SPEECHDX: A MULTI-TASK BENCHMARK FOR CLINICAL SPEECH AI

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ABSTRACT

Speech offers a uniquely informative window into health by simultaneously engaging neurological, motor, respiratory, and vocal systems. Current clinical speech AI methods have largely progressed through isolated condition-specific studies, making results difficult to compare and generalization difficult to assess. We introduce SpeechDx, a large-scale benchmark for clinical speech AI spanning 12 datasets and 27 tasks across diverse health conditions. To enable evaluation across shared clinical mechanisms, SpeechDx structures tasks by the stage of speech production they disrupt: conceptualization, formulation, and articulation. The benchmark tests generalization by including tasks with limited labeled data and evaluating the same health condition across multiple datasets, distinguishing clinically meaningful patterns from dataset artefacts. We systematically evaluate 12 state-of-the-art audio encoders across all tasks and under zero-shot cross-condition transfer. Results show that large-scale speech models represent the strongest overall baselines, domain-specific models improve performance only on closely matched tasks, and no current representation generalizes reliably across the clinical speech landscape. SpeechDx establishes a shared evaluation framework for tracking progress toward general-purpose clinical speech representations.

1 INTRODUCTION

Speech has been widely studied as a digital biomarker of human health. Its production requires the coordinated action of the respiratory, vocal, neurological, and cognitive systems, so disruptions to any of these systems due to disease or dysfunction leave measurable traces in the voice. Unlike many clinical assessment tools, speech can be captured non-invasively, remotely, and at negligible cost, making it particularly well-suited for continuous monitoring, population-level screening, and longitudinal disease tracking. Over the past few decades, this has motivated a substantial body of research exploring the automation of speech analysis for a wide range of conditions such as COVID-19 (1; 2), dysarthria (3; 4; 5), Parkinson's disease (6; 7; 8), Alzheimer's disease (9; 10; 11), depression (12; 13; 14), and vocal pathologies (15; 16). Dedicated challenges further demonstrate the potential of deep learning for health assessment from speech (17; 18; 19; 20; 21; 22).

Despite this potential, very few systems have achieved real-world clinical deployment. A recurring obstacle is the fragmented nature of the field. Research has progressed in silos, with models trained and evaluated on individual datasets under inconsistent protocols, limiting generalizability across conditions. Even within a single condition, models trained on small controlled corpora consistently fail to generalize to unseen data. This failure is largely attributed to models learning spurious correlations from confounding factors in the data — differences in recording conditions, demographic composition, and acquisition hardware — rather than the underlying clinical signal (23; 24; 25). The field lacks a standardized evaluation framework for quantifying progress, assessing generalization across datasets and conditions, and identifying robust modeling approaches.

We address this gap by introducing SpeechDx, a benchmark comprising 23 clinical and 4 affective-prosodic tasks derived from 12 publicly available speech datasets. One of SpeechDx's distinguishing features is its organization around the speech production process. Following the framework proposed by Berisha and Liss (26), we classify conditions and tasks according to the stage of speech production at which the condition exerts its primary effect: (1) conceptualization, when a communicative intention is formed; (2) formulation, when that intention is encoded into linguistic and phonological

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structure; and (3) articulation, where respiratory and motor systems execute the spoken output. Diverse health conditions disrupt different stages of this cascade, producing distinct types of acoustic irregularity.

We use SpeechDx to evaluate 12 state-of-the-art audio and speech encoders representing different representation learning paradigms. The evaluation includes linear probing, out-of-distribution evaluation, and zero-shot cross-condition transfer. We further examine model performance under limited labeled data regime, sensitivity to temporal aggregation and impact of parameter-efficient adaptation. To summarize, our contributions are as follows:

- We introduce SpeechDx, a reproducible benchmark of 23 clinical tasks and four auxiliary affective-prosodic tasks from 12 datasets, organized using the speech-production process.
- We provide a systematic evaluation of 12 state-of-the-art audio encoders, establishing a standardized and reproducible baseline for performance comparison across clinical domains.
- We conduct additional analyses to test out-of-distribution generalization and zero-shot cross-condition transfer, supplemented by analyses of temporal aggregation and parameter-efficient adaptation.
- We release an evaluation harness that standardizes dataset preparation, representation extraction, and downstream evaluation, enabling future encoders to be compared under the same protocol. The code is available at **REDACTED**.

2 Background and Related Work

2.1 Speech as a Biomarker

Deviations in vocal attributes such as pitch, intensity, resonance, and temporal structure constitute measurable markers of disordered voice production. Such deviations arise from perturbations in the biological systems underlying speech generation (27; 28). This sensitivity is fundamental to the utility of speech as a biomarker (29) and contributes to its recognition as a vital sign (30). Its non-invasive and low-cost acquisition further enables repeated and longitudinal measurements that support applications in screening, monitoring, and prognosis.

Berisha and Liss (26) propose a framework that organizes health conditions by how directly they disrupt the speech production mechanism. At one end of the spectrum, conditions directly impact the mechanics of acoustic speech production. On the other end, conditions disrupt cognitive-affective processes or linguistic planning, resulting in changes to speech content and formulation. SpeechDx adopts this framework as the basis for task selection and organization.

2.2 Clinical Speech Representations and Benchmarks

The field of clinical speech AI broadly studies computational methods that extract acoustic, prosodic, and linguistic information from speech to infer clinically relevant outcomes (31). Early work in the field relied on hand-engineered features (32) for tasks spanning COVID-19 detection (33), Parkinson's disease classification (34), and depression screening (35), among others (36; 37; 38). More recent work has shifted toward deep neural networks trained directly on audio waveforms or spectrograms (39; 40; 41; 42; 43; 44). However, both conventional and deep approaches are typically optimized for individual conditions. Although these models often achieve strong within-dataset performance, they frequently fail under distribution shift (23; 31; 45).

Innovations in self-supervised learning across vision (46; 47; 48) and language (49; 50; 51) have shown that it is possible to learn universal representations that transfer across several downstream tasks with minimal adaptation. An analogous capability is desirable in clinical speech AI since labeled datasets are small and costly to collect. A disease-agnostic representation could provide a shared basis for learning across multiple clinical tasks, reducing dependence on large labeled datasets for each disease. Initial studies using representations from models such as wav2vec 2.0 (52), HuBERT (53), and WavLM (54) have shown promising results on clinical speech tasks (55; 56; 57; 58; 59; 60), suggesting that pretrained speech encoders capture information relevant to health assessment.

Recent work has therefore shifted toward health-oriented audio representations. WavRx (61) extended WavLM with a modulation dynamics module to capture respiration and articulation abnormalities,

while HeAR (62) included a masked autoencoder trained on 313 million health acoustic clips. Both represent important steps towards general audio representations for health. However, their evaluation scope remains limited: WavRx covers six datasets and four pathologies, while HeAR was only tested on tasks spanning respiratory sounds like coughing and breathing. The broader scope of speech-affecting diseases spanning motor, cognitive-linguistic, and affective conditions remains largely unaddressed.

Standardized benchmarks have driven systematic progress in adjacent domains; SUPERB (63) established a shared multi-task evaluation protocol that accelerated semantic speech research, while HEAR (64) provided a framework that advanced general audio representation learning. SpeechDx serves this purpose for clinical speech AI, providing a catalyst for the development of general-purpose health audio representations that transfer across clinical tasks and populations.

3 Datasets and Tasks

Guided by clinical relevance and public availability, the dataset curation process yielded 12 datasets with 27 downstream tasks. Table 1 summarizes their key characteristics, with complete dataset and task descriptions provided in Appendices A and B. Below, we describe how the datasets are positioned under Berisha and Liss' framework for speech production (26).

3.1 Conceptualization Disorders

Conceptualization is the first stage of speech production, where the speaker forms a communicative intention and decides what to express. This stage is driven by cognitive and affective processes — how the speaker feels, what they want to communicate, and how much they elaborate. Disruptions here alter cognitive drivers that result in subtle acoustic changes such as reduced speaking rate, flattened pitch variation, truncated responses, and altered patterns of emphasis and timing.

Depression can reduce psychomotor drive and cognitive engagement, while affective state and emotions more broadly shape prosody and timing. EDAIC-WOZ (65) provides two clinical tasks: depression detection and PHQ-8 severity estimation. RAVDESS (66) and IEMOCAP (67), on the other hand, are not clinical cohorts. We retain their four emotion-recognition tasks as auxiliary probes of affective and prosodic information.

3.2 Formulation Disorders

The formulation stage involves encoding communicative intent into linguistic structures through word selection, syntactical rules, and phonetic sequencing. Disrupted formulation often results in speech that is acoustically fluent yet contains unusual sentence structures or phonemic substitutions.

Language disorders following neurological damage and neurodegenerative disease are the most common disruptors of this stage. Aphasia, arising from stroke or focal brain injury, directly impairs lexical retrieval and syntactic encoding. On the other hand, Alzheimer's disease progressively disrupts semantic memory and word access, with downstream effects on the coherence of spoken output. These conditions represent two of the most clinically prevalent acquired communication disorders in adults, and detecting them from speech alone is highly valuable for tracking disease progression. We use standardized discourse recordings from AphasiaBank (69) to detect the presence of aphasia and DementiaBank (68) to detect the presence and severity of Alzheimer's disease.

3.3 Articulation Disorders

Articulation is the stage at which planned speech is executed through coordinated movement of the respiratory, laryngeal, and articulatory systems. This execution can be broadly decomposed into two subsystems: (1) the neuromuscular articulatory subsystem, which modulates airflow into intelligible speech, and (2) the phonatory and respiratory subsystem, which generates airflow in the first place.

Neuromuscular Disorders. These disorders reduce the precision, speed, and coordination of the vocal articulators. This reduction results in speech that is imprecise and less intelligible. We represent this class of disorders with two examples: (1) dysarthria, a group of motor speech disorders characterized by weakness or incoordination of the speech musculature; and (2) disfluency, which

Table 1: The datasets and tasks comprising SpeechDx. Task types are either classification (C), multi-label classification (M), or regression (R). Dataset splits either entail a single train-validation-test split (TVT) or 5-fold subject-wise cross-validation (5-fold). Sample sizes denote the number of recordings, with the number of unique subjects shown in parentheses.

Category	Dataset	ID	Task	Type	Split	Samples (Subjects)
Conceptualization	EDAIC-WOZ (65)	T1	Depression / healthy	C	TVT	163 (163) / 56 (56) / 56 (56)
		T2	PHQ-8 score	R	TVT	163 (163) / 56 (56) / 56 (56)
	RAVDESS (66)	T3	Emotion classification	C	5-fold	1,140 (19) / 300 (5)
		T4	Negative / non-negative emotion	C	5-fold	1,140 (19) / 300 (5)
	IEMOCAP (67)	T5	Emotion classification	C	5-fold	5,843 (8) / 1,537 (2)
		T6	Negative / non-negative emotion	C	5-fold	5,843 (8) / 1,537 (2)
Formulation	DementiaBank (68)	T7	Dementia / healthy	C	TVT	237 (237) / 8 (8) / 46 (46)
		T8	MMSE score	R	TVT	236 (236) / 8 (8) / 46 (46)
	AphasiaBank (69)	T9	Aphasia / healthy	C	TVT	740 (143) / 160 (21) / 237 (42)
Articulation (Neuromuscular)	TORGO (70)	T10	Dysarthria / healthy	C	5-fold	7,605 (12) / 1,811 (3)
		T11	Dysarthria severity	R	5-fold	2,379 (6) / 802 (2)
	UASpeech (71)	T12	Dysarthria / healthy	C	5-fold	16,830 (22) / 4,590 (6)
	MDVR-KCL (72)	T13	Parkinson's / healthy	C	5-fold	59 (30) / 14 (7)
		T14	UPDRS-5 score	R	5-fold	59 (30) / 14 (7)
		T15	UPDRS-18 score	R	5-fold	59 (30) / 14 (7)
		T16	H&Y score	R	5-fold	59 (30) / 14 (7)
	KSoF-C (73)	T17	Disfluency / healthy	C	5-fold	4,307 (31) / 1,036 (6)
		T18	Disfluency classification	M	5-fold	4,394 (30) / 1,203 (7)
Articulation (Phonatory / Respiratory)	COVID-19 Sounds (74)	T19	Symptomatic / healthy (official subset)	C	TVT	6,565 (4,635) / 943 (663) / 1,948 (1,325)
		T20	Symptomatic / healthy	C	TVT	37,353 (25,252) / 5,271 (3,608) / 10,761 (7,216)
		T21	COVID-19 / non-COVID-19 (official subset)	C	TVT	1,017 (700) / 141 (100) / 324 (200)
		T22	COVID-19 / non-COVID-19	C	TVT	5,606 (3,711) / 804 (531) / 1,609 (1,061)
		T23	Symptom classification	M	TVT	19,541 (15,459) / 2,914 (2,209) / 5,591 (4,418)
	Coswara (75)	T24	Symptomatic / healthy	C	TVT	3,786 (1,896) / 542 (271) / 1,083 (542)
		T25	COVID-19 / non-COVID-19	C	TVT	2,915 (1,459) / 418 (209) / 834 (418)
		T26	Symptom classification	M	TVT	1,459 (731) / 210 (105) / 417 (209)
	AVFAD (76)	T27	Vocal pathology / healthy	C	TVT	3,968 (496) / 568 (71) / 1,135 (142)

disrupts the timing and sequencing of speech production. TORGO (70) and UASpeech (71) support dysarthria detection and severity estimation among speakers with diverse etiology. MDVR-KCL (72) targets hypokinetic dysarthria as observed in Parkinson's disease, which is characterized by reduced vocal loudness, monotone pitch, and imprecise articulation. Finally, KSoF-C (73) provides fluency-labeled recordings to enable disfluency classification and stuttering detection.

Phonatory and Respiratory Disorders. The respiratory and phonatory subsystem is responsible for the airflow and vocal fold vibration that underlie all voiced sounds. Conditions affecting this subsystem disrupt speech at its source, producing what could theoretically be the most directly measurable acoustic deviations. We consider both disease detection and symptom characterization in this category of disorders. The latter is particularly relevant for respiratory conditions that are accompanied by cough, cold, and breathing difficulty, each of which exhibits distinct acoustic patterns during speech. We use COVID-19 Sounds (74) and Coswara (75) for respiratory symptom characterization and COVID-19 detection, and AVFAD (76) for vocal pathology detection.

4 METHODS

4.1 AUDIO PREPROCESSING

All audio is resampled to 16 kHz, mono-channeled, and normalized prior to modeling. To accommodate variable-length recordings, inputs shorter than a model's minimum accepted length are zero-padded, and those exceeding the maximum accepted length are divided into non-overlapping chunks whose embeddings are mean-pooled to produce a single representation.

4.2 MODELS

We evaluate 12 state-of-the-art audio and speech models that have been widely used for spoken language, paralinguistic, and health-related tasks. These models are selected to cover a range of training data sources (general speech, general audio, and domain-specific audio), supervision paradigms, and learning objectives, enabling comparisons across varying levels of data scale and domain alignment. Model details are provided in Table 4, with expanded descriptions in Appendix C.

Speech Models. Following prior work demonstrating the use of self-supervised speech representations in clinical and paralinguistic applications (55; 58; 60; 77; 78; 57), we evaluate wav2vec 2.0 (52), HuBERT (53), WavLM (54), and MMS (79). These models utilize large-scale self-supervised speech pretraining followed by supervised fine-tuning for automatic speech recognition, but they differ in their pretraining objectives and data. We additionally include the Qwen3-TTS-Tokenizer (80), a neural audio codec trained on multilingual speech corpora with a self-supervised reconstruction objective; and Whisper (81), a fully supervised model trained on weakly labeled speech via sequence-to-sequence learning.

General Audio Models. General audio models are pretrained on broad audio corpora such as AudioSet (82), which include but are not limited to speech. This exposure provides them with a wider acoustic distribution than that of speech-only models. We include AudioMAE (83) and WavJEPA (84), which learn representations via self-supervised reconstruction and predictive objectives, respectively. We additionally include AST (85), a vision transformer adapted to audio via supervised training on AudioSet; and CLAP (86), trained via contrastive learning on audio-text pairs. Both of these models have been applied to audio classification tasks beyond speech (62; 87; 88).

Domain-specific Models. Domain-specific models are pretrained on audio from a targeted application domain. We include emotion2vec+ (89), pretrained on emotional speech through self-supervised teacher-student distillation, and OPERA (90), pretrained on respiratory audio using a multi-task self-supervised objective. Because IEMOCAP is included in the pretraining data for emotion2vec+, its results on IEMOCAP are treated as having documented pretraining overlap and are not used to support generalization claims.

