A Path Toward Precision Audiology: Familiar and Unfamiliar Steps

Dennis L. Barbour, MD, PhD

Department of Biomedical Engineering
Washington University in St. Louis

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Disclosure

Dennis Barbour has an ownership interest in Bonauria, LLC, and may financially benefit if the company is successful in commercializing products that are related to this research.

Outline

- Psychometric function estimation
- Comparison of machine learning audiogram (MLAG) to Hughson-Westlake audiogram (HWAG)
- How MLAG enables improvements
- MLAG extensions leading to augmented audiometry
  - Multitone audiometry (multiplexed estimation)
  - Bilateral audiometry (conjoint estimation)
  - Dynamic masking
  - Diagnostic classification (differential selection)
- MLAG as a metaphor for individualized diagnostics and therapeutics

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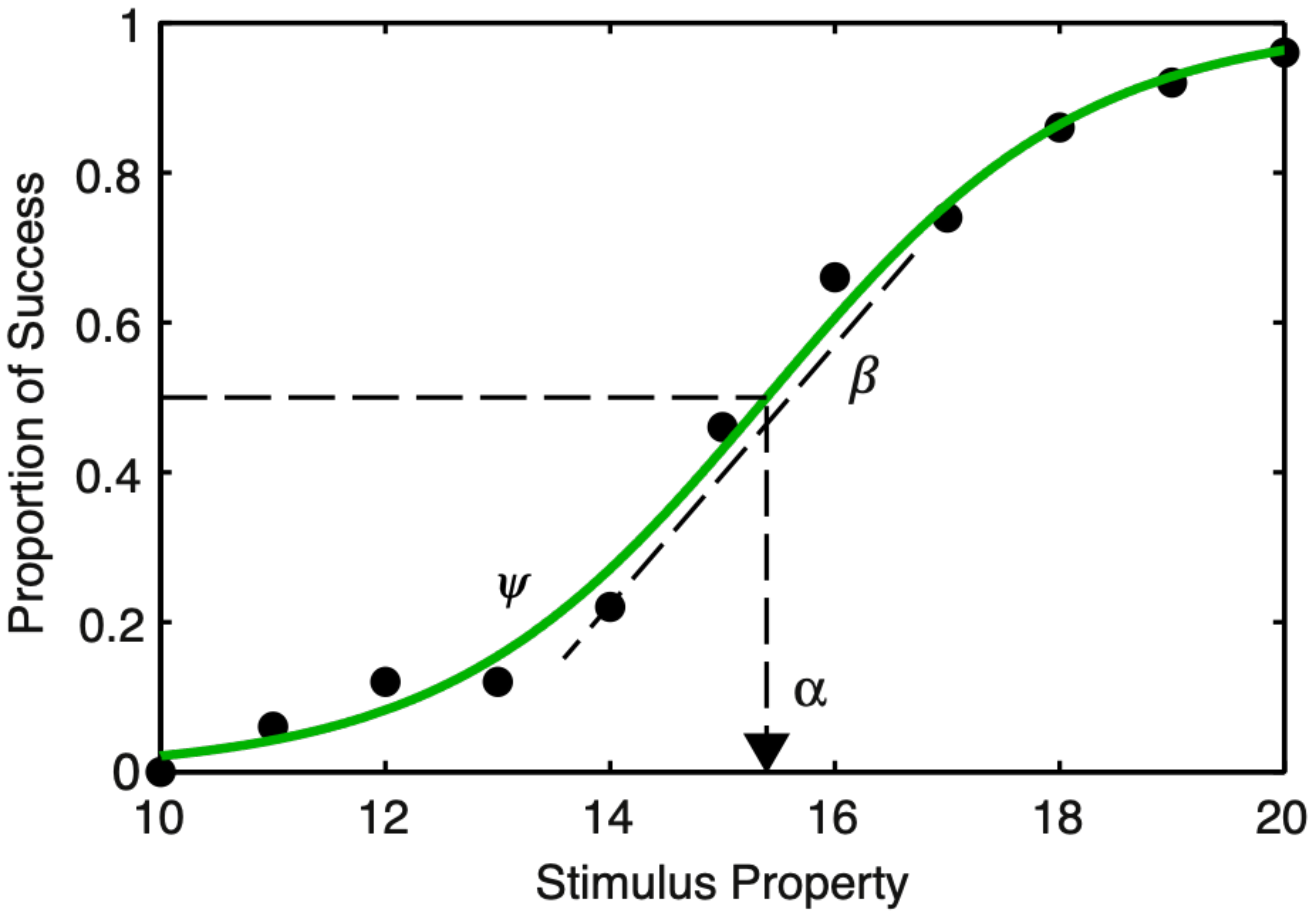
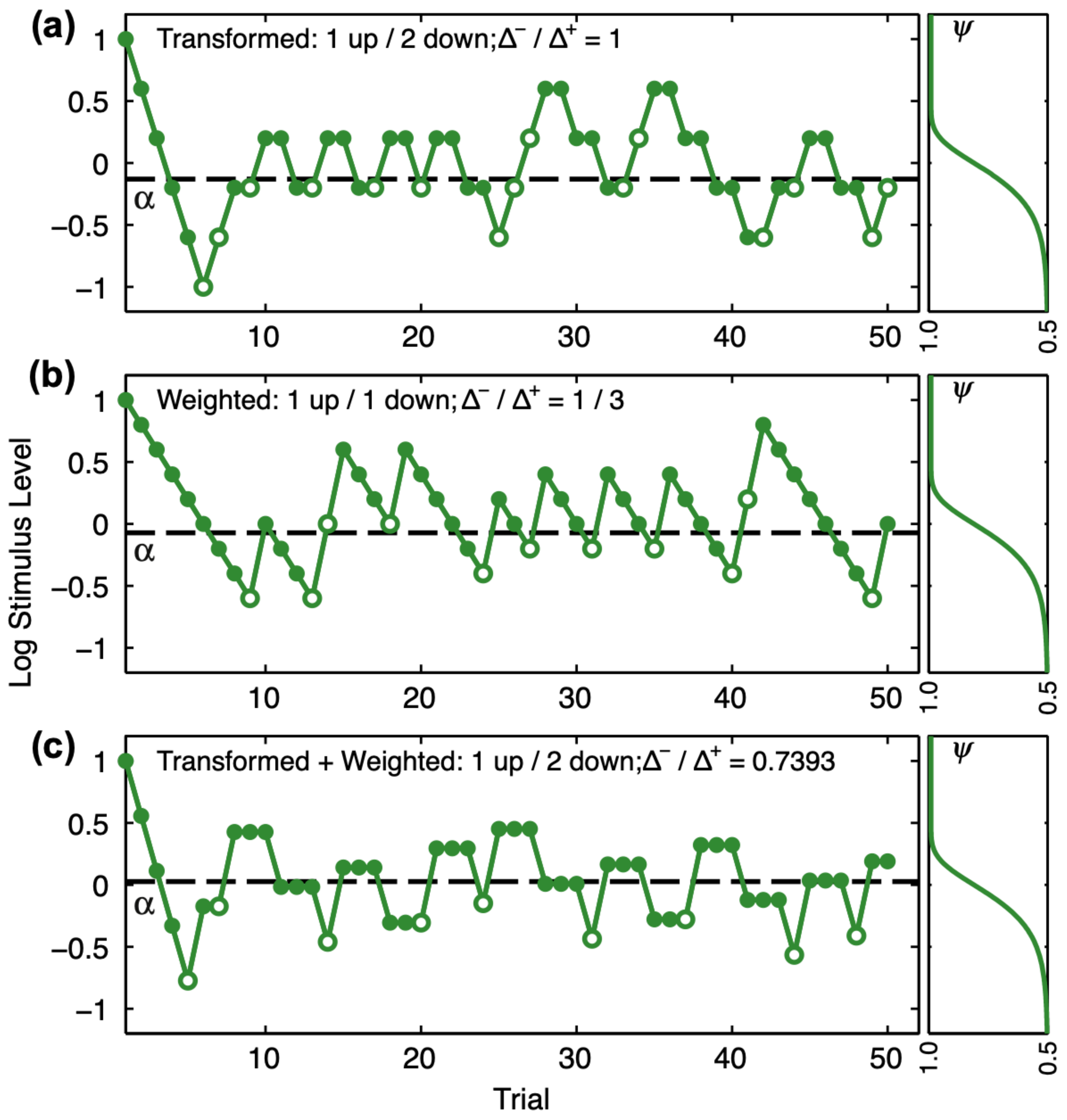
Psychometric functions include threshold and spread estimates



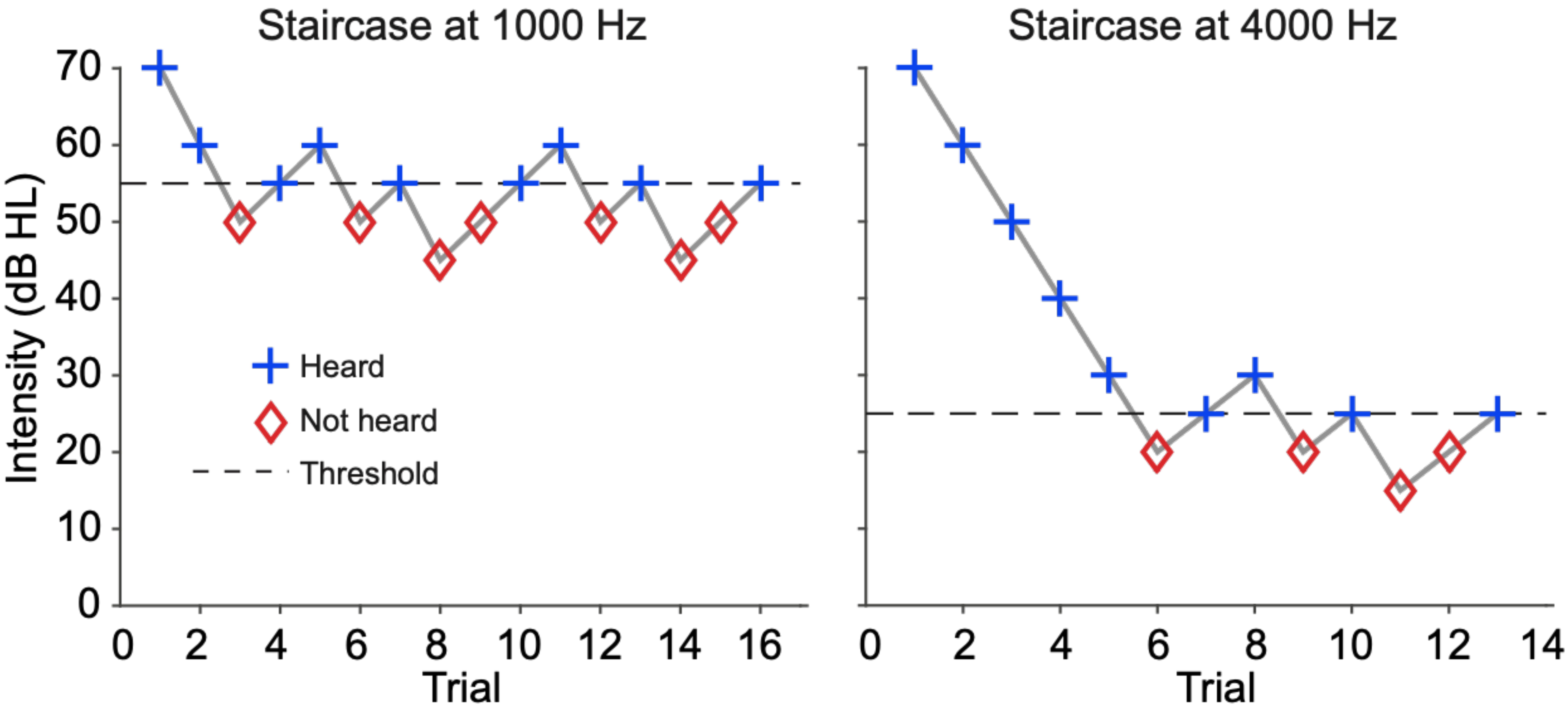
Psychophysics: A Practical Introduction, (Second Edition), by Kingdom, F.A.A. and Prins, N. Elsevier, Maarssen, Netherlands, 2016, p 63

Up-down or staircase procedures estimate thresholds only



Psychophysics: A Practical Introduction, (Second Edition), by Kingdom, F.A.A. and Prins, N. Elsevier, Maarssen, Netherlands, 2016, p 123

Up-down procedures are often repeated for multidimensional applications



Song, Wallace, et al, *Ear & Hearing* 36(6):e325-335, 2015

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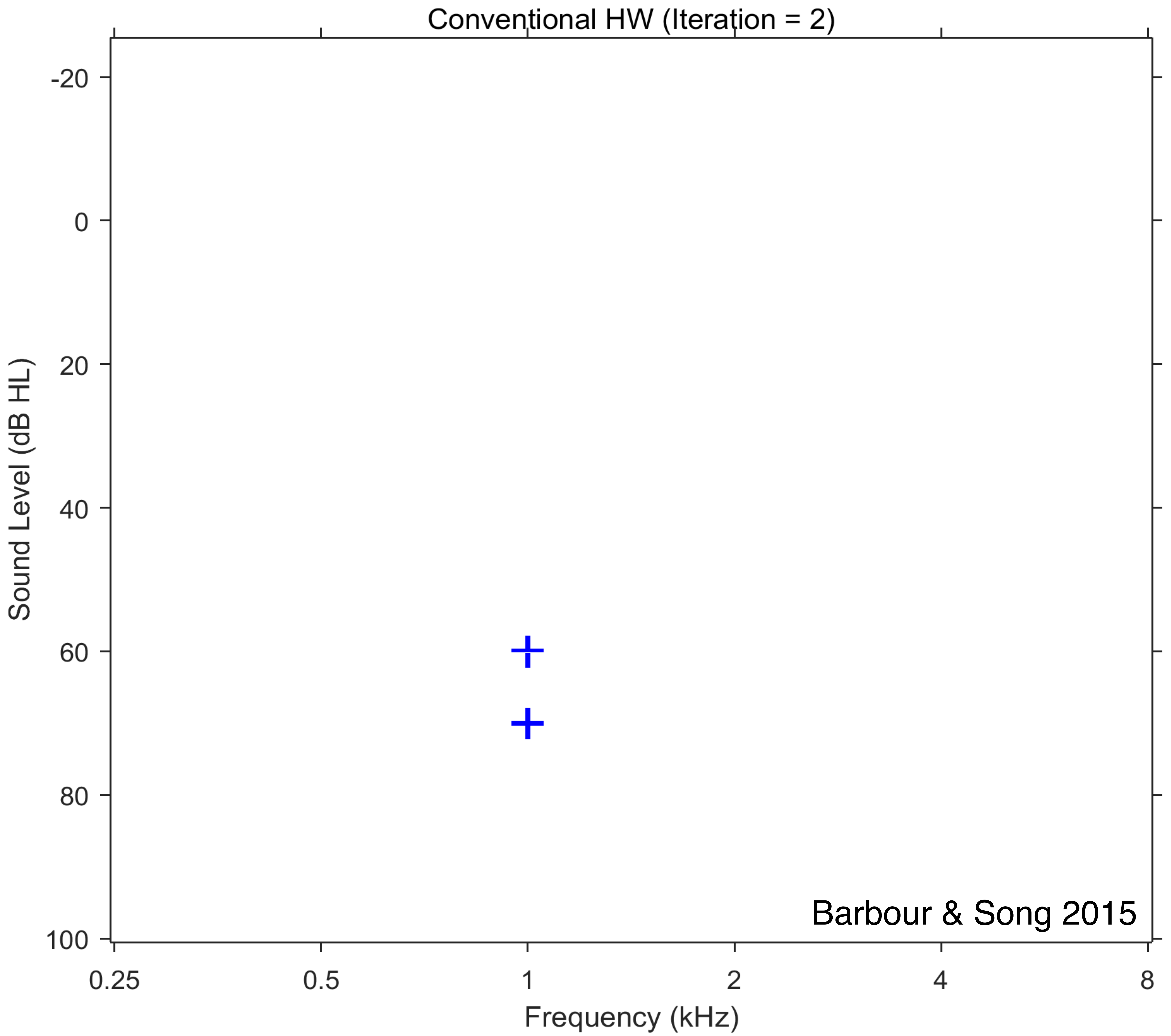
Hughson-Westlake AudioGram (HWAG) reflects a 2D psychometric function



