Emo-bias: A Large Scale Evaluation of Social Bias on Speech Emotion Recognition

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Abstract

The rapid growth of Speech Emotion Recognition (SER) has diverse global applications, from improving human-computer interactions to aiding mental health diagnostics. However, SER models might contain social bias toward gender, leading to unfair outcomes. This study analyzes gender bias in SER models trained with Self-Supervised Learning (SSL) at scale, exploring factors influencing it. SSL-based SER models are chosen for their cutting-edge performance. Our research pioneering research research gender bias in SER from both upstream model and data perspectives. Our findings reveal that females exhibit slightly higher overall SER performance than males. Modified CPC and XLS-R, two well-known SSL models, notably exhibit significant bias. Moreover, models trained with Mandarin datasets display a pronounced bias toward valence. Lastly, we find that gender-wise emotion distribution differences in training data significantly affect gender bias, while upstream model representation has a limited impact.

Index Terms: social bias, self-supervised learning, emotion recognition

1. Introduction

Speech emotion recognition (SER) aims to detect and interpret emotional states conveyed through speech signals. However, SER models may capture and learn social bias, leading to potential social harm. Biased SER systems may exacerbate existing inequalities by disproportionately affecting marginalized communities. For example, if a system is less accurate in recognizing emotions in individuals with disabilities, non-native speakers, or a specific gender, it could further marginalize these groups by denying them equitable access to services or opportunities.

While extensive research has addressed bias in various machine learning domains, such as Automatic Speech Recognition (ASR) [1, 2, 3], Speech Translation [4, 5], Facial Emotion Recognition [6], and Automatic Speaker Verification (ASV) [7], limited attention has been paid to social bias within SER systems. For instance, Gorrostieta et al. [8] evaluated gender bias within a specific model and dataset, proposing two adversarial debiasing approaches. However, their analysis was confined to a singular model and only one dataset, potentially limiting its applicability to broader contexts. Similarly, Chien et al. [9] investigated gender-specific emotion perception using the IEMOCAP dataset [10], presenting a perceptual emotion learning framework. Yet, they overlooked the impact of training dataset selection on emotional bias. This underscores the need for comprehensive investigations into gender bias across diverse SER models and datasets to ensure robust and generalizable results.

Recognizing such research gaps, our study delves into two inquiries: Firstly, do contemporary SER models exhibit gender bias? Secondly, what are the primary factors contributing to such bias? Specifically, we investigate whether upstream representations and downstream training data play a crucial role in shaping bias within these models.

Leveraging the cutting-edge advancements in speech self-supervised learning (SSL) [11, 12], we employ 15 SSL models and classical speech features like FBank to train SER systems. Through rigorous and comprehensive experimentation across six diverse emotion datasets, we carefully train and assess a total of 96 SER models.

Our work yields the following contributions:

- We conduct a large-scale evaluation of 15 SER models on six emotion datasets. Notably, females exhibit slightly superior overall emotion recognition performance to males, with a substantial gender-wise performance gap evident across individual emotions. Our analysis highlights two models, Modified CPC [13] and XLS-R [14], as exhibiting the highest bias in gender-wise SER F_1-score differences.

- We found that downstream training data distribution significantly affects gender bias for models trained with acted datasets while having a medium correlation with SER performance bias for real-world datasets.

- We analyze the gender-wise F_1-score difference on valence. We observe that "females have higher F_1-score on positive valence while males have higher F_1-score on negative valence" is apparent in models trained with Chinese datasets.

- We analyze the correlation between *gender-wise upstream representation bias* and *SER performance gap between two genders*. We find that SSL upstream representations barely influence the bias in SER performance.

2. Evaluation design

2.1. SSL model and downstream model

We chose SSL-based SER systems to evaluate gender bias, as these SOTA models are commonly preferred for emotion evaluation [15, 16], potentially amplifying the impact of any bias present. In the framework of speech SSL, model training consists of two stages. The first stage pre-trains a model (or upstream model) using self-supervised learning with a predefined pretext objective. The second stage uses representation from the upstream model to train a downstream task such as SER.

We use the SSL-based SER models in [17], which uses publicly available speech SSL models collected by the S3PRL toolkit [18]. The upstream models include models trained with generative approach: DeCoAR 2 [19], Autoregressive Predictive Coding (APC) [20], Vector-Quantized APC (VQ-APC)

Table 1: *Overview of mapping between valence and emotion. Surprise can have a positive or negative valence.*

Valence	Emotion
positive	Happiness, Excitement, Relax, Joy
negative	Anger, Disgust, Contempt, Frustration, Disappointment, Sadness, Fear
both	Surprise

[21], Nonautoregressive Predictive Coding (NPC) [22], TERA [23], Mockingjay (Mock) [24]; models trained with contrastive approach: Wav2Vec2-XLS-R-1B (XLS-R) [14], Wav2Vec 2.0 (W2V2) [25], Wav2Vec2 Large Robust (W2V2 R) [26], vq-wav2vec (VQ-W2V) [27], wav2vec (W2V) [28], and Contrastive Predictive Coding (M CPC) [13]; models trained with predictive approach: HuBERT [29], WavLM [30], Data2Vec (D2V) [31].