4.3 EVALUATION PROTOCOL

To evaluate the performance of pretrained representations across clinical speech tasks, we adopt a linear probing protocol following standard practice (90; 62; 64). Encoder weights are kept frozen throughout, and a single linear layer is trained on top of the mean-pooled encoder output. The output dimensionality is set to the number of target classes for classification tasks or a single unit for regression. Compared to full fine-tuning, this approach is computationally efficient and less prone to overfitting, making it appropriate for the limited dataset sizes typical in clinical tasks.

Official data splits are used where available; otherwise, datasets are partitioned in one of three ways depending on their size. Datasets with a large number of speakers are split into training (70%), validation (10%), and test (20%) sets with speaker-disjoint partitions stratified by label, sex, and age when possible. Datasets with a small number of speakers are split via 5-fold cross-validation with speaker-disjoint folds stratified by label. Finally, the official split for COVID-19 Sounds (74) is replaced with a custom speaker-disjoint partition due to speaker leakage in the original release.

Beyond within-dataset evaluation, we consider two transfer settings. Same-condition cross-dataset OOD evaluation trains a probe on one dataset and evaluates it on a disjoint dataset representing the same clinical condition. Cross-condition transfer applies a probe to a dataset representing a different condition. The latter tests whether a learned decision rule reuses discriminative speech information

across conditions and is not interpreted as evidence of shared pathology or clinical generalization. The source dataset is divided into training and validation sets, and the complete target dataset is used for testing. Both analyses are restricted to binary clinical tasks, with labels harmonized as clinically affected or control; for emotion datasets, non-negative emotions are mapped to controls and negative emotions to the affected class as the closest analogue to the clinical dichotomy.

We evaluate classification tasks using the area under the receiver operating characteristic curve (AUC), reported as the macro-average across classes for multi-class settings. Regression tasks are evaluated using mean absolute error (MAE). For datasets evaluated on a held-out test set, 95% confidence intervals for both AUC and MAE are estimated via bootstrap resampling ($n = 1{,}000$). For datasets evaluated under cross-validation, mean performance across folds is reported. To compare results across tasks with mixed metrics, we also report mean reciprocal rank (MRR) by ranking models on each task within a speech-production stage and averaging the reciprocal of those ranks across all tasks in the stage. Additional implementation details are provided in Appendix D.

4.4 Implementation Details

Embedding extraction for all 12 encoders across the benchmark was performed on compute nodes with 8× NVIDIA H100 80GB GPUs, with extraction parallelized across multiple GPUs and taking approximately 288 GPU-hours total. GPU utilization averaged 70% due to variable-length audio samples, with outlier samples requiring dedicated GPU memory; batching strategies could further optimize this process. Once embeddings were cached, all linear probing experiments (main benchmark, zero-shot transfer, and data efficiency) were executed locally with 8 concurrent jobs, requiring approximately 20 hours of wall-clock time.

5 Results

5.1 Benchmark Evaluation

Figure 1 shows the performance of 12 state-of-the-art audio encoders across all 27 tasks in SpeechDx according to per-task AUC and MAE results with 95% confidence intervals, alongside category-level and overall MRR scores. The results show that the speech-production taxonomy is a meaningful predictor of task difficulty. Conceptualization tasks are consistently difficult, with depression detection (T1) yielding an AUC between 0.40 and 0.65 and depression severity estimation (T2) showing similarly low performance across models. In contrast, tasks belonging to the formulation and neuromuscular articulation stages are more tractable. Aphasia detection (T9) reaches a maximum AUC of 0.97, and the best models exceed an AUC of 0.82 on all neuromuscular articulation classification tasks (T10, T12, T13, T17, T18).

However, performance is not determined by the speech-production stage alone. Although respiratory tasks directly affect breath support and vocal function, performance remains modest across models, with the best AUC reaching 0.79 for COVID-19 detection (T25). In contrast, vocal pathology detection (T27) is substantially more separable, with WavJEPA achieving an AUC of 0.93. This contrast suggests that heterogeneous recording conditions and label noise can attenuate the expected relationship between production-stage proximity and predictive performance. Unlike other datasets, several in the respiratory category are crowdsourced across diverse devices and environments, introducing acquisition variability and confounding factors that obscure the clinical signal.

Overall, no single encoder achieves uniformly strong performance across all conditions impacting speech. The strongest overall models are Whisper (MRR: 0.44), Qwen3-TTS-Tokenizer (MRR: 0.40), and WavLM (MRR: 0.37), whereas wav2vec 2.0 and OPERA are among the weakest performers. The strong aggregate performance of Whisper and Qwen3 suggests an association between scale and broader clinical utility, reflecting their status as the models with the most extensive pretraining. However, overall MRR masks stage-specific variation; emotion2vec+ dominates conceptualization tasks (MRR: 0.77), CLAP and Whisper perform best on neuromuscular articulation tasks (MRR: 0.43 each), and Qwen3 and Whisper lead phonatory / respiratory tasks (MRR: 0.54 and 0.53). These discrepancies indicate that current models encode different dimensions of clinical speech variation, but none provides a representation that generalizes reliably across clinical domains.

		General Speech						General Audio				Domain-specific	
Task	Metric	w2v2	HuBERT	WavLM	MMS	Qwen3	Whisper	AudioMAE	WavJEPA	AST	CLAP	emo2vec+	OPERA
Conceptualization													
T1 (Depression detection)	AUC	0.40 (0.22, 0.58)	0.59 (0.41, 0.75)	0.57 (0.40, 0.73)	0.55 (0.38, 0.70)	0.46 (0.29, 0.63)	0.55 (0.37, 0.72)	0.57 (0.41, 0.72)	0.57 (0.40, 0.74)	**0.65** (0.47, 0.82)	0.54 (0.38, 0.70)	0.64 (0.46, 0.80)	0.43 (0.28, 0.60)
T2 (Depression severity)	MAE ↓	5.46 (4.48, 6.50)	5.45 (4.46, 6.50)	5.37 (4.40, 6.37)	5.46 (4.46, 6.53)	5.31 (4.30, 6.38)	5.34 (4.35, 6.35)	**5.27** (4.31, 6.30)	5.43 (4.44, 6.50)	5.35 (4.36, 6.39)	5.57 (4.56, 6.72)	5.40 (4.44, 6.43)	5.33 (4.34, 6.38)
T3 (Emotion classification)	AUC	0.56 (0.50, 0.63)	0.79 (0.76, 0.83)	0.86 (0.84, 0.88)	0.77 (0.75, 0.78)	0.89 (0.86, 0.91)	0.87 (0.85, 0.90)	0.82 (0.79, 0.85)	0.83 (0.81, 0.85)	0.87 (0.86, 0.89)	0.86 (0.85, 0.88)	**0.98** (0.97, 0.99)	0.71 (0.67, 0.74)
T4 (Binary emotion classification)	AUC	0.60 (0.58, 0.63)	0.73 (0.69, 0.76)	0.76 (0.75, 0.78)	0.63 (0.57, 0.70)	0.78 (0.75, 0.81)	0.82 (0.79, 0.84)	0.71 (0.67, 0.74)	0.73 (0.68, 0.78)	0.77 (0.74, 0.81)	0.75 (0.71, 0.79)	**0.98** (0.96, 0.99)	0.62 (0.58, 0.65)
T5 (Emotion classification)	AUC	0.68 (0.65, 0.70)	0.78 (0.74, 0.82)	0.83 (0.81, 0.85)	0.79 (0.76, 0.82)	0.83 (0.81, 0.86)	0.86 (0.85, 0.88)	0.80 (0.76, 0.83)	0.78 (0.77, 0.80)	0.80 (0.79, 0.82)	0.79 (0.77, 0.81)	**0.92** (0.90, 0.93)	0.74 (0.73, 0.75)
T6 (Binary emotion classification)	AUC	0.64 (0.60, 0.67)	0.69 (0.66, 0.72)	0.76 (0.73, 0.80)	0.64 (0.62, 0.67)	0.78 (0.75, 0.81)	0.76 (0.73, 0.79)	0.70 (0.67, 0.73)	0.68 (0.65, 0.71)	0.71 (0.68, 0.73)	0.69 (0.66, 0.73)	**0.89** (0.88, 0.89)	0.62 (0.60, 0.64)
Mean Reciprocal Rank	MRR	0.09	0.15	0.21	0.11	0.38	0.32	0.29	0.15	0.36	0.14	**0.77**	0.13
Formulation													
T7 (Alzheimer's detection)	AUC	0.65 (0.49, 0.80)	0.58 (0.40, 0.74)	0.69 (0.53, 0.83)	0.62 (0.45, 0.77)	0.74 (0.58, 0.88)	**0.75** (0.59, 0.89)	0.59 (0.42, 0.75)	0.66 (0.47, 0.81)	0.47 (0.29, 0.66)	0.56 (0.37, 0.73)	0.64 (0.47, 0.80)	0.53 (0.35, 0.71)
T8 (Alzheimer's severity)	MAE ↓	6.86 (5.92, 7.82)	6.94 (5.95, 7.90)	8.58 (7.23, 9.87)	6.75 (5.79, 7.70)	10.75 (9.25, 12.20)	9.97 (8.60, 11.33)	6.72 (5.84, 7.73)	9.52 (8.26, 10.81)	8.14 (6.93, 9.36)	9.86 (8.51, 11.17)	6.83 (5.86, 7.84)	**6.09** (5.27, 6.94)
T9 (Aphasia detection)	AUC	0.92 (0.85, 0.97)	0.92 (0.86, 0.97)	0.96 (0.91, 0.99)	0.93 (0.86, 0.98)	**0.97** (0.92, 1.00)	0.92 (0.84, 0.98)	0.90 (0.80, 0.97)	0.92 (0.85, 0.98)	0.95 (0.89, 0.99)	0.95 (0.90, 0.99)	0.67 (0.53, 0.79)	0.94 (0.87, 0.99)
Mean Reciprocal Rank	MRR	0.17	0.14	0.32	0.21	**0.53**	0.41	0.24	0.16	0.16	0.18	0.17	0.43
Articulation (Neuromuscular)													
T10 (Dysarthria detection)	AUC	0.75 (0.62, 0.88)	0.88 (0.77, 0.99)	0.88 (0.76, 1.00)	0.75 (0.57, 0.93)	0.87 (0.77, 0.97)	**0.91** (0.84, 0.98)	0.83 (0.67, 0.98)	0.73 (0.53, 0.93)	0.70 (0.46, 0.93)	0.76 (0.57, 0.94)	0.79 (0.71, 0.86)	0.66 (0.44, 0.88)
T11 (Dysarthria severity)	MAE ↓	0.67 (0.49, 0.85)	0.51 (0.35, 0.67)	0.63 (0.37, 0.90)	0.53 (0.20, 0.87)	0.54 (0.33, 0.75)	**0.43** (0.27, 0.59)	0.56 (0.37, 0.75)	0.57 (0.23, 0.92)	0.48 (0.29, 0.68)	0.56 (0.27, 0.85)	0.69 (0.56, 0.81)	0.79 (0.45, 1.14)
T12 (Dysarthria detection)	AUC	0.83 (0.72, 0.94)	0.94 (0.87, 1.01)	0.96 (0.91, 1.01)	**0.99** (0.98, 0.99)	0.95 (0.90, 0.99)	0.97 (0.92, 1.01)	0.94 (0.88, 1.00)	0.95 (0.90, 1.01)	0.97 (0.94, 1.00)	0.97 (0.94, 0.99)	0.82 (0.69, 0.94)	0.94 (0.91, 0.98)
T13 (Parkinson's detection)	AUC	0.52 (0.37, 0.67)	0.60 (0.53, 0.66)	0.81 (0.75, 0.88)	0.73 (0.59, 0.86)	0.67 (0.51, 0.83)	0.73 (0.65, 0.81)	0.81 (0.64, 0.98)	0.66 (0.49, 0.84)	**0.82** (0.74, 0.91)	0.81 (0.76, 0.87)	0.74 (0.58, 0.89)	0.80 (0.75, 0.85)
T14 (Parkinson's severity)	MAE ↓	0.49 (0.30, 0.67)	0.51 (0.34, 0.67)	0.47 (0.29, 0.65)	0.62 (0.53, 0.71)	0.42 (0.30, 0.54)	0.49 (0.40, 0.57)	0.49 (0.35, 0.63)	0.49 (0.30, 0.69)	0.43 (0.31, 0.56)	0.41 (0.28, 0.54)	**0.41** (0.30, 0.51)	0.44 (0.32, 0.55)
T15 (Parkinson's severity)	MAE ↓	0.55 (0.41, 0.69)	0.57 (0.42, 0.71)	0.54 (0.40, 0.67)	0.64 (0.55, 0.73)	0.51 (0.44, 0.59)	0.49 (0.42, 0.55)	0.58 (0.44, 0.71)	0.56 (0.42, 0.71)	0.43 (0.35, 0.52)	**0.41** (0.29, 0.53)	0.47 (0.36, 0.59)	0.53 (0.41, 0.66)
T16 (Parkinson's severity)	MAE ↓	1.21 (1.06, 1.36)	1.19 (1.06, 1.32)	1.15 (0.98, 1.33)	1.20 (1.05, 1.36)	1.08 (0.98, 1.17)	1.17 (1.08, 1.26)	1.17 (1.09, 1.24)	1.23 (1.08, 1.38)	0.96 (0.80, 1.11)	**0.84** (0.56, 1.12)	1.09 (0.99, 1.19)	1.07 (0.90, 1.24)
T17 (Disfluency detection)	AUC	0.78 (0.73, 0.83)	0.84 (0.81, 0.88)	**0.86** (0.83, 0.88)	0.73 (0.63, 0.83)	0.81 (0.75, 0.86)	0.85 (0.81, 0.89)	0.72 (0.63, 0.81)	0.76 (0.73, 0.79)	0.74 (0.65, 0.83)	0.70 (0.66, 0.73)	0.59 (0.55, 0.64)	0.59 (0.49, 0.70)
T18 (Disfluency classification)	AUC	0.71 (0.69, 0.74)	0.79 (0.77, 0.80)	**0.84** (0.82, 0.85)	0.76 (0.74, 0.78)	0.78 (0.78, 0.79)	0.81 (0.78, 0.83)	0.74 (0.72, 0.76)	0.75 (0.72, 0.77)	0.73 (0.70, 0.76)	0.67 (0.64, 0.70)	0.59 (0.58, 0.61)	0.61 (0.59, 0.63)
Mean Reciprocal Rank	MRR	0.12	0.20	0.40	0.23	0.22	**0.43**	0.15	0.12	0.40	0.43	0.25	0.15
Articulation (Phonatory/Respiratory)													
T19 (Respiratory symptom detection)	AUC	0.56 (0.53, 0.59)	0.63 (0.60, 0.67)	0.68 (0.65, 0.71)	0.65 (0.63, 0.68)	**0.69** (0.66, 0.72)	0.68 (0.65, 0.71)	0.61 (0.58, 0.64)	0.63 (0.60, 0.66)	0.63 (0.60, 0.66)	0.58 (0.55, 0.61)	0.57 (0.54, 0.61)	0.62 (0.58, 0.65)
T20 (Respiratory symptom detection)	AUC	0.56 (0.55, 0.57)	0.60 (0.58, 0.61)	0.65 (0.64, 0.66)	0.62 (0.61, 0.63)	0.64 (0.62, 0.65)	**0.65** (0.64, 0.66)	0.59 (0.58, 0.61)	0.61 (0.59, 0.62)	0.60 (0.58, 0.61)	0.60 (0.58, 0.61)	0.57 (0.55, 0.58)	0.57 (0.55, 0.58)
T21 (COVID-19 detection)	AUC	0.60 (0.51, 0.68)	0.61 (0.52, 0.69)	**0.65** (0.56, 0.72)	0.54 (0.45, 0.64)	0.61 (0.52, 0.69)	0.61 (0.53, 0.69)	0.47 (0.39, 0.54)	0.53 (0.43, 0.61)	0.48 (0.41, 0.56)	0.54 (0.46, 0.62)	0.60 (0.52, 0.68)	0.50 (0.41, 0.59)
T22 (COVID-19 detection)	AUC	0.64 (0.59, 0.69)	0.66 (0.62, 0.71)	0.68 (0.63, 0.73)	0.69 (0.64, 0.74)	0.65 (0.59, 0.70)	**0.70** (0.65, 0.74)	0.62 (0.57, 0.67)	0.66 (0.61, 0.71)	0.64 (0.60, 0.68)	0.62 (0.57, 0.66)	0.54 (0.49, 0.59)	0.64 (0.59, 0.68)
T23 (Respiratory symptom classification)	AUC	0.55 (0.54, 0.56)	0.60 (0.59, 0.60)	0.60 (0.59, 0.61)	0.60 (0.59, 0.61)	0.60 (0.59, 0.61)	**0.61** (0.61, 0.62)	0.57 (0.56, 0.58)	0.59 (0.58, 0.60)	0.58 (0.57, 0.59)	0.58 (0.57, 0.59)	0.56 (0.55, 0.57)	0.57 (0.56, 0.57)
T24 (Respiratory symptom detection)	AUC	0.65 (0.61, 0.69)	0.71 (0.67, 0.75)	0.72 (0.68, 0.76)	0.66 (0.62, 0.70)	**0.73** (0.69, 0.77)	0.72 (0.68, 0.76)	0.68 (0.64, 0.73)	0.66 (0.61, 0.70)	0.69 (0.64, 0.73)	0.66 (0.61, 0.70)	0.66 (0.62, 0.71)	0.64 (0.59, 0.69)
T25 (COVID-19 detection)	AUC	0.74 (0.69, 0.79)	0.74 (0.69, 0.79)	0.77 (0.72, 0.81)	0.73 (0.68, 0.77)	**0.79** (0.74, 0.83)	0.77 (0.72, 0.81)	0.74 (0.70, 0.79)	0.70 (0.65, 0.75)	0.75 (0.70, 0.80)	0.71 (0.66, 0.77)	0.69 (0.65, 0.74)	0.67 (0.62, 0.71)
T26 (Respiratory symptom classification)	AUC	0.56 (0.53, 0.60)	0.58 (0.55, 0.62)	0.59 (0.56, 0.63)	0.57 (0.54, 0.60)	0.60 (0.57, 0.63)	0.59 (0.55, 0.62)	0.58 (0.54, 0.61)	**0.60** (0.57, 0.64)	0.60 (0.57, 0.65)	0.58 (0.55, 0.61)	0.56 (0.53, 0.60)	0.60 (0.56, 0.63)
T27 (Vocal pathology detection)	AUC	0.65 (0.60, 0.71)	0.72 (0.67, 0.78)	0.91 (0.87, 0.95)	0.91 (0.87, 0.95)	0.92 (0.87, 0.95)	0.81 (0.75, 0.86)	0.89 (0.84, 0.93)	**0.93** (0.89, 0.97)	0.91 (0.86, 0.95)	0.91 (0.87, 0.95)	0.67 (0.61, 0.72)	0.89 (0.83, 0.94)
Mean Reciprocal Rank	MRR	0.11	0.20	0.46	0.24	**0.54**	0.53	0.13	0.34	0.20	0.14	0.11	0.12
Overall													
Mean Reciprocal Rank	MRR	0.11	0.18	0.37	0.21	0.40	**0.44**	0.18	0.21	0.30	0.24	0.31	0.17