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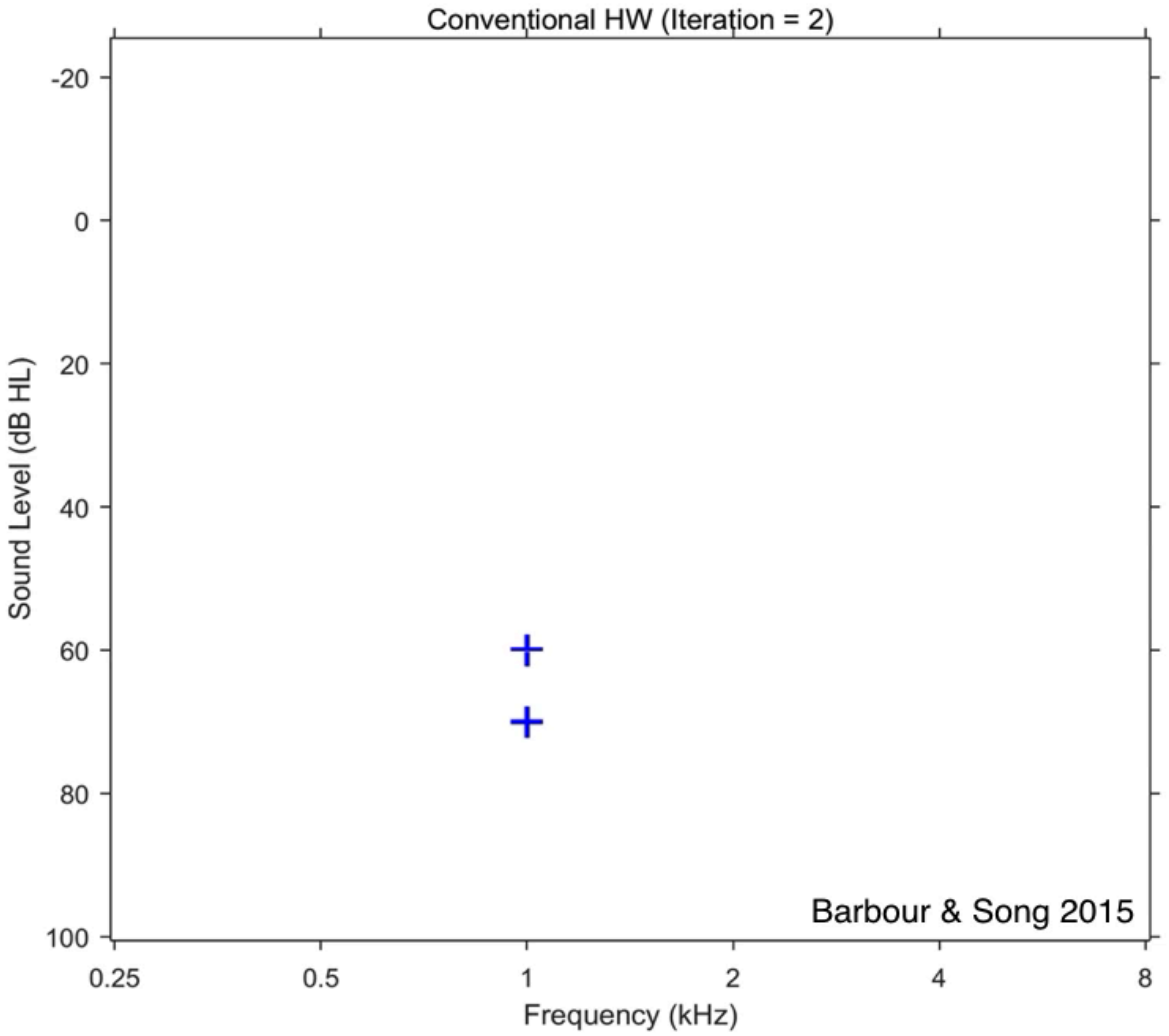
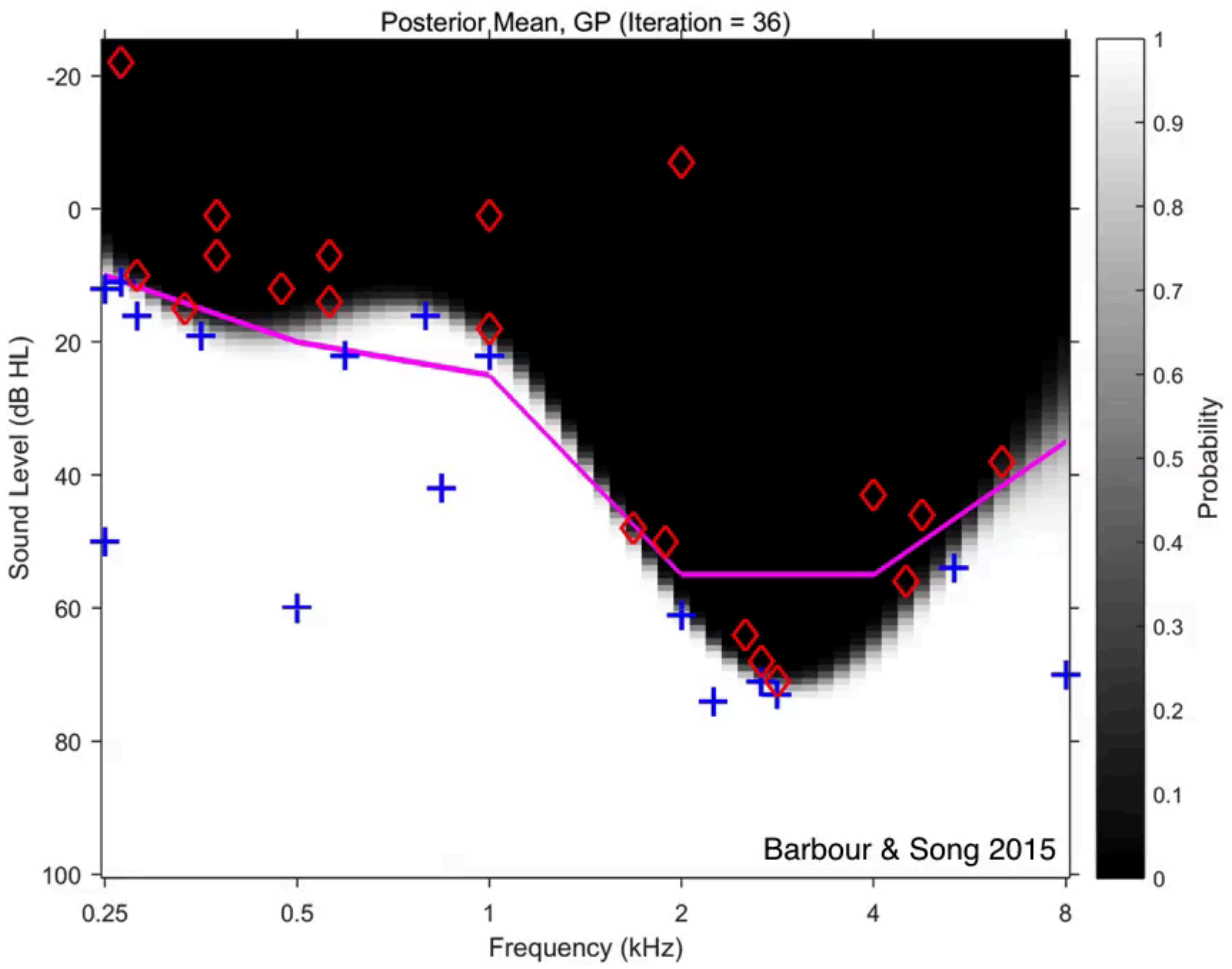


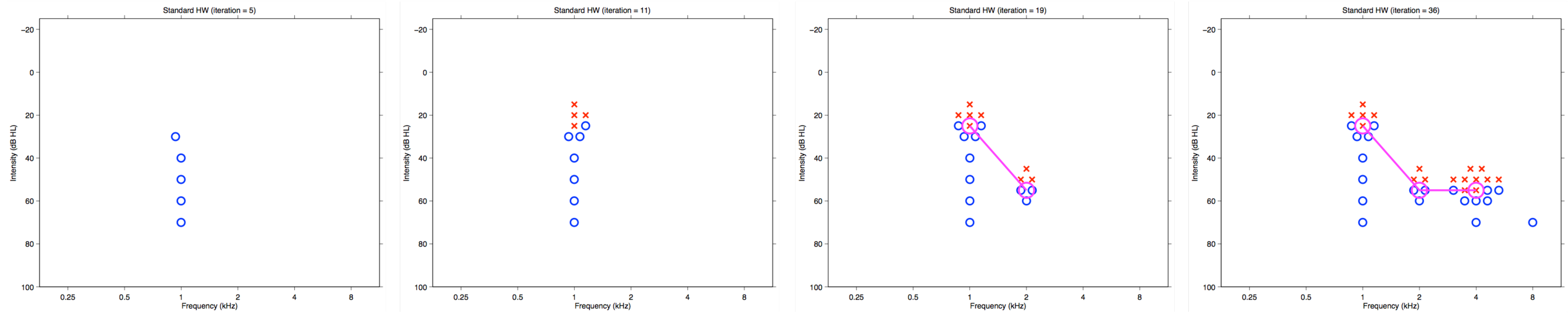
Song, Wallace, et al, *Ear & Hearing* 36(6):e325-335, 2015

Machine Learning AudioGram (MLAG) determines the most informative queries

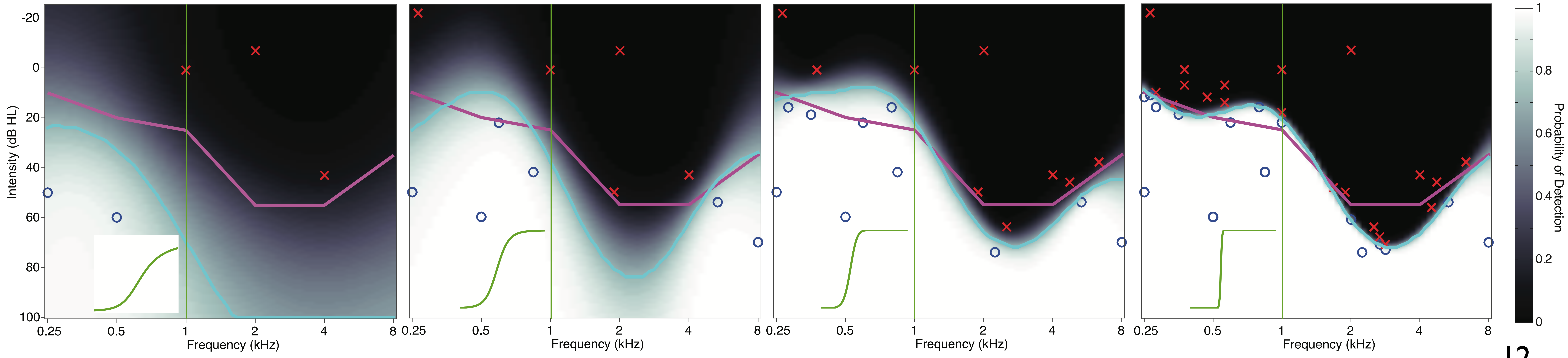


Song, Wallace, et al, *Ear & Hearing* 36(6):e325-335, 2015

MLAG delivers both threshold and slope estimates across frequency



5 trials | 11 trials | 19 trials | 36 trials



Song, Wallace, et al, *Ear & Hearing* 36(6):e325-335, 2015

MLAG threshold estimates are consistent with conventional HWAG

Frequency (kHz)	0.25	0.5	1	2	4	8	All
Mean differences and standard deviations vs. HW							
Mean difference (dB HL)	1.80	−1.43	0.138	0.244	1.14	−1.69	**−0.011**
Standard deviation (dB HL)	6.25	4.88	4.48	4.38	5.57	7.23	**5.61**
Absolute Mean differences and standard deviations vs. HW							
Mean absolute difference (dB HL)	4.80	3.75	3.44	3.53	4.48	5.17	**4.16**
Standard deviation (dB HL)	4.36	3.41	2.85	2.57	3.46	5.30	**3.76**
Percent 5-dB maximum difference from HW							
Percent 5-dB max difference	61.25	82.5	80.0	78.75	61.25	48.75	**68.75**

Song, Wallace, et al, *Ear & Hearing* 36(6):e325-335, 2015

Test-retest reliability of MLAG is within clinical criteria

Frequency (kHz)	0.25	0.5	1	2	4	8	All
Mean differences and standard deviations							
Mean difference (dB HL)	−0.15	1.55	1.63	0.26	1.03	0.032	**0.75**
Standard deviation (dB HL)	6.27	7.03	4.14	5.34	6.78	8.11	**6.29**
Mean absolute differences and standard deviations							
Mean absolute difference (dB HL)	4.80	5.05	3.58	3.95	5.03	4.74	**4.51**
Standard deviation (dB HL)	3.97	5.07	2.60	3.55	4.59	6.52	**4.45**

Song, Wallace, et al, *Ear & Hearing* 36(6):e325-335, 2015

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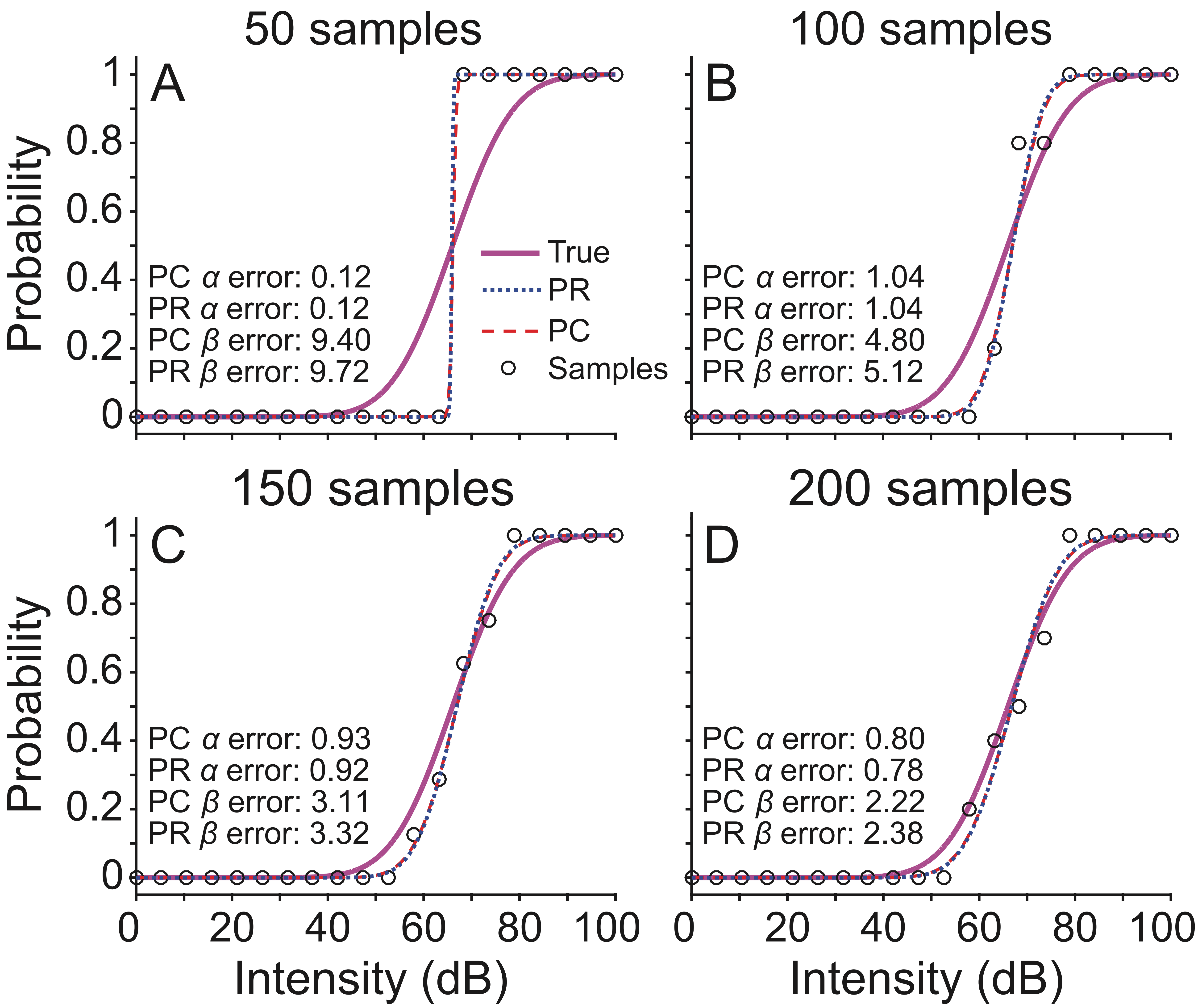
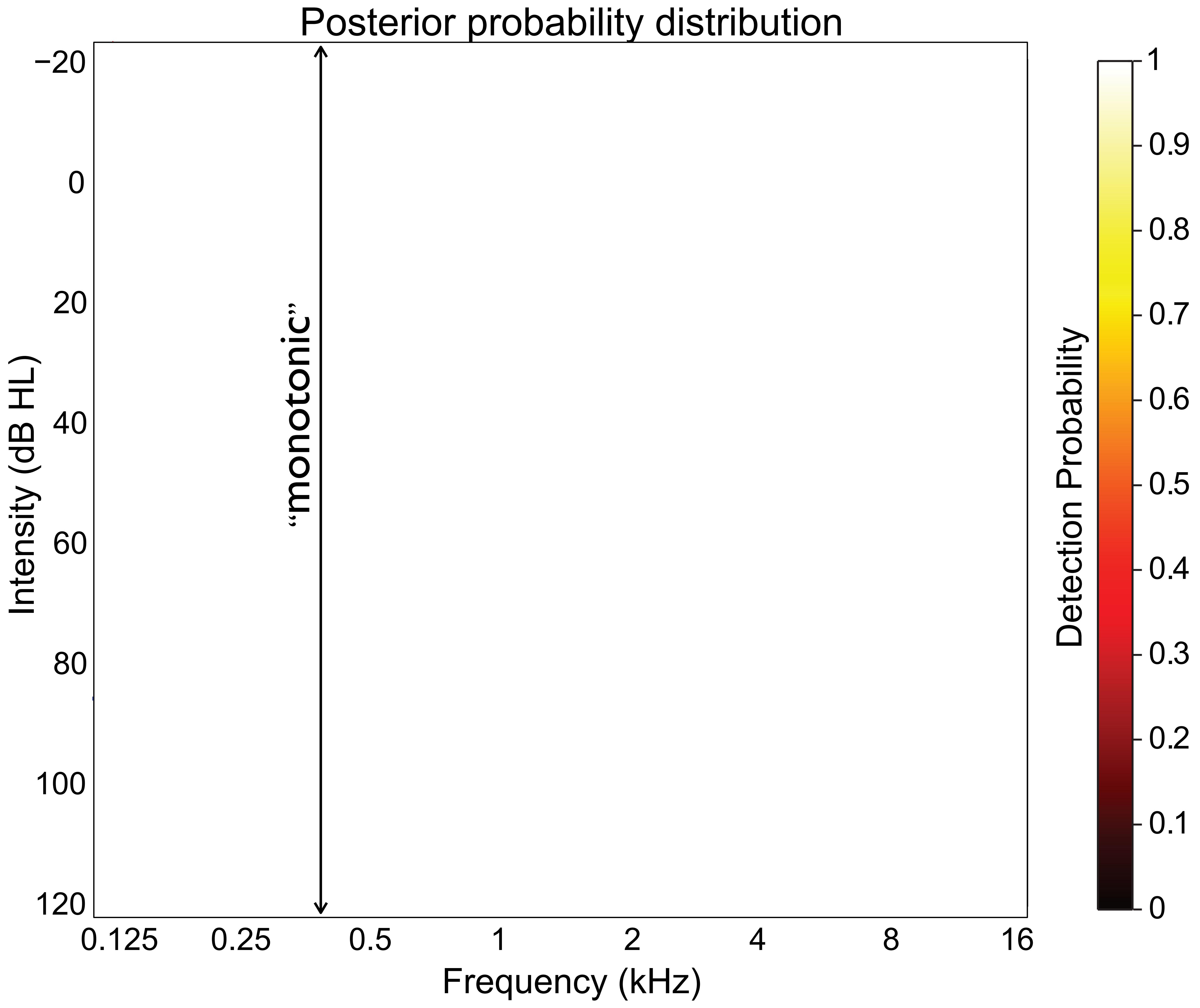
Probabilistic classification and probit regression exhibit similar error profiles as sample number increases