We use the same downstream model architecture as the SER task in the S3PRL toolkit [18], using three Conv1d, a self-attention pooling, and two linear layers. To capture the high-dimensional nature of emotion [32], we formulate emotion recognition as a multilabel classification problem. We first transform the emotion annotations to emotion distribution by frequency and then apply label smoothing by [33] using a smoothing parameter of 0.05 to obtain a soft label. We use the F_1 score as the evaluation metric for performance, which aligns with SER challenges[34] and benchmarks [17]. A label prediction is successful if the output emotion probability distribution is higher than $\frac{1}{n}$ for n emotion classification task. Our models are trained on Nvidia Tesla V100 GPUs with 32 GB of memory. The cumulative GPU runtime amounts to approximately 3,300 hours.

2.2. Bias evaluation

In our study, we employ three evaluation metrics to assess gender bias. We hope our evaluation plan can serve as a valuable reference for others.

2.2.1. F_1 score difference

We quantify the gender bias d_{e_i} on each emotion e_i by the difference of F_1 score on gender because F_1 score reflects both precision and recall. Furthermore, we define the corpus-level gender bias d_c by averaging the absolute value of d_{e_i} for all emotions e_i in the set of all emotion E in the corpus:

$$d_{e_i} = F_{1,e_i female} - F_{1,e_i male} \quad (1)$$
$$d_c = mean_{e_i \in E}|d_{e_i}|. \quad (2)$$

We further evaluate the gender bias on valence by Eq. 3.[1] The intuition is calculating the difference of d_{e_i} from positive valence and negative valence:

$$d_v = \Sigma_{e_i \in E_+} d_{e_i} - \Sigma_{e_i \in E_-} d_{e_i}$$
$$+ \Sigma_{e_i \in E_b}(p_+ d_{e_i,+} - p_- d_{e_i,-}). \quad (3)$$

E_+, E_-, and E_b are the set of emotions in the corpus that belong to positive valence, negative valence, and both valence, respectively. p_+ and p_- are the portions of speech belonging to positive and negative valence. $d_{e_i,+}$ and $d_{e_i,-}$ are the d_{e_i} of positive and negative valence speech, respectively. The detail of valence categorization is shown in Table 1, following the study [35].

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[1]We don't use absolute value on d_v as d_c, because we mean to compare it with upstream bias in section 2.2.2

2.2.2. Upstream representation bias on valence

We would like to know whether gender bias in the upstream model embedding propagates to downstream applications. To evaluate how the upstream model's embedding of stimuli representing females and males relates to its embedding of stimuli representing positive and negative valence, we use the Speech Embedding Association Test (SpEAT) [36] for detecting bias. SpEAT measures the relative cosine similarity between 4 groups of stimuli. Let X and Y represent sets of embeddings from female and male, and let A and B be sets of embeddings for positive and negative valence, respectively. SpEAT effect size d is the difference between sums over the respective target concept, normalized by the standard deviation to compute the magnitude of association:

$$d_s = \frac{\Sigma_{x \in X} s(x, A, B) - \Sigma_{y \in Y} s(y, A, B)}{std\_dev_{w \in X \cup Y} s(w, A, B)}, \quad (4)$$

where each term is the difference between the mean of cosine similarity of gender to each valence:

$$s(w, A, B) = mean_{a \in A} cos(w, a) - mean_{b \in B} cos(w, b). \quad (5)$$

In SpEAT, the embedding of speech segments is first done by averaging embedding in each layer and then averaging the aggregated embeddings across all layers, which we call the **Mean** aggregation. We further incorporate representation weights from SER models to achieve compatibility and comparability with the SSL paradigm. Assume SSL SER models with n layers are trained to use c_i as the weight for the input representation weighted sum of ith layer. We use c_i to weighted sum embeddings across layers, which is called **Weighted** aggregation. This enhances the similarity of our representations to those generated by ER models trained via SSL. We average c_i from SER models trained in different folds for cross-fold validation datasets defined in [17].