Figure 1: The benchmark evaluation of 12 audio encoders across 27 clinical speech tasks, grouped according to Berisha and Liss' framework of speech production (26). Classification tasks report AUC and regression tasks report MAE, with 95% bootstrap confidence intervals for tasks evaluated with a held-out test set or (μ - σ, μ + σ) for tasks evaluated with 5-fold cross-validation. MRR is computed within each category and overall. Model names are shortened as follows: w2v2 = wav2vec 2.0, Qwen3 = Qwen3-TTS-Tokenizer, emo2vec+ = emotion2vec+, and OPERA = OPERA-GT.

Domain-specific pretraining yields selective gains. The strong performance of emotion2vec+ on emotion tasks (T3–T6) is likely due to the inclusion of the IEMOCAP dataset in its pretraining corpus (89). Its poor performance on depression detection, a closely related conceptualization-stage

condition, illustrates that domain-specific pretraining does not generalize to even clinically proximate tasks. OPERA, another domain-specific model, shows a similar mismatch. Although pretrained on respiratory audio, it performs weakly on respiratory tasks (MRR: 0.12) and is instead most competitive on formulation tasks (MRR: 0.43). These patterns suggest that narrow domain alignment between pretraining and downstream tasks is insufficient for general clinical speech understanding. Additionally, to assess performance under data scarcity, a central constraint in clinical settings, we conduct data efficiency experiments varying training set size from 12.5% to 100% for the top three models, with results reported in Appendix E. Additional analyses examine sensitivity to temporal aggregation across all encoders in Appendix G and parameter-efficient adaptation for three leading encoders in Appendix H.

5.2 Zero-shot Cross-condition Transfer

To assess whether the representations learned by current audio encoders capture clinical structure beyond dataset-specific artefacts, we evaluate zero-shot transfer between datasets. Figure 2 reports the best zero-shot AUC and the corresponding model for each source–target pair; for cross-category transfer, source and target datasets are pooled within each stage. Complete results for all models and all transfer pairs are provided in Appendix F.

Within-category transfer. For many source–target pairs within a production stage, the best zero-shot transfer approaches within-dataset performance, with several cases meeting or exceeding it. Transfer is consistently weaker across phonatory / respiratory tasks (AUC: 0.57–0.69), identifying this category as the most resistant to cross-dataset generalization. Notably, the best zero-shot model differs from the best within-dataset model in roughly two-thirds of all source–target pairs. For example, AudioMAE exceeds the best within-dataset performance on Parkinson's detection when trained on UASpeech, and Whisper leads dysarthria-to-dysarthria transfer over the within-dataset leader MMS, indicating that within-dataset and zero-shot regimes reward different representational properties.

Cross-condition transfer. Across production stages, transfer is variable but reveals a clear asymmetry. Representations trained on phonatory / respiratory data transfer into conceptualization and formulation tasks at AUCs of 0.83 (emotion2vec+) and 0.88 (HuBERT) respectively, while transfer in the reverse direction does not exceed an AUC of 0.60. Notably, model rankings observed in the within-dataset evaluation do not predict cross-category transfer performance. Qwen3 achieves the highest within-dataset performance on phonatory / respiratory tasks but fails to transfer across categories, while emotion2vec+, which ranks poorly on phonatory / respiratory tasks within-dataset (MRR: 0.11), leads cross-category transfer to phonatory / respiratory targets. Progress on clinical speech AI will require representations that maintain performance across regimes, rather than models that excel within a single dataset; closing this gap remains an open challenge for future work.

6 Broader Impact and Limitations

Speech-based health assessment could transform everyday devices into diagnostic tools, extending healthcare access to underserved populations. The ubiquity of microphones available in smartphones, smart speakers, and even earbuds enables frequent monitoring with minimal user effort. These opportunities not only circumvent the logistical barriers inherent in traditional clinical assessments but also enable the capture of subtle physiological shifts.

Realizing the full diagnostic potential of clinical speech AI requires representations that generalize across conditions, populations, and recording settings. In pursuit of this objective, SpeechDx provides a unified evaluation infrastructure to drive progress toward clinically deployable models while ensuring that performance gains are meaningful rather than driven by dataset idiosyncrasies.

One key consideration for SpeechDx is the utility and objectivity of the underlying labels for each dataset. The majority of tasks are designed to reveal acoustic markers that classify people with and without a medical condition. The resulting markers would ideally be used to screen people with nascent symptoms; however, these datasets typically comprise people who are either completely healthy or have lived with the condition for multiple years. Several other tasks rely on patients' or clinicians' answers to standardized questionnaires (e.g., PHQ-8 (91), UPDRS (92)). Although the



Figure 2: The evaluation of zero-shot transfer for classification tasks. The top four grids show transfer across tasks within the same category, while the bottom grid shows averaged cross-category performance. Each cell reports the best model and the AUC it achieved for the given task.

questionnaires are clinically validated and human-reported responses should not be discredited, there is unavoidable subjectivity associated with anchoring bias, recall bias, and person-specific internal scaling that may obscure physiological information (93; 94).

Another consideration relates to the diversity of human subjects across the benchmark. SpeechDx primarily comprises English-language recordings, though diverse regional accents are represented through datasets collected outside North America. We did not conduct a formal analysis of how this factor might have confounded our zero-shot analysis, so this remains an opportunity for future work. Sex and age are other demographic factors that warrant further investigation, particularly since certain populations are predisposed to specific conditions (e.g., elderly women and dementia (95)).

Lastly, SpeechDx does not exhaustively cover the clinical domains in which speech-based assessment has shown promise. Conditions such as Huntington's disease (96), pediatric speech sound disorders (97), and chronic obstructive pulmonary disease (98; 36) are a subset of the diverse clinical domains where vocal biomarkers have shown promise, yet publicly available datasets are either unavailable or not sizable enough for thorough evaluation. Subsequent iterations will incorporate these and other emerging areas to provide an increasingly comprehensive evaluation of clinical speech AI.

7 Conclusion

SpeechDx establishes a comprehensive evaluation framework for clinical speech AI. While large-scale general-purpose speech models currently provide the most robust baselines, experiments with our benchmark reveal that no single representation yet generalizes reliably across the diverse clinical landscape. Moreover, cross-condition transfer analyses demonstrate critical gaps in model robustness and data efficiency. Ultimately, SpeechDx serves as a foundation for tracking progress toward truly generalizable representations capable of supporting real-world clinical monitoring.

AI USE STATEMENT

Generative AI tools were used for limited assistance with manuscript preparation, including language editing, organization, summarization of author-generated experimental results, and peripheral code refactoring and documentation. They were not used to develop the core methodology, generate or modify data, implement the core experimental pipeline, execute experiments, or produce the reported results. All AI-assisted material was reviewed by the authors, and numerical statements were verified against the original experimental outputs. We take responsibility for the final content of this work, including text, claims, and artifacts produced with the aid of generative AI.

ETHICS STATEMENT

This work involves no new human-subject recruitment or data collection. It uses previously published datasets made available through their respective access procedures and in accordance with their usage terms. The original studies obtained informed consent and institutional ethics approval, as documented by the dataset providers. Clinical speech can contain sensitive health and identity information, and benchmark performance should not be interpreted as evidence of clinical readiness. Models evaluated using SpeechDx may reflect demographic, linguistic, and recording biases present in the underlying datasets. Thus, any patient-facing use would require independent clinical validation and appropriate assessment of privacy, fairness, and regulatory requirements.

REPRODUCIBILITY STATEMENT

The main text describes the benchmark construction, task definitions, and common evaluation protocol. Appendices A and B provide dataset and task details, Appendix C documents the evaluated encoders, and Appendix D reports preprocessing, training, model-selection, and implementation details. Subsequent appendices provide complete results and configurations for the data efficiency, cross-dataset, temporal-aggregation, and parameter-efficient adaptation analyses. We provide an anonymized implementation in the supplementary material and will also be made available online at **REDACTED**, including speaker-disjoint splits, preprocessing and representation-extraction pipelines, experiment configurations, and evaluation scripts. The underlying datasets can be obtained from their original providers under their respective access and usage terms.

APPENDIX FOR SPEECHDX

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A DATASET DETAILS

This section provides a comprehensive description of the datasets utilized within the SpeechDx benchmark. The datasets are categorized according to the specific stage of speech production they represent. For each dataset, we describe the recruitment procedure, study protocol, and labeling process. Their access methods and licenses are listed in Table 2.

A.1 CONCEPTUALIZATION

Extended Distress Analysis Interview Corpus, Wizard-of-Oz (EDAIC-WOZ) (65) was developed at the Institute for Creative Technologies at the University of Southern California. A total of 275 participants (170 male, 105 female) drawn from the general population and American military veterans completed semi-structured clinical interviews with a virtually animated interviewer covering topics related to psychological distress, daily functioning, and mood, lasting approximately 16 minutes. For the 163 training and 56 validation participants, the interviewer was controlled by a human operator via a Wizard-of-Oz paradigm, while the 56 test participants were interviewed by a fully autonomous system, introducing a distributional shift relative to the training data. Prior to each interview, participants completed the Patient Health Questionnaire (PHQ-8) for depression severity (91); scores of 10 or above indicate a depressive disorder, yielding binary depression labels.

Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) (66) comprises 24 professional actors (12 female, 12 male) narrating two lexically matched statements (*"Kids are talking by the door"* and *"Dogs are sitting by the door"*) in a neutral North American English accent while expressing one of eight emotions: neutral, calm, happy, sad, angry, fearful, disgust, and surprised. Each emotion (except neutral) was produced at two intensity levels (normal and strong), yielding 60 recordings per actor. The speech subset is sampled at 48 kHz. Each recording was rated 10 times for emotional validity, intensity, and authenticity by 247 untrained participants with high inter-rater reliability. The dataset is fully balanced across actors, emotions, and intensity levels.

Interactive Emotional Dyadic Motion Capture (IEMOCAP) (67) was collected at the Speech Analysis and Interpretation Laboratory at the University of Southern California. The corpus contains approximately 12 hours of audiovisual recordings from 10 actors (5 male, 5 female) across five dyadic sessions, each with a unique male-female actor pair. Within each session, actors performed both scripted emotional dialogues and improvised hypothetical scenarios designed to elicit a range of emotional states. Utterances were segmented and annotated by trained raters using categorical emotion labels and dimensional ratings (valence, activation, dominance). The original annotations include neutral, happiness, sadness, anger, surprise, fear, disgust, frustration, excited, and other emotional states. Following standard practice (67), we use a four-class subset in which *excited* is merged with *happy*, *frustration* with *anger*, and *fear*, *disgust*, *surprise*, and *other* are excluded due to their limited representation.

Table 2: Access and licensing information for each dataset in SpeechDx.

Category	Dataset	Link	Availability	License
Conceptualization	EDAIC-WOZ (65)	https://dcapswoz.ict.usc.edu/	Available on request	DAIC-WOZ EULA
	RAVDESS (66)	https://zenodo.org/records/1188976	Open access	CC BY-NC-SA 4.0
	IEMOCAP (67)	https://sail.usc.edu/iemocap/iemocap_release.htm	Available on request	Custom
Formulation	DementiaBank (99; 68)	https://talkbank.org/dementia/	Available on request	TalkBank CC BY-NC-SA 3.0
	AphasiaBank (69)	https://talkbank.org/aphasia/	Available on request	TalkBank CC BY-NC-SA 3.0
Articulation (Neuromuscular)	TORGO (70)	https://www.cs.toronto.edu/~complingweb/data/TORGO/torgo.html	Open access	Custom
	UASpeech (71)	https://speechtechnology.web.illinois.edu/uaspeech/	Available on request	Custom
	MDVR-KCL (72)	https://zenodo.org/records/2867216	Open access	CC BY 4.0
	KSoF-C (17)	https://zenodo.org/records/7258757	Available on request	EULA KSoF Challenge
Articulation (Phonatory / Respiratory)	COVID-19 Sounds (74)	https://covid-19-sounds.org/en/blog/neurips_dataset	Available on request	Custom
	Coswara (75)	https://github.com/iiscleap/Coswara-Data	Open access	CC BY 4.0
	AVFAD (76)	https://acsa.web.ua.pt/AVFAD.htm	Available on request	Custom

A.2 Formulation

DementiaBank (ADReSS-M subset (68)) was collected as part of the Alzheimer and Related Dementias Study at the University of Pittsburgh. Participants completed the Cookie Theft Picture Description Task from the Boston Diagnostic Aphasia Examination (100), producing spontaneous speech descriptions of a kitchen scene. Participants also completed the Mini-Mental State Examination (MMSE) (101) to assess their level of cognitive impairment. We use the ADReSS-M challenge subset (68), released for the ICASSP 2023 Signal Processing Grand Challenge on multilingual Alzheimer's dementia recognition. The subset is statistically matched to mitigate common evaluation biases including repeated recordings from the same participant, audio quality variation, and demographic imbalance. The training partition consists of English-language recordings, and the test partition consists of Greek-language recordings from a separate cohort, making this the only cross-lingual evaluation in the benchmark.

AphasiaBank (69) is a publicly available database of structured discourse samples from individuals with post-stroke aphasia and neurologically healthy controls, hosted by the TalkBank consortium. We use a subset drawn from five sites — Adler, Kansas, Kurland, SCALE, and Wright — retaining first-session recordings only, yielding 206 participants (119 persons with aphasia, 87 controls). Persons with aphasia ranged in age from 36 to 91 years and spanned mild to severe impairment as measured by the Western Aphasia Battery Aphasia Quotient (102) (mean 67.6 ± 22.1). Aphasia types included Anomic, Broca's, Conduction, Wernicke's, and several transcortical variants. Each participant completed the AphasiaBank Discourse Protocol, from which we extracted four discourse tasks: (1) Cinderella story retell, (2) window picture sequence, (3) umbrella picture sequence, and (4) cat picture sequence.

A.3 Articulation (Neuromuscular)

TORGO (70) contains approximately 8 hours of English speech from 15 speakers: 8 with dysarthria (5 male, 3 female) resulting from cerebral palsy or ALS, and 7 age- and gender-matched healthy controls (4 male, 3 female). Speech was recorded using a head-mounted microphone and a directional microphone, but we only use the head-mounted channel. Speech material was drawn from multiple sources including the TIMIT database (103), lists of identified phonetic contrasts, and standardized speech intelligibility assessments. Each dysarthric speaker was assessed by a speech-language pathologist using the Frenchay Dysarthria Assessment (104).

