Improved emotion recognition in speech by autistics: design, validation, and implementation of acoustically modulated prosodies

By

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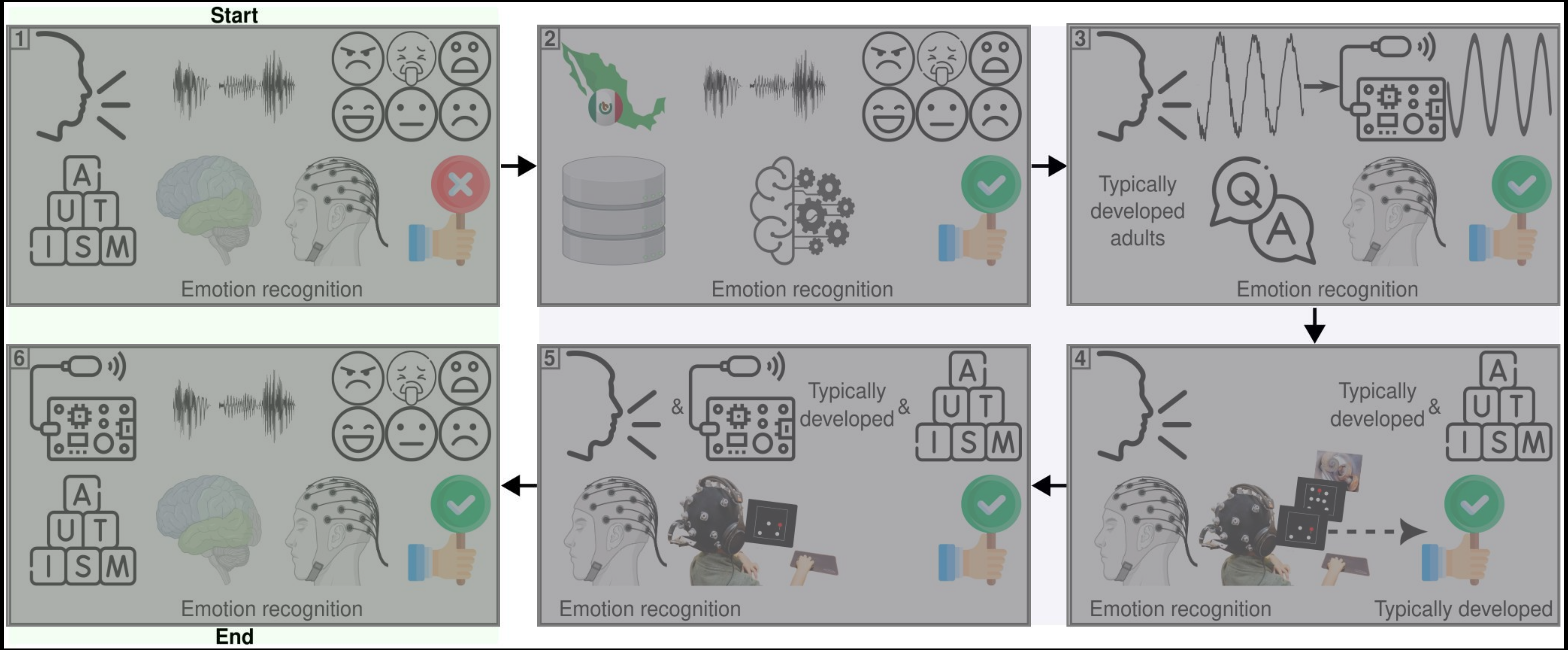
Rigoberto Martínez Méndez, PhD

Overview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Emotion recognition
6
Emotion recognition
End

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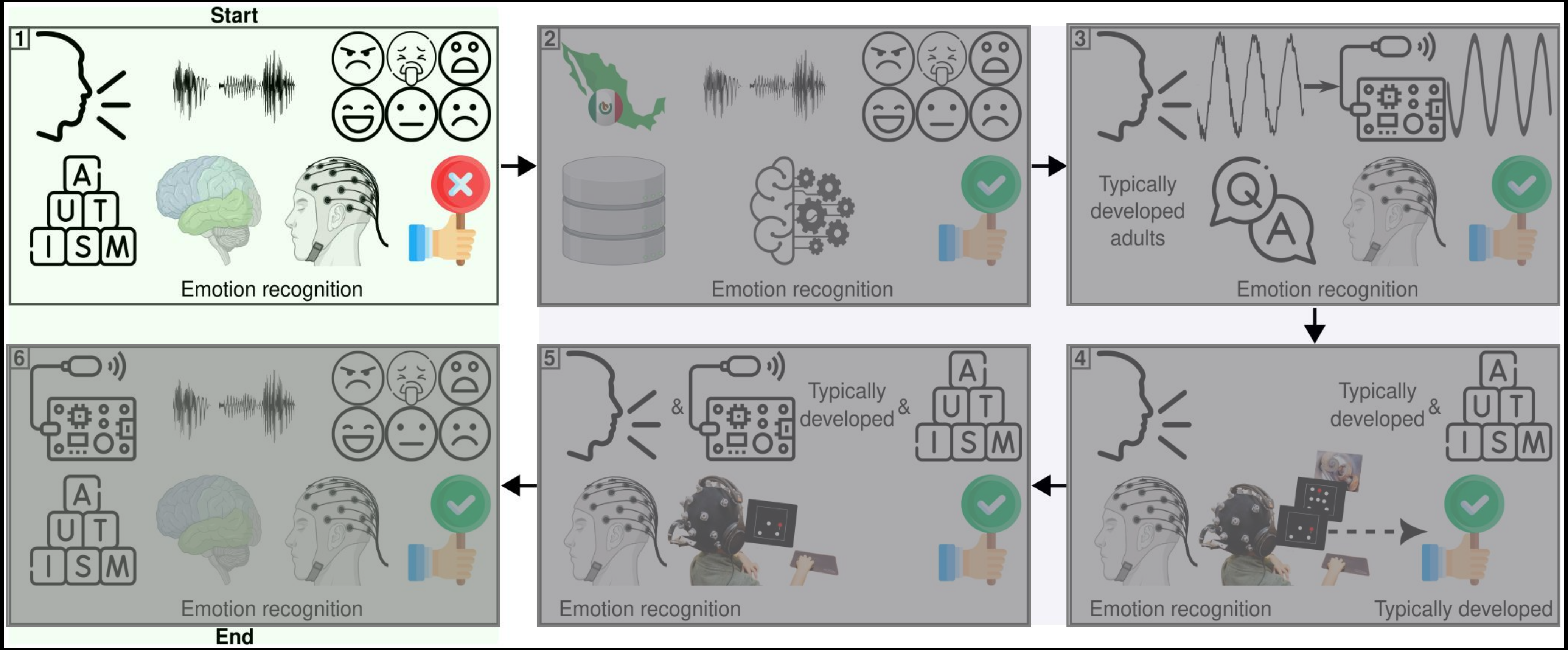
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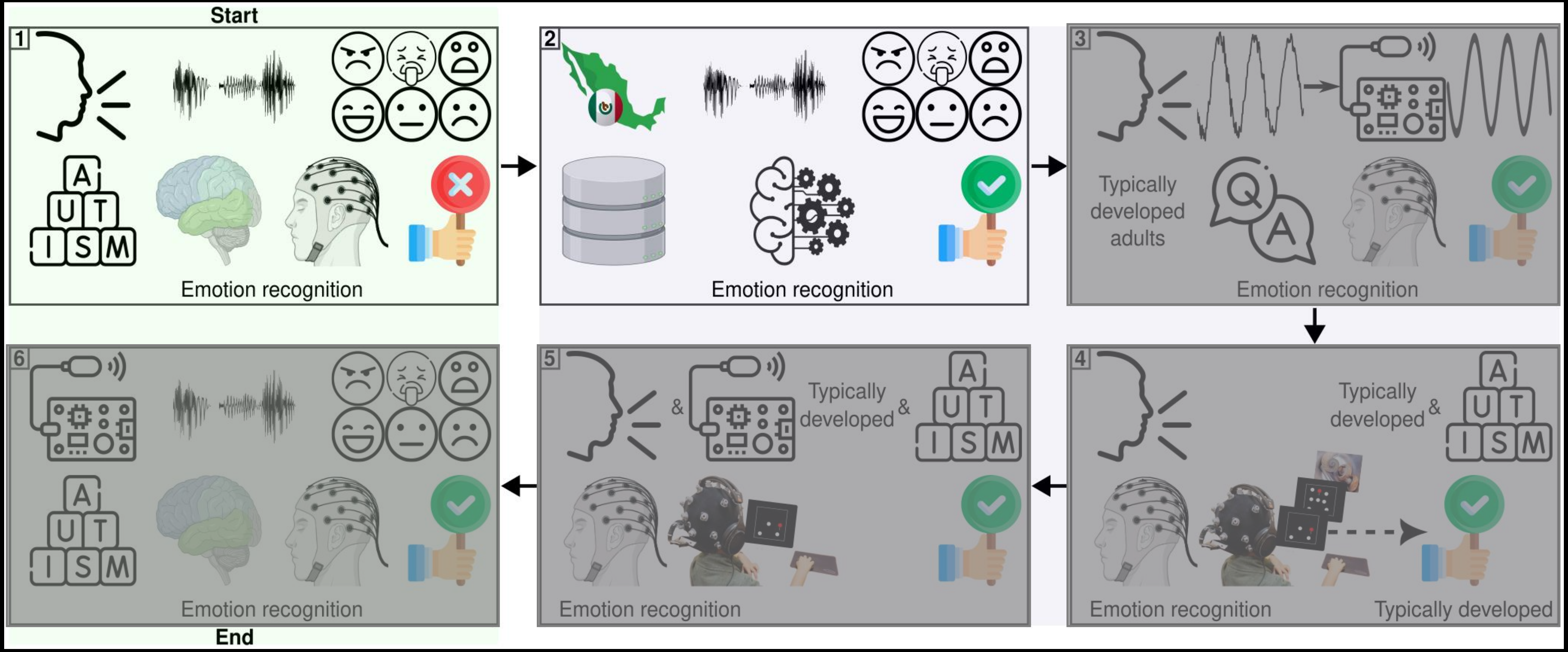

