‘gym shoes’ or ‘sneaker’ all refer to the same athletic footwear but will be heard with varying frequency depending on the geographic location). In the case of voice assistants, particularly within the music domain, lexical differences and regionalisms do not pose many issues given the short and straightforward nature of interactions. In a similar way, syntactic features (such as the use of ’done’ as an auxiliary verb in Southern English to express the past tense: I done had enough) do not pose many issues to speech recognition within voice assistant domains.

Regional varieties are also reflected in specific phonetic phenomena, such as non-rhoticity (dropping of the /r/ consonant in all environments except before a vowel, sometimes heard in Boston or New York), PIN-PEN merger (the two vowel sounds /I/ and /E/ merge before nasal sounds to sound the same, found in standard Southern American dialect), or COT-CAUGHT merger (/ɑ/ and /ɔ/ vowels to sound alike, heard in most of the country). Vowel quality and, more generally, phenomena related to the sound system of English pose more issues to voice recognition, especially in the music domain. Depending on how speakers pronounce music values and general queries, recognition may vary.

Identifying dialectal regions for any area or language is always imprecise. While what is defined in our data is one way of interpreting American English, there are of course many different ways of dividing regionality and the features that exist within these groups. Within any dialectal region, the prominence of the specific features of that dialect will vary greatly. While some may be inclined to further divide into even more specific groups, having data that represents multiple ages, genders and demographics within each dialectal region was also of importance.

The definition of dialectal region was also impacted by the necessity for adequate representation from each category, while also adhering to other constraints such as time and budget. Creating more dialectal groups would potentially impede the velocity of data collection or skew sample sizes.

Selecting these dialectal regions also facilitated easy identification of a user within a group. Without being able to listen to or speak with individuals to ‘verify’ their dialectal region selection, having no more than six dialectal groups facilitated data collection with straight-forward parameters based on geographic location.

The **Asian and LatinX** categories were defined by identifying other large speaker groups in the US that may interact with voice assistants. These two user groups were defined as follows: home country must be in Latin America for LatinX, in Southern or Eastern Asia for Asian native language must be Spanish for LatinX, any Asian language for Asian The definition of the LatinX group is different from the definition one may use for Chicano English (also known as Mexican-American English or Spanish English). Chicano English is primarily spoken by Mexican Americans in south-western states whose first language is English. We were interested in a larger pool than only Mexican American speakers. The speakers in our LatinX group are native Spanish speakers from any Latin American country. However, many of the features in Chicano English are also exhibited in the LatinX participant’s speech. For example, /ð/ stopping, or the replacing of the -th- sound with /d/ in words like ‘there’ (‘dere’) was still prevalent. The distinction between /ɪ/ and /i/ in some speakers is lost, making words like ‘fit’ and ‘feet’ sound alike.

General monophthongization, which may be directly due to the quality of vowels in Spanish, is another quality of Chicano English that was seen in the LatinX group. The motivation behind criteria based on language and country was again largely due to time constraints, as it can be difficult to find enough speakers when more constraints are applied to dialectal definitions. It also facilitated the identification of speakers - being able to identify based on home country and native language is easier for participants than asking if they think they speak a certain dialect of a language. The Asian group included Southern and Eastern Asian countries, in order to account for large populations of both regions in the US. While the Asian group has much more linguistic diversity within the speakers themselves, no further division was implemented based on budgeting and time constraints. Looking back, if we were to reproduce this approach, Indian English should probably have been separated from the other Asian groups.

A.2. Ontology description

Among all splits, there are $9,040$ unique transcripts, $8,114$ for `PlayMusic` and 926 for `Transport Control`. Table 3 provide the number of unique slot values for each *slot name*, e.g. there are 221 different radio names.

Slot name	# of unique values
abs_volume	13
activity	8
album_name	1626
artist_name	1715
call_sign	404
container_qualif_after_artist	7
container_qualif_before_artist	9
container_type	5
content_type	16
destination_group	1
destination_target	21
except	2
frequency	230
genre	272
implicit_content	1
instead	2
library	22
location	66
mood	2
only	1
origin_target	12
personal_container_name	58
playback_mode	8
playlist	599
program	86
provider	12
radio_name	221
rel_volume	10
shuffle	1
song_name	2643
target	298
target_exception	32
too	3
volume_down_subj	8
volume_obj	111
volume_set_subj	28
volume_shift_subj	9
volume_up_subj	6

Table 3: Number of unique slot values per slot name in the proposed dataset.