2.2.3. Training data bias on emotion distribution

We evaluate the bias in downstream training data distribution $\mathbf{d_d}$ by examining the difference in mean emotion distribution in training data (soft-label) for males and females. Take an emotion dataset with 4 emotions (neutral (N), anger (A), sadness (S), and happiness (H)) for example. We compute average training data distribution, $(N, A, S, H) = (0.2, 0.3, 0.4, 0.1)$ for females and $(N, A, S, H) = (0.1, 0.2, 0.4, 0.3)$ for males. Their training data bias is then $\mathbf{d_d} = (0.1, 0.1, 0.0, -0.2)$. For datasets with cross-fold validation, we compute the emotion distribution difference of the whole dataset.

2.3. Datasets

To make our evaluation comprehensive, we evaluate SER performance parity using six emotion datasets with diverse languages, speaker sources, and emotion types. The datasets include real-world datasets MSP-PODCAST (POD) [37], BIIC-PODCAST (BPO) [38], and actor performance datasets MSP-IMPROV (IMP) [39], IEMOCAP (IEM) [10], BIIC-NNIME (NNI) [40], CREMA-D (CRE) [41]. BIIC-NNIME and BIIC-Podcast are in Mandarin, and other datasets are in English.

We follow SpEAT, using the Morgan Emotional Speech Set (MESS) [42] for valence stimuli in upstream bias evaluation. We use the emotion datasets with both valence and speaker ID annotation in SER training (NNI, IMP, POD) as more valence

Table 2: *SER bias on emotion d_e across 6 emotion datasets and 9 models, in %. The emotions are abbreviated as follows. Angry: Ang, Disgusting: Disg, Contempt: Cont, Neutral: Neu, Surprise: Sur, Hap: Happy, Frustrated: Fru, Excited: Exc, Disappointed: Disa, Relax: Rel. **Mac** represents the macro-F_1 score over all emotions*

Model	BIIC-PODCAST									CREMA-D							IEMOCAP									
	Ang	Sad	Disg	Cont	Fear	Neu	Sur	Hap	**Mac**	Ang	Sad	Disg	Fear	Neu	Hap	**Mac**	Fru	Ang	Sad	Disg	Exc	Fear	Neu	Sur	Hap	**Mac**
XLS-R	6.3	12.0	0.0	-5.3	-0.9	-24.7	2.3	27.4	2.1	2.2	11.7	-2.8	2.9	-2.6	12.6	4.0	-0.4	7.2	2.2	-1.7	1.8	8.1	-2.5	6.5	7.7	3.2
WavLM	1.8	12.1	0.0	0.7	5.1	-24.1	7.7	28.0	2.9	3.7	11.0	1.3	3.3	-2.6	8.7	4.2	-0.6	6.7	0.7	0.0	2.5	8.9	-2.7	3.0	10.0	3.2
W2V2 R	6.6	7.7	0.0	-5.9	0.0	-25.2	6.7	28.9	2.3	3.1	11.8	-3.0	3.0	-2.6	13.4	4.3	0.4	6.3	2.0	-0.6	1.5	3.1	-3.5	3.8	7.9	2.3
W2V2	-3.3	9.5	0.0	-7.8	1.9	-27.6	8.3	28.8	1.2	1.2	6.4	0.1	4.6	-2.7	5.7	2.6	-1.2	5.3	2.0	0.0	0.5	1.0	-7.0	0.0	7.5	0.9
VQ-APC	-1.2	5.0	0.0	-6.3	0.0	-24.7	4.0	29.7	0.9	-1.9	6.9	-5.2	0.7	-3.1	10.7	1.3	-0.2	3.3	2.5	0.0	1.9	9.7	-4.0	-1.1	8.0	2.2
HuBERT	3.8	13.4	0.0	-6.3	2.7	-26.1	4.4	29.3	2.6	2.0	8.0	-1.5	1.9	-2.3	7.9	2.7	-0.3	6.4	2.5	-7.6	-2.0	2.7	-3.0	3.9	7.5	1.1
DeCoAR 2	3.9	2.4	0.0	-8.5	0.0	-24.9	1.7	29.3	0.5	1.9	6.2	-3.3	3.6	-2.6	10.1	2.7	-0.9	3.7	2.8	0.0	1.7	4.6	-4.4	3.4	6.3	1.9
D2V	0.0	8.0	0.0	-8.2	-2.3	-25.3	6.1	28.1	0.7	2.1	8.3	-4.5	4.1	-3.0	2.6	1.6	-0.6	3.3	1.8	0.0	1.3	13.9	-5.1	-3.7	6.9	1.3
APC	3.1	6.3	0.0	-8.4	0.0	-25.9	4.1	29.4	1.1	-0.7	7.5	-4.6	4.6	-2.6	9.7	2.3	-1.0	4.7	2.8	-0.7	0.2	5.4	-4.5	1.0	6.9	2.0
mean	0.7	5.9	0	-4.5	0.4	-25.4	7.1	29.2	1.7	0.9	8.3	-4	3.4	-2.9	9.1	2.5	-0.9	4.8	2.8	-0.7	0.2	5.4	-4.5	1.2	7.0	1.7

