Addressing challenges in speaker anonymization to maintain utility while ensuring privacy of pathological speech - Supplementary Information

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Supplementary Tables and Figures

Supplementary Table 1: Overview of some expected features for different clinical groups of the dataset.

Features	Description	Dysarthria	Dysglossia	Dysphonia	Cleft Lip and Palate
Phonation	Control and use of vocal folds and glottal configurations.	Yes	Sometimes	Yes	Sometimes
Phonetic	Clarity and accuracy of speech sounds production.	Yes	Yes	No	Yes
Prosody	Patterns of stress and intonation in speech.	Yes	Sometimes	No	Sometimes
Hypernasality	Excessive nasal resonance due to velopharyngeal insufficiency.	Sometimes	Sometimes	No	Yes
Hyponasality	Reduced nasal resonance, typically from nasal obstructions.	Sometimes	No	No	Sometimes
Loudness	Volume level of speech.	Sometimes	Sometimes	Sometimes	Sometimes
Rate	Speed at which speech sounds are articulated.	Yes	Sometimes	No	Sometimes

This table details the expected occurrence of different speech features across four clinical groups—Dysarthria[1-3], Dysglossia[4], Dysphonia[5], and Cleft Lip and Palate[6-9]. Each feature is evaluated for its presence in each disorder with labels Yes for consistently present, No for not associated, and Sometimes for variable presence. The label Sometimes specifically indicates that the manifestation of features like Loudness[2] can vary among individuals, reflecting the complexities of diagnosing and treating speech pathologies.

Supplementary Table 2: The effects of varying privacy levels on the utility of pathological speech.

McAdams Coefficient	Dysarthria		Dysglossia		Dysphonia		Cleft Lip and Palate	
	AUROC [%]	Accuracy [%]	AUROC [%]	Accuracy [%]	AUROC [%]	Accuracy [%]	AUROC [%]	Accuracy [%]
Original Data	97.33±0.51	93.80±0.73	97.73±0.41	92.87±0.84	99.12±0.42	97.37±0.59	96.44±0.21	90.99±0.44
0.5	97.05±0.39 (p=0.0035)	91.45±0.87 (p=4.2×10^{-19})	98.62±0.25 (p=1.8×10^{-17})	94.69±0.67 (p=6.2×10^{-16})	96.60±0.64 (p=1.1×10^{-27})	91.72±0.88 (p=3.6×10^{-37})	96.04±0.29 (p=1.8×10^{-10})	90.14±0.49 (p=7.1×10^{-11})
0.6	96.05±0.65 (p=1.9×10^{-14})	90.67±1.00 (p=1.0×10^{-22})	97.69±0.44 (p=0.58)	93.11±0.95 (p=0.19)	98.02±0.51 (p=1.4×10^{-15})	94.89±0.72 (p=1.2×10^{-23})	94.07±0.29 (p=1.4×10^{-41})	86.62±0.50 (p=3.5×10^{-41})