Table 4: List of available slot names per intent in the proposed dataset.

Intent	Corresponding slot names
AddToLibrary	• personal_container_name • provider • library • content_type • target
ChangeMusic	• provider • content_type • target
ChangeTarget	• instead • container_type • origin_target • destination_target
CheckBattery	• target
FollowArtist	• provider
Forward	• provider • target
GetInfos	• provider • content_type • target
GroupTargets	• only • target_exception • too • except • destination_group • target
Like	• provider • content_type • target
Mute	• container_type • only • target_exception • too • provider • except • target

Intent	Corresponding slot names
NextSong	• provider • container_type • target
Pause	• provider • container_type • target
Play	• container_type • only • volume_obj • target_exception • too • volume_down_subj • provider • except • volume_set_subj • instead • target
PlayMusic	• container_type • only • container_qualif_after_artist • genre • target_exception • radio_name • activity • call_sign • program • artist_name • frequency • container_qualif_before_artist • except • implicit_content • shuffle • song_name • album_name • target • playlist • playback_mode • mood • too • location • volume_obj • provider • volume_set_subj • library • instead

Intent	Corresponding slot names
PreviousSong	• provider • target
RemoveFromLibrary	• personal_container_name • provider • library • content_type • target
Repeat	• provider • content_type • target
RestartSong	• provider • container_type • target
Resume	• provider • container_type • target
Rewind	• provider • target
Shuffle	• provider • target
Stop	• container_type • only • target_exception • too • provider • except • target
StopAndStartTarget	• instead • container_type • origin_target • destination_target
StopMode	• playback_mode • provider • target
UnfollowArtist	• provider
UngroupTargets	• only • target_exception • too • except • target
Unlike	• provider • content_type • target
Unmute	• container_type • only • target_exception • too • provider • except • target

Intent	Corresponding slot names
VolumeDown	• container_type • only • abs_volume • target_exception • too • volume_shift_subj • rel_volume • volume_down_subj • provider • except • volume_set_subj • target
VolumeSet	• container_type • only • volume_obj • target_exception • too • except • volume_set_subj • target
VolumeUp	• container_type • only • abs_volume • volume_up_subj • target_exception • too • volume_shift_subj •rel_volume • provider • except • volume_set_subj • target

Table 4 provides the complete list of available slot names of each intent available in the SVC Bias Assessment Dataset.

A.3. Additional descriptive statistics per split

In this subsection of the appendix, we provide additional figures showing the distribution, in terms of both samples and speakers in each of the provided split in the Sonos Voice Control Bias Assessment Dataset.

A.3.1. Test split

Fig. 4 displays the speaker distribution in the test split for each demographic group.

A.3.2. Train split

Fig. 5 displays the audio sample distribution in the train split for each demographic group.

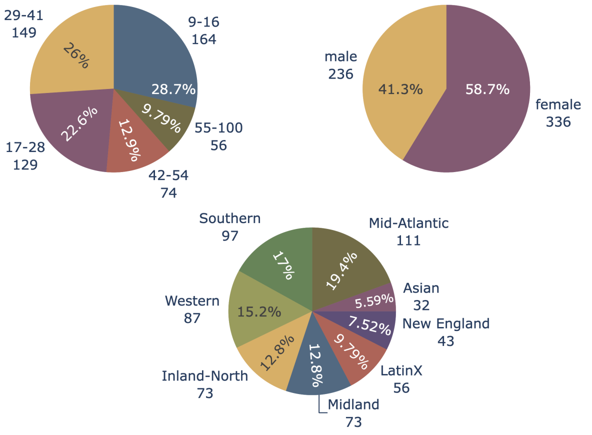


Figure 4: Speaker distribution in the test split of the dataset in terms of age, gender, and dialectal region. The number of speakers in each group is displayed under the group label.