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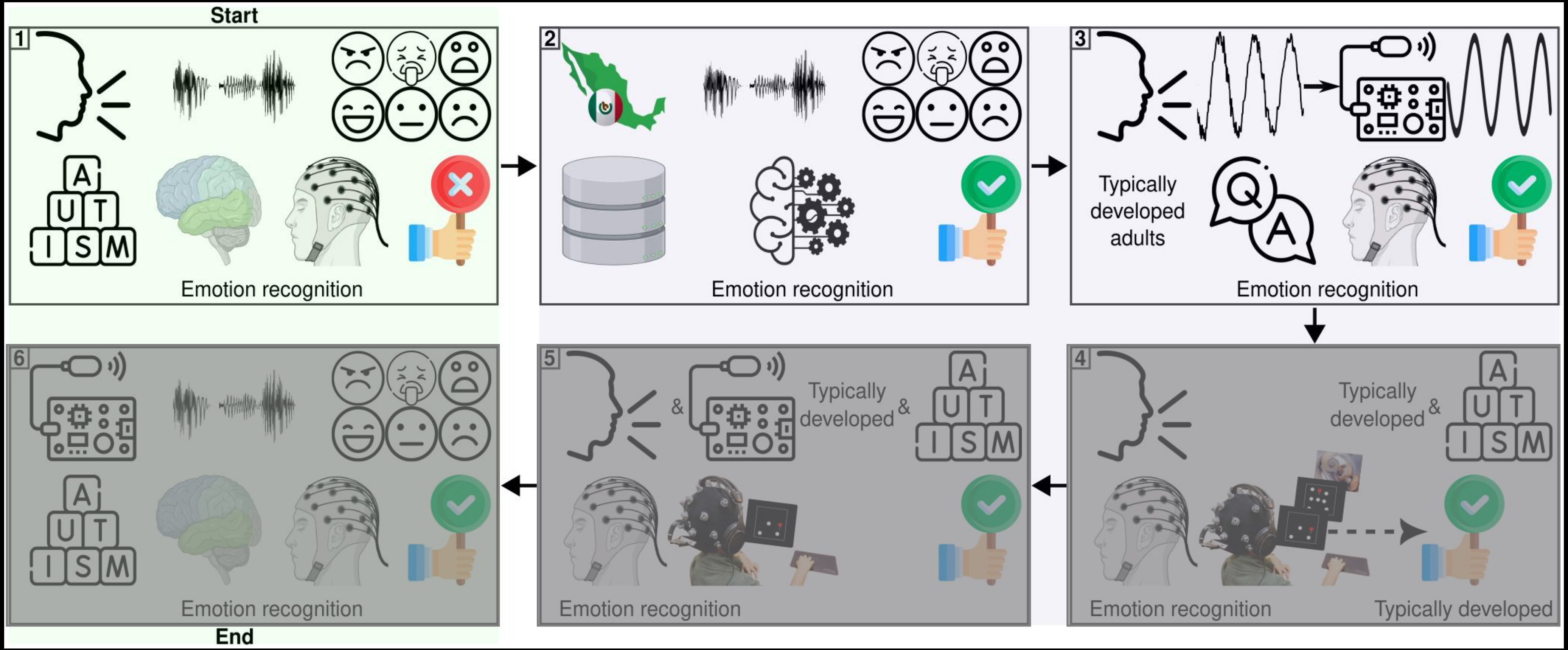

Overview
Introduction
Framework
MESD
Naturalness
Paradigm
Emotion ASD
Conclusions
Endorsement
Future
Adjacent work
References

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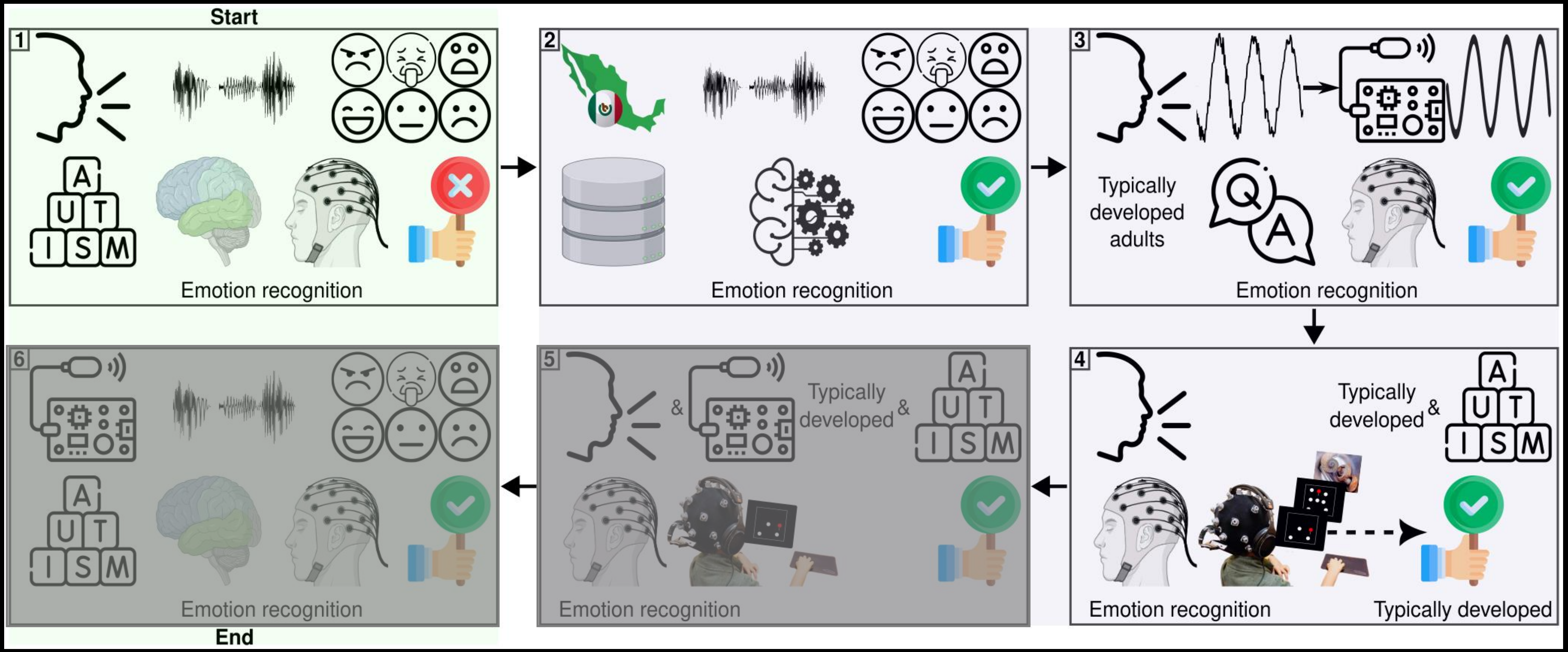