Model	MSP-IMPROV					BIIC-NNIME												MSP-PODCAST								
	Ang	Sad	Neu	Hap	**Mac**	Ang	Fru	Disa	Sad	Fear	Neu	Sur	Exc	Hap	Rel	Joy	**Mac**	Ang	Sad	Disg	Cont	Fear	Neu	Sur	Hap	**Mac**
XLS-R	6.7	9.2	-5.3	6.0	4.1	-6.1	-9.1	-6.8	4.9	2.5	0.3	5.7	11.1	1.2	-1.1	6.0	0.8	10.1	-0.5	-4.1	-6.5	6.3	-3.2	4.5	2.1	1.1
WavLM	1.7	8.4	-6.0	2.6	1.7	-5.9	-9.9	-2.0	3.9	0.2	2.0	7.8	2.5	5.1	11.7	14.0	2.7	9.5	-0.5	-3.3	-0.6	3.6	-3.0	0.6	2.0	1.0
W2V2 R	1.5	9.9	-3.7	4.4	3.0	-10.2	-0.1	-2.9	-1.6	1.0	1.5	18.2	10.1	-2.3	-1.2	3.4	1.5	10.3	-0.9	-7.7	-7.3	3.2	-3.1	3.6	1.8	0.0
W2V2	1.3	8.6	-5.8	1.6	1.4	-8.7	-4.7	-8.0	-0.3	-0.2	0.2	4.2	4.4	-2.8	-1.6	6.1	-1.0	8.6	-1.6	-6.9	-9.2	0.3	-3.4	3.0	2.2	-0.9
VQ-APC	-3.5	9.5	-5.1	-1.2	-0.1	-5.3	-7.6	-7.9	1.6	-3.8	-0.6	11.5	6.4	-2.2	0.1	10.1	0.2	7.6	-3.8	0.0	-11.9	0.3	-3.5	3.2	0.9	-0.9
HuBERT	4.4	7.1	-6.3	2.7	1.9	-5.7	-1.9	-5.6	1.5	0.0	1.3	4.7	9.7	2.3	3.2	7.9	1.6	9.4	-1.1	-5.7	-4.9	1.8	-3.1	2.3	1.8	0.0
DeCoAR 2	2.1	9.9	-6.0	0.3	1.6	-5.6	-7.7	-0.3	2.7	-0.8	0.1	12.1	5.7	5.0	-3.2	5.5	1.2	8.5	-2.8	-5.7	-11.3	1.0	-3.3	1.8	1.8	-1.2
D2V	2.0	10.0	-5.5	1.9	2.1	-6.5	-3.9	-5.5	4.9	2.3	0.0	5.7	5.6	0.8	-1.0	1.4	0.3	9.1	-1.2	-4.9	-6.1	1.4	-3.0	5.1	1.8	0.3
APC	-0.4	10.6	-6.3	-1.2	0.7	-5.1	-7.3	-4.3	2.5	-1.4	-0.3	9.7	6.7	-2.2	-3.3	8.9	0.3	8.1	-3.6	-1.2	-11.8	0.8	-3.6	3.7	0.9	-0.8
mean	0.6	9.3	-6.1	1.6	1.3	-6.9	-5.7	-3.6	2.0	0.7	0.2	9.6	6.5	1.3	-0.2	6.7	1.0	8.0	-2.7	-2.6	-8.7	1.3	-3.4	3.3	1.4	-0.4

stimuli for fair comparison. We use the Speech Accent Archive [43] for male and female stimuli. The selection criteria for stimuli are the same as those for SpEAT, with the goal of ensuring that differences in association with positive and negative valence do not stem from variations among the speakers.

3. Result and Discussion

3.1. Downstream performance difference

Table 2 shows the difference in F_1 score between females and males on each dataset and each emotion. Due to space limitations, we report the result for models across 3 different training objectives and achieve top-9 performance in EMO-SUPERB. It shows that despite most ER models only exhibiting a slightly high macro-F_1 score for females, a high parity exists between the F_1 score for each emotion. For instance, in the BPO dataset, males exhibit approximately a 25% higher F_1 score than females for neutral emotion, whereas they demonstrate a 29% lower F_1 score for happy emotion.