UASpeech (71) contains isolated word recordings from 15 speakers with cerebral palsy and 13 age-matched healthy controls. Each participant uttered 765 isolated words: 300 uncommon words,

3 repetitions of 100 common words, and 165 digits, radio alphabet letters, and computer commands. Audio was recorded using an 8-microphone array, but we use the single close-talking microphone channel. Intelligibility was assessed by five listeners who transcribed the recordings word by word; each speaker's intelligibility score was computed as the average percentage of words correctly transcribed. Speakers were subsequently grouped into four intelligibility categories: very low, low, mid, and high. The distribution of dysarthric speakers across these categories is skewed toward lower intelligibility, with the very low and low groups together accounting for the majority.

MDVR-KCL (72) was released by King's College London and contains speech recordings from 37 participants: 16 with Parkinson's disease and 21 healthy controls. Recordings were made at 44.1 kHz in a phone-call scenario where participants held the recording device to their preferred ear. Participants read two passages: the fable *North Wind and the Sun* and an excerpt from *Computer Applications in Geography*. Each participant was assessed along three clinically validated scales by experts: the Hoehn and Yahr (H&Y) scale (105), Unified Parkinson's Disease Rating Scale (UPDRS) Part II Item 5 (activities of daily living and speech), and UPDRS Part III Item 18 (motor examination and speech) (92).

KSoF-C (17) is a subset of the Kassel State of Fluency (KSoF) dataset (73), a German-language stuttering corpus recorded during therapy sessions. The full KSoF corpus contains 5,597 three-second clips extracted from 214 recordings of 37 persons who stutter (28 male, 9 female). A distinctive property of this corpus is that all speakers had undergone fluency-shaping therapy, making it the only public dataset to include post-therapy stuttered speech; therefore, speakers exhibit both dysfluent events and therapy-specific speech modifications alongside fluent speech. Clips were annotated with one of six labels by three trained annotators: blocks, prolongations, sound repetitions, word repetitions, interjections, and speech modifications. KSoF-C is the subset released for the ACM Multimedia 2022 ComParE challenge (17); we use this split with its predefined train, validation, and test partitions.

A.4 Articulation (Phonatory / Respiratory)

COVID-19 Sounds (74) was collected by the University of Cambridge via a smartphone and web application. We use the speech recordings, in which participants read the sentence *"I hope my data can help to manage the virus pandemic"* three times in their native language. The full corpus contains 53,449 samples from 36,116 participants, totaling over 552 hours of audio. Along with audio, the participants self-reported their COVID-19 status and respiratory symptoms. The dataset comes with two curated subsets widely used for benchmarking: one balanced for respiratory symptoms and the other balanced for COVID-19 status, each screened for recording quality and released as controlled English-language partitions.

Coswara (75) was collected by the Indian Institute of Science via Android and Web applications. We use the normal-pace counting speech recordings, in which participants count from 1 to 20 in English. Participants self-reported their symptoms and COVID-19 status by selecting one of three categories: negative, positive, or recovered. The control group is heterogeneous, comprising completely healthy individuals alongside those with respiratory ailments and COVID-like symptoms, reflecting realistic variability in population-level screening settings.

Advanced Voice Function Assessment Databases (AVFAD) (76) contains Portuguese recordings from 709 individuals: 346 with clinically diagnosed vocal pathology and 363 without vocal alterations. The pathological group encompasses 26 distinct diagnoses, the most prevalent being vocal fold nodules, polyps, cysts, and Reinke's edema. All diagnoses were registered according to the Classification Manual of Voice Disorders-I (106).

B Task Details

This section provides a detailed description of all 27 tasks formulated in the SpeechDx benchmark. The tasks are again organized by the stage of speech production. For each task, we describe the prediction target, the dataset used, and any relevant details regarding label construction or subset selection. The demographic statistics are summarized in Table 3.

B.1 CONCEPTUALIZATION

T1. This task aims to classify speakers in the EDAIC-WOZ dataset (65) as either depressed or healthy. The EDAIC-WOZ dataset contains clinical interview recordings of participants scored on the PHQ-8 depression scale (91), where speakers with a score of 10 or above are labeled as depressed.

Table 3: Demographic data and label distributions for each task in SpeechDx. Label distributions are reported as healthy % / disease % for binary classification tasks and as [range of label], mean ± standard deviation for regression tasks. Details are directly reported from publications and documentation.

Category	Dataset	ID	Country	Age	Sex	Label Distribution
Conceptualization	EDAIC-WOZ (65)	T1	USA	N/A	M: 61.8% F: 38.2%	24.0% / 76.0%
		T2	USA	N/A	M: 61.8% F: 38.2%	$[0, 23],\ \mu = 6.94 \pm 6.11$
	RAVDESS (66)	T3	Canada	N/A	M: 50% F: 50%	Calm: 13.3%; Happy: 13.3%; Sad: 13.3%; Angry: 13.3%; Fearful: 13.3%; Disgust: 13.3%; Surprised: 13.3%; Neutral: 6.7%
		T4	Canada	N/A	M: 50% F: 50%	53.3% / 46.7%
	IEMOCAP (67)	T5	USA	N/A	M: 50.8% F: 49.2%	Neutral: 23.1%; Anger / Frustrated: 40.0%; Sad: 14.7%; Happy / Excited: 22.2%
		T6	USA	N/A	M: 50.8% F: 49.2%	54.7% / 45.3%
Formulation	DementiaBank (99)	T7	USA; Greece	$\mu = 68.1 \pm 7.0$	M: 33.0% F: 67.0%	50.9% / 49.1%
		T8	USA; Greece	$\mu = 68.0 \pm 7.0$	M: 32.8% F: 67.2%	$[3, 30],\ \mu = 23.58 \pm 6.61$
	AphasiaBank (69)	T9	USA	$\mu = 62.4 \pm 13.6$	M: 55.4% F: 44.2%	72.0% / 28.0%
Articulation (neuromuscular)	TORGO (70)	T10	Canada	N/A	M: 58.1% F: 41.9%	33.8% / 66.2%
		T11	Canada	N/A	M: 55.0% F: 45.0%	$[1, 3],\ \mu = 1.84 \pm 0.94$
	UASpeech (71)	T12	USA	N/A	M: 71.4% F: 28.6%	53.6% / 46.4%
	MDVR-KCL (72)	T13	UK	N/A	N/A	42.5% / 57.5%
		T14	UK	N/A	N/A	$[0, 3],\ \mu = 0.34 \pm 0.65$
		T15	UK	N/A	N/A	$[0, 3],\ \mu = 0.40 \pm 0.70$
		T16	UK	N/A	N/A	$[0, 4],\ \mu = 1.10 \pm 1.36$
	KSoF-C (73)	T17	Germany	N/A	M: 86.0% F: 14.0%	74.1% / 25.9%
		T18	Germany	N/A	M: 86.2% F: 13.8%	Block: 20.7%; Prolongation: 12.0%; Sound rep.: 14.8%; Word rep.: 3.9%; Modified: 24.4%; Interjection: 13.0%; No dysfluency: 24.7%; Garbage: 3.1%
Articulation (phonatory / respiratory)	COVID-19 Sounds (74)	T19	Intl.	$\mu = 39.4 \pm 14.1$	M: 46.4% F: 52.3% Unk.: 1.2%	48.7% / 51.3%
		T20	Intl.	$\mu = 39.2 \pm 15.2$	M: 61.6% F: 37.2% Unk.: 1.2%	52.5% / 47.5%
		T21	Intl.	$\mu = 40.0 \pm 13.7$	M: 50.9% F: 48.4% Unk.: 0.7%	49.4% / 50.6%
		T22	Intl.	$\mu = 41.3 \pm 14.4$	M: 56.0% F: 42.9% Unk.: 1.1%	19.6% / 80.4%
		T23	Intl.	$\mu = 36.9 \pm 14.1$	M: 56.3% F: 42.6% Unk.: 1.2%	Dry cough: 49.2%; Wet cough: 23.0%; Fever: 8.1%; Headache: 22.9%; Muscle ache: 14.2%; Dizziness: 6.7%; Sore throat: 27.8%; Short breath: 13.0%; Tightness: 12.8%; Runny/blocked nose: 5.3%; Smell/taste loss: 6.1%; Runny: 16.3%
	Coswara (75)	T24	India	$\mu = 35.1 \pm 14.1$	M: 69.0% F: 30.9% Unk.: 0.1%	38.6% / 61.4%
		T25	India	$\mu = 35.2 \pm 13.9$	M: 69.9% F: 30.0% Unk.: 0.1%	32.5% / 67.5%

Continued on next page

(Table 3 continued)

Category	Dataset	ID	Country	Age	Sex	Label Distribution
		T26	India	$\mu = 38.6 \pm 16.0$	M: 62.7% F: 37.2% Unk.: 0.1%	Cold: 46.4%; Cough: 61.9%; Fever: 38.7%; Diarrhoea: 5.0%; Loss of smell: 16.2%; Muscular pain: 30.9%; Breathing difficulty: 20.1%; Fatigue: 36.3%; Sore throat: 28.0%; Other respiratory: 6.8%
	AVFAD (76)	T27	Portugal	$\mu = 52.3 \pm 15.8$	M: 29.6% F: 70.4%	48.8% / 51.2%

T2. This task aims to regress the continuous PHQ-8 depression severity score for each speaker in the EDAIC-WOZ dataset (65), using the same recordings as in T1.

T3. This task aims to classify speakers in the RAVDESS dataset (66) into one of seven emotion categories: neutral, calm, happy, sad, angry, fearful, disgust, or surprised. The RAVDESS dataset contains acted speech recordings from 24 professional actors, with each emotion represented equally across speakers.

T4. This task aims to classify speakers in the RAVDESS dataset (66) as either expressing negative or non-negative emotion using the same recordings as T3. Negative emotions comprise sad, angry, fearful, and disgust. Non-negative emotions comprise neutral, calm, happy, and surprised.

T5. This task aims to classify recordings in the IEMOCAP dataset (67) into one of four emotion categories: angry, neutral, happy, or sad. The IEMOCAP dataset contains dyadic conversation recordings across five sessions, with emotion labels assigned through majority agreement among multiple annotators.

T6. This task aims to classify speakers in the IEMOCAP dataset (67) as either expressing negative or non-negative emotion using the same recordings as T5. Negative emotions comprise angry and sad. Non-negative emotions comprise neutral and happy.

B.2 Formulation

T7. This task aims to classify speakers in the ADReSS-M challenge (68) as either having Alzheimer's disease or being cognitively healthy. The ADReSS-M challenge is a subset of the DementiaBank dataset (99) containing picture description recordings from the Cookie Theft task, with binary labels derived from clinical diagnosis of Alzheimer's disease.

T8. This task aims to regress the continuous MMSE cognitive severity score for each speaker in the DementiaBank dataset, using the same picture description recordings as T7. MMSE scores range from 0 to 30, with lower scores indicating greater cognitive impairment.

T9. This task aims to classify speakers in the AphasiaBank dataset (69) as either aphasic or healthy. The AphasiaBank dataset contains standardized discourse recordings from speakers of varying etiology and severity alongside healthy controls.

B.3 Articulation (Neuromuscular)

T10. This task aims to classify speakers in the TORGO dataset (70) as either dysarthric or healthy. The TORGO dataset contains speech recordings from speakers with motor speech disorders of varying etiology and severity alongside healthy controls.

T11. This task aims to regress the dysarthria severity score for each speaker in the TORGO dataset (70), using the same recordings as T10. Severity is rated on a scale from 0 to 3, where higher scores indicate greater articulatory impairment.

T12. This task aims to classify speakers in the UASpeech dataset (71) as either dysarthric or healthy. The UASpeech dataset contains speech recordings from speakers with cerebral palsy alongside healthy controls, with dysarthria severity ranging from mild to profound.

T13. This task aims to classify speakers in the MDVR-KCL dataset (72) as either having Parkinson's disease or being healthy. The MDVR-KCL dataset contains read speech and spontaneous monologue recordings from speakers with Parkinson's disease alongside healthy controls.

T14. This task aims to regress the UPDRS Part II Item 5 score for each speaker in the MDVR-KCL dataset (72), using the same recordings as T13. UPDRS Part II Item 5 is a patient-reported measure of speech impairment in daily living, scored from 0 to 3.

T15. This task aims to regress the UPDRS Part III Item 18 score for each speaker in the MDVR-KCL dataset, using the same recordings as T13. UPDRS Part III Item 18 is a clinician-rated measure of speech quality during motor examination, scored on a scale from 0 to 3.

T16. This task aims to regress the H&Y scale score for each speaker in the MDVR-KCL dataset, using the same recordings as T13. The Hoehn and Yahr scale is a clinician-rated measure of Parkinson's disease progression scored from 0 to 4, where higher scores indicate greater motor impairment.

T17. This task aims to classify speakers in the KSoF-C dataset (73) as either disfluent or fluent. The KSoF-C dataset contains read speech recordings from speakers who stutter alongside fluent controls, with disfluency labels assigned at the utterance level.

T18. This task aims to classify the disfluency type for each utterance in the KSoF-C dataset. This is a multi-label classification task, with each utterance being assigned one or more of six disfluency categories: modified speech, blocks, sound repetitions, interjections, prolongations, and word repetitions. Two additional classes are included to account for utterances with no disfluency and those with poor audio quality or recording errors.

B.4 Articulation (Phonatory / Respiratory)

T19. This task aims to classify speakers in the COVID-19 Sounds dataset (74) as either symptomatic or healthy. The dataset contains crowdsourced speech recordings from participants who reported their symptoms at the time of participation. Those in the symptomatic group reported at least one of the following respiratory symptoms: dry cough, sore throat, wet cough, headache, muscle ache, shortness of breath, chest tightness, fever, dizziness, smell/taste loss or runny nose. This task uses an official curated subset with controlled recording quality, balanced class distribution, and primarily English recordings.

T20. The dataset and prediction target are the same as T19, but T20 is based on the full COVID-19 Sounds dataset (74) rather than the curated subset, resulting in a larger sample size with greater variation in recording quality, language, and class balance.

T21. This task aims to classify speakers in the COVID-19 Sounds dataset (74) as either COVID-19 positive or negative based on their PCR test result. This task uses an official curated subset specifically balanced for COVID-19 status, with controlled recording quality and primarily English recordings.

T22. The dataset and prediction target are the same as T21, but T22 is based on the full COVID-19 Sounds dataset (74) rather than the curated subset, resulting in a heavily imbalanced class distribution with 20% positive and 80% negative cases.

T23. This task aims to classify the respiratory symptom type for each speaker in the COVID-19 Sounds dataset (74). As a multi-label classification task, only speakers who reported at least one symptom are included, with each speaker labeled with one or more of the following symptom categories: dry cough, sore throat, wet cough, headache, muscle ache, shortness of breath, chest tightness, fever, dizziness, smell/taste loss, runny or blocked nose.

T24. This task aims to classify speakers in the Coswara dataset (75) as either symptomatic or healthy, where the symptomatic group consists of participants who reported at least one of the following respiratory symptoms: cough, cold, fever, fatigue, muscle pain, sore throat, breathing difficulty, loss of smell, and diarrhoea.

T25. This task aims to classify speakers in the Coswara dataset (75) as either COVID-19 positive or negative, using the same recordings as T24. The COVID-19 labels are based on self-reported test results and only speakers who reported a test outcome are included.

T26. This task aims to classify the respiratory symptom type for each speaker in the Coswara dataset (75). As a multi-label classification task, only speakers who reported at least one symptom are included, with each speaker labeled with one or more of the following symptom categories: cough, cold, fever, fatigue, muscle pain, sore throat, breathing difficulty, loss of smell, and diarrhoea.

Table 4: The models evaluated on SpeechDx. Pretraining dataset sizes are approximated for models trained on aggregated or pseudo-labeled datasets. FT indicates additional fine-tuning on labeled data.

Model	Objective	Input	Supervision	Pretraining Source	Pretraining Amount (Hours)	Params (M)
wav2vec 2.0 (52)	Contrastive masked prediction	Raw audio	Self-supervised + supervised FT	Libri-Light; FT on LibriSpeech	60k + 960	317
HuBERT (53)	Masked prediction over clustered units	Raw audio	Self-supervised + supervised FT	Libri-Light; FT on LibriSpeech	60k + 960	316
WavLM (54)	Masked prediction + denoising	Raw audio	Self-supervised	Libri-Light + GigaSpeech + VoxPopuli	94k	316
MMS-1B (79)	wav2vec2.0-style SSL	Raw audio	Self-supervised	Multilingual speech corpus	∼500k	1000
Qwen3-TTS-Tokenizer-12Hz (80)	Neural audio codec reconstruction	Raw audio	Self-supervised	Multilingual speech corpus	>5M	150
Whisper Large-v3 (81)	Sequence-to-sequence speech-to-text	Spectrogram	Supervised / pseudo-supervised	Web-scale speech–text pairs	∼5M	1550
AudioMAE (83)	Masked spectrogram reconstruction	Spectrogram	Self-supervised	AudioSet	∼5.8k	85.6
WavJEPA-Nat (84)	Latent representation prediction (JEPA)	Raw audio	Self-supervised	AudioSet (naturalistic scenes)	∼4.8k	∼200
AST (85)	Audio event classification	Spectrogram	Supervised	AudioSet	∼5.8k	86.6
CLAP (86)	Audio–text contrastive learning	Spectrogram	Cross-modal contrastive	LAION-Audio-630K + AudioSet	∼10k	∼400
emotion2vec+ Large (89)	Multi-scale emotion learning	Raw audio	Pseudo-supervised	Large-scale emotional speech	∼160k	∼300
OPERA-GT (90)	Generative reconstruction	Spectrogram	Self-supervised	Multi-source respiratory audio	404	21

T27. This task aims to classify speakers in the AVFAD dataset (76) as either having a vocal pathology or not. The AVFAD dataset contains multiple speech tasks, and we use the read speech recordings for this task.