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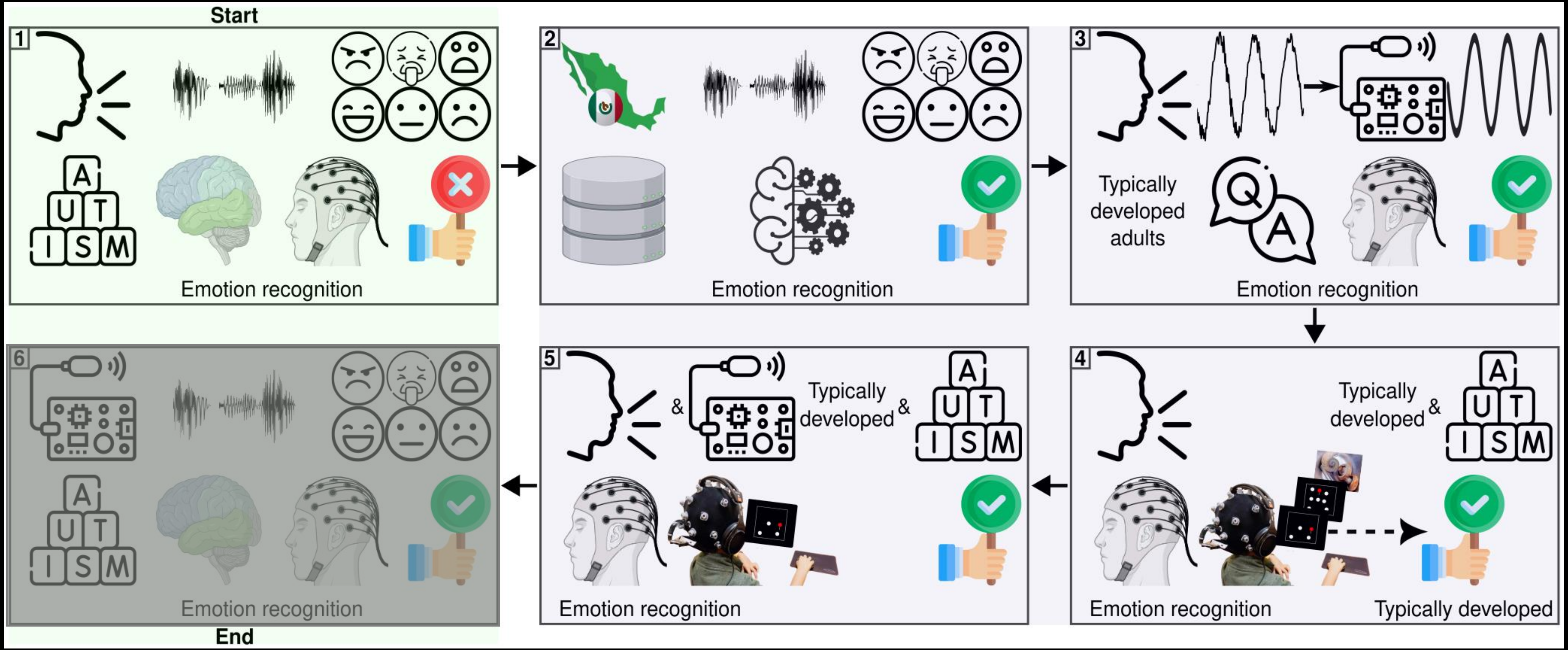

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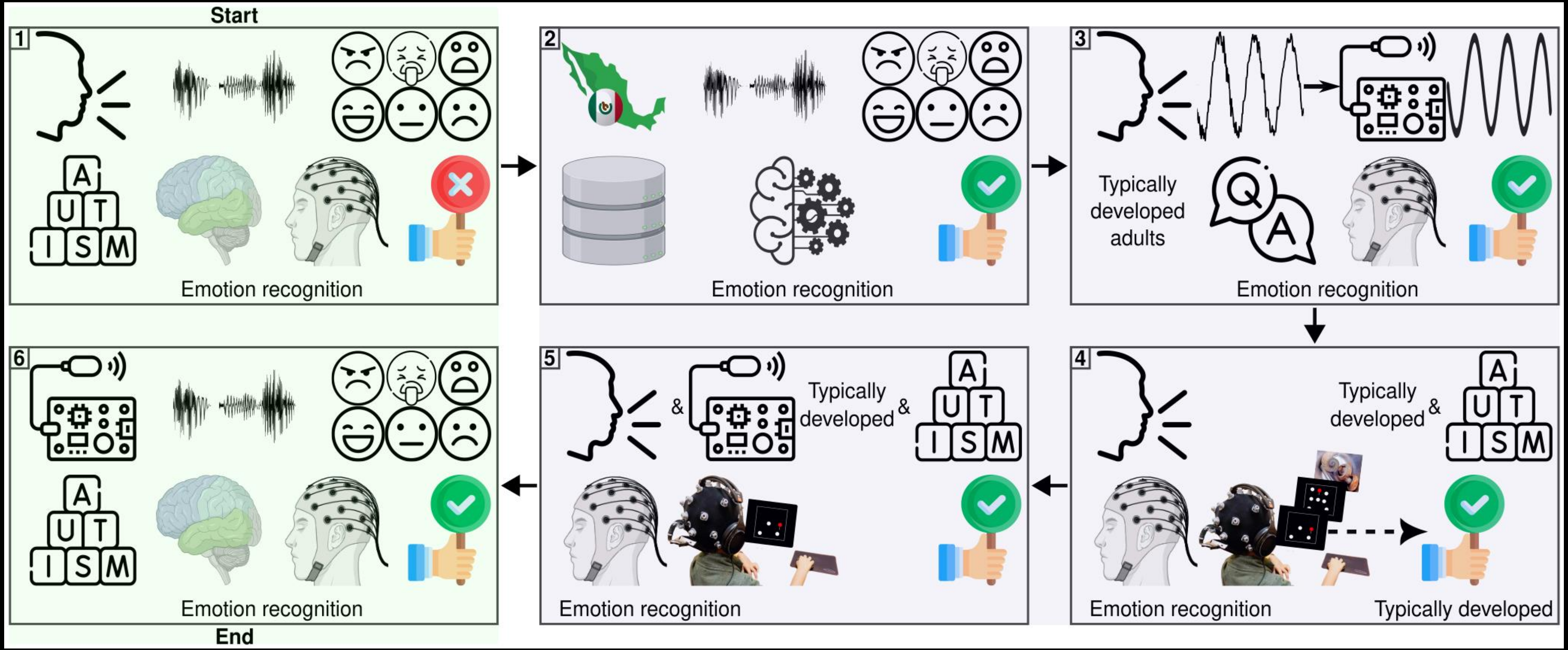

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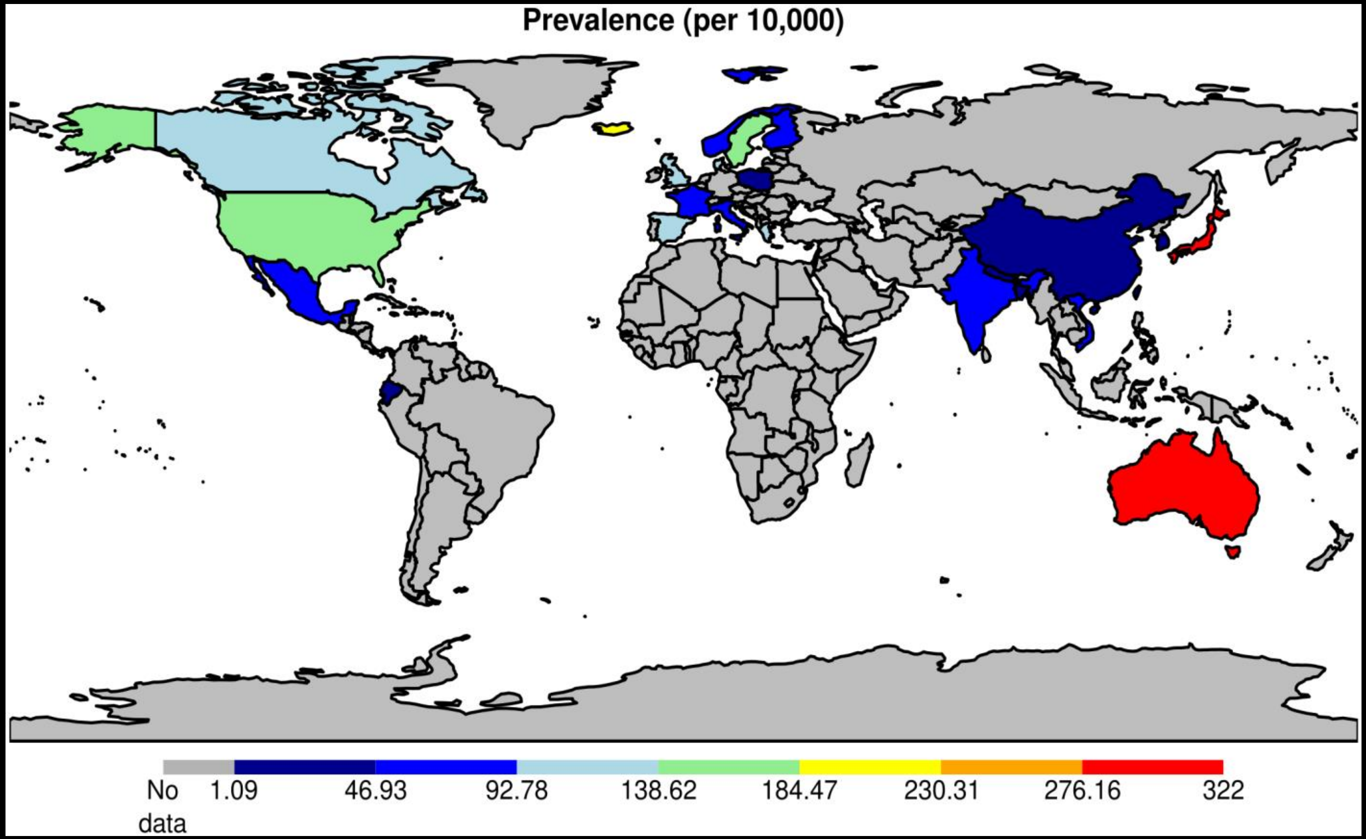
Adaptation of emotional prosodies to Mexico