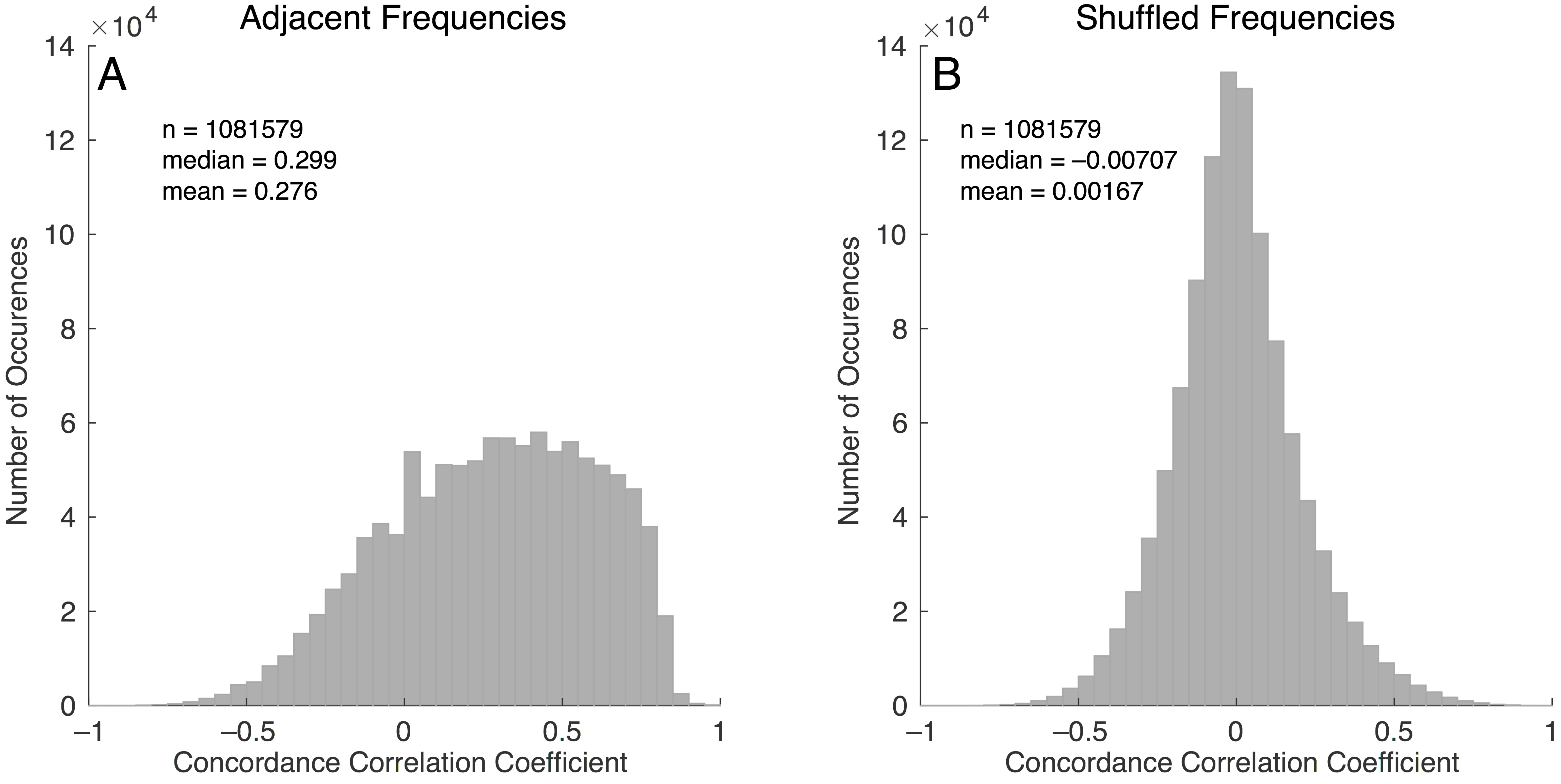


Song, Garnett & Barbour, *J Acoust Soc Am.* 141(4):2513, 2017

Audiogram model constraint for intensity is monotonicity

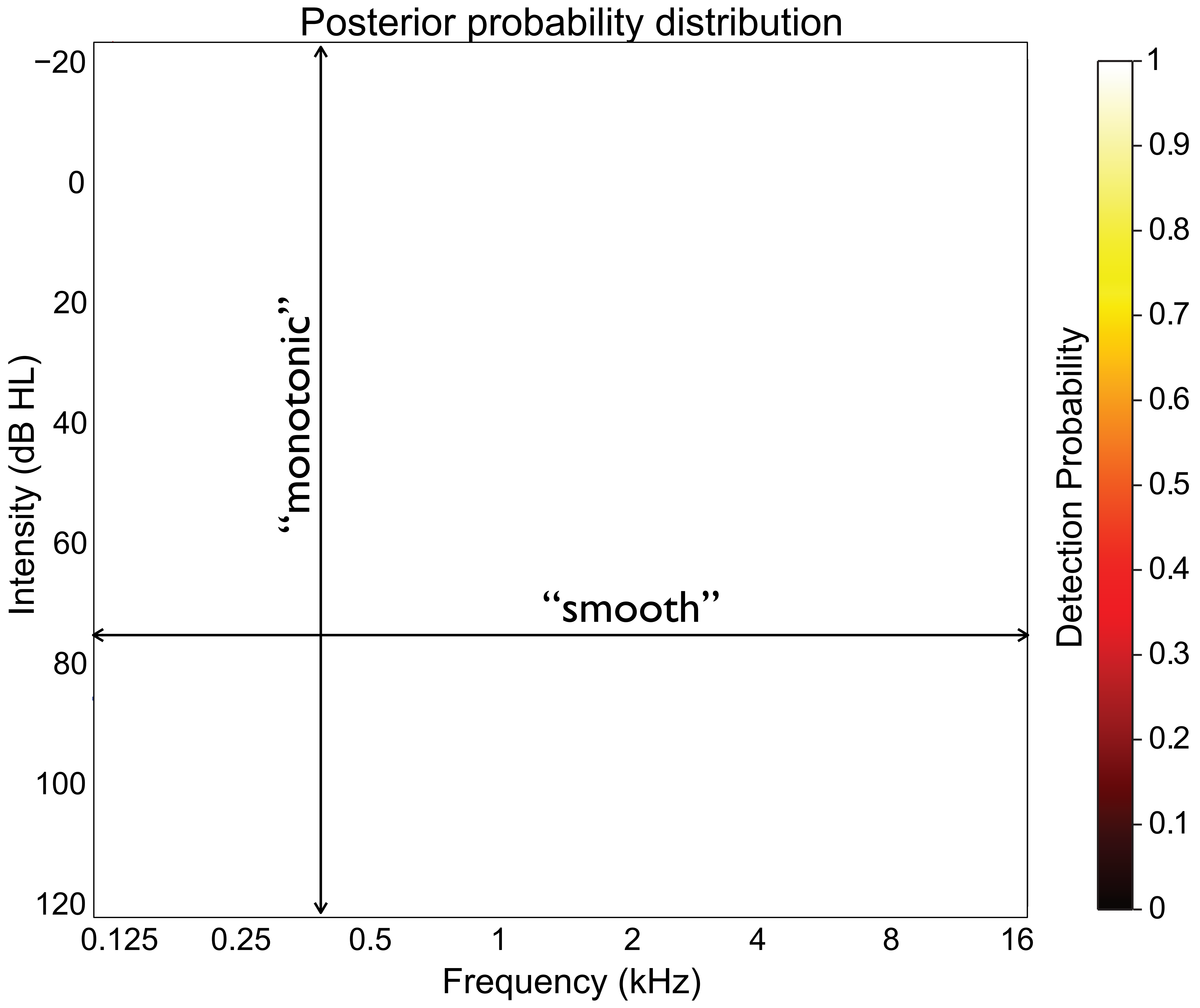


Hearing thresholds vary systematically across frequency

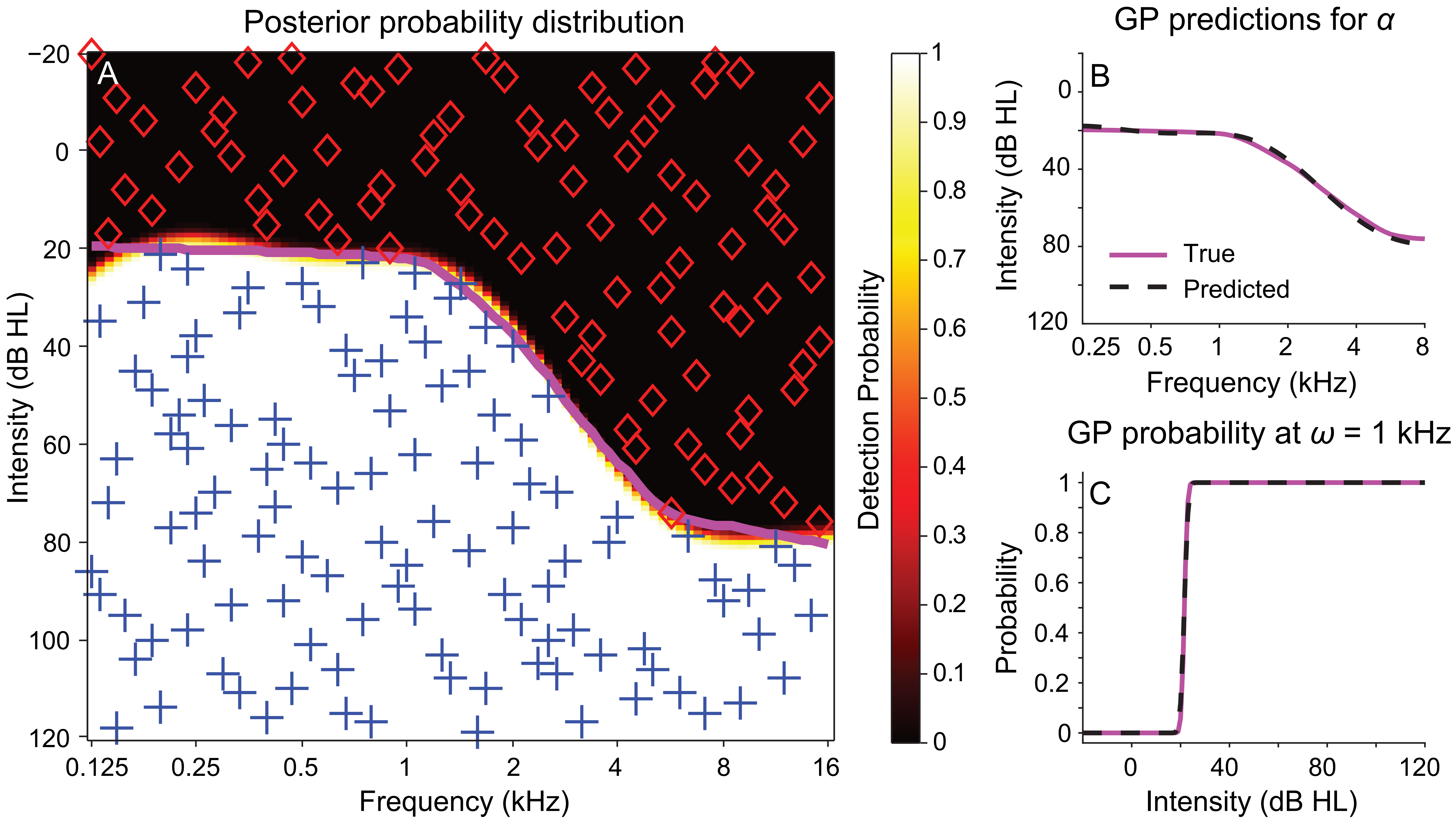


Barbour, DiLorenzo, et al, *Behav Res Meth,* 561(3):1271-1285, 2019; Masterson, Tak, et al., *Am J Indust Med*, 56(6), 670-681, 2013

Audiogram model constraints for frequency are continuity and smoothness



Gaussian process classification provides accurate threshold and spread estimates for the multidimensional audiogram