C Model Details

This section describes the models used in our benchmark, including their training objectives, pretraining data, and the specific variants used. All models are used with publicly available pretrained weights without additional fine-tuning unless otherwise specified.

C.1 Speech Models

wav2vec 2.0 (52) is a self-supervised speech representation model trained using a contrastive objective over discretized latent units. The large (LV-60) configuration is pretrained on approximately 60k hours of Libri-Light (107) and subsequently fine-tuned on 960 hours of LibriSpeech (108) for automatic speech recognition.

HuBERT (Large) (53) is a self-supervised speech model trained via masked prediction of offline cluster assignments derived from k-means clustering of acoustic features. Unlike wav2vec 2.0, it relies on iterative refinement of cluster targets rather than contrastive learning. The large variant is pretrained on 60k hours of Libri-Light (107) and fine-tuned on LibriSpeech (108) for automatic speech recognition.

WavLM (Large) (54) extends HuBERT by incorporating a denoising objective and training on mixtures of overlapping speech to improve robustness to real-world acoustic conditions. It combines masked prediction with augmentation strategies that simulate multi-speaker environments. The large configuration is pretrained on approximately 94k hours of speech spanning Libri-Light (107), GigaSpeech (109), and VoxPopuli (110).

MMS-1B (79) is a multilingual extension of wav2vec 2.0 designed to scale speech representation learning across languages. It is trained using self-supervised learning on approximately 500k hours of speech covering over 1,400 languages. We evaluate the 1B-parameter configuration.

Qwen3-TTS-Tokenizer (12Hz) (80) is a neural audio codec that encodes speech into discrete tokens at a fixed temporal resolution (12.5 Hz) and reconstructs the waveform from these tokens. The model is trained using a self-supervised reconstruction objective on large-scale multilingual speech data as part of the Qwen3-TTS model.

Whisper (Large-v3) (81) is a sequence-to-sequence encoder–decoder model trained to map audio to text. It is trained on approximately 5 million hours of weakly and pseudo-labeled audio–text pairs, enabling robust performance across languages and domains. The model jointly learns multiple tasks including speech recognition, translation, and language identification through task conditioning. We evaluate the Large-v3 configuration.

C.2 General Audio Models

AudioMAE (83) is a masked autoencoder that learns audio representations by reconstructing missing regions of log-mel spectrogram inputs. A large proportion of the input patches are masked during training, encouraging the model to capture global acoustic structure. The base configuration is pretrained on approximately 5.8k hours of audio from AudioSet (82).

WavJEPA-Nat (84) is trained using a joint-embedding predictive architecture that learns to predict high-level latent representations of masked audio segments rather than reconstructing the input signal directly. The model is designed to capture semantic structure while being robust to low-level variations. It is pretrained on AudioSet (82) with additional naturalistic augmentations such as noise and reverberation. We use the naturalistic base variant.

AST (85) adapts vision transformers to audio classification by operating on log-mel spectrogram patches. It leverages ImageNet-pretrained weights for initialization and is fine-tuned on AudioSet (82) for supervised audio classification. This transfer from vision to audio enables strong performance with relatively limited audio data.

CLAP (86) is a dual-encoder model trained to align audio and text representations using a contrastive objective. We evaluate a general-domain configuration trained on diverse audio–text pairs drawn from sources such as LAION-Audio (111) and AudioSet (82) with caption augmentation rather than variants specialized for music or speech.

C.3 Domain-specific Models

emotion2vec+ (Large) (89) is designed to capture emotional characteristics in speech using a multi-stage training pipeline. It first learns representations from labeled emotional speech data and then scales to large unlabeled corpora via pseudo-labeling in a teacher–student framework. The large configuration is trained on emotional speech datasets totaling approximately 160k hours, with filtering applied during training.

OPERA-GT (90) is a domain-specific model designed for respiratory sound analysis. It is trained using a self-supervised generative objective that reconstructs spectrogram representations, along with auxiliary tasks designed to capture clinically relevant acoustic features. The model is pretrained on approximately 400 hours of curated respiratory audio data. We use the generative (GT) variant.

D Implementation Details

This section describes the implementation details of the SpeechDx benchmark, including data augmentation, loss functions, class weighting, and hyperparameter optimization.

D.1 Data Augmentation

To improve robustness and partially compensate for limited dataset sizes, each training sample is augmented to produce additional training instances. Three augmentation strategies are applied jointly:

(1) additive noise drawn from the Microsoft SNSD corpus (112) at a randomly sampled signal-to-noise ratio in $[0, 15]$ dB; (2) convolutive reverberation using room impulse responses from the MIT IR Survey (113); and (3) speed perturbation uniformly sampled from $[90\%, 110\%]$. For COVID-19 Sounds, speed perturbation is restricted to $[95\%, 105\%]$ to preserve the integrity of breathing patterns. Three augmented versions are produced per training sample for most datasets; this is increased to five for MDVR-KCL given its small sample count, and reduced to one for COVID-19 Sounds, where the full dataset is already used in training. Augmentation is applied exclusively to training data; validation and test sets are evaluated on clean audio only. All augmentation is implemented using SpeechBrain (114; 115).

D.2 Training Setup

All binary and multi-label classification tasks are trained with binary cross-entropy loss, multi-class tasks with categorical cross-entropy loss, and regression tasks with weighted mean squared error (MSE). To mitigate the class imbalance that is prevalent across clinical datasets, all tasks use inverse-frequency weighting. For binary and multi-label tasks, positive class weights are computed per label as the ratio of negative to positive samples. For multi-class tasks, per-class weights are computed analogously. For regression tasks, sample weights are assigned via binning. Clinically established severity thresholds directly define the bins when available: MMSE scores are binned as severe (≤ 9), moderate (10–18), mild (19–23), and normal (≥ 24) (101); and PHQ-8 scores are binned as [0–4], [5–9], [10–14], [15–19], and [20+] (91). For tasks with discrete ordinal severity ratings (T11 and T14–T16), bin edges are derived from midpoints between consecutive unique values. Each sample is assigned a weight equal to the inverse frequency of its bin, normalized so that the mean per-sample weight equals 1 to maintain a stable loss scale across tasks.

D.3 Hyperparameter Optimization

For each model-task combination, hyperparameters are selected via Optuna (116) over five trials to optimize validation loss. The learning rate is sampled log-uniformly over $[10^{-4}, 10^{-3}]$ and decayed linearly to one-tenth of its initial value over the training run. Weight decay (L2 regularization) is sampled log-uniformly over $[0.01, 0.1]$. All models are trained with a batch size of 16 in 32-bit floating-point precision for up to 50 epochs. Early stopping is triggered after 5 consecutive epochs without improvement in validation loss; the first 4 epochs are excluded from the early stopping criterion to allow sufficient warm-up. All experiments use a global random seed.

E Data Efficiency Analysis

Clinical speech datasets are typically small, and label acquisition is costly. To characterize how different encoders perform under data scarcity, we train linear probes using 12.5%, 25%, 50%, and 100% of the available training data. This analysis is conducted for Qwen3-TTS-Tokenizer (80), WavLM (54), and Whisper (81), which were identified as the top-performing models in Section 5.1. For each data regime, training subsets are constructed using the same stratification protocol as the main experiments. This ensures that the label distribution is preserved across all data regimes. All models use identical subsampled splits at each fraction, and all probes are evaluated on the same test set. All per-task results are reported in Table 5, while Figure 3 summarizes AUC trajectories grouped by speech production stage.

Qwen3 emerges as the most data-efficient model, leading 11 out of 27 tasks when trained on the least amount of data. Whisper exhibits competitive performance at higher amounts of training data but demonstrates reduced effectiveness at the lowest fraction. WavLM exhibits substantial performance variability across tasks and data regimes; while it achieves strong performance on specific tasks at low amounts of training data (e.g., AUC: 0.54 for T1 at 12.5%, AUC: 0.85 for T12 at 12.5%), it also demonstrates severe performance degradation on others (e.g., AUC: 0.33 for T7 at 12.5%). This variability precludes reliable deployment of WavLM in low-data regimes without task-specific validation.

At the task level, several conditions demonstrate strong performance with minimal training data. Aphasia detection (T9) achieves robust performance even at 12.5% of training data, with Qwen3 reaching an AUC of 0.90 and improving to 0.97 at 100%, indicating that aphasia-relevant speech

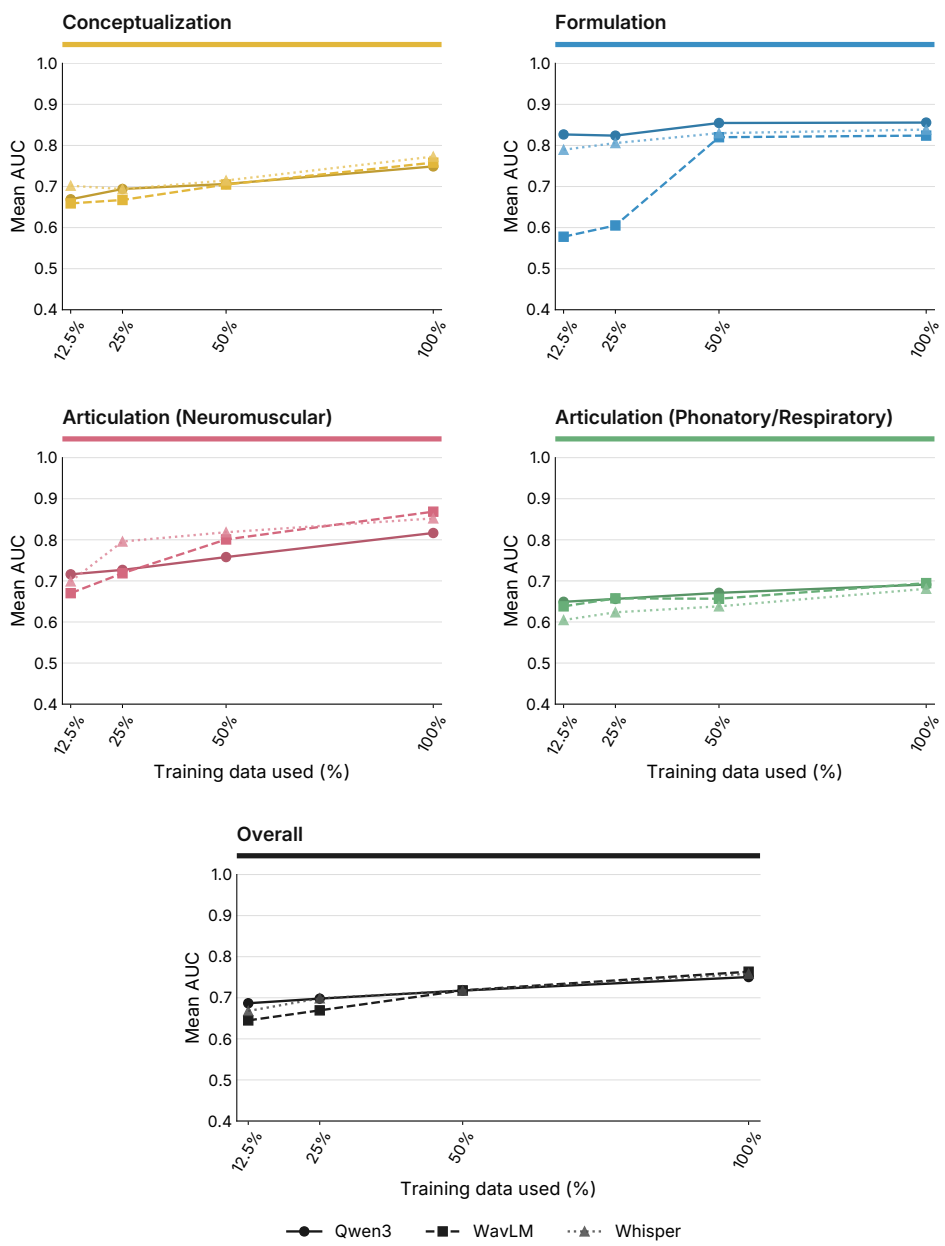

Figure 3: The data efficiency of Qwen3-TTS-Tokenizer (80), WavLM (54), and Whisper (81) with various amounts of training data.

patterns can be captured with limited supervision. Similarly, dysarthria detection (T10, T12), disfluency classification (T18), and multiple respiratory symptom tasks (T19, T20, T21, T23, T25, T26) exhibit relatively flat learning curves, with most models approaching within 0.05-0.10 AUC of their full-data performance using only 25% of the training set.

Parkinson's detection (T13) and Alzheimer's detection (T7) demonstrate the steepest data requirements. For T13, the AUC of Whisper improves from 0.61 to 0.73, while WavLM exhibits a more pronounced improvement from an AUC of 0.56 to 0.81. It is important to note that these proportions of training data reflect different absolute sample sizes across tasks: 12.5% of training data corresponds to as few as 4 training samples for small datasets like MDVR-KCL (37 total subjects) and as many as 3,156 samples for larger datasets like COVID-19 Sounds (25,252 total samples), which partially accounts for the observed task-level variability in data efficiency.

Table 5: Data-efficiency results. Per-task performance for Qwen3, WavLM, and Whisper when trained on 12.5%, 25%, 50%, and 100% of the available training data. Each cell reports the metric value with the bootstrapped 95% confidence interval below. The best of the three models for each task and training fraction is shown in bold.