Bangla Greek Sp (ES) En (CA)

Lack of adaptation and validation to **culture**:
- Screening and diagnostic
- Interventions

Unreliability and inefficiency

We created and validated materials adapted to Mexico
- ✓ **Mexican Emotional Speech Database (MESD)**

1–5

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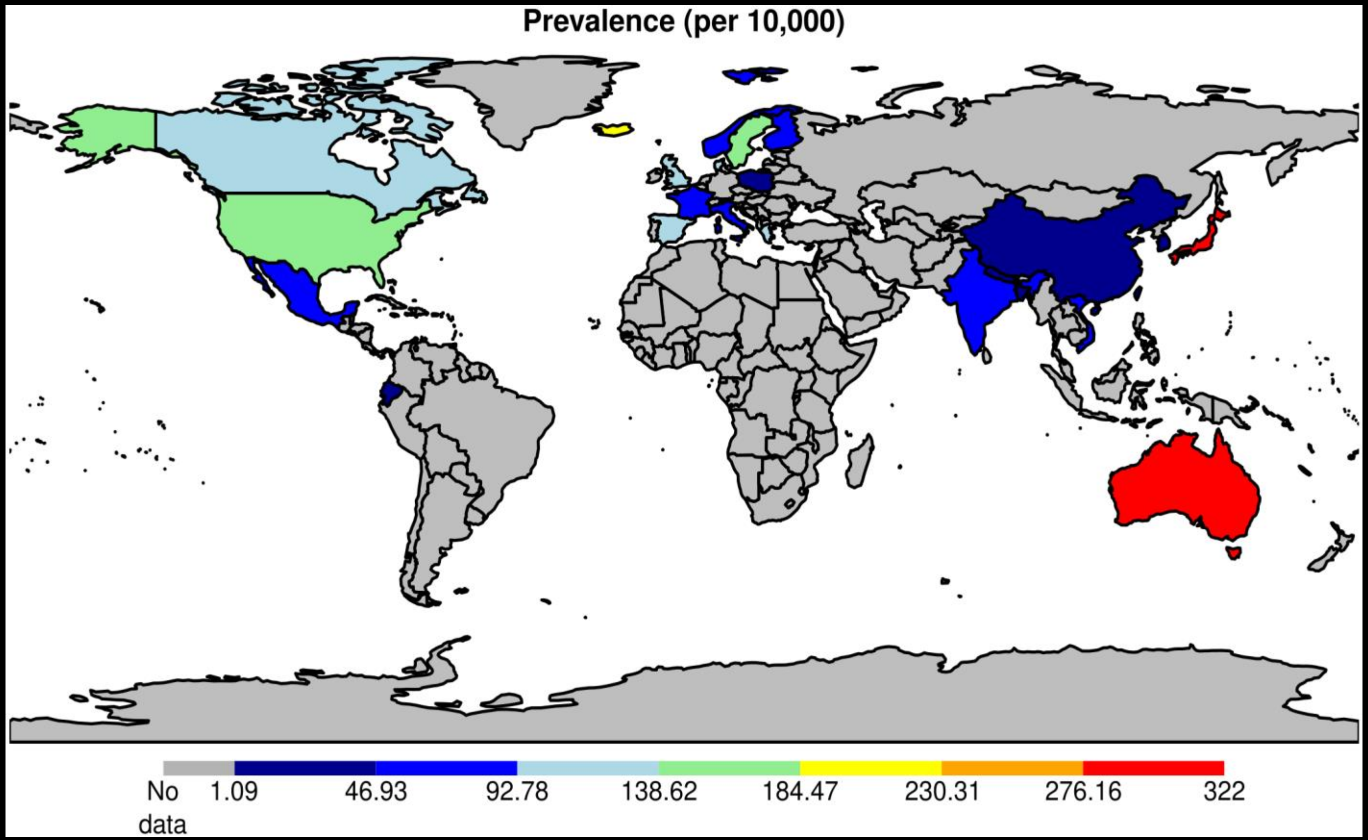

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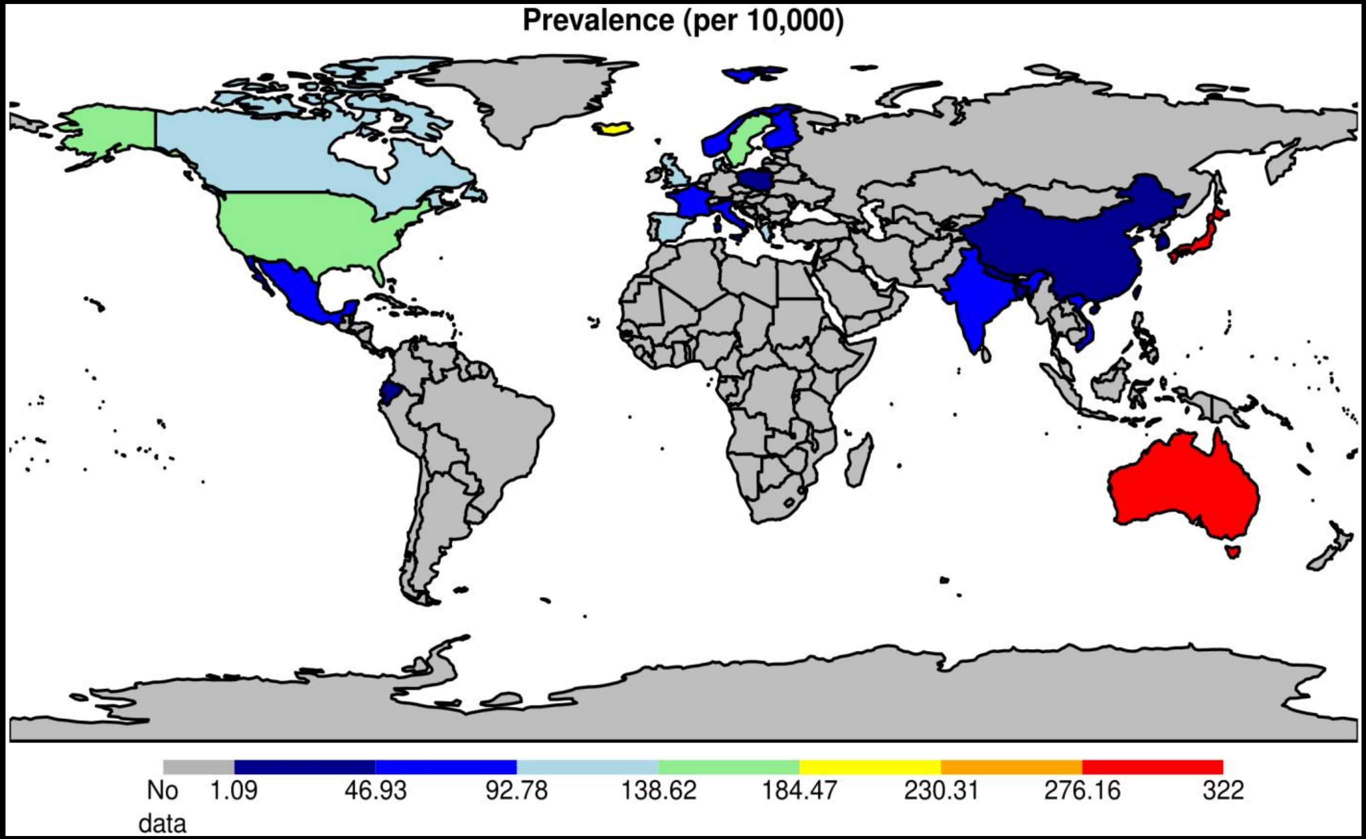