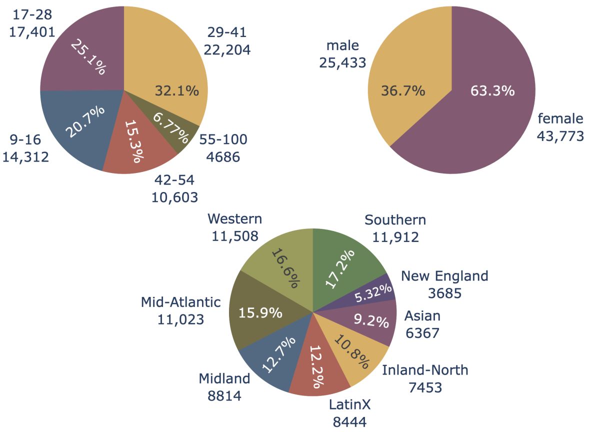


Figure 5: Audio sample distribution in the train split of the dataset in terms of age, gender, and dialectal region. The number of samples in each group is displayed under the group label.

Fig. 6 displays the speaker distribution in the test split for each demographic group.

A.3.3. Development split

Fig. 7 displays the audio sample distribution in the development split for each demographic group.

Fig. 8 displays the speaker distribution in the development split for each demographic group.

There is no non-native speaker (Asian or LatinX). This is primarily due to the small size of this set comprising only 38 speakers.

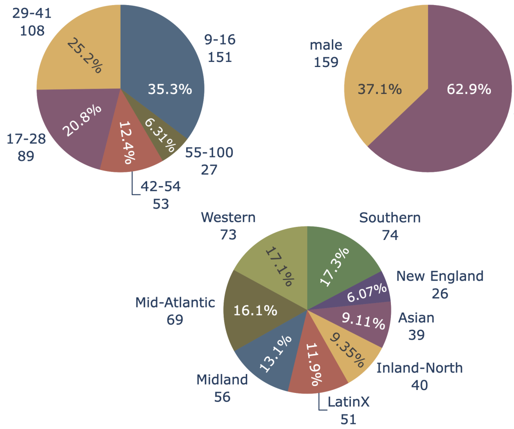


Figure 6: Speaker distribution in the train split of the dataset in terms of age, gender, and dialectal region. The number of samples in each group is displayed under the group label.

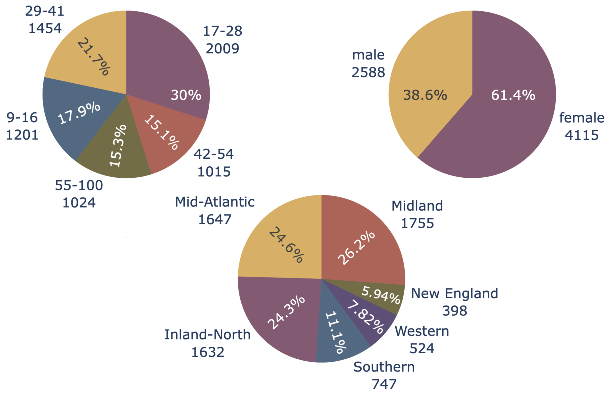


Figure 7: Audio sample distribution in the development split of the dataset in terms of age, gender, and dialectal region. The number of samples in each group is displayed under the group label.

A.4. Ethnicity dataset

Race and ethnicity are inherently difficult to define, as these words can mean different things to different people. There are also constraints on what can be asked or assumed of participants when working with third party providers. For these reasons, users were asked to self-identify and we operated under the assumption that a person of any racial or ethnic group would know their own identification better than us enforcing any strict parameters. It should also be noted that dialects such as African American Vernacular English (AAVE) are social dialects and are therefore not tied to geographical location. While not all members of an ethnic group, such as African American/Black, will exhibit features of the associated dialect, for example AAVE, this approach was agreed upon with the third party provider in charge of hiring speakers.