Task	Metric	12.5%			25%			50%			100%		
		Qwen3	WavLM	Whisper	Qwen3	WavLM	Whisper	Qwen3	WavLM	Whisper	Qwen3	WavLM	Whisper
Conceptualization													
T1 (Depression detection)	AUC	0.43 (0.27, 0.59)	**0.54** (0.36, 0.70)	0.47 (0.29, 0.63)	0.46 (0.29, 0.63)	**0.49** (0.32, 0.65)	0.38 (0.20, 0.55)	0.44 (0.26, 0.61)	**0.47** (0.30, 0.63)	0.39 (0.21, 0.56)	0.46 (0.29, 0.63)	**0.57** (0.40, 0.73)	0.55 (0.37, 0.72)
T2 (Depression severity)	MAE	5.34 (4.34, 6.43)	7.09 (5.67, 8.73)	**5.26** (4.31, 6.23)	**5.25** (4.32, 6.23)	6.62 (5.28, 8.17)	5.25 (4.32, 6.16)	**5.42** (4.34, 6.59)	5.84 (4.74, 7.10)	5.48 (4.45, 6.59)	**5.31** (4.30, 6.38)	5.37 (4.40, 6.37)	5.34 (4.35, 6.35)
T3 (Emotion classification)	AUC	0.74 (0.70, 0.77)	0.72 (0.70, 0.74)	**0.81** (0.80, 0.83)	0.78 (0.74, 0.83)	0.76 (0.72, 0.80)	**0.82** (0.80, 0.84)	0.84 (0.82, 0.86)	0.81 (0.79, 0.84)	**0.85** (0.83, 0.88)	**0.89** (0.86, 0.91)	0.86 (0.84, 0.88)	0.87 (0.85, 0.90)
T4 (Binary emotion classification)	AUC	0.62 (0.58, 0.67)	0.59 (0.48, 0.70)	**0.72** (0.68, 0.75)	0.68 (0.60, 0.75)	0.65 (0.54, 0.76)	**0.76** (0.72, 0.79)	0.66 (0.64, 0.68)	0.70 (0.61, 0.80)	**0.76** (0.73, 0.79)	0.78 (0.75, 0.81)	0.76 (0.75, 0.78)	**0.82** (0.79, 0.84)
T5 (Emotion classification)	AUC	0.81 (0.78, 0.84)	0.78 (0.76, 0.81)	**0.82** (0.80, 0.84)	0.81 (0.78, 0.84)	0.78 (0.76, 0.81)	**0.82** (0.80, 0.84)	0.82 (0.80, 0.85)	0.81 (0.78, 0.84)	**0.84** (0.81, 0.87)	0.83 (0.81, 0.86)	0.83 (0.81, 0.85)	**0.86** (0.85, 0.88)
T6 (Binary emotion classification)	AUC	**0.75** (0.70, 0.79)	0.66 (0.62, 0.70)	0.69 (0.68, 0.71)	**0.75** (0.70, 0.79)	0.66 (0.62, 0.70)	0.69 (0.68, 0.71)	**0.77** (0.74, 0.80)	0.73 (0.70, 0.76)	0.73 (0.70, 0.76)	**0.78** (0.75, 0.81)	0.76 (0.73, 0.80)	0.76 (0.73, 0.79)
Formulation													
T7 (Alzheimer's detection)	AUC	0.75 (0.59, 0.89)	0.33 (0.17, 0.50)	**0.76** (0.61, 0.90)	**0.75** (0.59, 0.89)	0.31 (0.16, 0.49)	0.73 (0.56, 0.87)	**0.76** (0.59, 0.90)	0.69 (0.53, 0.84)	0.75 (0.59, 0.89)	0.74 (0.58, 0.88)	0.69 (0.53, 0.83)	**0.75** (0.59, 0.89)
T8 (Alzheimer's severity)	MAE	**13.44** (11.68, 15.04)	21.92 (20.31, 23.37)	18.87 (17.21, 20.37)	**12.02** (10.35, 13.56)	18.91 (17.25, 20.44)	13.89 (12.15, 15.42)	11.08 (9.44, 12.68)	13.61 (11.93, 15.16)	**9.67** (8.29, 10.98)	10.75 (9.25, 12.20)	**8.58** (7.23, 9.87)	9.97 (8.60, 11.33)
T9 (Aphasia detection)	AUC	**0.90** (0.81, 0.98)	0.83 (0.69, 0.94)	0.82 (0.68, 0.93)	0.90 (0.79, 0.99)	**0.90** (0.79, 0.99)	0.89 (0.78, 0.97)	**0.95** (0.89, 0.99)	0.95 (0.89, 0.99)	0.91 (0.82, 0.98)	**0.97** (0.92, 1.00)	0.96 (0.91, 0.99)	0.92 (0.84, 0.98)
Articulation (Neuromuscular)													
T10 (Dysarthria detection)	AUC	**0.79** (0.67, 0.91)	0.59 (0.44, 0.75)	0.61 (0.38, 0.84)	0.68 (0.37, 0.99)	0.66 (0.48, 0.85)	**0.84** (0.71, 0.97)	0.75 (0.44, 1.06)	0.75 (0.48, 1.03)	**0.87** (0.75, 1.00)	0.87 (0.77, 0.97)	0.88 (0.76, 1.00)	**0.91** (0.84, 0.98)
T11 (Dysarthria severity)	MAE	**0.56** (0.36, 0.76)	0.57 (0.35, 0.78)	0.61 (0.32, 0.89)	0.49 (0.33, 0.65)	0.54 (0.33, 0.74)	**0.37** (0.27, 0.48)	0.61 (0.31, 0.92)	0.61 (0.38, 0.84)	**0.47** (0.29, 0.66)	0.54 (0.33, 0.75)	0.63 (0.37, 0.90)	**0.43** (0.27, 0.59)
T12 (Dysarthria detection)	AUC	**0.93** (0.87, 0.99)	0.85 (0.63, 1.06)	0.90 (0.84, 0.96)	0.92 (0.85, 0.98)	0.90 (0.80, 1.01)	**0.94** (0.87, 1.00)	0.92 (0.81, 1.03)	0.91 (0.76, 1.05)	**0.95** (0.89, 1.01)	0.95 (0.90, 0.99)	0.96 (0.91, 1.01)	**0.97** (0.92, 1.01)
T13 (Parkinson's detection)	AUC	0.55 (0.37, 0.74)	0.56 (0.40, 0.72)	**0.61** (0.50, 0.71)	0.60 (0.41, 0.80)	0.56 (0.45, 0.68)	**0.73** (0.66, 0.81)	0.61 (0.52, 0.70)	**0.74** (0.61, 0.86)	0.72 (0.63, 0.80)	0.67 (0.51, 0.83)	**0.81** (0.75, 0.88)	0.73 (0.65, 0.81)
T14 (Parkinson's severity)	MAE	0.49 (0.38, 0.60)	**0.43** (0.26, 0.60)	0.50 (0.38, 0.61)	0.51 (0.37, 0.64)	**0.43** (0.26, 0.59)	0.51 (0.37, 0.64)	0.48 (0.38, 0.58)	**0.46** (0.30, 0.62)	0.51 (0.38, 0.64)	**0.42** (0.30, 0.54)	0.47 (0.29, 0.65)	0.49 (0.40, 0.57)
T15 (Parkinson's severity)	MAE	0.58 (0.43, 0.73)	**0.50** (0.36, 0.64)	0.57 (0.43, 0.71)	0.62 (0.47, 0.77)	**0.51** (0.37, 0.65)	0.57 (0.43, 0.71)	0.54 (0.46, 0.61)	**0.53** (0.40, 0.67)	0.54 (0.45, 0.63)	0.51 (0.44, 0.59)	0.54 (0.40, 0.67)	**0.49** (0.42, 0.55)
T16 (Parkinson's severity)	MAE	1.19 (1.00, 1.37)	**1.14** (0.93, 1.34)	1.20 (1.04, 1.36)	1.19 (1.00, 1.38)	**1.14** (0.95, 1.33)	1.19 (1.04, 1.34)	1.18 (1.01, 1.34)	**1.16** (0.99, 1.33)	1.18 (1.04, 1.33)	**1.08** (0.98, 1.17)	1.15 (0.98, 1.33)	1.17 (1.08, 1.26)
T17 (Disfluency detection)	AUC	0.68 (0.56, 0.80)	0.71 (0.65, 0.78)	**0.74** (0.69, 0.78)	0.76 (0.66, 0.87)	0.77 (0.68, 0.85)	**0.77** (0.71, 0.83)	0.77 (0.72, 0.83)	**0.82** (0.79, 0.86)	0.79 (0.75, 0.83)	0.81 (0.75, 0.86)	**0.86** (0.83, 0.88)	0.85 (0.81, 0.89)
T18 (Disfluency classification)	AUC	0.62 (0.60, 0.65)	**0.64** (0.61, 0.67)	0.64 (0.57, 0.70)	0.67 (0.63, 0.71)	0.70 (0.66, 0.74)	**0.70** (0.68, 0.72)	0.74 (0.71, 0.76)	**0.78** (0.77, 0.79)	0.76 (0.75, 0.78)	0.78 (0.78, 0.79)	**0.84** (0.82, 0.85)	0.81 (0.78, 0.83)
Articulation (Phonatory / Respiratory)													
T19 (Respiratory symptom detection)	AUC	**0.58** (0.55, 0.61)	0.57 (0.54, 0.61)	0.55 (0.51, 0.58)	0.62 (0.58, 0.65)	**0.63** (0.60, 0.66)	0.57 (0.54, 0.61)	**0.64** (0.60, 0.68)	0.62 (0.59, 0.66)	0.58 (0.55, 0.62)	**0.69** (0.66, 0.72)	0.68 (0.65, 0.71)	0.68 (0.65, 0.71)
T20 (Respiratory symptom detection)	AUC	**0.59** (0.58, 0.60)	0.58 (0.56, 0.59)	0.56 (0.55, 0.58)	0.59 (0.58, 0.60)	0.59 (0.58, 0.61)	**0.60** (0.58, 0.61)	0.61 (0.60, 0.62)	**0.62** (0.60, 0.63)	0.62 (0.60, 0.63)	0.64 (0.62, 0.65)	0.65 (0.64, 0.66)	**0.65** (0.64, 0.66)
T21 (COVID-19 detection)	AUC	**0.64** (0.56, 0.72)	0.54 (0.46, 0.62)	0.49 (0.41, 0.57)	**0.60** (0.52, 0.69)	0.56 (0.48, 0.64)	0.50 (0.41, 0.58)	**0.59** (0.50, 0.67)	0.49 (0.41, 0.56)	0.49 (0.40, 0.57)	0.61 (0.52, 0.69)	**0.65** (0.56, 0.72)	0.61 (0.53, 0.69)
T22 (COVID-19 detection)	AUC	0.63 (0.57, 0.67)	**0.64** (0.58, 0.69)	0.60 (0.55, 0.65)	0.64 (0.59, 0.69)	**0.66** (0.61, 0.71)	0.65 (0.59, 0.69)	0.61 (0.56, 0.66)	**0.65** (0.60, 0.69)	0.62 (0.57, 0.66)	0.65 (0.59, 0.70)	0.68 (0.63, 0.73)	**0.70** (0.65, 0.74)
T23 (Respiratory symptom classification)	AUC	**0.57** (0.57, 0.58)	0.57 (0.56, 0.58)	0.56 (0.55, 0.57)	**0.59** (0.58, 0.59)	0.58 (0.57, 0.59)	0.58 (0.57, 0.58)	0.60 (0.59, 0.60)	0.60 (0.59, 0.60)	**0.60** (0.60, 0.61)	0.60 (0.59, 0.61)	0.60 (0.59, 0.61)	**0.61** (0.61, 0.62)
T24 (Respiratory symptom detection)	AUC	0.68 (0.63, 0.72)	0.68 (0.64, 0.72)	**0.69** (0.65, 0.74)	0.69 (0.64, 0.73)	0.70 (0.66, 0.74)	**0.71** (0.67, 0.75)	0.71 (0.67, 0.76)	0.71 (0.67, 0.75)	**0.72** (0.67, 0.76)	**0.73** (0.69, 0.77)	0.72 (0.68, 0.76)	0.72 (0.68, 0.76)
T25 (COVID-19 detection)	AUC	**0.76** (0.71, 0.81)	0.75 (0.70, 0.79)	0.73 (0.68, 0.77)	0.73 (0.68, 0.78)	0.74 (0.68, 0.78)	**0.75** (0.70, 0.79)	**0.78** (0.73, 0.83)	0.74 (0.69, 0.78)	0.76 (0.71, 0.80)	**0.79** (0.74, 0.83)	0.77 (0.72, 0.81)	0.77 (0.72, 0.81)
T26 (Respiratory symptom classification)	AUC	0.55 (0.51, 0.58)	**0.55** (0.51, 0.58)	0.54 (0.51, 0.57)	0.55 (0.52, 0.59)	**0.56** (0.53, 0.60)	0.55 (0.52, 0.58)	**0.58** (0.54, 0.61)	0.57 (0.53, 0.61)	0.57 (0.53, 0.60)	**0.60** (0.57, 0.63)	0.59 (0.56, 0.63)	0.59 (0.55, 0.62)
T27 (Vocal pathology detection)	AUC	0.85 (0.80, 0.90)	**0.87** (0.83, 0.92)	0.72 (0.67, 0.77)	0.89 (0.85, 0.93)	**0.90** (0.86, 0.94)	0.72 (0.65, 0.78)	0.92 (0.87, 0.95)	**0.92** (0.87, 0.96)	0.79 (0.73, 0.85)	**0.92** (0.87, 0.95)	0.91 (0.87, 0.95)	0.81 (0.75, 0.86)

These results expose substantial heterogeneity in data efficiency across both tasks and models. While the majority of tasks plateau by 25-50% of available training data, specific conditions consistently require larger training sets across all evaluated encoders. Significant instability under data scarcity indicates that current self-supervised speech encoders lack robustness when training supervision is limited. Overall, data efficiency depends critically on the interaction between encoder architecture, pretraining strategy, and the specific acoustic manifestations of each clinical condition.

F Zero-shot Transfer Analysis

Beyond the aggregate cross-category patterns reported in Section 5.2, individual task-level transfer pairs reveal several insights into which clinical manifestations produce generalizable representations and which tasks exhibit fragmentation. Table 6 reports complete zero-shot transfer results for all model-source-target combinations.

Transfer Asymmetries Within Production Stages. Bidirectional transfer within the same production stage reveals which task representations are more generalizable. Alzheimer's → Aphasia (T7 → T9) achieves an AUC of 0.94 (HuBERT) while Aphasia → Alzheimer's (T9 → T7) reaches only 0.74 (Whisper), indicating that dementia-trained representations capture broader language disruption patterns that extend to aphasia, whereas aphasia-specific features are less informative for Alzheimer's detection. Similarly, dysarthria transfer is asymmetric: TORGO → UASpeech (T10 → T12) achieves an AUC of 0.92 (Whisper) while UASpeech → TORGO (T12 → T10) reaches only 0.76. TORGO includes speakers with more severe dysarthria (primarily cerebral palsy), while UASpeech covers a broader range of severities. These asymmetries suggest that certain clinical manifestations yield more generalizable acoustic signatures than others, though the mechanisms differ: severity in the case of dysarthria, and potentially the involvement of multiple linguistic domains in the case of dementia, versus focal language impairment in aphasia.

COVID-19 and Respiratory Task Fragmentation. COVID-19 and respiratory tasks show minimal cross-transfer. COVID-19 Sounds → Coswara achieves a maximum AUC of 0.69 (COVID-19, T21 → T25) and 0.64 (symptoms, T19 → T24). Transfer between vocal pathology (T27) and the respiratory tasks stays at AUC $\leq$ 0.69. This fragmentation reflects differences in recording protocols (cough vs. sustained phonation) or population characteristics, and that current encoders fail to extract protocol-invariant respiratory features.

Sample Size versus Feature Alignment in Emotion → Depression Transfer. Emotion-labeled data provides modest benefits for depression detection, likely through sample size rather than feature alignment. Emotion → Depression transfer (maximum AUC: 0.75) exceeds performance when trained and tested for depression itself (maximum AUC: 0.65), but the gain is small relative to the multi-fold increase in training samples (4,246 vs. 163), indicating that general affective prosody and clinical depression capture partially overlapping but distinct acoustic patterns.

Cross-category Transfer Reveals Acoustic Hierarchy. Phonatory / Respiratory → Conceptualization (maximum AUC: 0.83) and Phonatory / Respiratory → Formulation (maximum AUC: 0.88) succeed, while reverse transfers fail (AUC $\leq$ 0.60). Conceptualization tasks produce the weakest cross-category transfer as sources (AUC $\leq$ 0.67). This asymmetry suggests that low-level acoustic features, such as voice quality and phonation characteristics, provide useful priors for higher-level cognitive-linguistic tasks, raising the possibility that multi-stage screening pipelines could leverage simpler phonatory tasks as initial filters before deploying more specialized models for cognitive assessment.

G Sensitivity to Temporal Aggregation

The primary evaluation of SpeechDx uses global mean pooling because it is computationally efficient and provides a standardized measure of information immediately accessible from each frozen representation. However, global averaging may suppress short or unevenly distributed events. Therefore, to assess the effect of temporal aggregation, we repeat the evaluation using attentive statistical pooling (ASP) across all 12 encoders and 27 tasks. ASP learns task-specific attention weights over frame-level outputs and summarizes their weighted mean and standard deviation while keeping the encoder frozen. Since the attention weights are additional trainable parameters, we do not treat ASP as a replacement for the primary protocol. Its results reflect both representation content and the ability of a more expressive downstream model to access that content.

Figure 4 reports relative performance change with respect to linear probe. ASP improves 204 of 252 classification tasks and increases aggregate mean AUC from 0.712 to 0.755. For regression, ASP reduces MAE in 63 of 72 tasks, improves five of six task-level averages, and yields a mean relative MAE reduction of 21.4%. However, the gains are not uniform. ASP does not improve 46 classification pairs or nine regression pairs and produces only marginal average classification gains for emotion2vec+ (+0.003 AUC) and OPERA (+0.005).

Encoder rankings are also sensitive to the aggregation strategy. The best performing model changes for 19 of 27 tasks. These shifts suggest that task-specific temporal weighting can recover information obscured by global averaging. They may also reflect the additional capacity of ASP and its sensitivity to optimization on small clinical datasets. We therefore retain mean pooling as the primary benchmark protocol for controlled and reproducible representation comparison.

H Targeted Parameter-efficient Adaptation

The primary evaluation of SpeechDx keeps encoder parameters frozen. To assess whether strong representations benefit from parameter-efficient adaptation, we apply LoRA (117) to WavLM, Qwen3-TTS-Tokenizer, and Whisper across all 27 tasks. These encoders were selected based on their performance in the primary linear probe evaluation. LoRA applies a low-rank update $\Delta W = (\alpha/r)BA$ to the query and value projections while keeping the pretrained weights frozen. We use rank $r = 8$, $\alpha = 16$, and adapter dropout $p = 0.05$. We restrict this analysis to three encoders because task-specific adaptation is substantially more computationally expensive than probing cached frozen representations.

Table 6: Zero-shot transfer performance within and across categories, reported as AUC with 95% confidence intervals.