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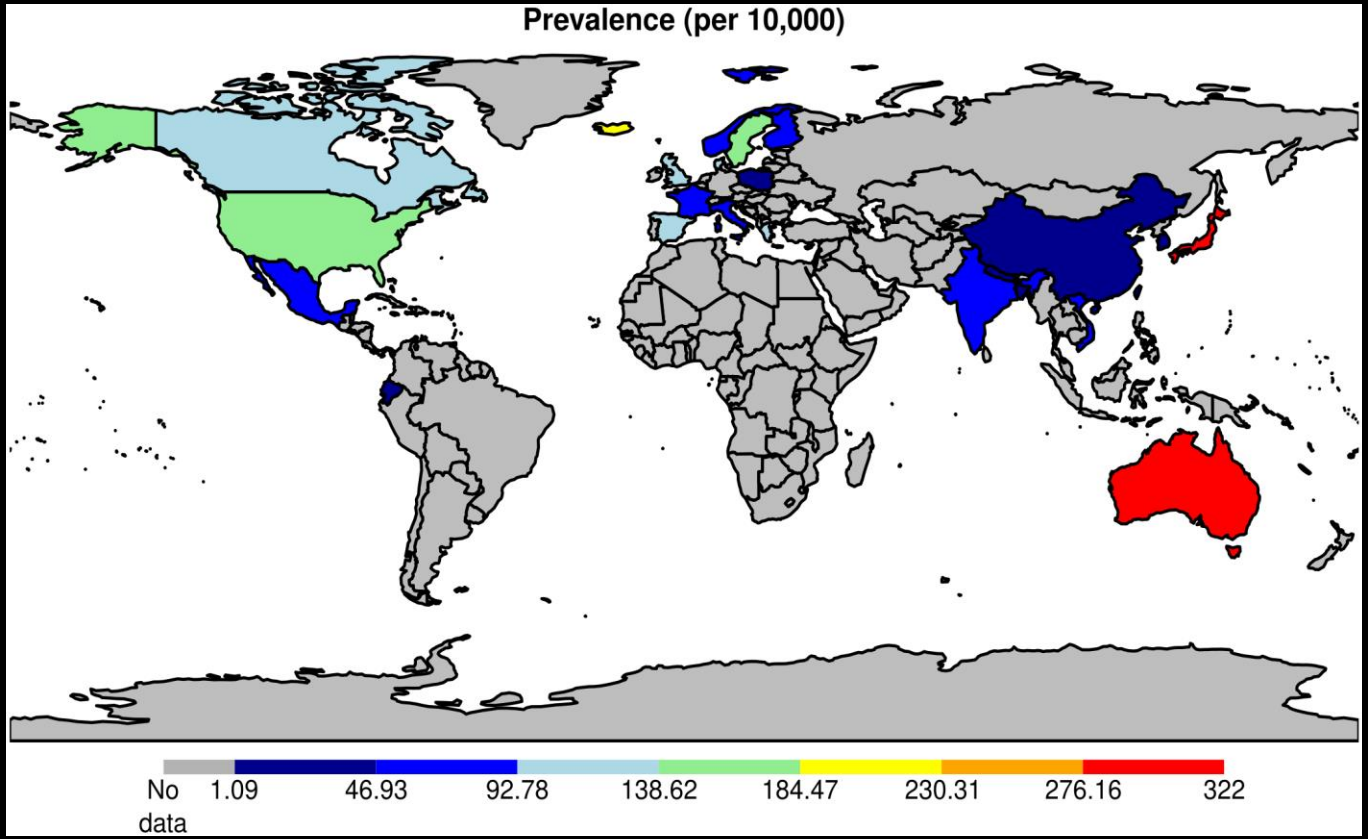

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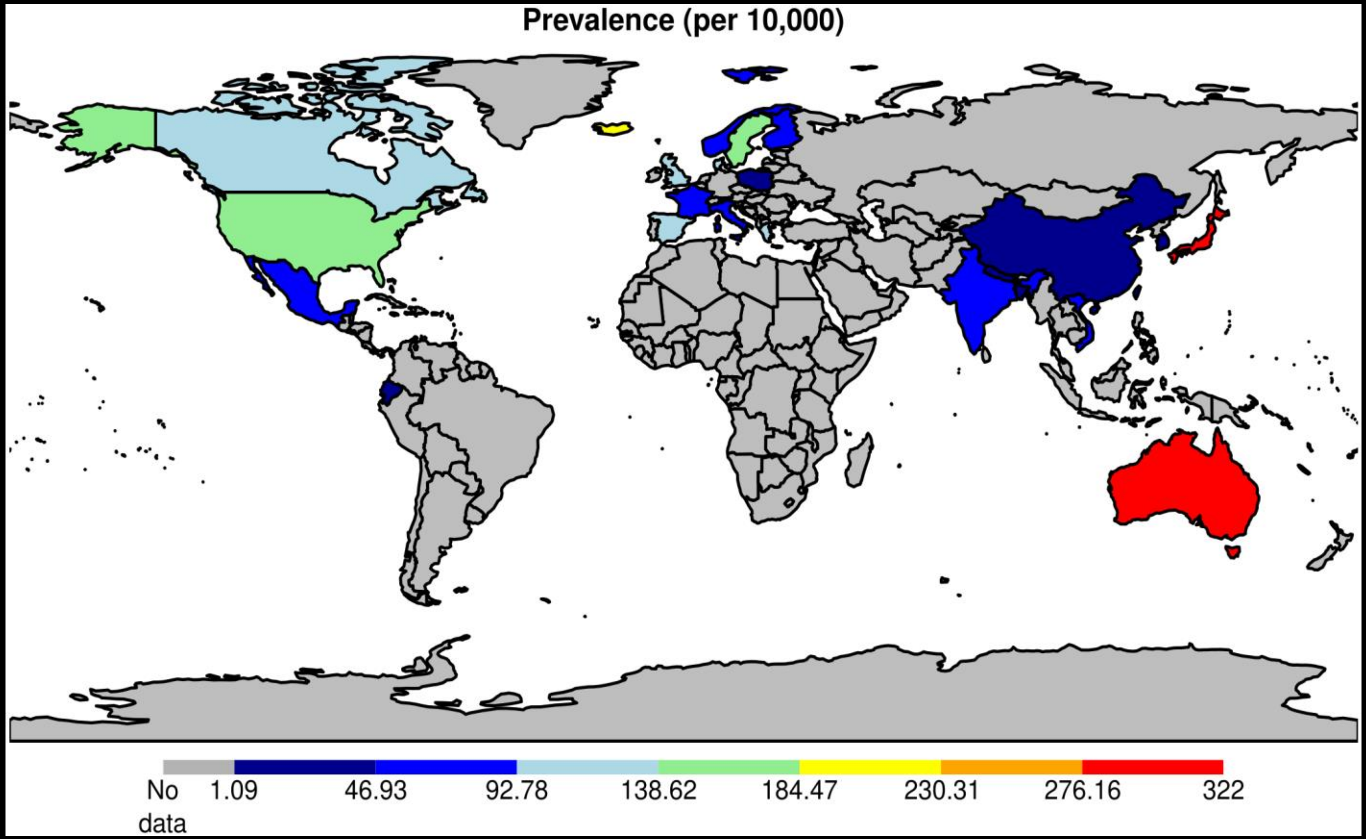

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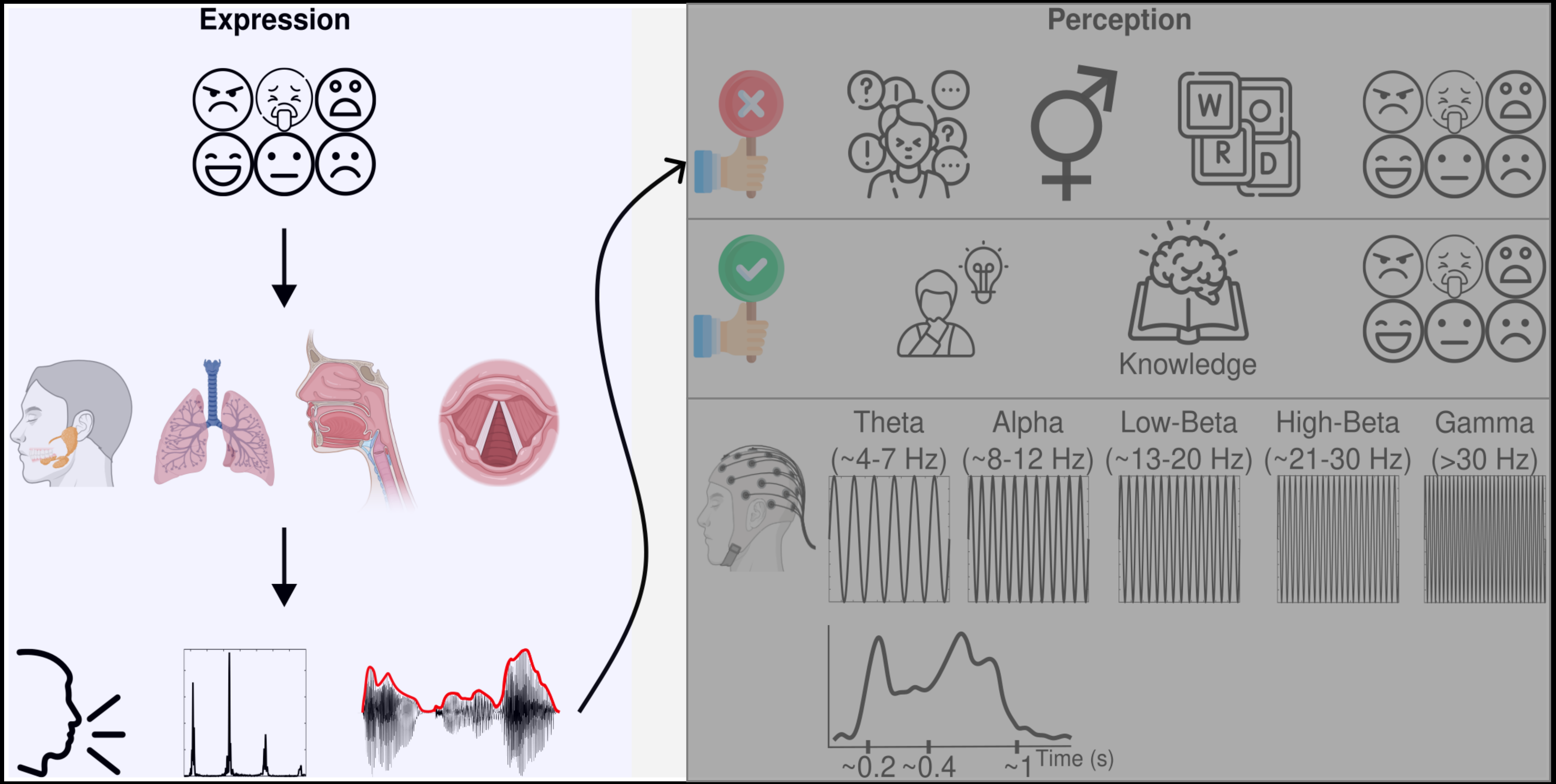