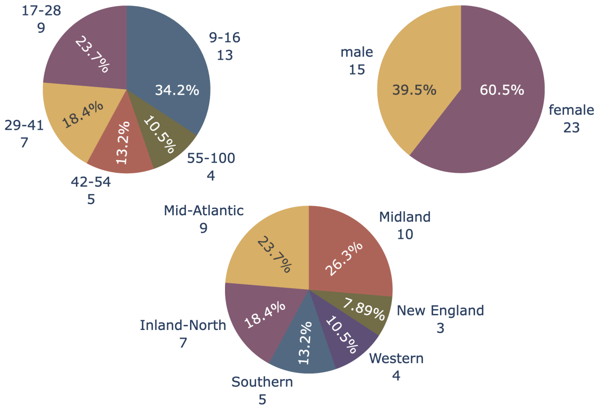


Figure 8: Speaker distribution in the development split of the dataset in terms of age, gender, and dialectal region. The number of samples in each group is displayed under the group label.

The **ethnicity** tag was only reported in the second campaign that we launched for which 98 speakers have been recruited: 50 Caucasian and 48 African American speakers. We refer to this smaller dataset, only present in the test split, as the `ethnicity dataset`.

Fig. 9 displays the audio samples distribution in the ethnicity subset for each demographic group.

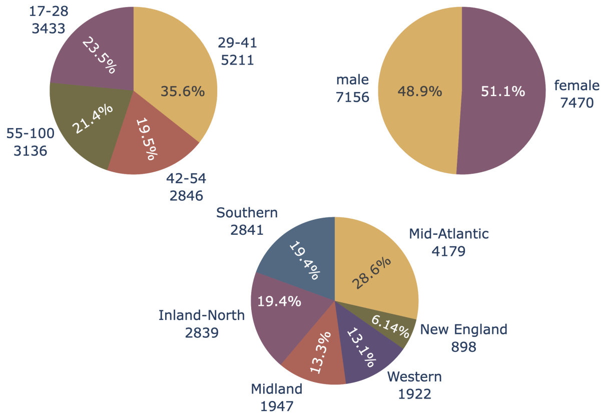


Figure 9: Audio sample distribution in ethnicity dataset in terms of age, dialectal region and gender.

Fig. 10 displays the speaker distribution in the ethnicity subset for each demographic group.

There is no children in this dataset as their recruitment proved difficult. The distribution among the dialectal regions is similar as the one of the original test split. It is also balanced in terms of gender (49% of male and 51% of female speakers).

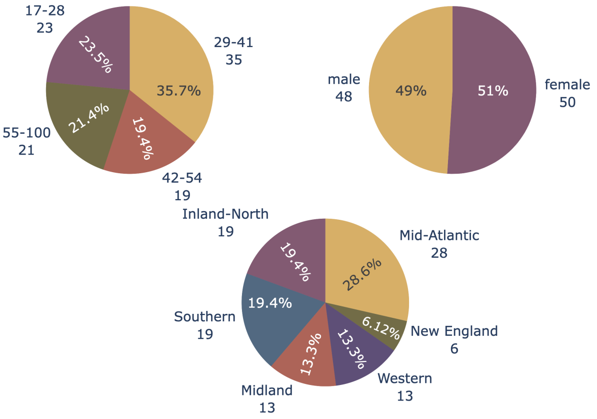


Figure 10: Speaker distribution in ethnicity dataset in terms of age, dialectal region and gender.

B. Appendix B: Confusion bias

In this section of the Appendix, we provide the complete confusion bias analysis.

B.1. Age

Similarly as in Table 2, Table 5 provides the gender and dialectal region distribution for each age group in the test split. In bold, we highlight the categories for which there are less than 10% of data points.