The bias observed in emotion F_1 scores varies across datasets but shows a consistent trend across emotion recognition models. Specifically, we take BPO and POD as examples since they have identical emotion categories. While the POD dataset exhibits a slight SER bias d_e in the happy and neutral emotion, the BPO dataset displays a significant F_1 score disparity in these categories, indicating substantial dissimilarity. Furthermore, all SER models trained with BPO consistently show the largest d_e on happy and the smallest d_e on neutral. Conversely, all SER models trained with the POD dataset consistently exhibit the highest d_e values for emotion angry and the lowest for contempt. These observations underscore the potential correlation between gender bias in SER and the characteristics of the emotion dataset, with less influence from the upstream model. We conduct further analysis in section 3.2 and 3.3.

We further compare the average F_1 score parity d_c across models and datasets in Table 3(a). It shows that gender bias is closely related to datasets. SER models trained with BPO exhibit higher d_c than those trained with other datasets, while SER models trained with IEM are less biased. Furthermore, the mean d_c across datasets shows Modified CPC is more biased than all

Table 3: *(a) Corpus level (b) Valence gender bias on SER models in %. Bold texts represent the model is the most biased within the same corpus.*

	(a) Corpus level							(b) Valence					
	BPO	CRE	IEM	IMP	NNI	POD	avg	BPO	NNI	IEM	IMP	CRE	POD
XLS-R	9.9	5.8	**4.2**	**6.8**	5.0	**4.7**	6.1	15.1	25.4	-4.3	-9.9	-1.4	-0.5
WavLM	9.9	5.1	3.9	4.7	5.9	2.9	5.4	10.7	37.2	1.2	-7.5	-10.5	-5.2
W2V	10.3	5.8	3.1	4.9	4.1	4.6	5.5	26.4	11.4	2.2	-11.9	-4.8	7.0
W2V2 R	10.1	6.1	3.2	4.9	4.8	**4.7**	5.6	20.8	8.1	0.1	-7.0	-1.4	3.0
W2V2	10.9	3.5	2.7	4.3	3.7	4.4	4.9	27.5	24.8	9.4	-8.4	-6.7	9.9
VQW2V	8.9	4.7	3.0	5.3	3.6	4.1	4.9	26.4	17.2	-1.6	-8.6	-6.3	1.2
VQ-APC	8.9	4.7	3.4	4.8	5.2	3.9	5.2	32.9	31.8	-4.8	-7.2	10.2	8.3
TERA	8.4	5.6	3.3	5.0	5.1	4.6	5.3	33.6	34.9	4.6	-9.5	1.8	9.2
NPC	8.9	**6.8**	2.7	5.6	5.4	**4.7**	5.7	44.2	22.9	3.8	-8.9	11.1	19.2
M CPC	**11.3**	6.0	3.7	**6.3**	**6.3**	3.9	**6.3**	41.0	8.7	-4.2	-5.3	11.1	8.6
Mock	9.2	6.3	3.5	4.5	5.0	3.4	5.3	30.8	33.4	2.6	-9.6	10.5	9.3
HuBERT	10.7	4.0	4.0	5.1	4.0	3.8	5.2	14.5	31.4	2.8	-8.8	-2.6	3.4
FBANK	7.6	0.6	3.2	2.6	1.3	0.7	2.7	36.0	5.4	-17.8	3.5	0.0	-1.3
DeCoAR 2	8.8	4.6	3.1	4.6	4.4	4.5	5.0	34.3	21.4	1.8	-11.8	1.7	12.5
D2V	9.8	4.1	2.9	4.9	3.4	4.1	4.9	28.9	13.0	0.8	-10.1	-7.4	2.4
APC	9.6	4.9	4.1	4.6	4.7	4.2	5.4	28.8	14.0	-2.4	-11.5	2.8	8.1

the other models, while XLS-R shows the most biased result on a majority of emotion datasets. Conversely, the baseline feature, FBank, shows less bias across corpora. This is caused by its low classification accuracy and recall of models trained with this feature.

Also, we analyze the gender bias on valence d_v by observing whether females have higher F_1 scores on positive valence and males have higher F_1 scores on negative valence. The result in Table 3 (b) indicates that SER models trained with Chinese datasets (BPO and NNI) have higher d_v than SER models trained with English datasets, and these models associate female speech with positive valence and male speech with negative valence. In contrast, SER models trained with English datasets demonstrate positive and negative d_v values across different datasets, suggesting a more varied impact.

Since the downstream model architecture is the same across all SER models trained with SSL fashion, the bias may only come from two possible sources: training data and upstream representation. We try to find out the most influential factor of gender bias via the following experiments.