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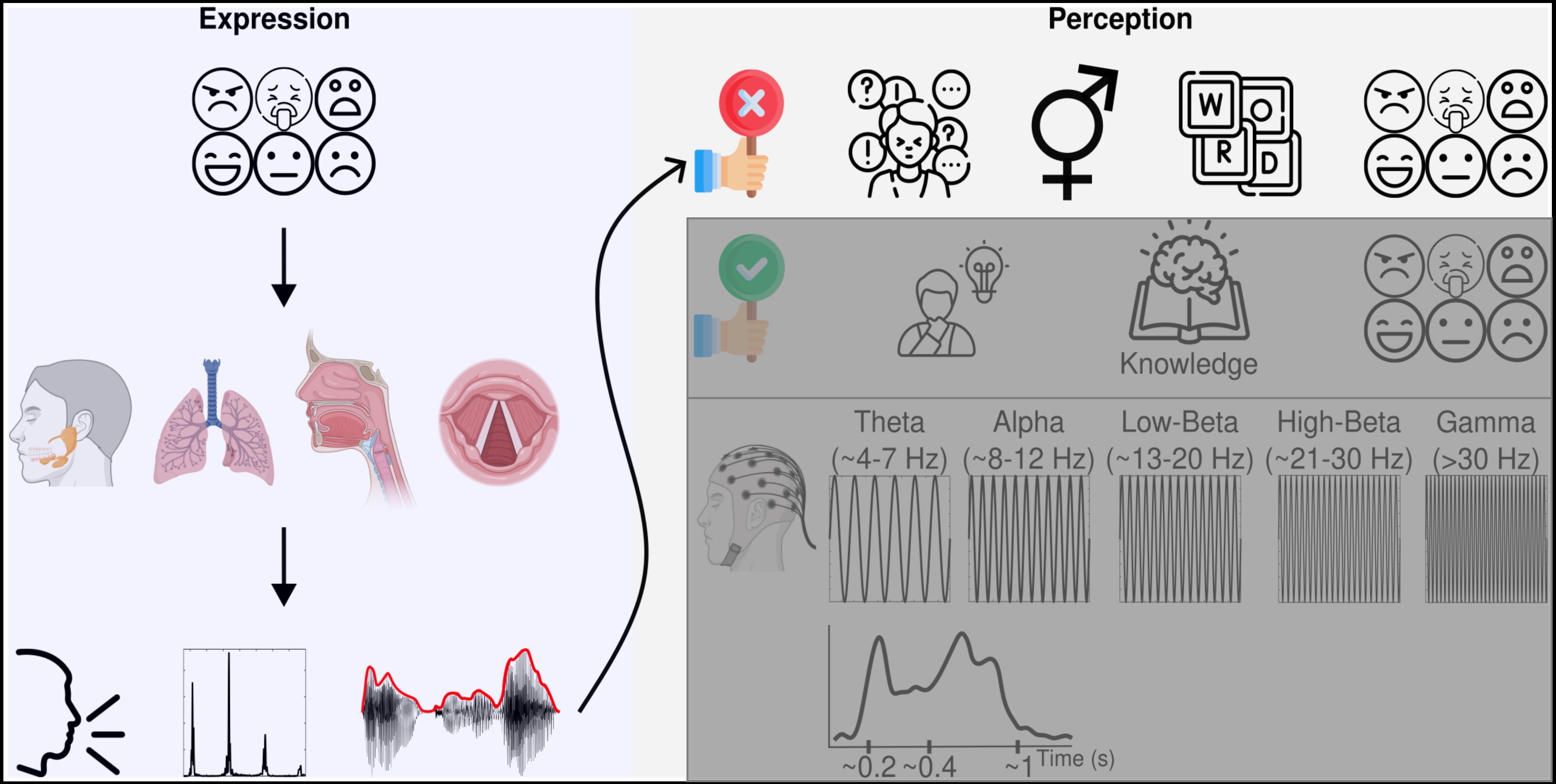

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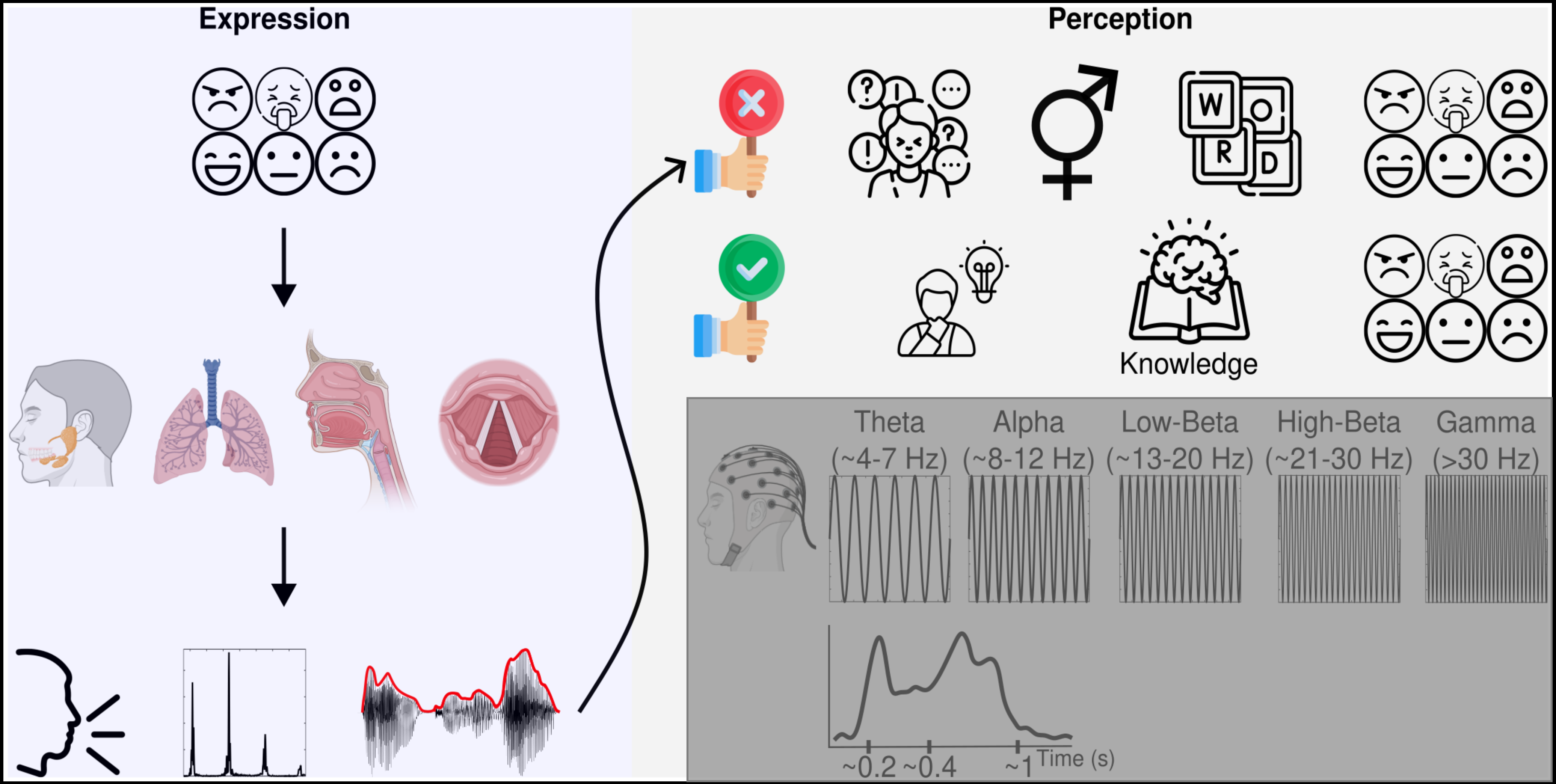