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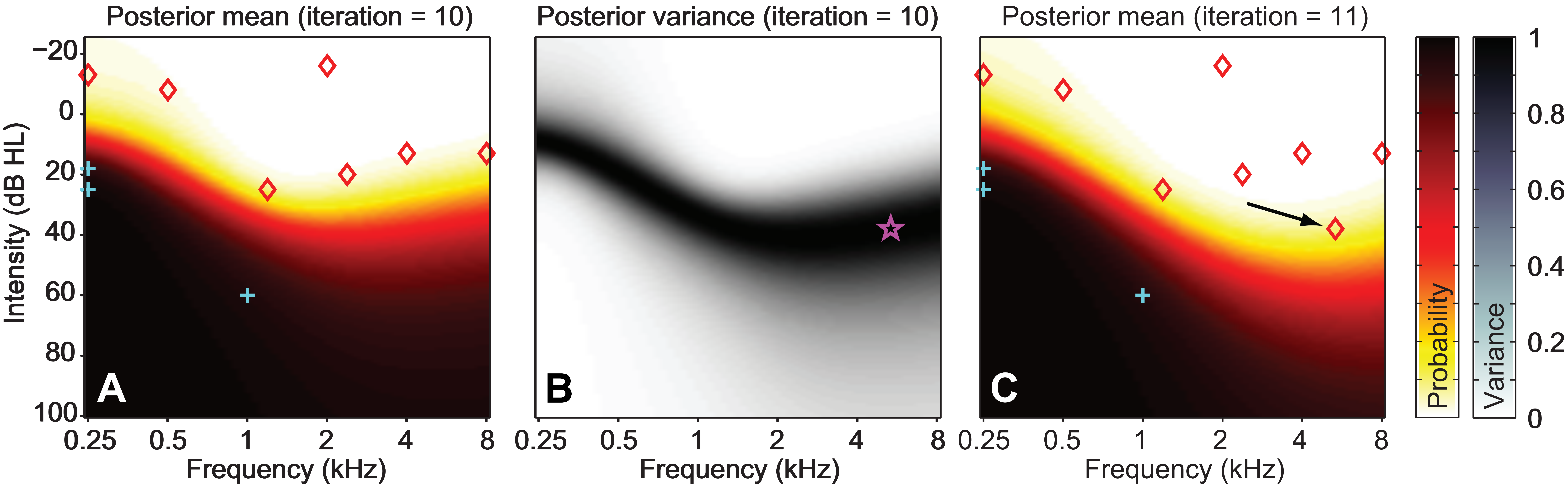
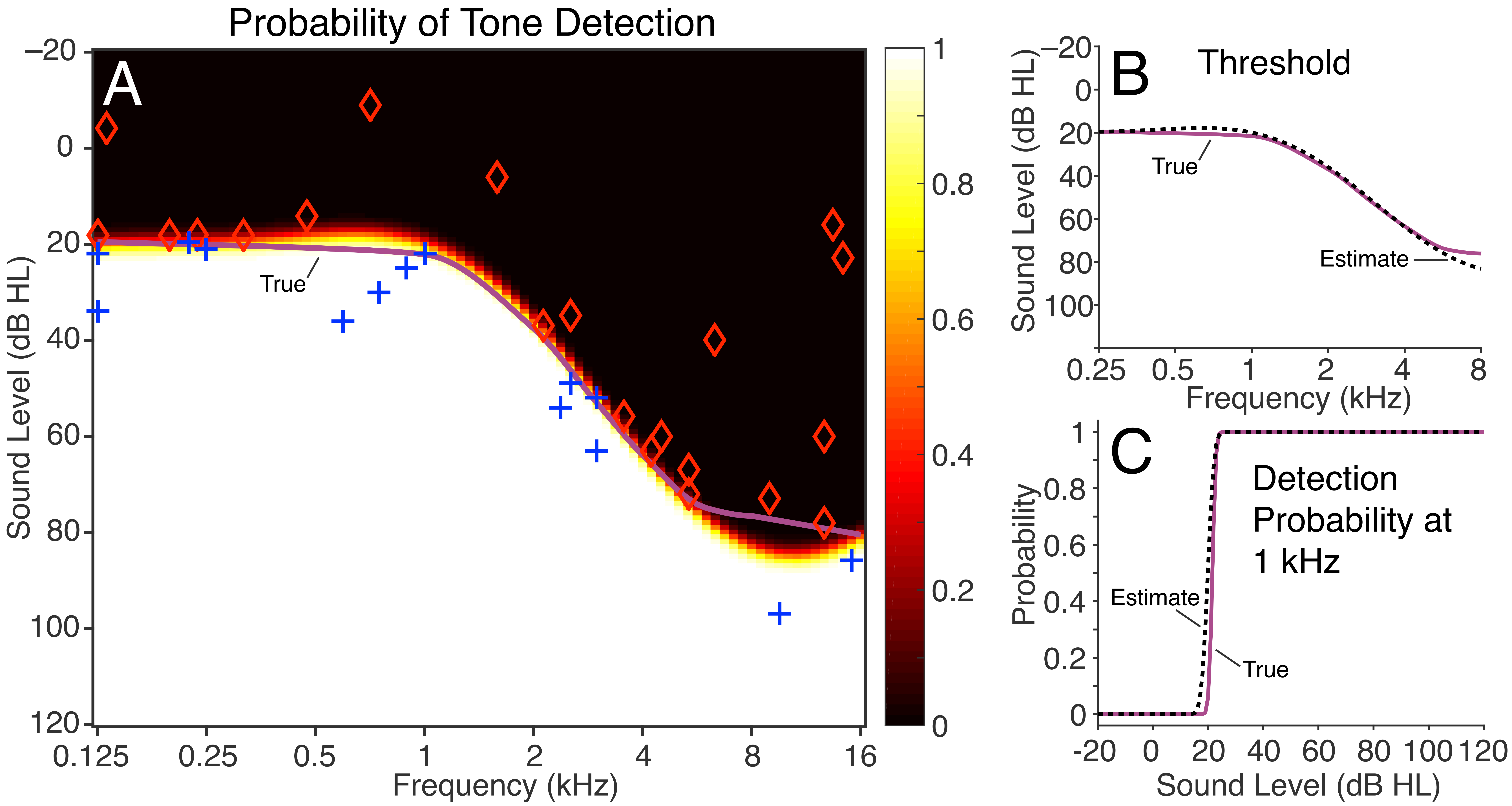
Bayesian active learning ensures that samples are acquired where needed most



Song, Wallace, et al, *Ear & Hearing* 36(6):e325-335, 2015

Gaussian process classification with Bayesian active learning yields accurate multidimensional psychometric threshold and spread estimates with few samples

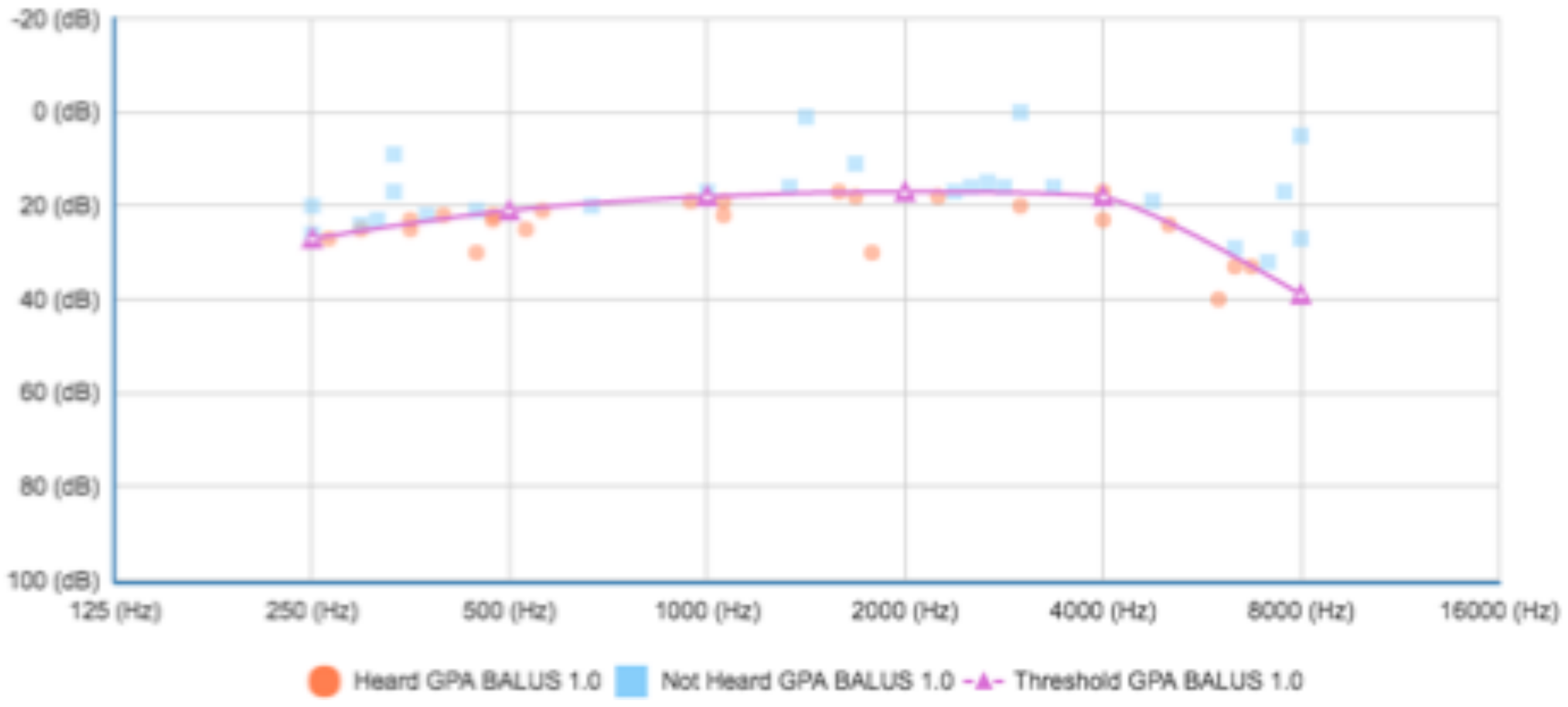


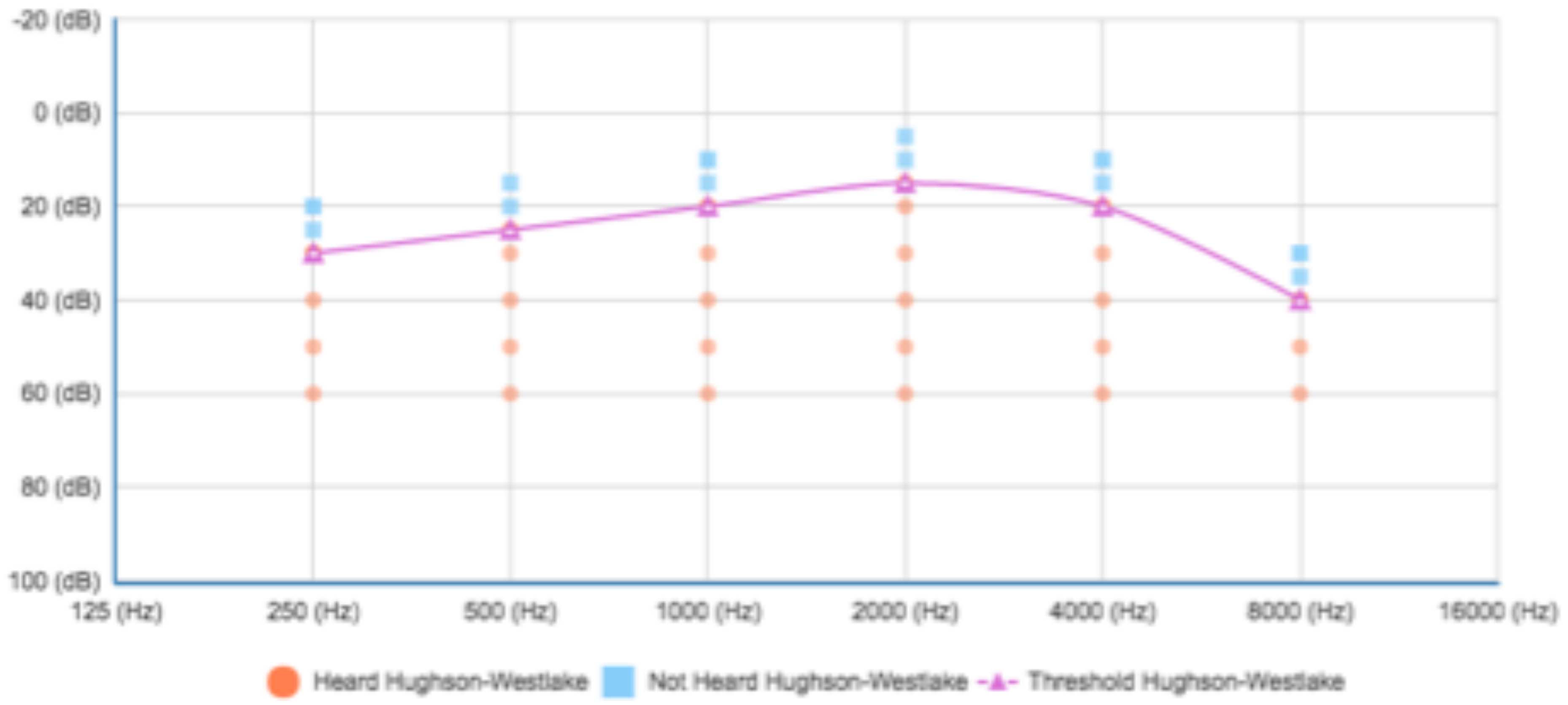
Song, Sukesan and Barbour, *Atten, Perc & Psychophys*, 80:798-812, 2018

Online MLAG can be compared directly to online HWAG

Test Parameters

Test Type:	GPA BALUS 1.0	**Tone Type:**	Pulse
Hardware Profile:*	Uncalibrated*	**Ear:**	Both Ears (Simultaneous)
Minimum Test Frequency (Hz):	250	**Maximum Test Frequency (Hz):**	8000
Minimum Tone Count:	20	**Maximum Tone Count:**	40
Hyperparameter Learning:	Off	**Sample Resolution:**	Standard





Barbour, Howard, et al, *Ear Hear*, 40(4):918-926, 2019

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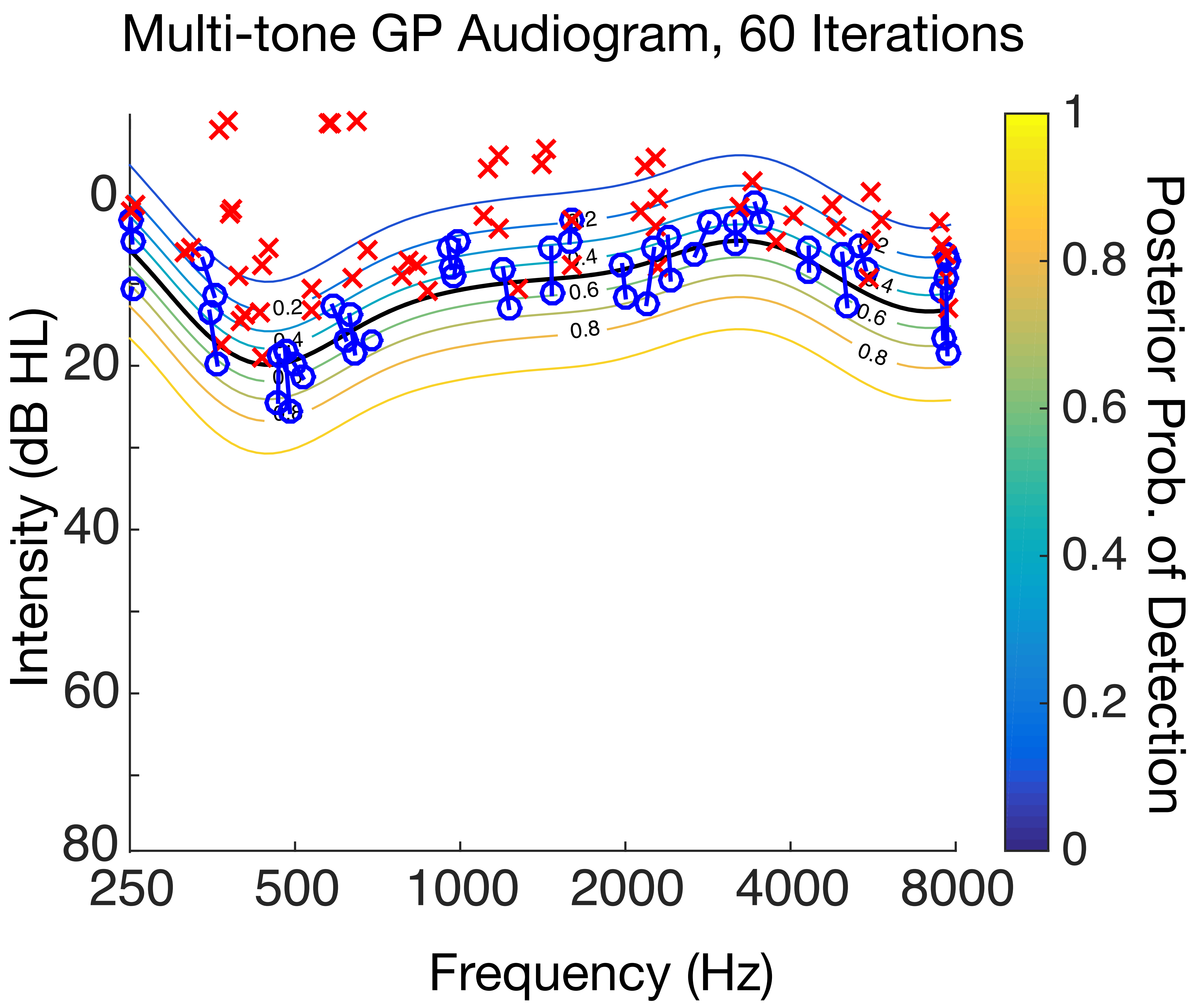
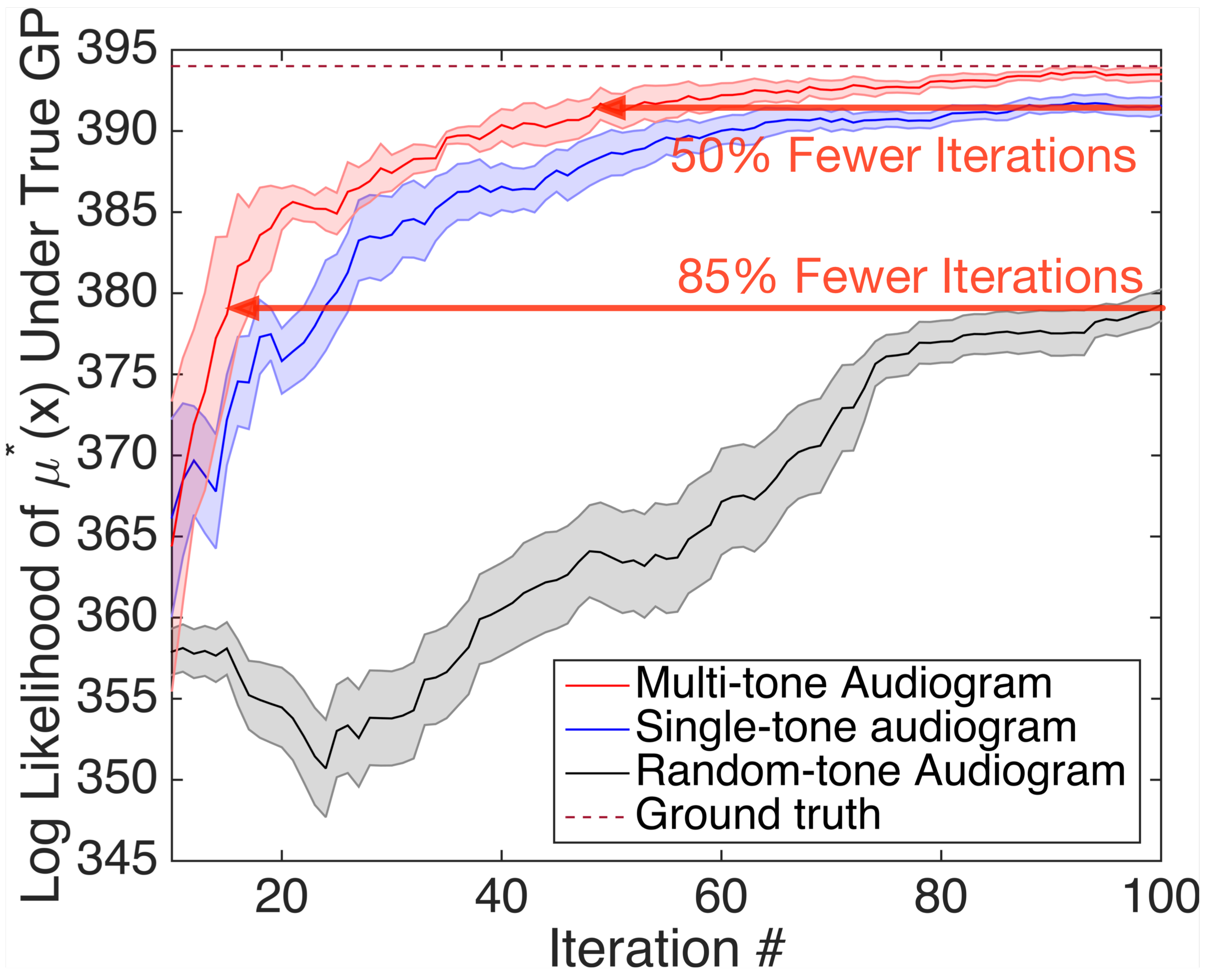
Multitone audiometry accelerates active learning