Age group	Samples	Speakers	Gender distribution	Dialectal region distribution
9-16	15788	164	Female: 62% Male: 38%	Asian: 7% **Inland-North:** 8% LatinX: 10% Mid-Atlantic: 20% Midland: 13% **New England:** 9% Southern: 16% Western: 17%
17-28	25414	129	Female: 56% Male: 44%	**Asian:** 7% Inland-North: 12% LatinX: 13% Mid-Atlantic: 17% Midland: 13% New England: 9% Southern: 14% Western: 15%
29-41	28920	149	Female: 60% Male: 40%	**Asian:** 6% Inland-North: 15% LatinX: 12% Mid-Atlantic: 17% Midland: 14% **New England:** 7% Southern: 18% Western: 12%
42-54	14528	74	Female: 60% Male: 40%	**Asian:** 2% Inland-North: 15% **LatinX:** 5% Mid-Atlantic: 25% Midland: 14% **New England:** 4% Southern: 16% Western: 19%
55-100	9854	56	Female: 61% Male: 39%	**Asian:** 1% Inland-North: 18% **LatinX:** 3% Mid-Atlantic: 28% Midland: 14% **New England:** 6% Southern: 18% Western: 12%

Table 5: Statistical distribution of audio samples for each age group in terms of gender and dialectal region in the test split.

B.2. Gender

The following Table 6 provides the age and dialectal region distribution for each gender in the test split. In bold, we highlight the categories for which there are less than 10% of data points.

Gender	Samples	Speakers	Age distribution	Dialectal region distribution
Female	55988	336	$9-16:17\%$ $17-28:25\%$ $29-41:31\%$ $42-54:15\%$ $55-100:11\%$	**Asian:** 6% Inland-North: 12% LatinX: 11% Mid-Atlantic: 19% Midland: 14% **New England:** 8% Southern: 15% Western: 15%
Male	38516	236	$9-16:16\%$ $17-28:29\%$ $29-41:30\%$ $42-54:15\%$ $55-100:10\%$	**Asian:** 5% Inland-North: 15% **LatinX:** 8% Mid-Atlantic: 21% Midland: 12% **New England:** 6% Southern: 18% Western: 14%

Table 6: Statistical distribution of audio samples for each gender in terms of age and dialectal region in the test split.

B.3. Ethnicity

Table 7 provides the age, gender and dialectal region distribution for each ethnicity group in the test split.

Ethnicity	African American	Caucasian
Samples	7443	7183
Speakers	50	48
Age distrib.	$17-28:32\%$ $29-41:42\%$ $42-54:14\%$ $55-100:12\%$	$17-28:15\%$ $29-41:29\%$ $42-54:25\%$ $55-100:31\%$
Gender distrib.	Female: 54% Male: 46%	Female: 48% Male: 52%
Dialectal region distrib.	Inland-North: 20% Mid-Atlantic: 42% Midland: 10% Southern: 18% Western: 10%	Inland-North: 19% Mid-Atlantic: 15% Midland: 17% New England: 12% Southern: 20% Western: 17%

Table 7: Statistical distribution of audio samples for each ethnicity tag in terms of age, gender and dialectal region in the test split.

C. Appendix C: Experiments – Exhaustive statistical analysis

We display here additional results obtained with the off-the-shelf ASR model wav2vec2.0 and JointBERT SLU model, demonstrating the capabilities of our proposed dataset and methodology to quantify demographic bias in voice assistants. Consequently, we remind the reader that the ASR and SLU models have not been particularly optimized for bias mitigation.

C.1. Univariate tests

While results of all univariate logistic regressions were given in Section 5.2, we also performed additional, but not mandatory, univariate tests that can be seen as complementary to the logistic regression.

C.1.1. Logistic regression on the ethnicity subset

The 98 speakers for which we have an ethnicity tag recorded $14,626$ audio samples forming the ethnicity subset of the released dataset.

Performing univariate logistic regression for variable on this subset revealed interesting results.

No evidence of demographic bias based on **age** and **gender** was found. However, the univariate logistic regression for **dialectal region** is statistically significant at the 5%-level. Looking deeper in the statistical results, we see that the p-value is close to the threshold (0.0049) and only the coefficient of `Mid-Atlantic` has a p-value below this threshold (0.003). For all the other dialects, there is no evidence of statistical bias with respect to the reference category (Inland-North). Looking at the odds-ratio, speakers belonging to the Mid-Atlantic group have 0.6 times less chance to be recognized than speakers from the Inland-North group.