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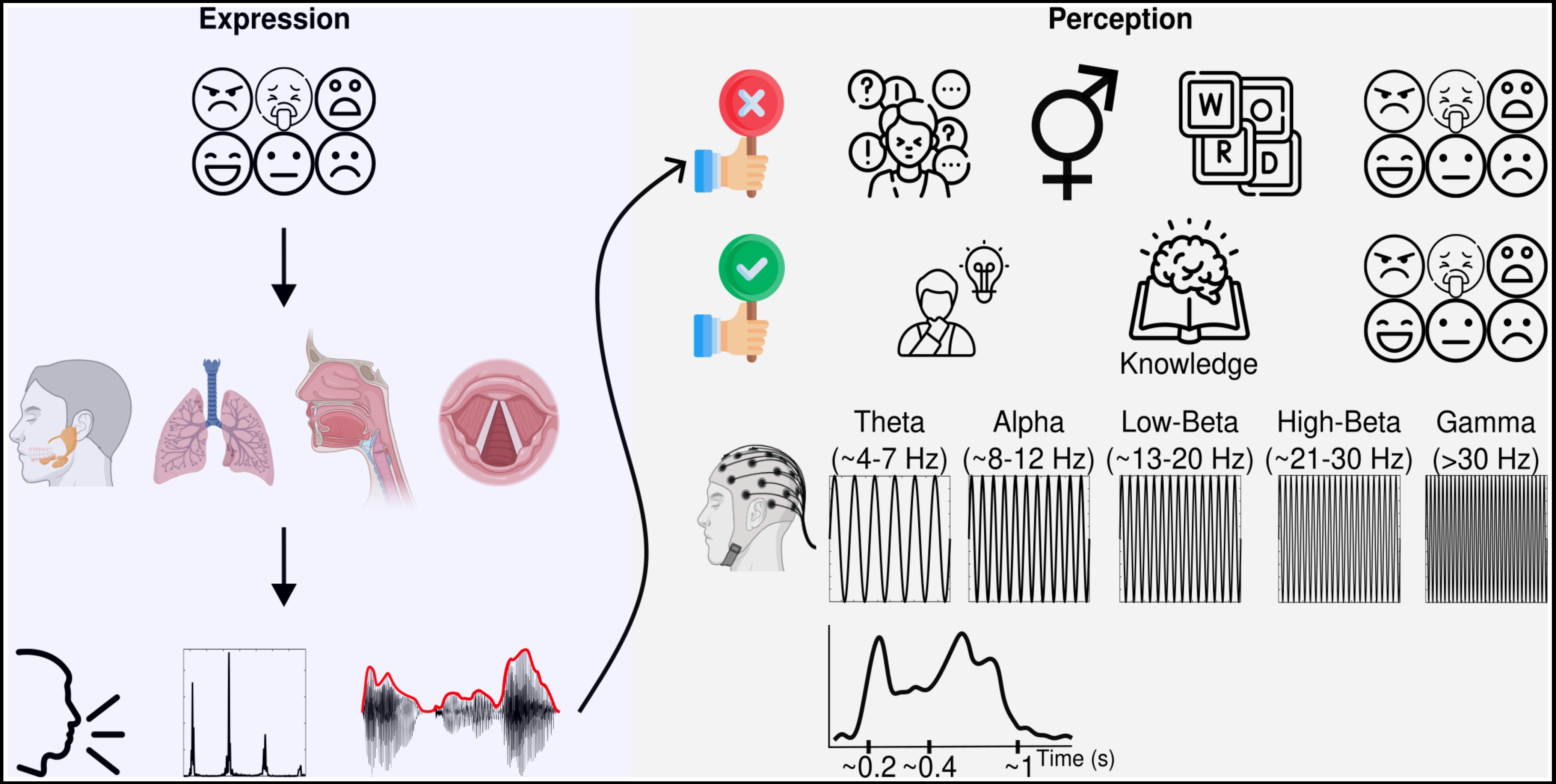

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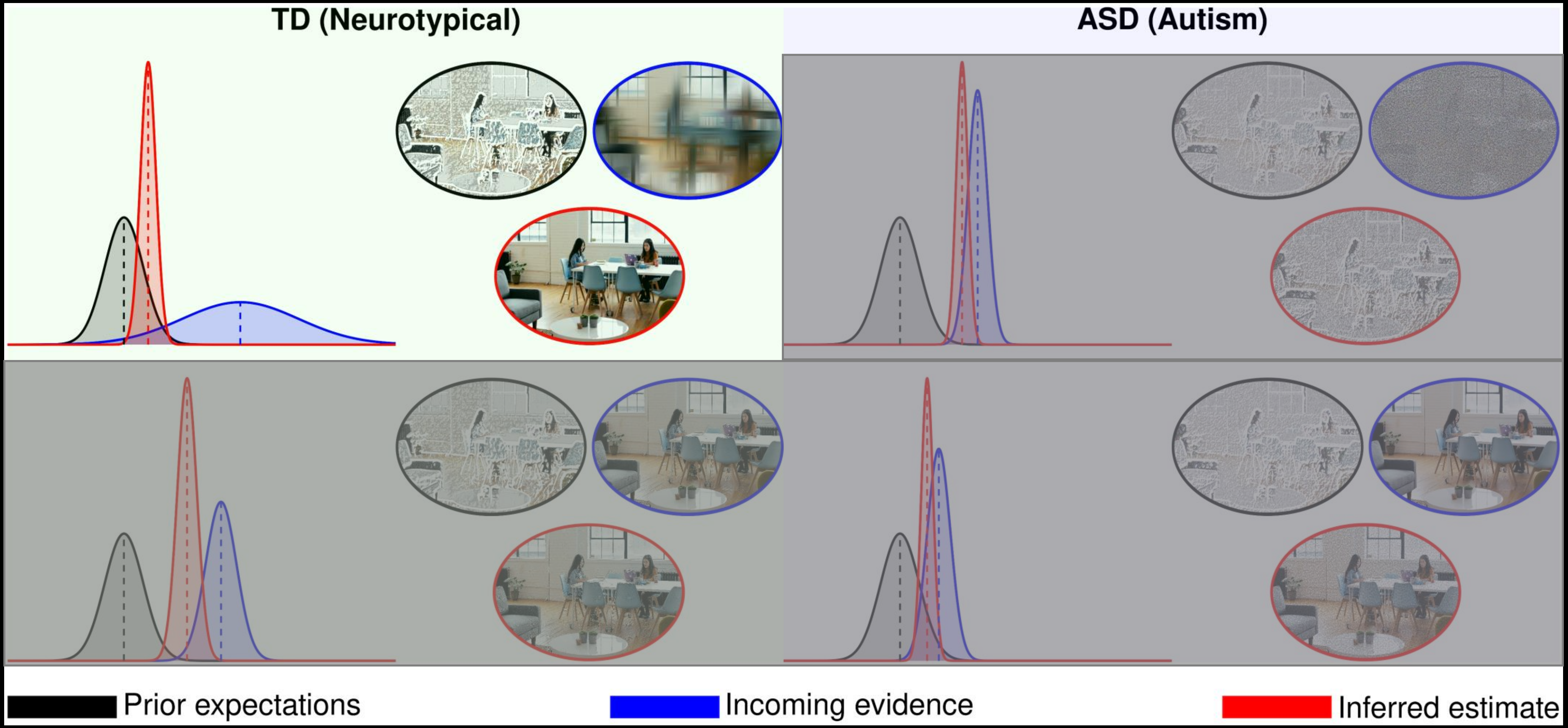
ASD: unbalanced precision-weighting



23-28

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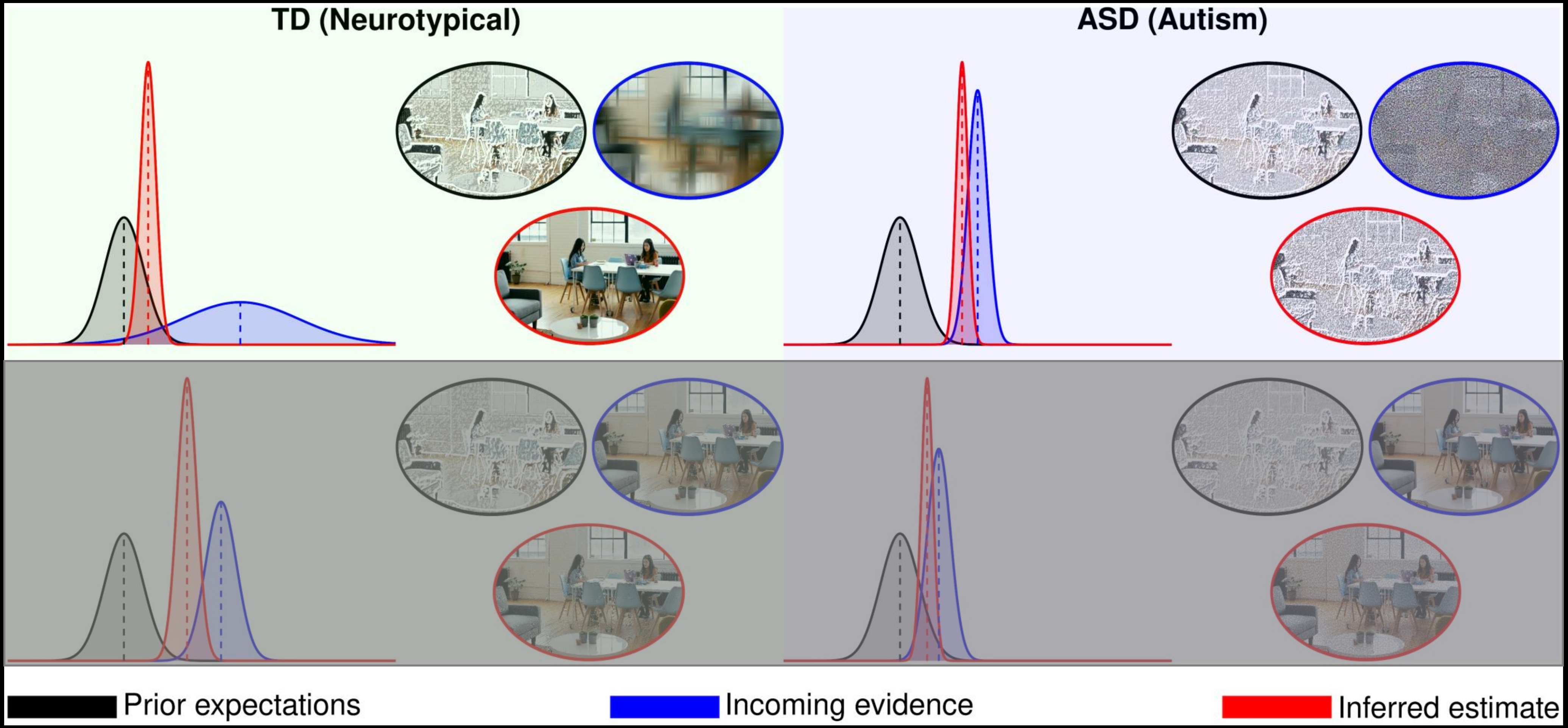