Gardner, et al, *UAI*, 286-295, 2015

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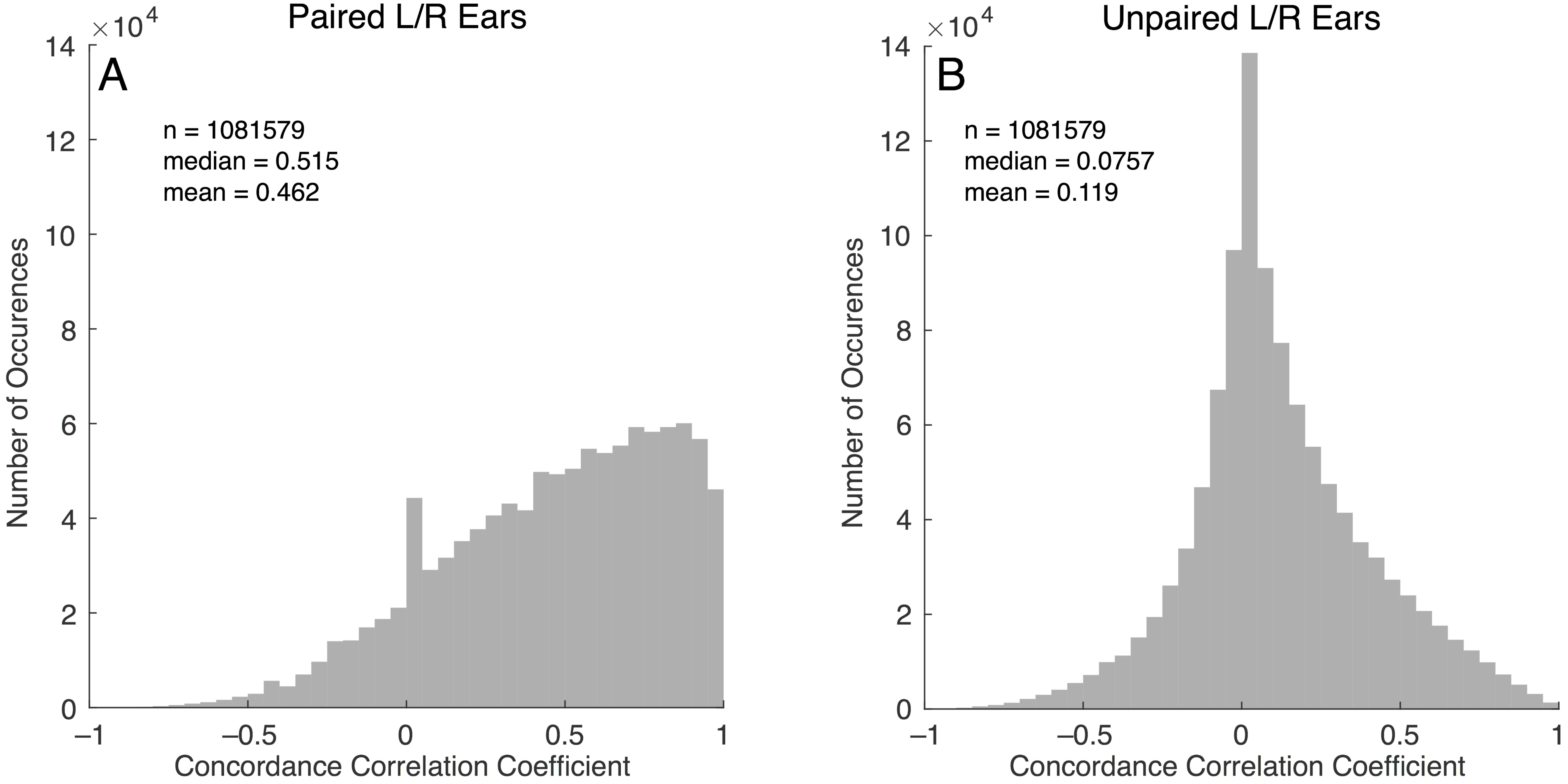
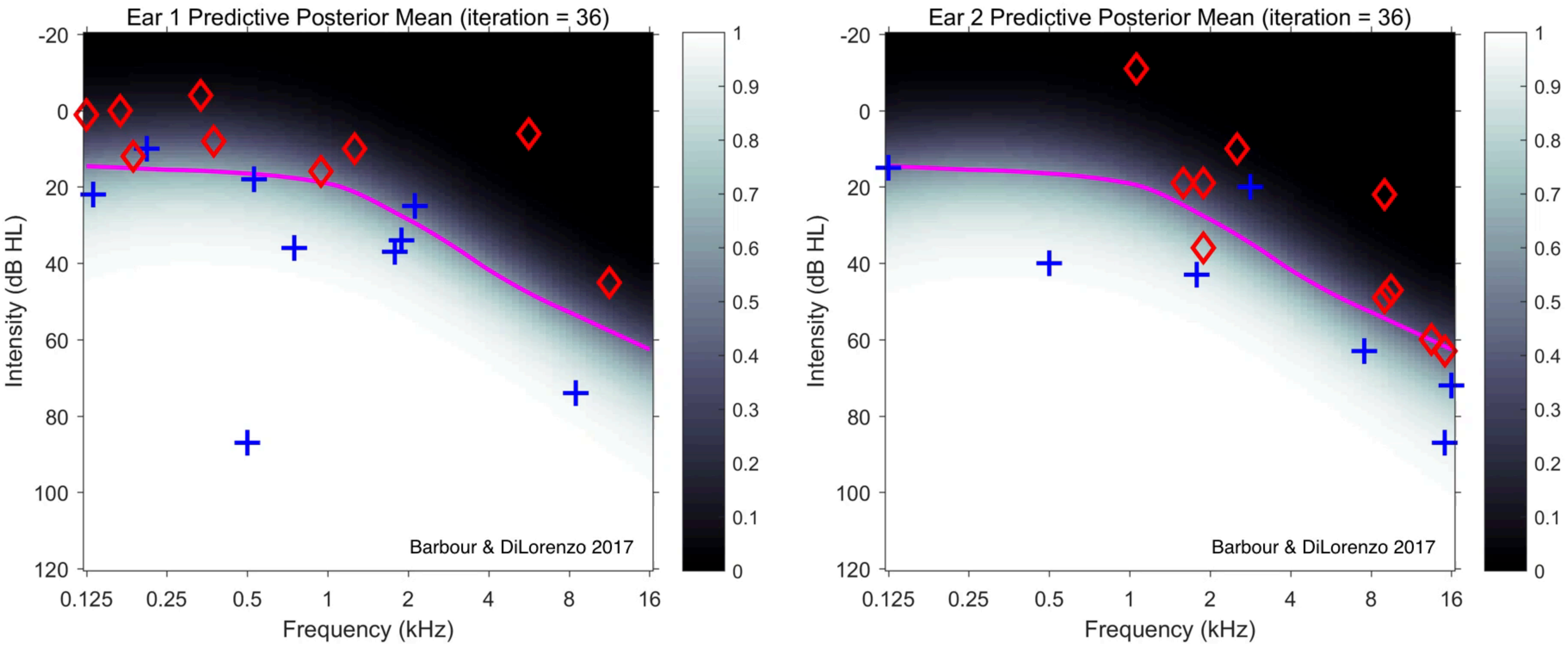
Hearing thresholds of a person's two ears are highly correlated



Barbour, DiLorenzo, et al, *Behav Res Meth* 51(3):1271-1285, 2019; Masterson, Tak, et al., *Am J Indust Med*, 56(6), 670-681, 2013

Active mutual conjoint estimation enables rapid assessment of both ears



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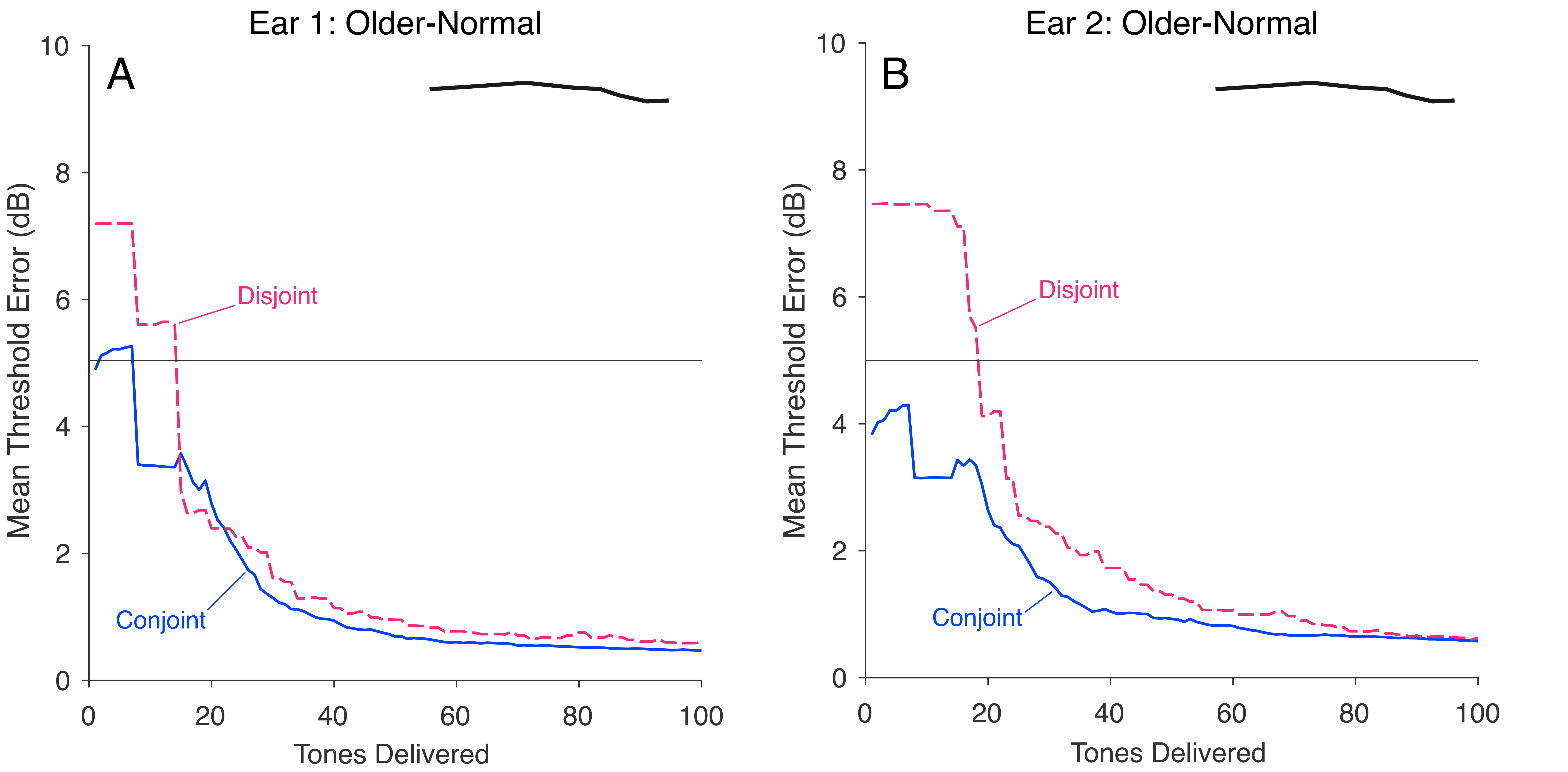
Conjoint estimates tend to converge faster than disjoint estimates



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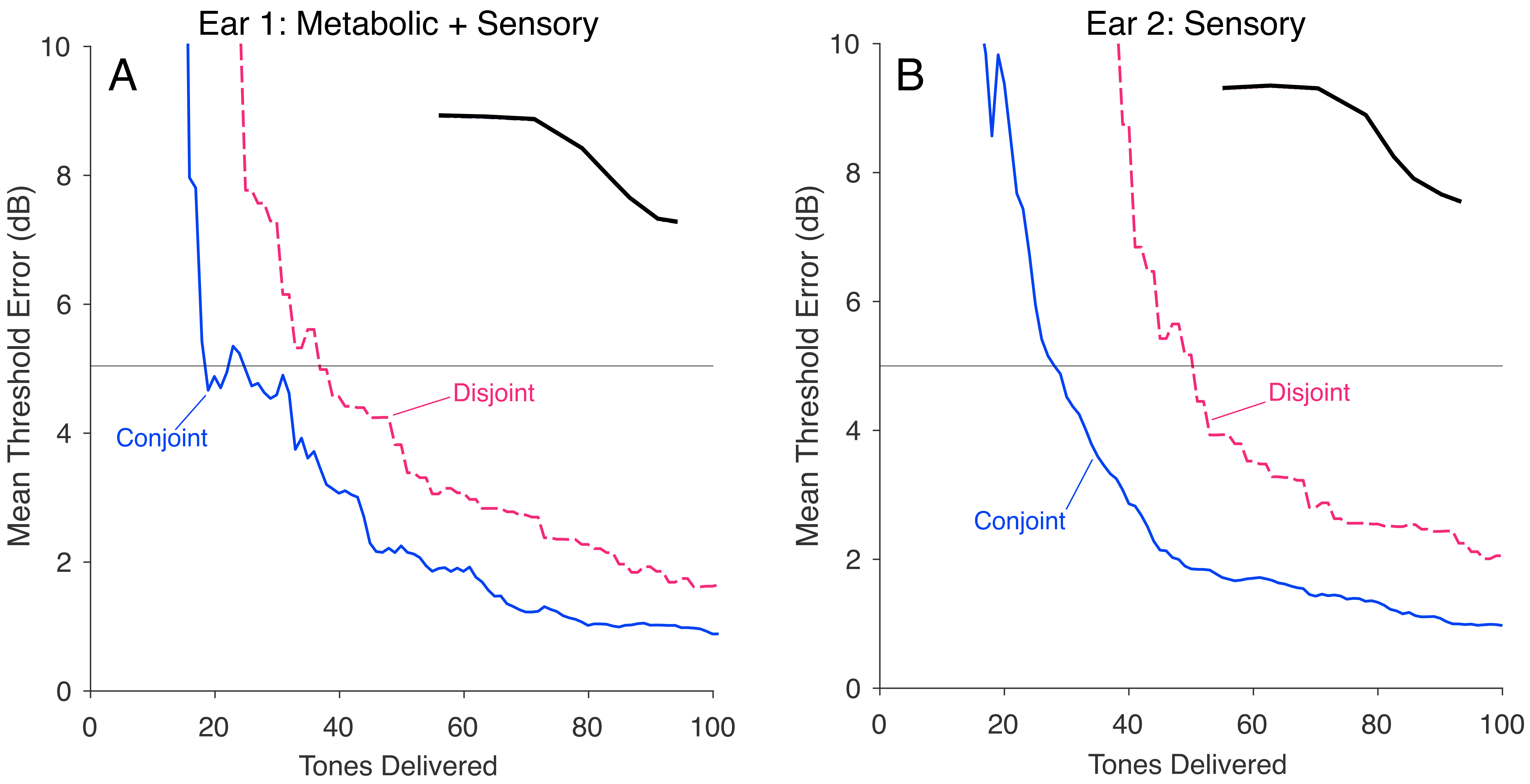