C.1.2. Chi2 contingency test

The **chi-squared** test (Pearson (1900)) is a statistical hypothesis test used to test for the independence of several categories within a given population. However, unlike the univariate logistic regression, one cannot infer the direction of the bias since there are no coefficient or odd ratios associated to this test.

Applied on the released test split, the **chi-squared** tests confirm what the univariate logistic regressions uncovered. All tests are statistically significant at the 5%-level: **gender** (p-value $= 0.01$), **age** (p-value $= 3\text{e}{-80}$), **dialect** (p-value $\simeq 0$), **ethnicity** (p-value $= 4\text{e}{-5}$).

C.1.3. One-way ANOVA test

Another complementary univariate test is the One-way ANOVA test (notably used in Meyer et al. (2020) on the Character Error Rate). This test is also known as the ”analysis of variance”. It compares the means of at least 2 independent groups to assess whether there is statistical evidence that the associated population means are significantly different.

With this test, we only found significant evidence of bias for **age** (p-value $= 1.36\text{e}{-15}$) and **dialectal region** (p-value $= 3.41\text{e}{-44}$).

C.2. Multivariate tests

Regarding potential mixed effects, we highlighted the ones found in Section 5.2. Here we provide the exhaustive and systematic analysis of all multivariate tests.

First, gender is not a confounding factor for age: the test is statistically significant ($T = 6 > q_{1,0.05} = 3.84$) but the p-values of the multivariate and the univariate tests are very close, therefore we cannot conclude that gender is a confounding factor for age. The conclusion is similar for age on gender: the test is statistically significant at the 5%-level ($T = 388 > q_{4,0.05} = 9.49$) but the p-values and odds-ratios are very close, therefore there is no confounding factor.

Similarly, there is no evidence that age is a confounding factor for dialectal region as even if the test is statistically significant ($T = 1559 > q_{7,0.05} = 14.07$), the p-values and odds-ratios are close, maintaining the conclusions of the univariate test unchanged. We reach the same conclusion for dialectal region with the age variable ($T = 193 > q_{4,0.05} = 9.49$).

Gender is not a confounding factor for dialectal region since the test is not significant ($T = 0.05 < q_{1,0.05} = 3.84$). The test is however significant the other way around ($T = 1748 > q_{7,0.05} = 14.07$) and the coefficient for male is no longer significant at the 5%-level. We conclude that dialectal region is a confounding factor for gender.

Each of the previous analysis are done on the smaller ethnicity dataset in order to evaluate potential mixed effects linked with ethnicity.