Source Task ID	Source Task	Target Task ID	Target Task	Qwen3	WavLM	AST	AudioMAE	CLAP	emotion2vec+	HuBERT	MMS	OPERA-GT	wav2vec 2.0	WavJEPA	Whisper
Conceptualization															
T4	Emotion Classification	T6	Emotion Classification	0.49 (0.48, 0.50)	0.49 (0.46, 0.52)	0.57 (0.54, 0.59)	0.54 (0.52, 0.56)	0.50 (0.48, 0.52)	**0.86** (0.84, 0.87)	0.44 (0.41, 0.47)	0.49 (0.47, 0.51)	0.56 (0.54, 0.57)	0.37 (0.34, 0.40)	0.55 (0.54, 0.57)	0.58 (0.56, 0.60)
T6	Emotion Classification	T4	Emotion Classification	0.56 (0.52, 0.60)	0.54 (0.48, 0.60)	0.58 (0.55, 0.62)	0.65 (0.61, 0.69)	0.56 (0.52, 0.59)	**0.82** (0.79, 0.84)	0.59 (0.54, 0.63)	0.44 (0.40, 0.48)	0.51 (0.47, 0.55)	0.41 (0.38, 0.43)	0.62 (0.59, 0.65)	0.71 (0.67, 0.75)
T6	Emotion Classification	T1	Depression Detection	0.58 (0.50, 0.65)	0.50 (0.43, 0.58)	0.41 (0.34, 0.48)	0.44 (0.36, 0.52)	0.48 (0.41, 0.56)	**0.75** (0.68, 0.81)	0.56 (0.48, 0.64)	0.43 (0.35, 0.51)	0.45 (0.37, 0.53)	0.54 (0.46, 0.63)	0.58 (0.50, 0.65)	0.50 (0.43, 0.57)
T4	Emotion Classification	T1	Depression Detection	0.38 (0.31, 0.46)	0.41 (0.33, 0.50)	0.39 (0.31, 0.46)	0.39 (0.32, 0.47)	0.55 (0.48, 0.63)	**0.74** (0.67, 0.80)	0.47 (0.39, 0.56)	0.58 (0.49, 0.66)	0.40 (0.32, 0.48)	0.46 (0.38, 0.55)	0.57 (0.49, 0.65)	0.40 (0.33, 0.47)
T1	Depression Detection	T4	Emotion Classification	0.35 (0.31, 0.38)	0.56 (0.51, 0.60)	0.43 (0.40, 0.46)	0.45 (0.42, 0.48)	0.53 (0.49, 0.57)	**0.93** (0.90, 0.95)	0.40 (0.36, 0.44)	0.44 (0.40, 0.48)	0.42 (0.38, 0.45)	0.54 (0.50, 0.58)	0.49 (0.47, 0.52)	0.49 (0.44, 0.54)
T1	Depression Detection	T6	Emotion Classification	0.58 (0.56, 0.60)	0.54 (0.51, 0.56)	0.45 (0.42, 0.47)	0.54 (0.51, 0.56)	0.51 (0.50, 0.54)	**0.82** (0.79, 0.84)	0.61 (0.58, 0.64)	0.45 (0.43, 0.47)	0.43 (0.41, 0.45)	0.55 (0.53, 0.57)	0.53 (0.50, 0.55)	0.59 (0.56, 0.62)
Formulation															
T9	Aphasia Detection	T7	Alzheimer's Detection	0.70 (0.64, 0.76)	0.74 (0.68, 0.80)	0.65 (0.58, 0.71)	0.65 (0.58, 0.72)	0.56 (0.49, 0.62)	0.48 (0.41, 0.55)	0.73 (0.67, 0.79)	0.74 (0.68, 0.80)	0.66 (0.60, 0.72)	0.69 (0.62, 0.74)	0.68 (0.62, 0.73)	**0.74** (0.68, 0.80)
T7	Alzheimer's Detection	T9	Aphasia Detection	0.82 (0.77, 0.87)	0.90 (0.86, 0.93)	0.84 (0.79, 0.89)	0.84 (0.78, 0.88)	0.76 (0.70, 0.82)	0.61 (0.56, 0.66)	**0.94** (0.92, 0.96)	0.83 (0.78, 0.88)	0.88 (0.83, 0.91)	0.78 (0.72, 0.84)	0.83 (0.77, 0.88)	0.88 (0.83, 0.92)
Articulation (Neuromuscular)															
T10	Dysarthria Detection	T17	Disfluency Detection	0.60 (0.48, 0.68)	**0.73** (0.65, 0.80)	0.59 (0.50, 0.67)	0.57 (0.45, 0.66)	0.56 (0.47, 0.66)	0.56 (0.53, 0.60)	0.71 (0.67, 0.76)	0.70 (0.62, 0.77)	0.63 (0.55, 0.70)	0.66 (0.61, 0.71)	0.70 (0.60, 0.78)	0.73 (0.66, 0.77)
T12	Dysarthria Detection	T17	Disfluency Detection	0.66 (0.58, 0.72)	0.64 (0.57, 0.70)	0.62 (0.54, 0.69)	0.60 (0.52, 0.67)	0.65 (0.54, 0.73)	0.60 (0.55, 0.64)	0.57 (0.52, 0.61)	0.57 (0.44, 0.66)	0.61 (0.51, 0.69)	0.65 (0.60, 0.69)	0.68 (0.60, 0.74)	**0.70** (0.65, 0.74)
T10	Dysarthria Detection	T12	Dysarthria Detection	0.83 (0.72, 0.92)	0.90 (0.83, 0.96)	0.78 (0.63, 0.90)	0.78 (0.62, 0.90)	0.64 (0.48, 0.77)	0.76 (0.65, 0.86)	0.91 (0.83, 0.96)	0.80 (0.68, 0.90)	0.55 (0.41, 0.68)	0.82 (0.72, 0.91)	0.52 (0.39, 0.64)	**0.92** (0.84, 0.98)
T12	Dysarthria Detection	T13	Parkinson's Detection	0.56 (0.41, 0.70)	0.67 (0.56, 0.79)	0.54 (0.37, 0.73)	**0.83** (0.70, 0.93)	0.65 (0.49, 0.80)	0.67 (0.54, 0.80)	0.67 (0.51, 0.83)	0.61 (0.50, 0.72)	0.30 (0.16, 0.47)	0.55 (0.48, 0.62)	0.79 (0.66, 0.88)	0.65 (0.56, 0.73)
T12	Dysarthria Detection	T10	Dysarthria Detection	0.62 (0.45, 0.81)	0.72 (0.54, 0.89)	0.66 (0.48, 0.84)	0.63 (0.45, 0.81)	0.67 (0.51, 0.83)	0.71 (0.60, 0.82)	0.68 (0.53, 0.84)	0.60 (0.41, 0.80)	0.51 (0.36, 0.67)	0.71 (0.59, 0.86)	0.71 (0.58, 0.86)	**0.76** (0.58, 0.93)
T10	Dysarthria Detection	T13	Parkinson's Detection	0.50 (0.34, 0.65)	0.52 (0.36, 0.68)	0.46 (0.28, 0.65)	0.65 (0.48, 0.80)	0.34 (0.18, 0.52)	0.42 (0.25, 0.60)	0.56 (0.41, 0.72)	0.56 (0.40, 0.73)	0.45 (0.28, 0.63)	0.54 (0.43, 0.65)	0.51 (0.34, 0.67)	**0.72** (0.57, 0.85)
T13	Parkinson's Detection	T12	Dysarthria Detection	0.47 (0.32, 0.62)	0.62 (0.53, 0.71)	0.71 (0.58, 0.81)	0.53 (0.39, 0.67)	0.60 (0.43, 0.76)	0.70 (0.62, 0.77)	**0.74** (0.69, 0.79)	0.26 (0.18, 0.32)	0.28 (0.17, 0.40)	0.35 (0.26, 0.44)	0.58 (0.46, 0.70)	0.48 (0.36, 0.58)
T13	Parkinson's Detection	T10	Dysarthria Detection	0.30 (0.17, 0.46)	0.48 (0.37, 0.57)	0.58 (0.38, 0.80)	0.49 (0.35, 0.65)	**0.72** (0.57, 0.87)	0.55 (0.43, 0.65)	0.56 (0.49, 0.63)	0.55 (0.44, 0.65)	0.58 (0.50, 0.67)	0.40 (0.30, 0.53)	0.47 (0.39, 0.55)	0.56 (0.47, 0.63)
T13	Parkinson's Detection	T17	Disfluency Detection	0.49 (0.40, 0.58)	0.57 (0.51, 0.64)	0.50 (0.39, 0.61)	0.41 (0.33, 0.50)	0.39 (0.31, 0.48)	0.55 (0.49, 0.60)	0.41 (0.36, 0.45)	0.57 (0.53, 0.62)	0.46 (0.39, 0.55)	**0.58** (0.52, 0.64)	0.54 (0.43, 0.63)	0.52 (0.45, 0.58)
T17	Disfluency Detection	T13	Parkinson's Detection	0.29 (0.15, 0.45)	0.50 (0.32, 0.68)	0.57 (0.42, 0.73)	0.34 (0.19, 0.49)	0.67 (0.51, 0.81)	0.47 (0.32, 0.63)	0.37 (0.27, 0.47)	**0.76** (0.60, 0.89)	0.44 (0.24, 0.65)	0.53 (0.43, 0.63)	0.58 (0.42, 0.73)	0.55 (0.41, 0.70)
T17	Disfluency Detection	T12	Dysarthria Detection	0.76 (0.65, 0.85)	0.72 (0.61, 0.83)	0.53 (0.40, 0.64)	0.72 (0.59, 0.83)	0.72 (0.60, 0.81)	0.81 (0.71, 0.89)	0.61 (0.50, 0.71)	0.54 (0.43, 0.65)	0.76 (0.65, 0.85)	0.62 (0.53, 0.70)	0.52 (0.43, 0.62)	**0.88** (0.80, 0.95)
T17	Disfluency Detection	T10	Dysarthria Detection	0.66 (0.55, 0.80)	0.73 (0.59, 0.85)	0.57 (0.46, 0.70)	0.66 (0.50, 0.83)	0.66 (0.48, 0.85)	0.69 (0.60, 0.78)	0.74 (0.61, 0.88)	0.69 (0.53, 0.84)	0.48 (0.33, 0.65)	0.62 (0.54, 0.71)	0.64 (0.55, 0.76)	**0.74** (0.61, 0.90)
Articulation (Phonatory / Respiratory)															
T24	Respiratory Symptoms	T19	Respiratory Symptoms	0.54 (0.53, 0.56)	0.55 (0.54, 0.57)	0.53 (0.52, 0.55)	0.50 (0.49, 0.51)	0.49 (0.47, 0.50)	0.58 (0.57, 0.60)	0.55 (0.54, 0.57)	**0.61** (0.60, 0.62)	0.49 (0.48, 0.50)	0.53 (0.51, 0.54)	0.54 (0.53, 0.55)	0.51 (0.50, 0.53)
T27	Vocal pathology detection	T19	Respiratory Symptoms	0.51 (0.49, 0.52)	0.58 (0.57, 0.59)	0.53 (0.51, 0.54)	0.56 (0.54, 0.57)	0.51 (0.50, 0.53)	**0.58** (0.57, 0.60)	0.57 (0.56, 0.59)	0.58 (0.56, 0.59)	0.53 (0.52, 0.55)	0.54 (0.53, 0.56)	0.56 (0.55, 0.58)	0.54 (0.53, 0.56)
T27	Vocal pathology detection	T21	COVID-19 Detection	0.46 (0.42, 0.50)	0.48 (0.45, 0.52)	0.46 (0.43, 0.50)	0.50 (0.46, 0.53)	0.45 (0.42, 0.49)	**0.57** (0.54, 0.61)	0.52 (0.48, 0.56)	0.53 (0.50, 0.57)	0.47 (0.43, 0.51)	0.47 (0.43, 0.51)	0.51 (0.48, 0.55)	0.52 (0.48, 0.56)
T27	Vocal pathology detection	T25	COVID-19 Detection	0.41 (0.38, 0.43)	0.42 (0.40, 0.45)	0.44 (0.42, 0.46)	0.38 (0.36, 0.41)	0.51 (0.49, 0.53)	0.62 (0.60, 0.64)	**0.69** (0.67, 0.71)	0.56 (0.54, 0.58)	0.49 (0.47, 0.51)	0.54 (0.52, 0.56)	0.49 (0.46, 0.51)	0.65 (0.62, 0.67)
T27	Vocal pathology detection	T24	Respiratory Symptoms	0.42 (0.40, 0.44)	0.46 (0.44, 0.48)	0.48 (0.46, 0.50)	0.42 (0.40, 0.45)	0.50 (0.47, 0.52)	0.61 (0.59, 0.62)	**0.69** (0.67, 0.70)	0.59 (0.57, 0.61)	0.50 (0.49, 0.52)	0.58 (0.56, 0.60)	0.51 (0.49, 0.53)	0.65 (0.63, 0.67)
T19	Respiratory Symptoms	T27	Vocal pathology detection	0.58 (0.55, 0.61)	0.55 (0.53, 0.58)	0.65 (0.62, 0.68)	0.66 (0.62, 0.69)	0.63 (0.60, 0.66)	0.60 (0.57, 0.62)	0.59 (0.56, 0.61)	0.56 (0.54, 0.59)	0.50 (0.47, 0.54)	0.56 (0.54, 0.59)	**0.68** (0.65, 0.71)	0.57 (0.55, 0.59)
T21	COVID-19 Detection	T27	Vocal pathology detection	0.43 (0.40, 0.45)	0.45 (0.43, 0.47)	0.46 (0.44, 0.49)	0.42 (0.40, 0.45)	**0.63** (0.60, 0.65)	0.62 (0.60, 0.65)	0.54 (0.52, 0.56)	0.53 (0.51, 0.55)	0.52 (0.49, 0.56)	0.55 (0.53, 0.58)	0.46 (0.42, 0.49)	0.56 (0.54, 0.58)
T19	Respiratory Symptoms	T24	Respiratory Symptoms	0.61 (0.59, 0.63)	**0.64** (0.62, 0.66)	0.55 (0.53, 0.57)	0.53 (0.51, 0.55)	0.48 (0.46, 0.50)	0.62 (0.60, 0.64)	0.52 (0.50, 0.53)	0.63 (0.61, 0.65)	0.46 (0.44, 0.48)	0.44 (0.42, 0.46)	0.57 (0.55, 0.59)	0.52 (0.50, 0.54)
T21	COVID-19 Detection	T25	COVID-19 Detection	0.56 (0.54, 0.59)	**0.69** (0.67, 0.71)	0.54 (0.52, 0.56)	0.56 (0.54, 0.58)	0.48 (0.46, 0.51)	0.64 (0.62, 0.66)	0.68 (0.66, 0.70)	0.47 (0.45, 0.49)	0.42 (0.40, 0.44)	0.65 (0.63, 0.67)	0.48 (0.45, 0.50)	0.68 (0.66, 0.70)
T25	COVID-19 Detection	T27	Vocal pathology detection	0.53 (0.50, 0.56)	0.37 (0.34, 0.39)	0.55 (0.52, 0.58)	0.48 (0.45, 0.51)	0.58 (0.55, 0.61)	**0.64** (0.62, 0.67)	0.51 (0.48, 0.52)	0.53 (0.50, 0.55)	0.42 (0.38, 0.45)	0.53 (0.52, 0.55)	0.58 (0.55, 0.61)	0.63 (0.61, 0.66)
T24	Respiratory Symptoms	T27	Vocal pathology detection	0.47 (0.44, 0.50)	0.44 (0.42, 0.47)	0.58 (0.55, 0.61)	0.52 (0.50, 0.55)	0.49 (0.46, 0.52)	0.63 (0.60, 0.65)	0.57 (0.54, 0.59)	0.57 (0.55, 0.59)	0.49 (0.46, 0.52)	0.58 (0.57, 0.60)	**0.64** (0.62, 0.67)	0.63 (0.61, 0.66)
T25	COVID-19 Detection	T21	COVID-19 Detection	0.54 (0.50, 0.58)	0.61 (0.57, 0.65)	0.55 (0.51, 0.58)	0.51 (0.47, 0.54)	0.51 (0.47, 0.54)	0.57 (0.53, 0.61)	0.57 (0.52, 0.61)	**0.61** (0.57, 0.65)	0.51 (0.47, 0.55)	0.57 (0.53, 0.61)	0.55 (0.51, 0.59)	0.54 (0.50, 0.58)
Cross-category															
Conceptualization		Formulation		0.66 (0.60, 0.72)	0.49 (0.43, 0.55)	**0.67** (0.61, 0.72)	0.33 (0.29, 0.39)	0.42 (0.37, 0.48)	0.61 (0.57, 0.65)	0.27 (0.22, 0.32)	0.60 (0.54, 0.66)	0.55 (0.48, 0.60)	0.26 (0.21, 0.30)	0.51 (0.45, 0.57)	0.27 (0.23, 0.30)
Conceptualization		Articulation (Neuromuscular)		0.49 (0.39, 0.59)	0.52 (0.42, 0.61)	0.53 (0.43, 0.62)	**0.64** (0.53, 0.74)	0.37 (0.25, 0.51)	0.62 (0.53, 0.71)	0.49 (0.42, 0.55)	0.48 (0.39, 0.58)	0.57 (0.45, 0.69)	0.31 (0.25, 0.39)	0.49 (0.37, 0.59)	0.63 (0.51, 0.74)
Conceptualization		Articulation (Phonatory / Respiratory)		0.48 (0.46, 0.49)	0.50 (0.49, 0.51)	0.55 (0.54, 0.57)	0.48 (0.46, 0.49)	0.46 (0.44, 0.47)	**0.60** (0.59, 0.62)	0.49 (0.48, 0.51)	0.45 (0.44, 0.46)	0.50 (0.49, 0.52)	0.44 (0.43, 0.46)	0.45 (0.44, 0.46)	0.55 (0.54, 0.56)
Formulation		Conceptualization		0.51 (0.49, 0.54)	0.46 (0.44, 0.49)	0.52 (0.49, 0.55)	0.53 (0.51, 0.56)	0.50 (0.48, 0.53)	**0.74** (0.71, 0.76)	0.48 (0.47, 0.51)	0.53 (0.51, 0.55)	0.52 (0.50, 0.54)	0.49 (0.47, 0.52)	0.47 (0.45, 0.50)	0.45 (0.43, 0.47)
Formulation		Articulation (Neuromuscular)		0.62 (0.54, 0.69)	0.72 (0.64, 0.79)	0.81 (0.72, 0.89)	0.82 (0.73, 0.89)	**0.87** (0.80, 0.92)	0.51 (0.44, 0.58)	0.58 (0.48, 0.67)	0.58 (0.49, 0.68)	0.67 (0.57, 0.76)	0.49 (0.44, 0.55)	0.54 (0.47, 0.62)	0.44 (0.37, 0.52)
Formulation		Articulation (Phonatory / Respiratory)		0.51 (0.50, 0.52)	0.53 (0.52, 0.54)	0.58 (0.57, 0.59)	0.53 (0.52, 0.55)	0.54 (0.53, 0.55)	**0.58** (0.57, 0.59)	0.54 (0.53, 0.56)	0.53 (0.52, 0.54)	0.54 (0.53, 0.55)	0.52 (0.51, 0.54)	0.54 (0.53, 0.55)	0.49 (0.48, 0.50)
Articulation (Neuromuscular)		Conceptualization		0.53 (0.51, 0.57)	0.54 (0.52, 0.57)	0.57 (0.55, 0.59)	0.57 (0.55, 0.60)	**0.57** (0.55, 0.60)	0.45 (0.42, 0.50)	0.51 (0.49, 0.55)	0.55 (0.54, 0.56)	0.56 (0.55, 0.58)	0.42 (0.40, 0.47)	0.51 (0.49, 0.53)	0.56 (0.54, 0.59)
Articulation (Neuromuscular)		Formulation		0.78 (0.74, 0.82)	0.86 (0.82, 0.89)	0.73 (0.68, 0.77)	0.45 (0.39, 0.51)	0.79 (0.74, 0.83)	0.50 (0.44, 0.55)	**0.87** (0.84, 0.90)	0.85 (0.82, 0.88)	0.68 (0.64, 0.73)	0.85 (0.81, 0.88)	0.82 (0.78, 0.86)	0.78 (0.74, 0.81)
Articulation (Neuromuscular)		Articulation (Phonatory / Respiratory)		0.52 (0.51, 0.53)	0.54 (0.52, 0.55)	0.55 (0.54, 0.56)	0.53 (0.52, 0.54)	0.52 (0.50, 0.53)	**0.58** (0.57, 0.60)	0.54 (0.53, 0.56)	0.52 (0.51, 0.53)	0.52 (0.51, 0.54)	0.56 (0.54, 0.57)	0.55 (0.54, 0.57)	0.54 (0.53, 0.55)
Articulation (Phonatory / Respiratory)		Conceptualization		0.46 (0.43, 0.48)	0.45 (0.42, 0.49)	0.50 (0.47, 0.55)	0.48 (0.45, 0.51)	0.47 (0.45, 0.51)	**0.83** (0.82, 0.85)	0.50 (0.47, 0.54)	0.47 (0.45, 0.51)	0.46 (0.44, 0.48)	0.46 (0.44, 0.50)	0.45 (0.42, 0.48)	0.57 (0.54, 0.63)
Articulation (Phonatory / Respiratory)		Formulation		0.64 (0.59, 0.68)	0.79 (0.75, 0.82)	0.73 (0.68, 0.77)	0.80 (0.75, 0.84)	0.72 (0.67, 0.77)	0.61 (0.57, 0.65)	**0.88** (0.85, 0.90)	0.73 (0.69, 0.77)	0.55 (0.49, 0.61)	0.81 (0.77, 0.85)	0.57 (0.51, 0.63)	0.86 (0.83, 0.89)
Articulation (Phonatory / Respiratory)		Articulation (Neuromuscular)		0.65 (0.55, 0.73)	0.58 (0.49, 0.67)	0.64 (0.54, 0.74)	0.72 (0.62, 0.80)	0.59 (0.47, 0.69)	0.69 (0.60, 0.78)	0.75 (0.67, 0.82)	0.62 (0.52, 0.71)	0.56 (0.45, 0.66)	0.67 (0.62, 0.72)	0.59 (0.46, 0.71)	**0.75** (0.67, 0.83)