0.7	94.06±0.92 (p=1.6×10^{-26})	90.07±1.01 (p=7.8×10^{-26})	98.68±0.23 (p=1.0×10^{-18})	94.66±0.79 (p=1.5×10^{-14})	97.62±0.47 (p=1.1×10^{-21})	92.31±0.83 (p=8.7×10^{-36})	97.56±0.20 (p=1.3×10^{-30})	92.87±0.48 (p=6.3×10^{-25})
0.8	96.29±0.60 (p=2.4×10^{-12})	91.16±1.32 (p=2.4×10^{-16})	97.55±0.28 (p=0.011)	92.62±0.58 (p=0.086)	97.71±0.57 (p=1.4×10^{-18})	94.40±0.85 (p=4.4×10^{-25})	98.62±0.12 (p=5.3×10^{-48})	94.48±0.34 (p=2.2×10^{-40})
0.9	98.27±0.28 (p=3.3×10^{-15})	94.93±0.85 (p=5.0×10^{-19})	98.12±0.31 (p=3.6×10^{-6})	93.60±0.84 (p=7.7×10^{-5})	98.63±0.35 (p=8.2×10^{-8})	94.53±0.72 (p=3.0×10^{-26})	97.48±0.19 (p=1.1×10^{-29})	91.88±0.51 (p=3.6×10^{-12})
1.0	98.48±0.39 (p=6.3×10^{-17})	95.84±0.69 (p=5.9×10^{-19})	98.52±0.24 (p=1.6×10^{-15})	94.12±0.66 (p=1.0×10^{-10})	96.19±0.59 (p=1.0×10^{-31})	90.78±1.08 (p=3.1×10^{-37})	97.15±0.17 (p=3.2×10^{-23})	91.43±0.40 (p=4.4×10^{-6})
McAdams Coefficient	Sensitivity [%]	Specificity [%]	Sensitivity [%]	Specificity [%]	Sensitivity [%]	Specificity [%]	Sensitivity [%]	Specificity [%]
Original Data	94.11±1.05	92.68±1.03	92.55±1.51	93.49±1.36	97.10±0.71	97.70±0.76	90.22±0.98	91.64±1.07
0.5	90.42±1.88 (p=4.6×10^{-16})	91.60±1.55 (p=0.00017)	94.15±1.13 (p=3.2×10^{-7})	94.73±1.28 (p=2.5×10^{-5})	92.46±1.54 (p=4.1×10^{-24})	91.03±1.73 (p=6.5×10^{-29})	90.32±0.94 (p=0.61)	90.60±0.84 (p=2.6×10^{-6})
0.6	89.25±1.84 (p=5.9×10^{-21})	91.27±1.95 (p=4.7×10^{-5})	91.67±1.82 (p=0.010)	93.50±1.40 (p=0.97)	94.67±1.08 (p=1.8×10^{-17})	95.24±0.98 (p=2.1×10^{-18})	85.40±1.58 (p=4.3×10^{-23})	89.17±1.40 (p=5.3×10^{-13})
0.7	86.40±1.85 (p=1.7×10^{-29})	89.73±2.05 (p=7.7×10^{-12})	94.61±1.49 (p=1.5×10^{-8})	93.70±1.60 (p=0.48)	92.24±1.37 (p=8.7×10^{-27})	92.41±1.55 (p=3.4×10^{-26})	92.50±0.74 (p=2.3×10^{-17})	93.48±0.66 (p=1.2×10^{-13})
0.8	90.41±1.80 (p=1.3×10^{-16})	90.47±1.88 (p=3.5×10^{-9})	93.39±1.30 (p=0.0045)	92.13±1.55 (p=2.7×10^{-5})	94.35±1.07 (p=1.0×10^{-19})	94.61±1.04 (p=9.3×10^{-22})	94.67±0.60 (p=1.0×10^{-30})	94.65±0.65 (p=8.7×10^{-22})
0.9	93.91±1.19 (p=0.39)	94.71±1.27 (p=1.9×10^{-11})	93.53±1.12 (p=0.00066)	93.96±1.10 (p=0.065)	93.94±1.42 (p=1.6×10^{-18})	95.17±1.04 (p=3.6×10^{-18})	89.35±1.25 (p=0.00040)	93.85±0.99 (p=3.1×10^{-14})
1.0	94.98±1.03 (p=0.00014)	95.17±0.99 (p=2.9×10^{-16})	94.51±1.17 (p=3.9×10^{-9})	93.94±1.42 (p=0.11)	90.90±1.28 (p=1.6×10^{-32})	90.76±1.53 (p=1.0×10^{-31})	92.57±0.87 (p=9.7×10^{-17})	91.54±0.85 (p=0.63)