Table 4: *Pearson correlation coefficient between F_1-score gap on gender d_e and training data distribution difference.*

Model	BPO	CRE	IEM	IMP	NNI	POD
XLS-R	0.31	0.78	0.64	1.00	0.62	0.48
WavLM	0.43	0.88	0.58	0.92	0.66	0.40
W2V	0.40	0.74	0.73	0.70	0.39	0.34
W2V2 R	0.34	0.77	0.74	0.86	0.35	0.43
W2V2	0.53	0.96	0.79	0.89	0.62	0.46
VQW2V	0.34	0.76	0.75	0.86	0.73	0.22
VQ-APC	0.47	0.69	0.50	0.61	0.61	0.38
TERA	0.44	0.76	0.66	0.80	0.60	0.40
NPC	0.52	0.69	0.63	0.65	0.46	0.46
M CPC	0.62	0.62	0.78	0.59	0.53	0.28
Mock	0.48	0.68	0.64	0.94	0.65	0.41
HuBERT	0.39	0.82	0.63	0.98	0.55	0.42
FBANK	0.47	0.87	0.94	0.89	0.56	0.48
DeCoAR 2	0.36	0.78	0.72	0.85	0.64	0.45
D2V	0.48	0.76	0.70	0.87	0.63	0.40
APC	0.40	0.78	0.41	0.75	0.65	0.39

3.2. Downstream training data distribution

We evaluate the Pearson correlation coefficient between *training data distribution bias* $\mathbf{d_d}$ and *the F_1-score gap between gender* $[d_{e_1}, d_{e_2}, ...d_{e_i}]$ on dataset with i emotions $e_1, e_2...e_i$. Table 4 (a) reveals significant correlation coefficients for datasets featuring acted performances (CRE, IEM, IMP, NNI), suggesting a strong influence of data source on bias. Conversely, real-world datasets (BPO and POD) exhibit moderate correlation. This observation underscores the importance of considering the variance in emotion distribution across diverse social groups, as it might propagate to SER performance.

3.3. Upstream representation

We first evaluate the upstream representation bias using SpEAT. As showcased in Table 5, our findings unveil substantial levels of representation bias across most models, especially VQ-APC, NPC, and APC, which have larger d_s values. In contrast, D2V and M CPC have smaller gender biases among these models. Moreover, our analysis reveals that aggregating layerwise representations via weighted sum yields consistent outcomes akin to mean pooling, underscoring the robustness and stability of our bias evaluation metric across diverse SER tasks.

We further evaluate the Pearson correlation coefficient between the downstream F_1 score gap on valence d_v and upstream bias on valence d_s among all models. Table 6 shows low or no correlation between upstream and downstream valence bias on different stimuli and aggregation methods. This implies gen-

Table 5: *Upstream representation bias d_s measured on models with different representation aggregation methods. 'mean' denotes taking the average embedding over all layers. Other columns named by datasets denote using the weighted sum of embedding from ER models trained with the dataset.*

Model	mean	BPO	CRE	IEM	IMP	NNI	POD
XLS-R	1.06	1.08	1.06	1.06	1.06	1.06	1.08
WavLM	1.43	1.43	1.43	1.43	1.43	1.43	1.48
W2V	1.33	1.35	1.34	1.36	1.36	1.35	1.35
W2V2 R	0.29	0.79	0.86	0.89	0.87	0.76	0.83
W2V2	0.58	0.58	0.56	0.58	0.57	0.58	0.57
VQW2V	0.67	0.65	0.61	0.64	0.65	0.65	0.66
VQ-APC	1.77	1.76	1.75	1.75	1.75	1.76	1.77
TERA	1.38	1.43	1.43	1.42	1.43	1.42	1.43
NPC	1.69	1.70	1.69	1.69	1.69	1.70	1.70
M CPC	0.53	0.55	0.57	0.52	0.52	0.52	0.59
Mock	1.05	1.06	1.06	1.06	1.06	1.06	1.07
HuBERT	0.99	1.03	0.99	0.99	0.99	0.99	1.02
DeCoAR 2	1.49	1.46	1.48	1.48	1.48	1.48	1.46
D2V	0.45	0.58	0.49	0.44	0.45	0.46	0.50
APC	1.66	1.68	1.69	1.68	1.68	1.68	1.69

Table 6: *Pearson correlation coefficient between F_1-score gap on gender d_e and upstream representation bias d_s using different valence stimuli and aggregation methods (Aggr.).*