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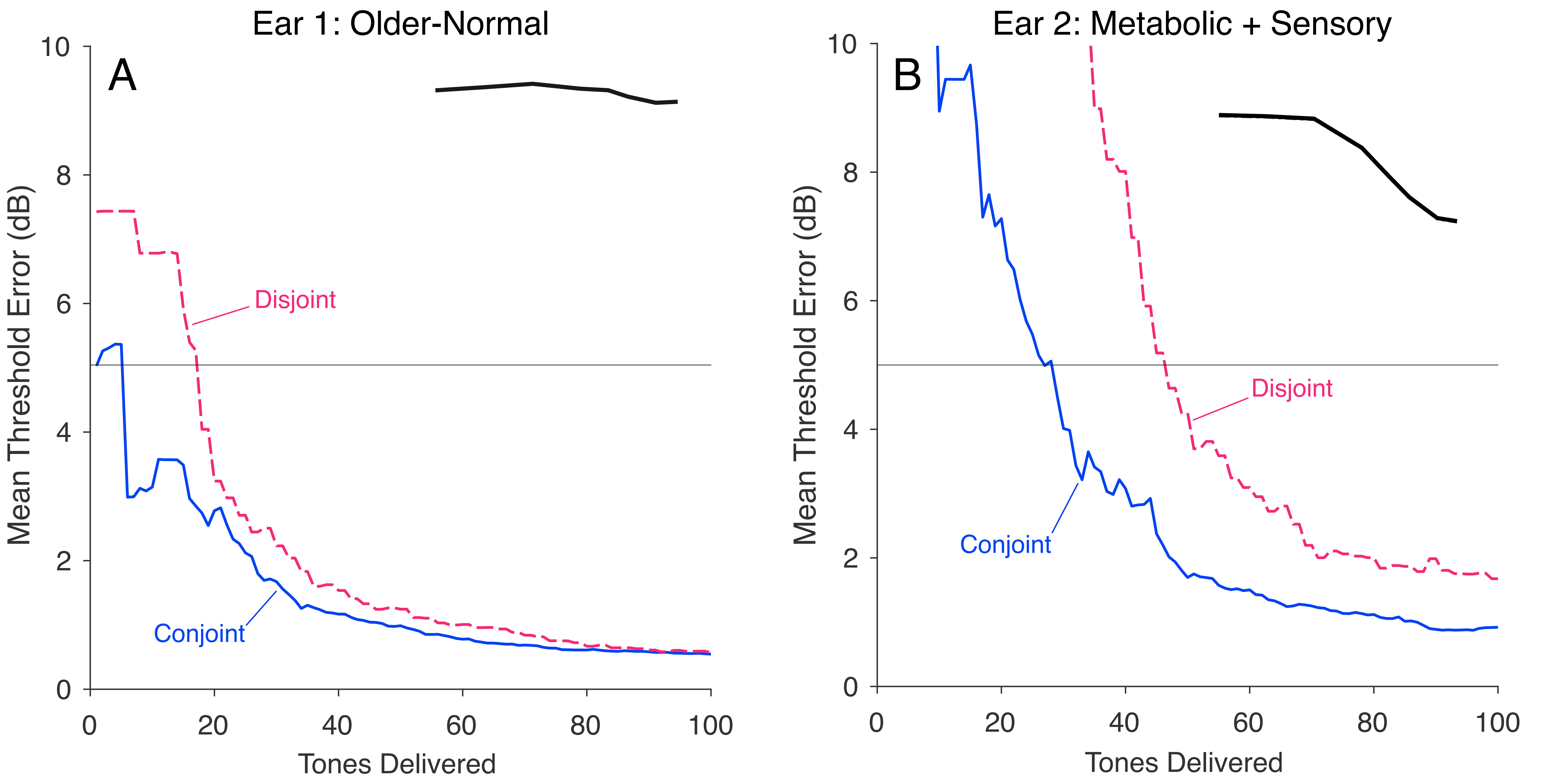

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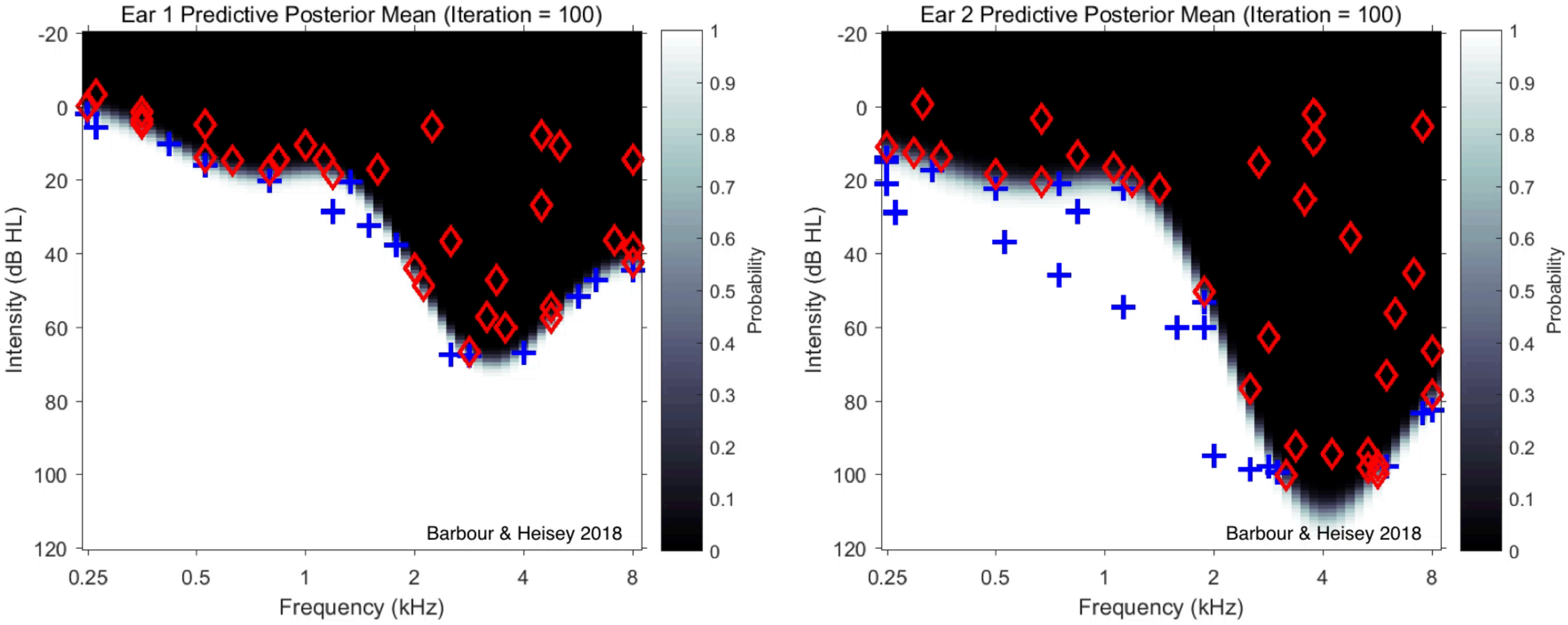
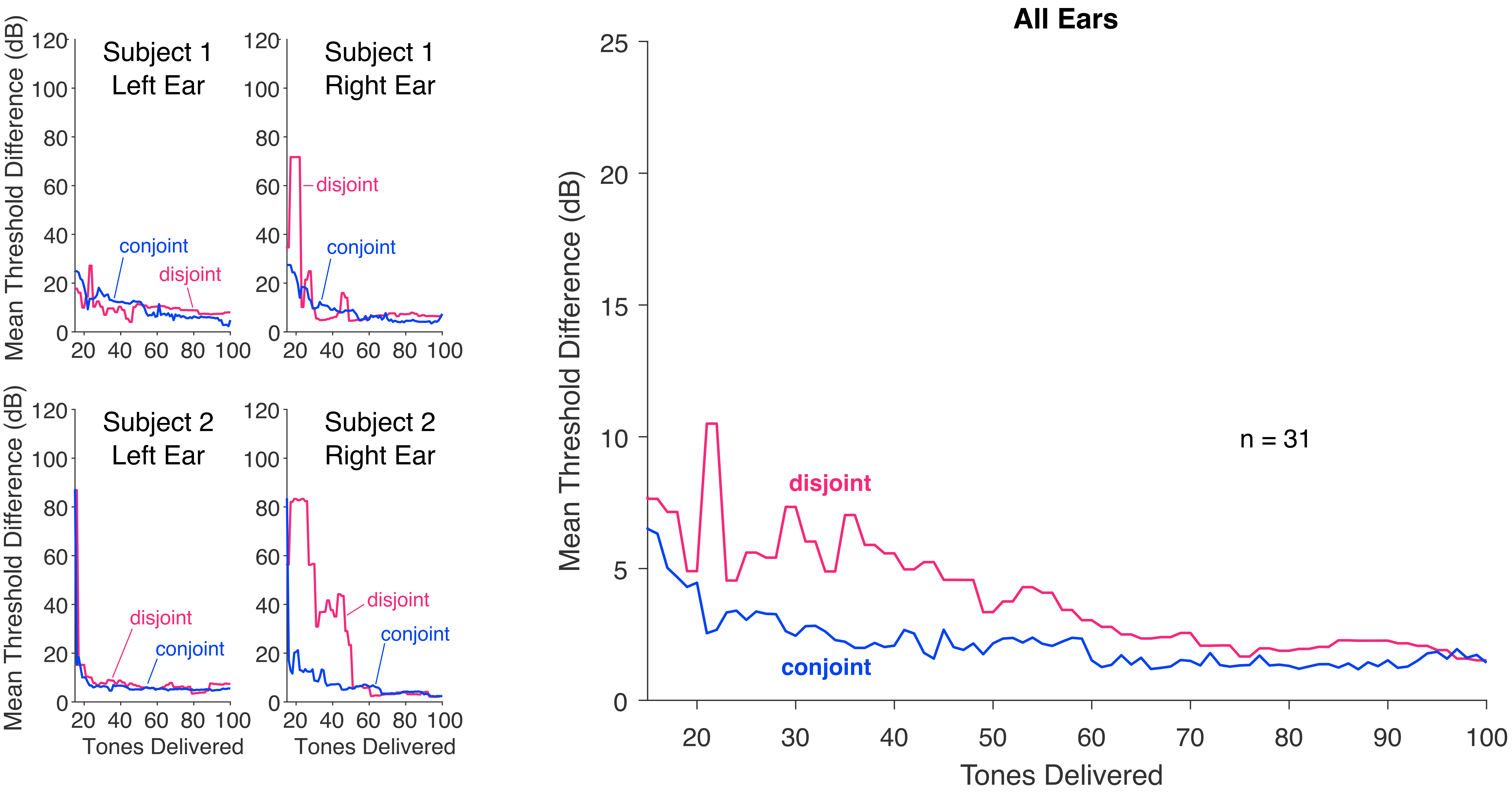


Heisey, Buchbinder & Barbour, *Acta Acustica* 104(5):762-764, 2018

Conjoint estimates converge faster on average than disjoint estimates



Heisey, Buchbinder & Barbour, *Acta Acustica* 104(5):762-764, 2018

Conjoint estimates tend to converge faster than disjoint for various subgroups

	Conjoint	Disjoint	n
All	18 ± 8.8	45 ± 10	31
Normal	5 ± 4.7	23 ± 5.5	8
Loss	21 ± 14	49 ± 15	23
Symmetric	17 ± 6.5	33 ± 7.5	19
Asymmetric	43 ± 17	71 ± 18	12

mean ± standard deviation tone count to 5 dB threshold accuracy

Heisey, Buchbinder & Barbour, *Acta Acustica* 104(5):762-764, 2018

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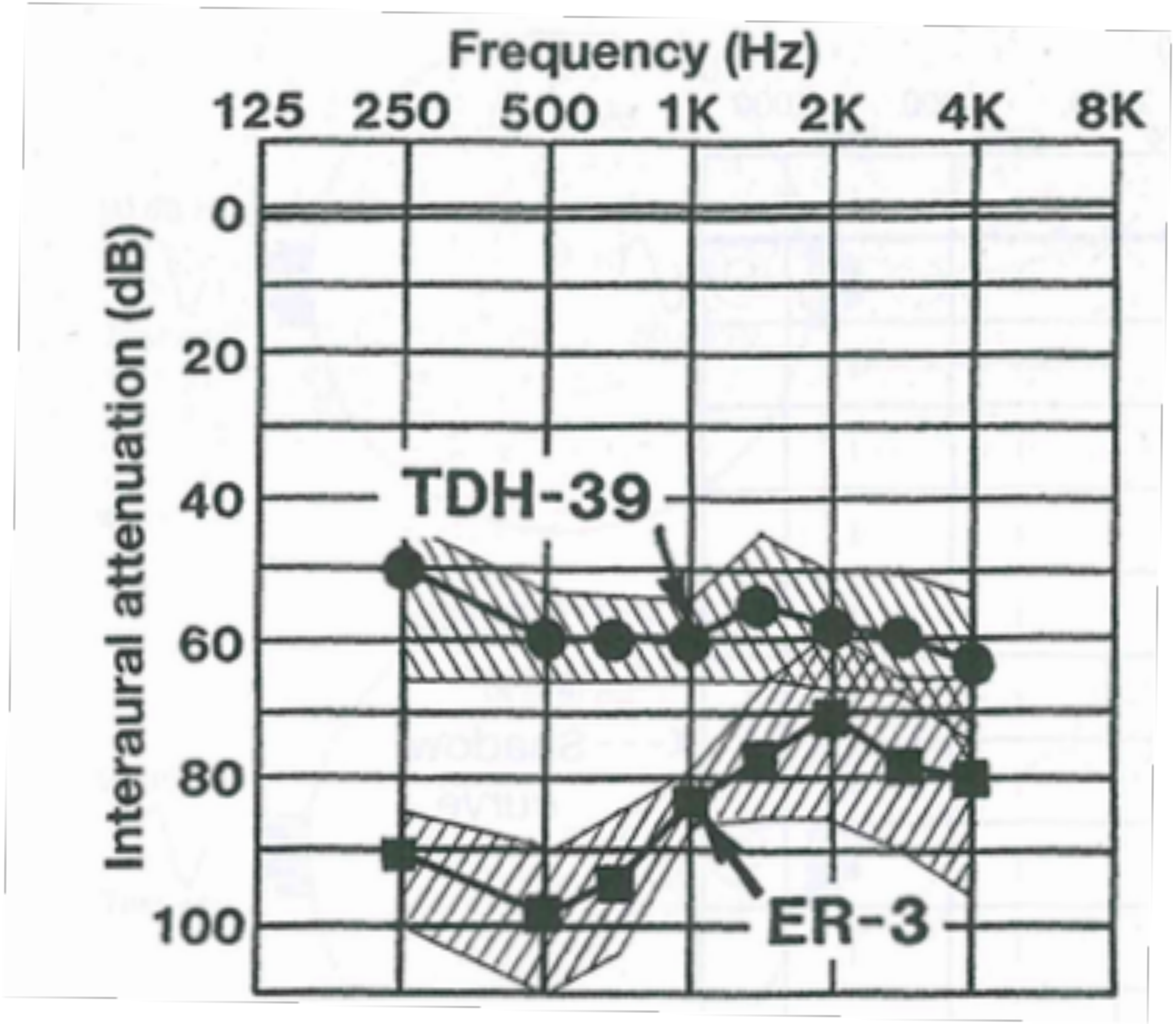
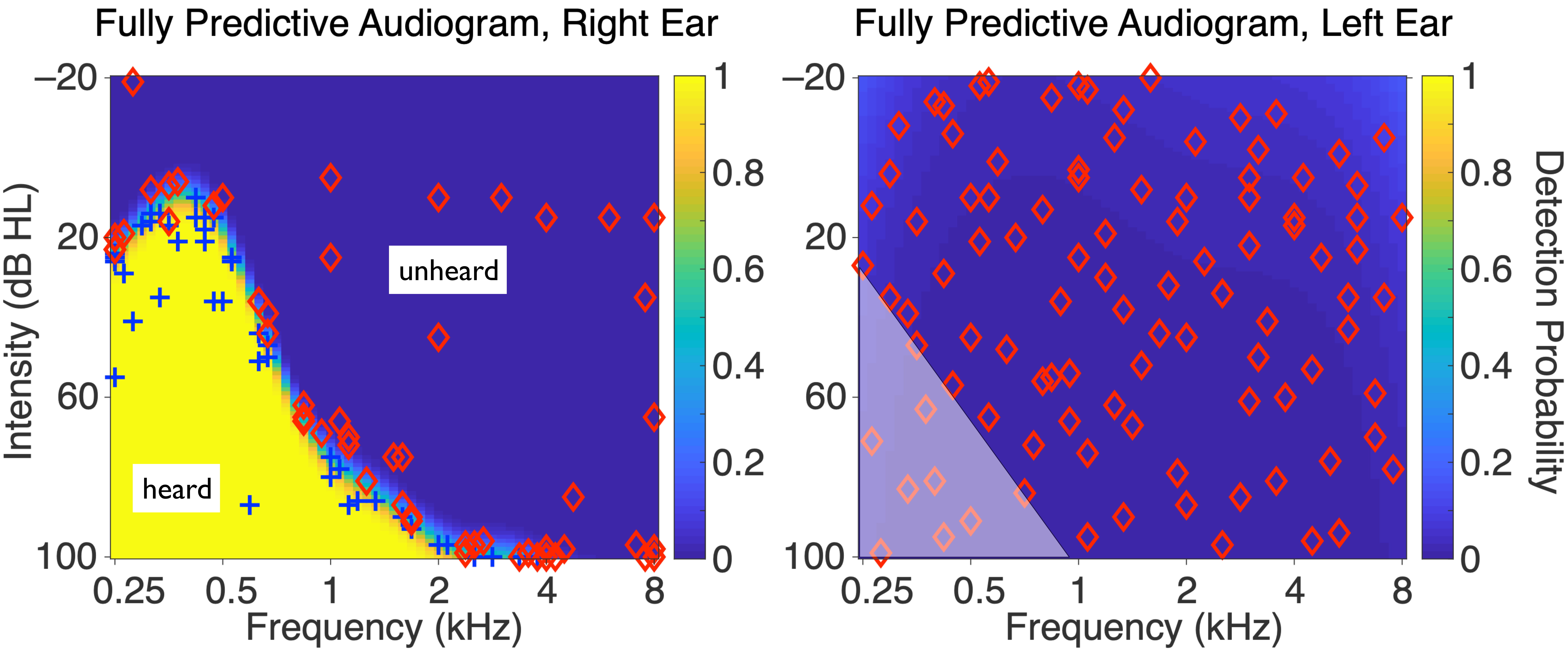
Interaural attenuation for two transducers measured in a reference group