This table presents the outcomes of applying randomized McAdams coefficient anonymization method to the pathological speech data. The McAdams coefficient was systematically adjusted from 0.5 to 1.0 (in increments of 0.1) and pretrained ResNet34[10] models were trained separately for classification of different disorders including Dysarthria, Dysglossia, Dysphonia, and Cleft Lip and Palate (CLP) and quantified using

AUROC, accuracy, sensitivity, and specificity. The results are presented as mean ± standard deviation. Statistical significance between original and anonymized data for these utility metrics was determined using a two-tailed unpaired t-test, with p-values noted. Training sets comprised n=168 speakers (Dysarthria detection), n=168 (Dysglossia detection), n=110 (Dysphonia detection), and n=887 (CLP detection). Corresponding test sets included n=73 (Dysarthria detection), n=73 (Dysglossia detection), n=49 (Dysphonia detection), and n=381 (CLP detection).

Supplementary Fig. 1: The proposed randomized pitch shift algorithm for anonymization.

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for all speakers do
    extract log-Mel-spectrograms by performing data preprocessing as described in classification process;
    if speaker is a female then
        if age < 8 then
            S = a random number sampled from (-1.2, -1.0);
        else then
            S = a random number sampled from (-1.2, -0.8);
    else if speaker is a male then
        p = randomly sample a number from (0, 1);
        if p < 0.5 then
            S = a random number sampled from (-1.2, -0.8);
        else then
            if age < 10 then
                S = a random number sampled from (0.5, 0.8);
            else if 10 < age < 20 then
                S = a random number sampled from (0.6, 1.0);
            else then
                S = a random number sampled from (0.8, 1.2);
    shift the pitch with S steps (semitones);
    MEAN = a random number sampled from (0, 0.2);
    STD = a random number sampled from (0, 0.005);
    apply additive Gaussian noise with MEAN and STD;
    synthesize the resulting modified Mel-spectrogram using a pretrained Hi-Fi GAN model;
    if S > 0 then
        perform spectral gating noise reduction;
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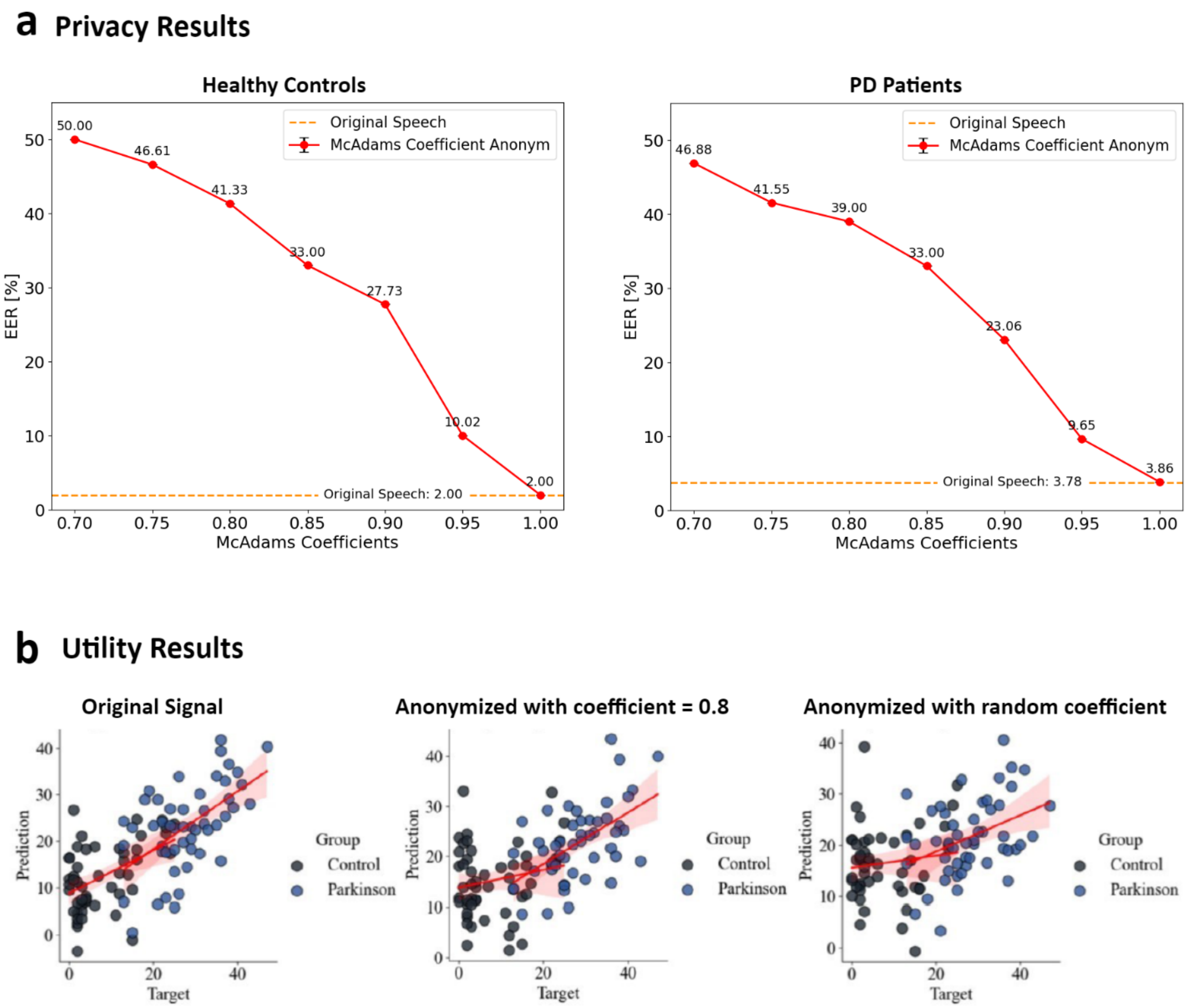
Supplementary Fig. 2: The utility and privacy results of the anonymization on the PC-GITA Spanish dataset[11].



a The privacy results show the equal error rate (EER) values for both healthy controls and Parkinson's Diseases (PD) patients. Whiskers show the error bars, which indicate the standard deviation values. **b** shows the utility results where a linear support vector regression machine[12] was applied to predict the maximum phonation duration.

Supplementary References

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