Stimuli	Aggr.	BPO	CRE	IEM	IMP	NNI	POD
MESS	Mean	0.06	0.31	0.31	-0.56	0.56	0.44
	Weighted	0.01	0.33	0.34	-0.58	0.53	0.42
NNIME	Mean	-0.45	-0.37	-0.01	0.02	-0.22	-0.43
	Weighted	-0.47	-0.39	-0.03	0.03	-0.22	-0.46
IMPROV	Mean	0.20	0.44	0.06	-0.31	0.11	0.38
	Weighted	0.13	0.45	0.07	-0.33	0.09	0.32
PODCAST	Mean	-0.30	-0.16	-0.09	0.04	-0.03	-0.32
	Weighted	-0.25	-0.13	-0.10	0.03	0.06	-0.29

der bias in upstream representation might hardly propagate to downstream emotion classification tasks, which contradicts the conclusion in SpEAT. Two possible reasons might contribute to the difference between our work and SpEAT: (1) SpEAT trains the downstream valence prediction model with only 1800 speech samples, while we train multilabel emotion classification models and then calculate the difference between gender F_1 parity of positive and negative valence emotions, with at least 4000 speech samples per model. (2) SpEAT asserts that the group identified as positive valence by the pre-trained model tends to exhibit a similar association with positive valence in the downstream SER model, framing the challenge as a binary classification problem. However, our analysis transcends binary classification by discussing the correlation between metrics representing continuous scales that reflect the extent of association between upstream and downstream bias. Our analysis suggests that we should use upstream bias metrics carefully as the bias might not reflect in application-level performance.

4. Discussion and Limitation

Gender is a spectrum rather than a solely male/woman binary [44]. However, existing speech emotion classification dataset datasets only have labels on binary gender. Including a broader range of gender identities in the dataset would better reflect the reality of human diversity and improve the performance and fairness of the models, which can be our future work.

5. Conclusion and Future Work

This work provides extensive insights into the gender bias in SER models trained with the SSL paradigm. We identify that females exhibit superior overall SER performance compared to males. Also, a substantial gender-wise performance gap exists across individual emotions. Furthermore, our investigation underscores the influence of dataset characteristics, revealing Mandarin datasets to exhibit a pronounced bias toward valence compared to their English counterparts. Importantly, we find that downstream training data distribution plays a pivotal role in exacerbating gender bias, while upstream representation exerts minimal influence. These findings have far-reaching implications for developing ER technologies. Our forthcoming efforts aim to rectify biases inherent in these ER systems. Our research sets the stage for more inclusive and ethical approaches to designing and deploying AI systems.

6. References

[1] M. K. Ngueajio and G. Washington, "Hey ASR system! Why aren't you more inclusive? Automatic speech recognition systems' bias and proposed bias mitigation techniques. A literature

review," in *International Conference on Human-Computer Interaction*, 2022.

[2] S. Feng *et al.*, "Quantifying bias in automatic speech recognition," *arXiv preprint arXiv:2103.15122*, 2021.

[3] G. Attanasio *et al.*, "Multilingual Speech Models for Automatic Speech Recognition Exhibit Gender Performance Gaps," *arXiv preprint arXiv:2402.17954*, 2024.

[4] B. Savoldi *et al.*, "Under the Morphosyntactic Lens: A Multi-faceted Evaluation of Gender Bias in Speech Translation," in *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2022.

[5] M. Gaido *et al.*, "How to Split: the Effect of Word Segmentation on Gender Bias in Speech Translation," in *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, 2021.

[6] A. Domnich and G. Anbarjafari, "Responsible AI: Gender bias assessment in emotion recognition," 2021.

[7] G. Fenu *et al.*, "Exploring algorithmic fairness in deep speaker verification," in *Computational Science and Its Applications–ICCSA 2020: 20th International Conference, Cagliari, Italy, July 1–4, 2020, Proceedings, Part IV 20*, 2020.

[8] C. Gorrostieta *et al.*, "Gender De-Biasing in Speech Emotion Recognition." in *Interspeech*, 2019.

[9] W.-S. Chien and C.-C. Lee, "Achieving Fair Speech Emotion Recognition via Perceptual Fairness," in *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2023.

[10] C. Busso *et al.*, "IEMOCAP: Interactive emotional dyadic motion capture database," *Journal of Language Resources and Evaluation*, 2008.

[11] A. Mohamed *et al.*, "Self-supervised speech representation learning: A review," *IEEE Journal of Selected Topics in Signal Processing*, 2022.

[12] B. T. Atmaja and A. Sasou, "Evaluating self-supervised speech representations for speech emotion recognition," *IEEE Access*, 2022.

[13] M. Riviere *et al.*, "Unsupervised pretraining transfers well across languages," in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020.

[14] A. Babu *et al.*, "XLS-R: Self-supervised cross-lingual speech representation learning at scale," *arXiv preprint arXiv:2111.09296*, 2021.

[15] J. Wagner *et al.*, "Dawn of the Transformer Era in Speech Emotion Recognition: Closing the Valence Gap," *IEEE Transactions on Pattern Analysis & Machine Intelligence*, 2023.

[16] E. Morais *et al.*, "Speech Emotion Recognition Using Self-Supervised Features," in *ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2022.

[17] H. Wu *et al.*, "EMO-SUPERB: An In-depth Look at Speech Emotion Recognition," 2024.