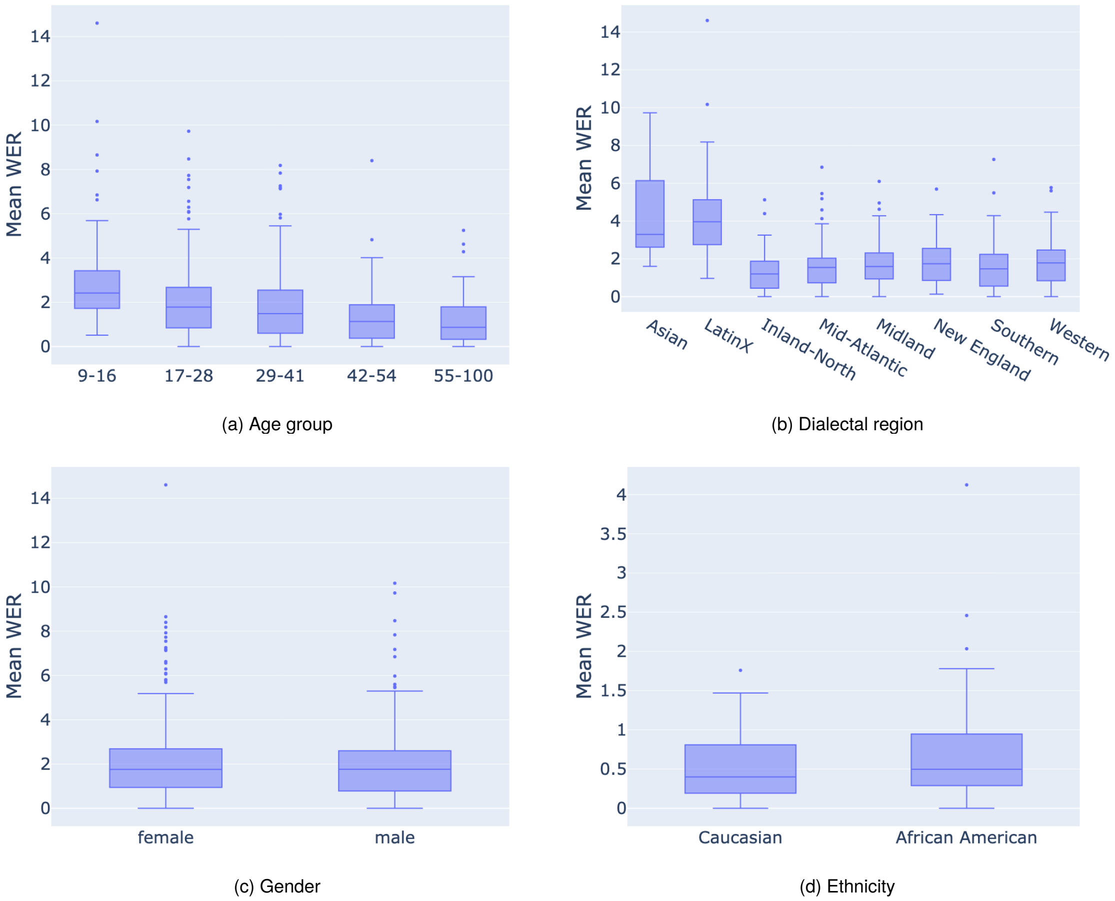
First, age is not a confounding factor for ethnicity as the test is not significant ($T = 1.7 < q_{3,0.05} = 7.81$). The adjustment test of ethnicity on age is significant ($T = 14 > q_{1,0.05} = 3.84$) but there is no change on the conclusions about age (still no significant age coefficients).

Similarly as above, gender is not a confounding factor for ethnicity ($T = 0.14 < q_{1,0.05} = 3.81$). Even the adjustment test is significant the other way around ($T = 16.8 > q_{1,0.05} = 3.84$), conclusions for gender are unchanged (still not significant). Therefore ethnicity is not a confounding factor for gender.

Again, the conclusion is similar for dialectal region and ethnicity. The dialect is not a confounding factor for ethnicity ($T = 11 < q_{5,0.05} = 11.07$). And ethnicity is not a confounding factor for the dialect ($T = 11 > q_{1,0.05} = 3.84$ but the conclusions of the univariate test remain unchanged).

C.3. Word Error Rate

We obtained a WER of 2.5% with the fine-tuned w2v (Baevski et al., 2020). Fig. 11 displays the variation of WER per demographic group.



(a) Age group

(b) Dialectal region

(c) Gender

(d) Ethnicity

Figure 11: Word Error Rate (WER) per speaker's demographic group. Points indicate individual speakers.

Similarly as in Fig. 2, there are some cases of high standard deviation.

C.4. Speaker variability

Fig. 2 in the main text, as well as Fig. 11 in the previous section, showcase high standard deviations in EMR and WER per speaker. Some individual speakers (outlier points) are much less well understood than others in the same demographic group. This is consistent with the literature (for instance Tatman and Kasten (2017); Tatman (2020) also observe much larger WERs for some individuals). Feng et al. (2024) note that the recognition performance is affected by the large variability both in the pronunciation and in language use within a given speaker group.

Though it is not always possible to identify the cause just by listening to the corresponding audio clips, some speakers may have slight disfluencies or hesitations when recording. Hesitation is difficult to perfect in the world of speech recognition, as other constraints such as endpointing rules may come into play and end recognition before the user is finished speaking. Other speakers that simply utter at a slower pace may also be less consistently understood.

Lisps and other speech impediments are a third example. Most speakers in the dataset do not have any speech impediments, but it should be noted that this can greatly affect the quality of transcription. Most training data does not comprise atypical speech and therefore it is expected that these cases would be less consistently understood.