Killion, Wilber & Gudmundsen. *Hear Instr* 39(1): 14-18, 1988

Dynamically masked MLAG estimates true thresholds despite asymmetry

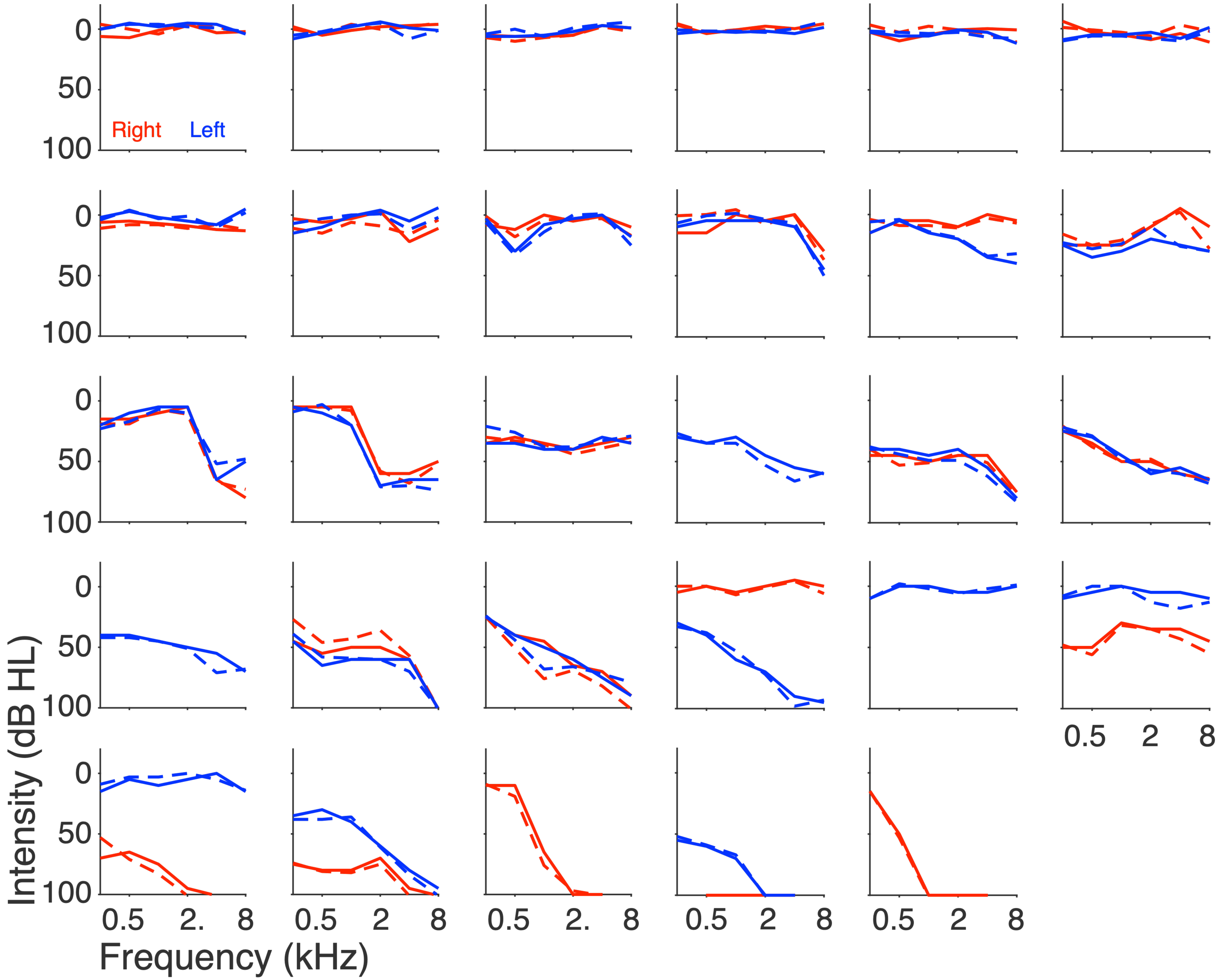


Heisey, Walker, et al., *Ear & Hearing*, 41(6):1692-1702, 2020

Dynamically masked MLAG matches conventional thresholds in less time

– – – – – –
conventional audiogram
~14 min

———
machine learning audiogram
~6 min

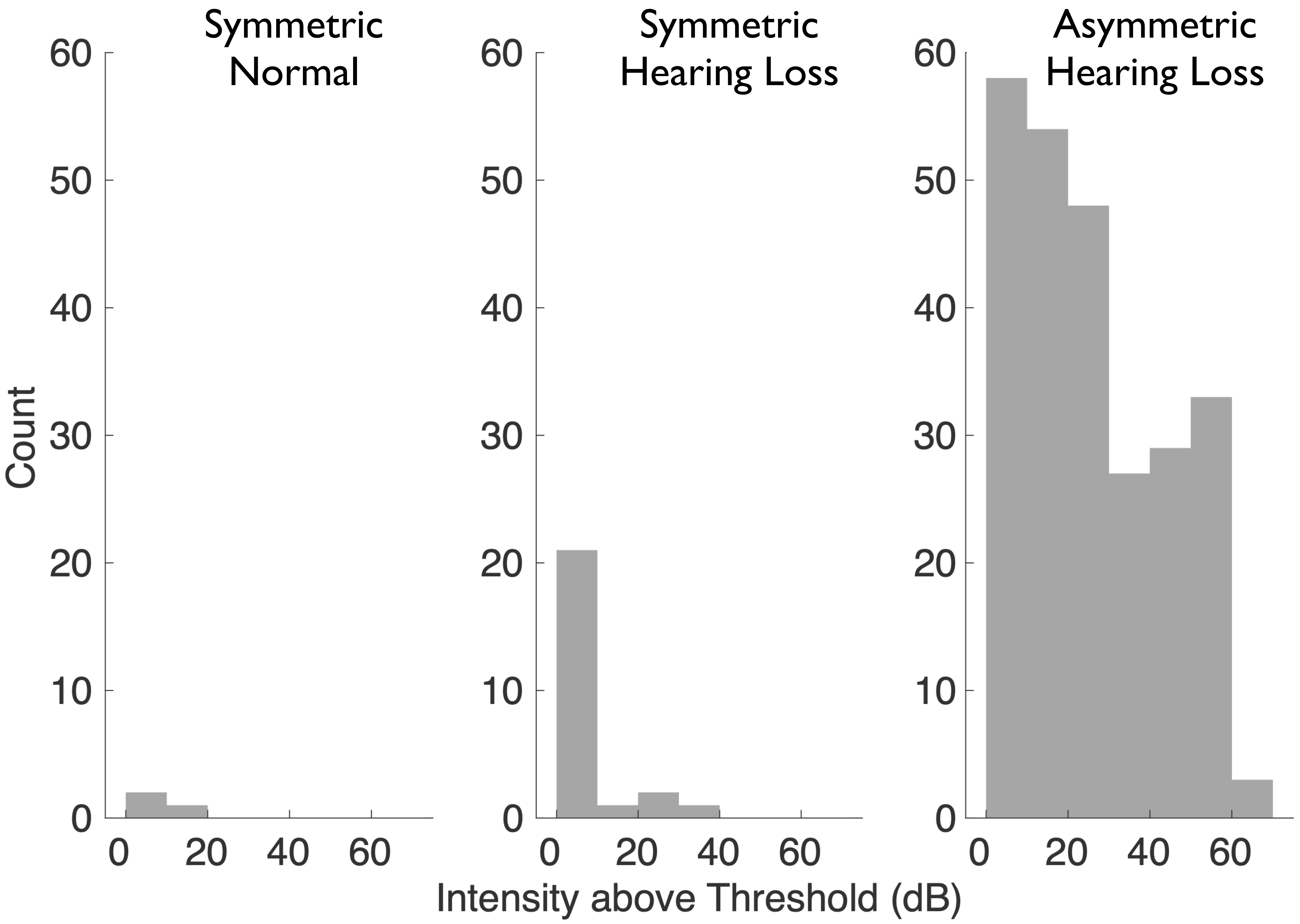


mean signed difference = 0.737 dB

root mean square difference = 4.65 dB

Heisey, Walker, et al., *Ear & Hearing*, 41(6):1692-1702, 2020

Few contralateral maskers are delivered over threshold for symmetric hearing



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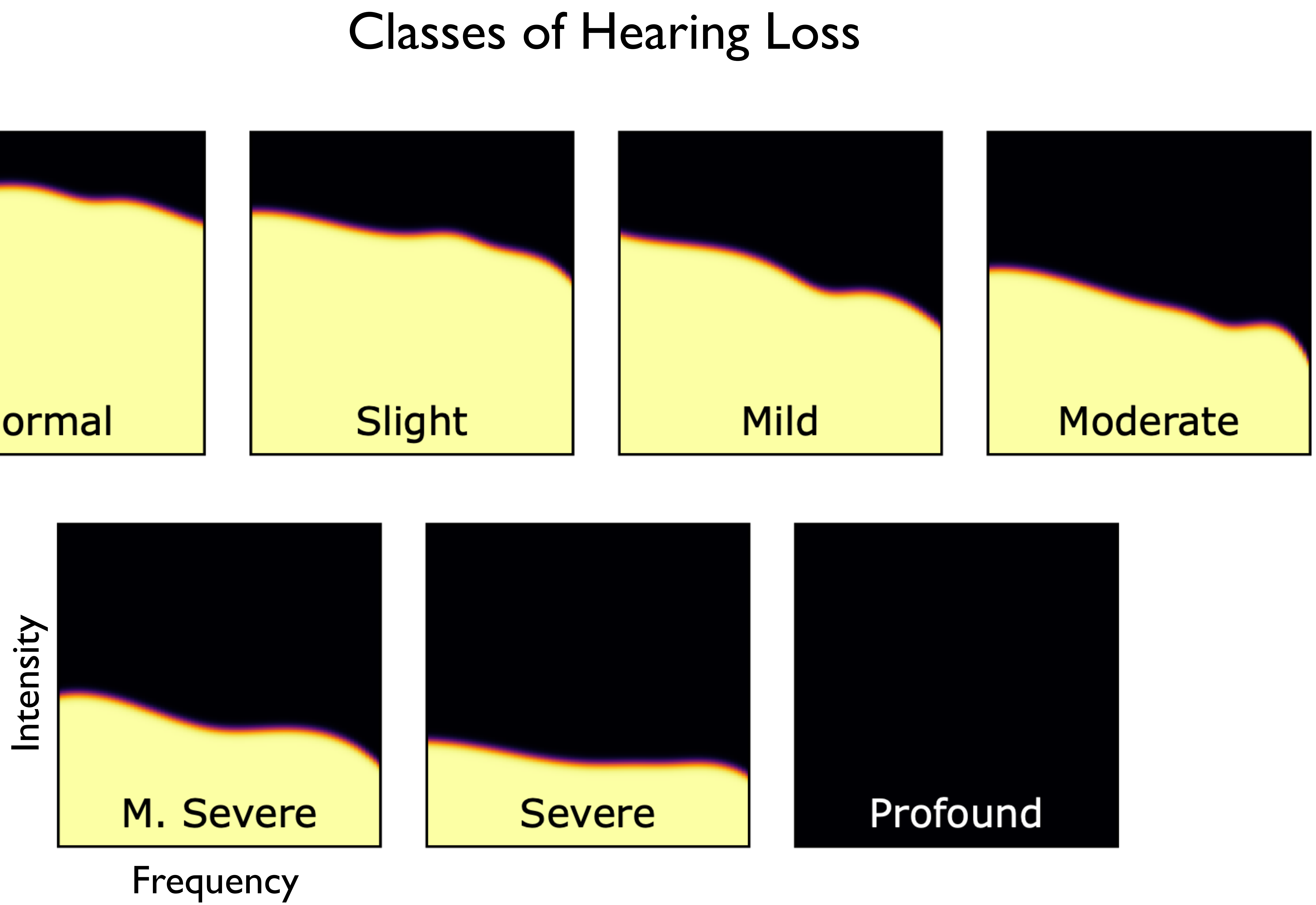
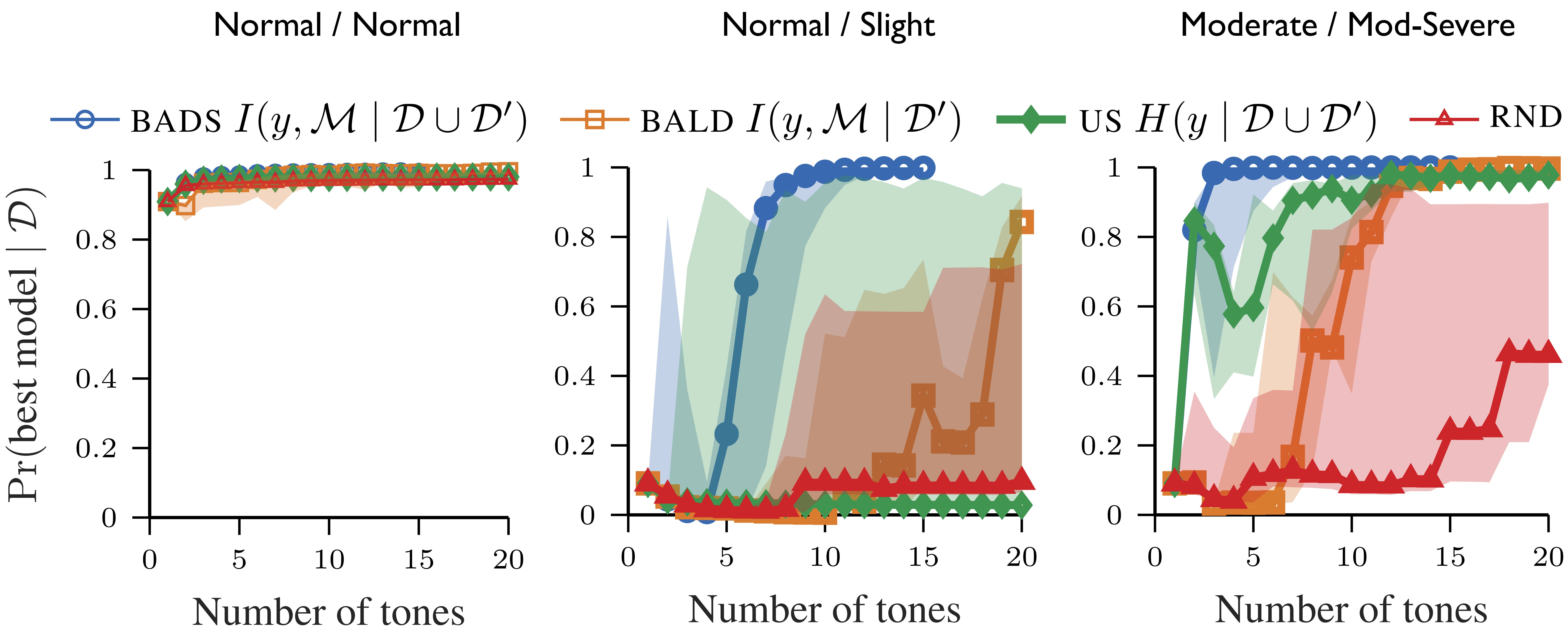
Models of hearing created from a large database of adult audiograms



Larsen, Malkomes & Barbour, *NeurIPS ML4H*, 2019; *AAAI*, 2020; Clark, *ASHA*, 23(7), 493–500, 1981; Masterson, Tak, et al., *Am J Indust Med*, 56(6), 670-681, 2013