[18] S. wen Yang *et al.*, "SUPERB: Speech Processing Universal PERformance Benchmark," in *Proc. Interspeech 2021*, 2021.

[19] S. Ling and Y. Liu, "DeCoAR 2.0: Deep Contextualized Acoustic Representations with Vector Quantization," 2020.

[20] Y.-A. Chung *et al.*, "An Unsupervised Autoregressive Model for Speech Representation Learning," in *Proc. Interspeech 2019*, 2019.

[21] ——, "Vector-Quantized Autoregressive Predictive Coding," in *Proc. Interspeech 2020*, 2020.

[22] A. H. Liu *et al.*, "Non-autoregressive predictive coding for learning speech representations from local dependencies," *arXiv preprint arXiv:2011.00406*, 2020.

[23] A. T. Liu *et al.*, "TERA: Self-Supervised Learning of Transformer Encoder Representation for Speech," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2021.

[24] ——, "Mockingjay: Unsupervised Speech Representation Learning with Deep Bidirectional Transformer Encoders," in *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020.

[25] A. Baevski *et al.*, "wav2vec 2.0: A framework for self-supervised learning of speech representations," *Advances in neural information processing systems*, 2020.

[26] W.-N. Hsu *et al.*, "Robust wav2vec 2.0: Analyzing Domain Shift in Self-Supervised Pre-Training," in *Proc. Interspeech 2021*, 2021.

[27] A. Baevski *et al.*, "vq-wav2vec: Self-Supervised Learning of Discrete Speech Representations," in *International Conference on Learning Representations*, 2020.

[28] S. Schneider *et al.*, "wav2vec: Unsupervised pre-training for speech recognition," *arXiv preprint arXiv:1904.05862*, 2019.

[29] W.-N. Hsu *et al.*, "Hubert: Self-supervised speech representation learning by masked prediction of hidden units," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2021.

[30] S. Chen *et al.*, "WavLM: Large-Scale Self-Supervised Pre-Training for Full Stack Speech Processing," *IEEE Journal of Selected Topics in Signal Processing*, 2022.

[31] A. Baevski *et al.*, "data2vec: A General Framework for Self-supervised Learning in Speech, Vision and Language," in *Proceedings of the 39th International Conference on Machine Learning*, 2022.

[32] A. S. Cowen and D. Keltner, "Semantic Space Theory: A Computational Approach to Emotion," *Trends in Cognitive Sciences*, 2021.

[33] C. Szegedy *et al.*, "Rethinking the Inception Architecture for Computer Vision," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[34] L. Goncalves and C. Busso, "Improving Speech Emotion Recognition Using Self-Supervised Learning with Domain-Specific Audiovisual Tasks," in *Proc. Interspeech 2022*, 2022, pp. 1168–1172.

[35] A. S. Cowen *et al.*, "Mapping 24 Emotions Conveyed by Brief Human Vocalization," *American Psychologist*, 2019.

[36] I. Slaughter *et al.*, "Pre-trained Speech Processing Models Contain Human-Like Biases that Propagate to Speech Emotion Recognition," in *Findings of the Association for Computational Linguistics: EMNLP 2023*, 2023.

[37] R. Lotfian and C. Busso, "Building Naturalistic Emotionally Balanced Speech Corpus by Retrieving Emotional Speech From Existing Podcast Recordings," *IEEE Transactions on Affective Computing*, 2019.

[38] S. G. Upadhyay *et al.*, "An Intelligent Infrastructure Toward Large Scale Naturalistic Affective Speech Corpora Collection," in *2023 11th International Conference on Affective Computing and Intelligent Interaction (ACII)*, 2023.

[39] C. Busso *et al.*, "MSP-IMPROV: An Acted Corpus of Dyadic Interactions to Study Emotion Perception," *IEEE Transactions on Affective Computing*, 2017.

[40] H.-C. Chou *et al.*, "NNIME: The NTHU-NTUA Chinese interactive multimodal emotion corpus," in *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*, 2017.

[41] H. Cao *et al.*, "CREMA-D: Crowd-Sourced Emotional Multimodal Actors Dataset," *IEEE Transactions on Affective Computing*, 2014.

[42] S. D. Morgan, "Categorical and dimensional ratings of emotional speech: Behavioral findings from the Morgan emotional speech set," *Journal of Speech, Language, and Hearing Research*, 2019.

[43] S. H. Weinberger and S. A. Kunath, "The Speech Accent Archive: towards a typology of English accents," in *Corpus-based studies in language use, language learning, and language documentation*, 2011.

[44] M. Bass *et al.*, "Rethinking gender: The nonbinary approach," *American Journal of Health-System Pharmacy*, 2018.