		General Speech						General Audio				Domain-specific	
Task	Metric	w2v2	HuBERT	WavLM	MMS	Qwen3	Whisper	AudioMAE	WavJEPA	AST	CLAP	emo2vec+	OPERA
Conceptualization													
T1 (Depression detection)	AUC	+49.1%	-19.0%	+21.0%	+2.6%	+59.9%	-16.4%	-2.6%	-18.2%	-7.6%	-3.0%	-2.5%	+35.9%
T2 (Depression severity)	MAE ↓	-0.5%	-0.3%	-1.2%	-1.5%	+2.8%	+1.1%	+2.8%	-0.9%	+1.1%	-5.9%	-0.6%	+2.2%
T3 (Emotion classification)	AUC	+46.0%	+16.5%	+10.8%	+22.3%	+4.4%	+11.1%	+14.9%	+12.8%	+3.9%	+0.9%	+0.1%	-1.5%
T4 (Binary emotion classification)	AUC	+32.4%	+21.0%	+19.9%	+46.9%	+16.5%	+18.6%	+30.8%	+24.7%	+12.8%	+2.6%	+0.6%	+0.3%
T5 (Emotion classification)	AUC	+23.4%	+12.9%	+5.5%	+8.7%	+1.6%	+5.8%	+4.9%	+4.8%	+1.0%	+1.6%	+0.6%	-2.1%
T6 (Binary emotion classification)	AUC	+20.0%	+20.8%	+8.6%	+24.9%	+2.8%	+17.3%	+13.0%	+13.0%	+6.1%	+3.7%	+0.7%	-1.8%
Formulation													
T7 (Alzheimer's detection)	AUC	-3.4%	-8.5%	-5.2%	+17.1%	-17.6%	-18.1%	+2.9%	+5.9%	+19.7%	+2.9%	+4.4%	-10.0%
T8 (Alzheimer's severity)	MAE ↓	-20.3%	-12.4%	-31.0%	-41.4%	-46.3%	-14.6%	-11.5%	-35.6%	-40.8%	-35.2%	+1.9%	+15.3%
T9 (Aphasia detection)	AUC	+5.1%	+6.7%	+3.3%	+7.1%	+0.1%	+8.1%	+10.2%	+8.1%	+3.7%	+2.5%	-2.0%	0.0%
Articulation (Neuromuscular)													
T10 (Dysarthria detection)	AUC	+12.0%	+3.0%	+0.4%	+7.6%	-4.4%	-0.6%	-3.8%	+12.7%	+4.2%	-3.8%	+0.1%	+1.1%
T11 (Dysarthria severity)	MAE ↓	-30.7%	-9.0%	-23.2%	-29.9%	-35.9%	-27.5%	-28.0%	-11.5%	-23.8%	-9.2%	+4.8%	-1.0%
T12 (Dysarthria detection)	AUC	+13.2%	+4.0%	+2.8%	+0.9%	+4.7%	+2.4%	+6.3%	+3.0%	+0.7%	+0.9%	+2.4%	0.0%
T13 (Parkinson's detection)	AUC	+12.1%	+16.7%	+7.1%	+4.4%	+32.5%	+32.5%	+15.3%	+25.5%	+12.6%	+9.2%	-3.7%	-1.8%
T14 (Parkinson's severity)	MAE ↓	-16.2%	-28.8%	-25.8%	-46.5%	-20.0%	-35.9%	-24.0%	-19.4%	-23.9%	-10.3%	+0.5%	-9.5%
T15 (Parkinson's severity)	MAE ↓	-14.3%	-23.0%	-27.5%	-44.2%	-18.7%	-30.0%	-29.5%	-31.9%	-24.4%	-6.8%	-5.4%	-16.2%
T16 (Parkinson's severity)	MAE ↓	-2.9%	-30.8%	-48.9%	-44.2%	-30.5%	-50.2%	-40.8%	-49.4%	-35.5%	-11.9%	-1.4%	-19.6%
T17 (Disfluency detection)	AUC	+10.2%	+4.6%	+6.3%	+23.7%	+5.0%	+12.1%	+17.4%	+10.0%	+5.1%	+3.6%	+2.4%	+1.2%
T18 (Disfluency classification)	AUC	+14.1%	+8.8%	+5.1%	+15.2%	+4.1%	+15.8%	+12.9%	+9.5%	+4.6%	+3.4%	0.0%	-0.1%
Articulation (Phonatory/Respiratory)													
T19 (Respiratory symptom detection)	AUC	+13.2%	+16.5%	+10.0%	+11.8%	+5.9%	+10.7%	+8.8%	+9.0%	+6.3%	+11.0%	+0.5%	-1.2%
T20 (Respiratory symptom detection)	AUC	+7.7%	+4.6%	+2.7%	+6.3%	+2.1%	+4.9%	+4.0%	+6.9%	+2.5%	+0.8%	+0.4%	-2.0%
T21 (COVID-19 detection)	AUC	-1.8%	+0.9%	-8.7%	+14.1%	+2.0%	-2.5%	+21.2%	+17.5%	+2.5%	-3.2%	+2.1%	+14.7%
T22 (COVID-19 detection)	AUC	+4.9%	-3.1%	+4.0%	+1.7%	-1.9%	+0.3%	+5.1%	+1.6%	+1.4%	+2.3%	+2.8%	-2.6%
T23 (Respiratory symptom classification)	AUC	+4.7%	+0.2%	0.0%	-1.2%	-2.2%	-2.4%	+0.1%	+1.4%	-0.4%	-3.6%	+0.4%	-2.2%
T24 (Respiratory symptom detection)	AUC	+8.4%	+5.2%	+5.3%	+15.2%	+3.1%	+4.7%	+3.8%	+13.1%	+6.8%	+2.2%	-0.4%	+0.8%
T25 (COVID-19 detection)	AUC	+4.7%	+7.0%	+4.1%	+12.7%	+4.3%	+3.9%	+8.5%	+16.2%	+7.1%	+4.2%	+2.5%	+2.9%
T26 (Respiratory symptom classification)	AUC	+1.4%	+3.6%	-3.0%	+4.1%	+0.9%	+1.7%	+3.8%	+3.4%	+1.4%	+1.9%	-0.5%	-1.7%
T27 (Vocal pathology detection)	AUC	+27.4%	+24.6%	+1.0%	+3.1%	+1.1%	+13.9%	+3.3%	-1.6%	+1.3%	+1.6%	-1.2%	-0.5%

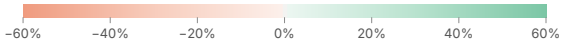

Figure 4: The relative performance change from global mean pooling (linear probe) to attentive statistical pooling across all audio encoders and all clinical speech tasks in SpeechDx. Each cell reports the percentage change in AUC for classification tasks or the percentage reduction in MAE for regression tasks. Positive values indicate improved performance with attentive statistical pooling.

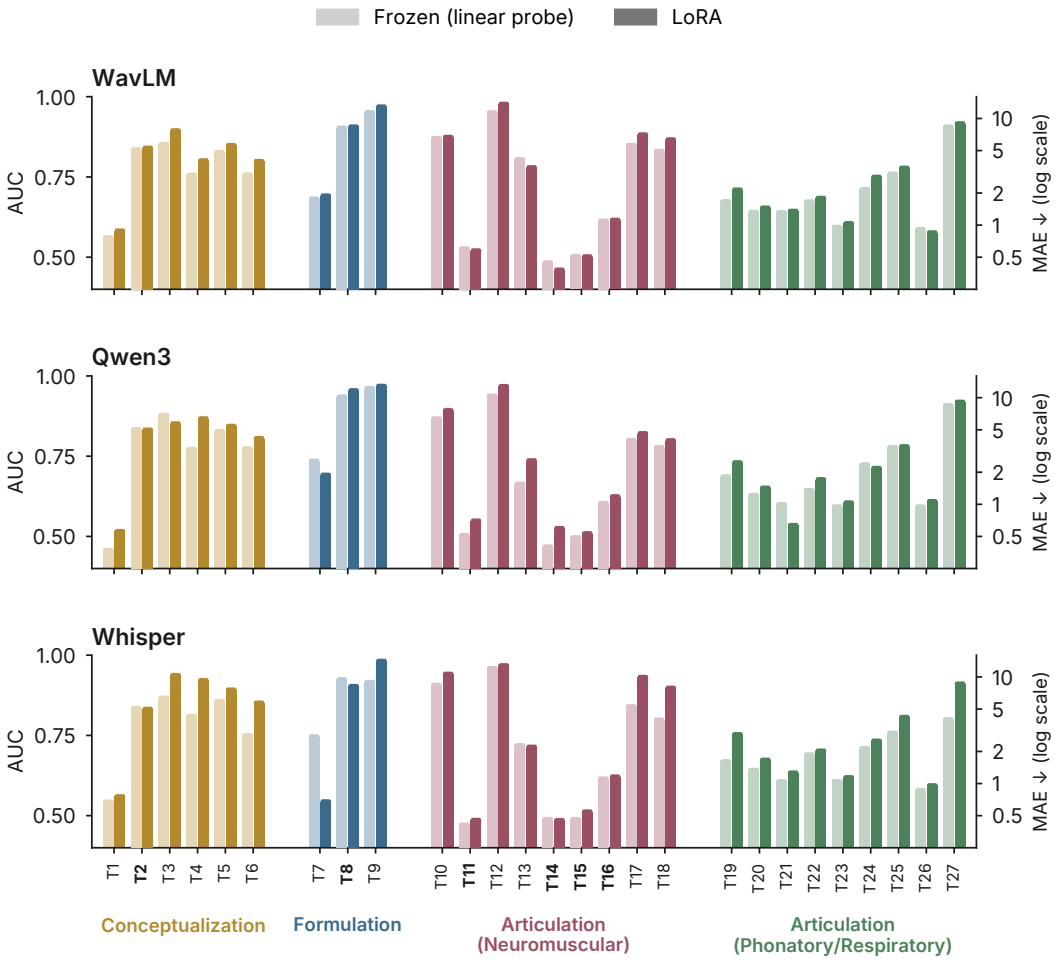

Figure 5: The evaluation of parameter-efficient adaptation for WavLM, Qwen3-TTS-Tokenizer, and Whisper across all 27 SpeechDx tasks. Light bars show performance with frozen mean-pooled representations and linear probing, while dark bars show performance after LoRA adaptation. Classification tasks report AUC on the left axis and regression tasks, indicated by bold task labels, report MAE on the log-scaled right axis. Task colors correspond to the four stages of speech production.

Figure 5 compares LoRA with frozen linear probing using absolute performance on each task. LoRA increases mean classification AUC from 0.756 to 0.782, with improvements on 19 of the 21 classification tasks. Whisper obtains the largest mean increase of 0.039 AUC, followed by WavLM at 0.021 and Qwen3-TTS-Tokenizer at 0.018. These gains are not universal. Mean performance decreases by 0.078 AUC for Alzheimer's disease detection and by 0.012 for one COVID-19 detection task. LoRA is also less effective for regression. It does not improve the task-level mean on any of the six regression outcomes, and the mean MAE increases by 3.1

These results suggest that parameter-efficient adaptation can improve classification performance but its benefits do not extend consistently across tasks or outcome types. The regression results may reflect sensitivity to optimization, the low-rank constraint, or overfitting on small clinical datasets. Overall, parameter-efficient adaptation provides broad gains for classification but not regression, showing that the value of adapting speech encoders depends on the downstream objective.

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