BADS enables diagnostic decisions faster than other methods



Larsen, Malkomes & Barbour, *NeurIPS ML4H*, 2019; *AAAI*, 2020

Correct decisions of "same" or "different" fall into different clusters

Patient Models

OLD \ NEW	Normal	Slight	Mild	Moderate	M. Severe	Severe	Profound
Normal	7.2 ± 1.6	5.8 ± 2.9	3.8 ± 0.79	3.7 ± 0.48	3.5 ± 0.53	3.7 ± 0.48	3.5 ± 0.53
Slight	5.0 ± 0.47	5.4 ± 0.70	9.9 ± 1.8	3.2 ± 0.42	3.3 ± 0.48	3.1 ± 0.32	3.0 ± 0
Mild	4.5 ± 0.53	6.7 ± 3.6	4.1 ± 0.32	12 ± 2.5	2.7 ± 0.48	2.9 ± 0.32	2.9 ± 0.32
Moderate	4.1 ± 0.32	4.5 ± 0.53	7.4 ± 4.1	3.8 ± 0.63	11 ± 2.6	3.0 ± 0	2.6 ± 0.52
M. Severe	4.4 ± 0.52	4.3 ± 0.48	7.5 ± 2.8	16 ± 8.0	3.9 ± 0.88	11 ± 2.6	2.8 ± 0.42
Severe	4.2 ± 0.63	4.2 ± 0.42	4.3 ± 0.48	8.2 ± 3.4	14 ± 9.2	4.2 ± 1.1	2.7 ± 0.48
Profound	3.0 ± 0	3.0 ± 0	3.5 ± 0.53	3.6 ± 0.84	3.3 ± 0.48	4.2 ± 0.63	—

Reference Models

conclude "different"

conclude "same"

conclude "different"

Larsen, Malkomes & Barbour, *NeurIPS ML4H*, 2019; *AAAI*, 2020

Query counts for correct conclusions at high confidence are generally low

Patient Models

Reference Models: OLD \ NEW	Normal	Slight	Mild	Moderate	M. Severe	Severe	Profound
Normal	7.2 ± 1.6	5.8 ± 2.9	3.8 ± 0.79	3.7 ± 0.48	3.5 ± 0.53	3.7 ± 0.48	3.5 ± 0.53
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Profound	3.0 ± 0	3.0 ± 0	3.5 ± 0.53	3.6 ± 0.84	3.3 ± 0.48	4.2 ± 0.63	—

Comparison of HWAG and MLAG properties

	Stimuli	Data	Reso-lution	Relia-bility	Auto-matable?	Exten-dable?	Confi-dence?	Spread Estimate?	Predic-tive?	Under-standable?
HWAG	tones	more	octave	3–4 dB	yes	no	no	no	no	yes
MLAG	tones (or other)	less	arbitrary	4–5 dB	yes	yes	yes	yes	yes	no

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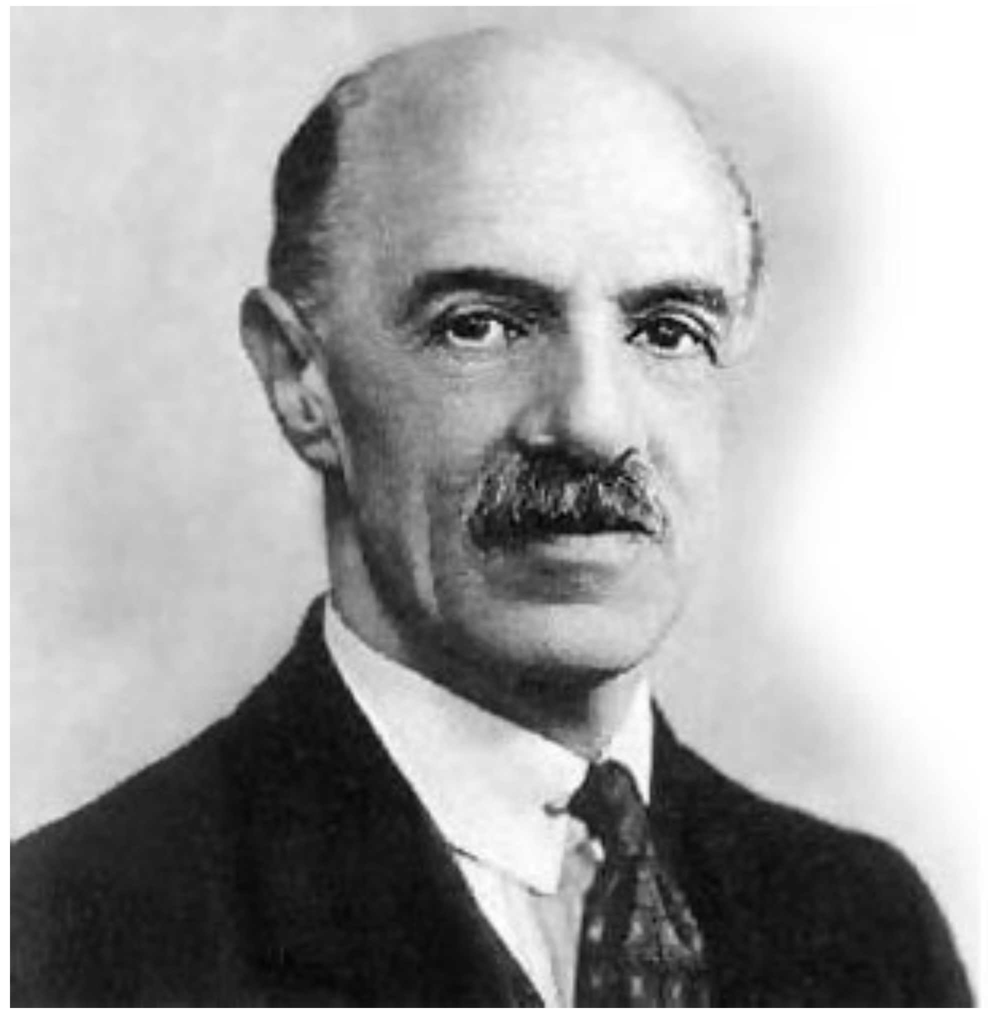
Science is widely regarded to be about patterns across entities

All knowledge—beyond that of bare isolated occurrence—deals with uniformities.

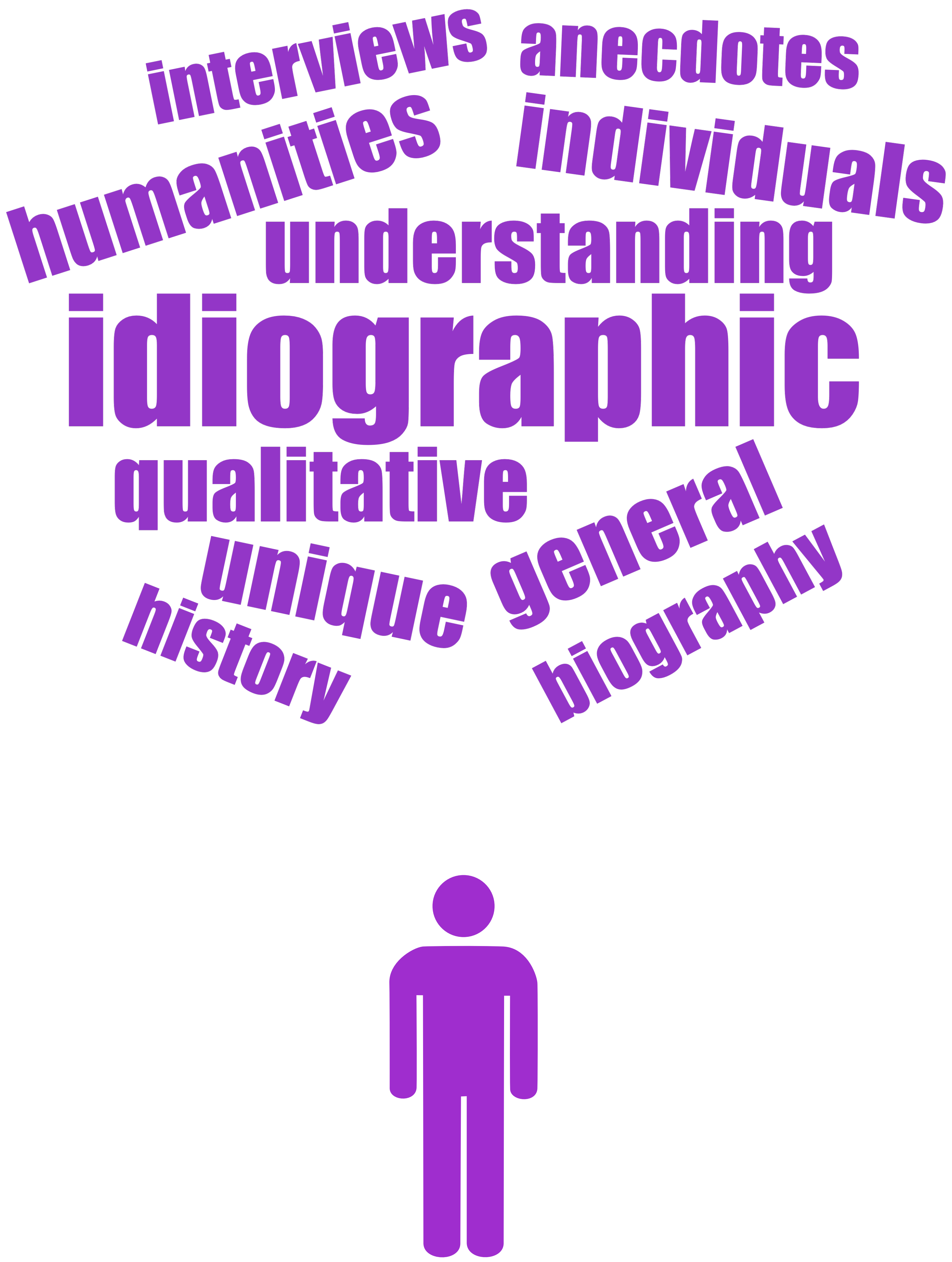
[S]ome few [uniformities] have a claim to be considered absolute, such as mathematical implications and mechanical laws. But the vast majority are only partial; medicine does not teach that smallpox is inevitably escaped by vaccination, but that it is so generally….

Charles Spearman, 1904



Spearman, *Int J of Epidemiol* 39:1137–1150, 2010

Inference can be drawn either across or within individuals



Diagnostic expansion of lung cancer site over the decades

ICD-2, 1910
051 Malignant neoplasm of the left lung
052 Malignant neoplasm of the right lung
059 Malignant neoplasm of the lung, unspecified

ICD-10-CM, 2015
01458 Malignant neoplasm of bronchus and lung
01459 Malignant neoplasm of main bronchus
01460 Malignant neoplasm of unspecified main bronchus
01461 Malignant neoplasm of right main bronchus
01462 Malignant neoplasm of left main bronchus
01463 Malignant neoplasm of upper lobe, bronchus or lung
01464 Malignant neoplasm of upper lobe, unsp bronchus or lung
01465 Malignant neoplasm of upper lobe, right bronchus or lung
01466 Malignant neoplasm of upper lobe, left bronchus or lung
01467 Malignant neoplasm of middle lobe, bronchus or lung
01468 Malignant neoplasm of lower lobe, bronchus or lung
01469 Malignant neoplasm of lower lobe, unsp bronchus or lung
01470 Malignant neoplasm of lower lobe, right bronchus or lung
01471 Malignant neoplasm of lower lobe, left bronchus or lung
01472 Malignant neoplasm of overlapping sites of bronchus and lung
01473 Malignant neoplasm of ovrlp sites of unsp bronchus and lung
01474 Malignant neoplasm of ovrlp sites of right bronchus and lung
01475 Malignant neoplasm of ovrlp sites of left bronchus and lung
01476 Malignant neoplasm of unspecified part of bronchus or lung
01477 Malignant neoplasm of unsp part of unsp bronchus or lung
01478 Malignant neoplasm of unsp part of right bronchus or lung
01479 Malignant neoplasm of unsp part of left bronchus or lung

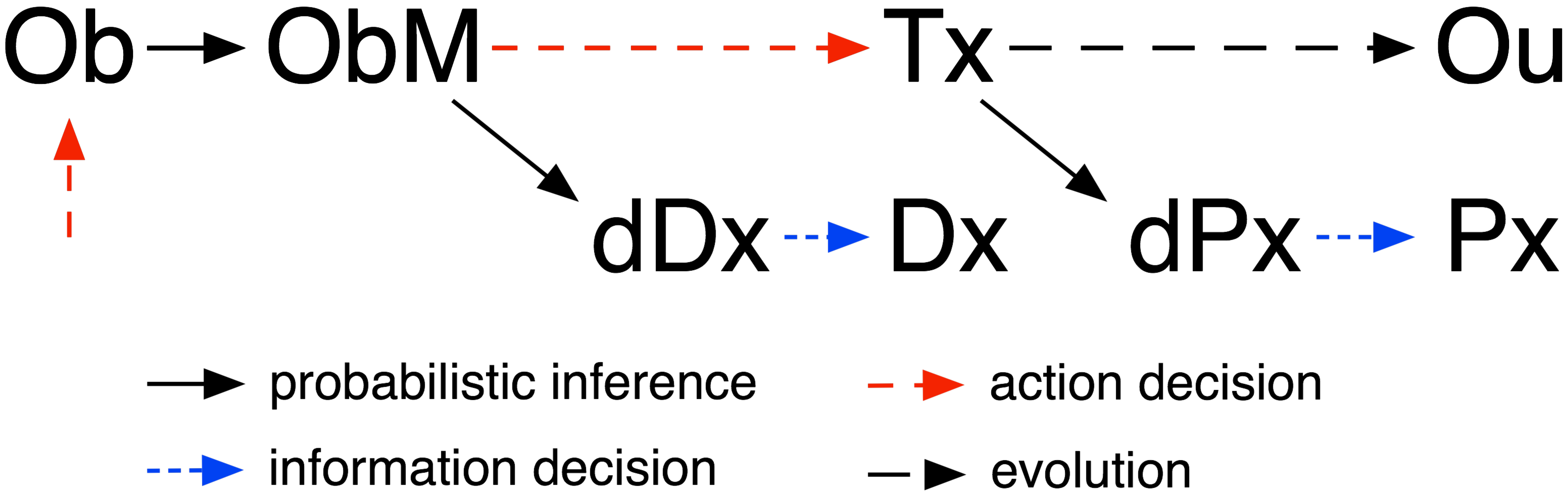
Traditional medical inference employs a taxonomy of disease

Ob → dDx → Dx → Px → Tx - → Ou

→ decision - → evolution

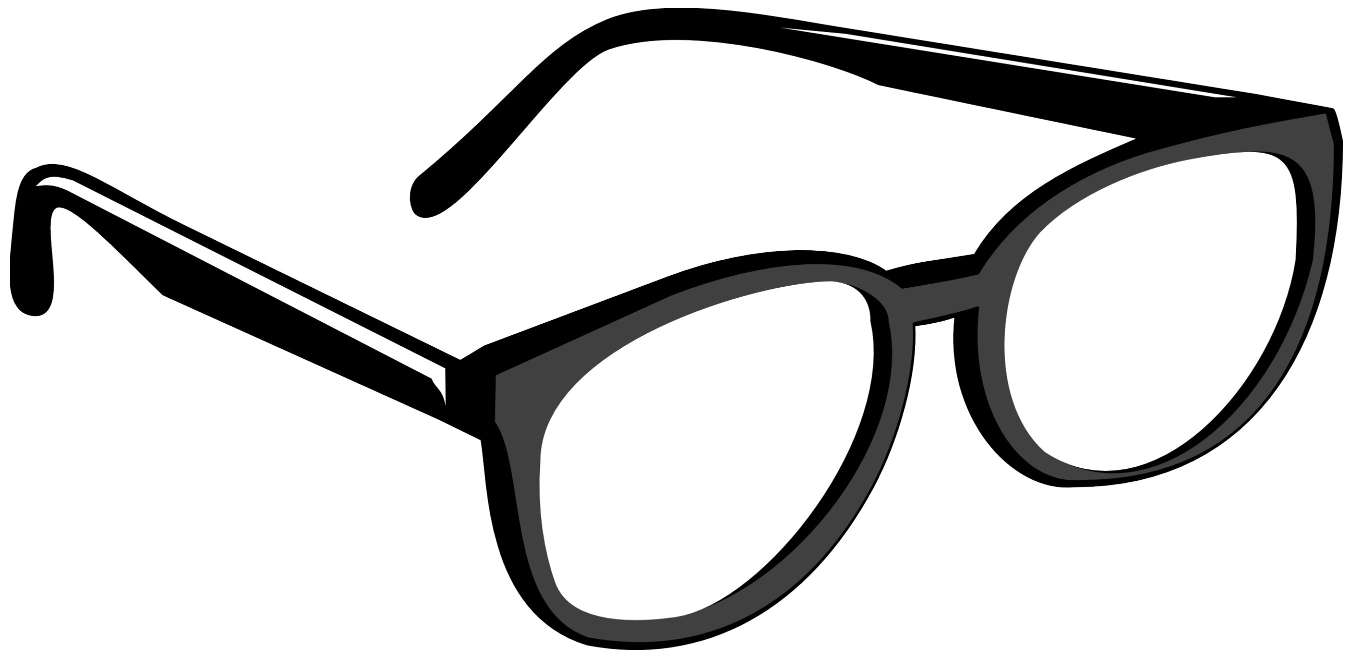
Barbour, D. L.. *Advanced Inferential Medicine*[SM]. Open Science Framework. https://osf.io/4nmkv, 2017

Advanced medical inference centralizes individual predictivity



Barbour, D. L.. *Advanced Inferential Medicine*SM. Open Science Framework. https://osf.io/4nmkv, 2017

Partial observation models are already utilized in some clinical fields



OD (Right)	(SPH) +0.25	(CYL) –1.00	Axis 107
OS (Left)	(SPH) 0.00	(CYL) –1.00	Axis 90
NV-ADD	None		
PD: 68			

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