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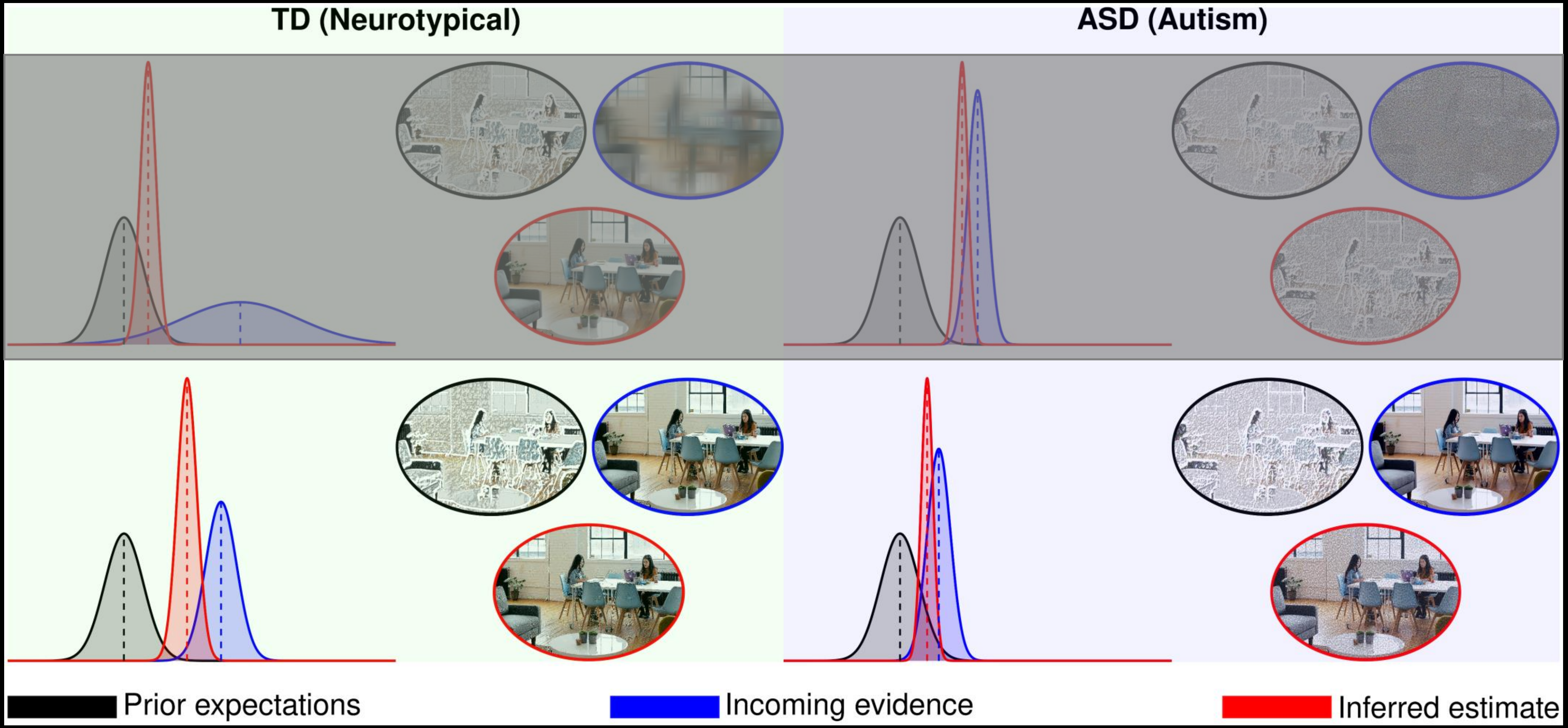

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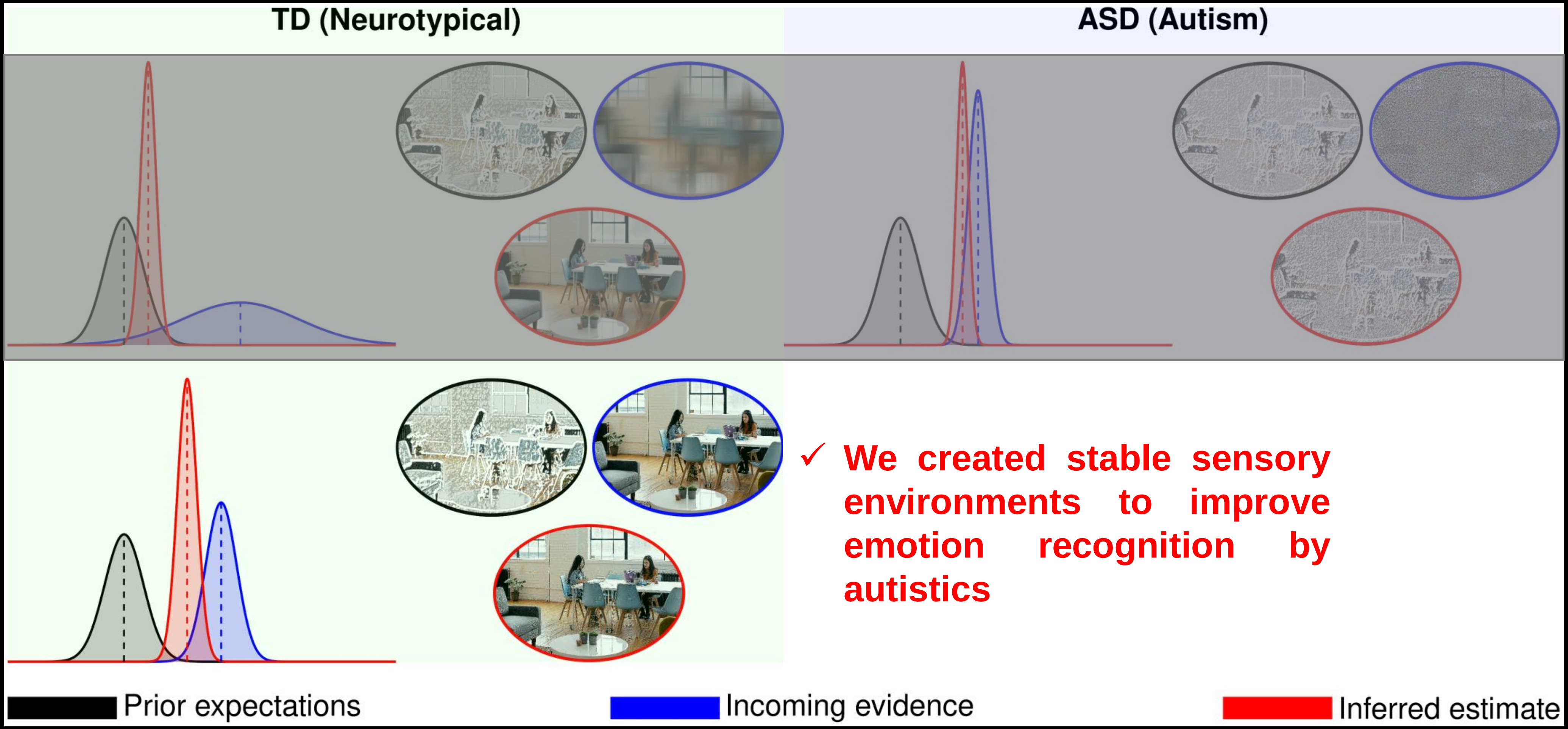

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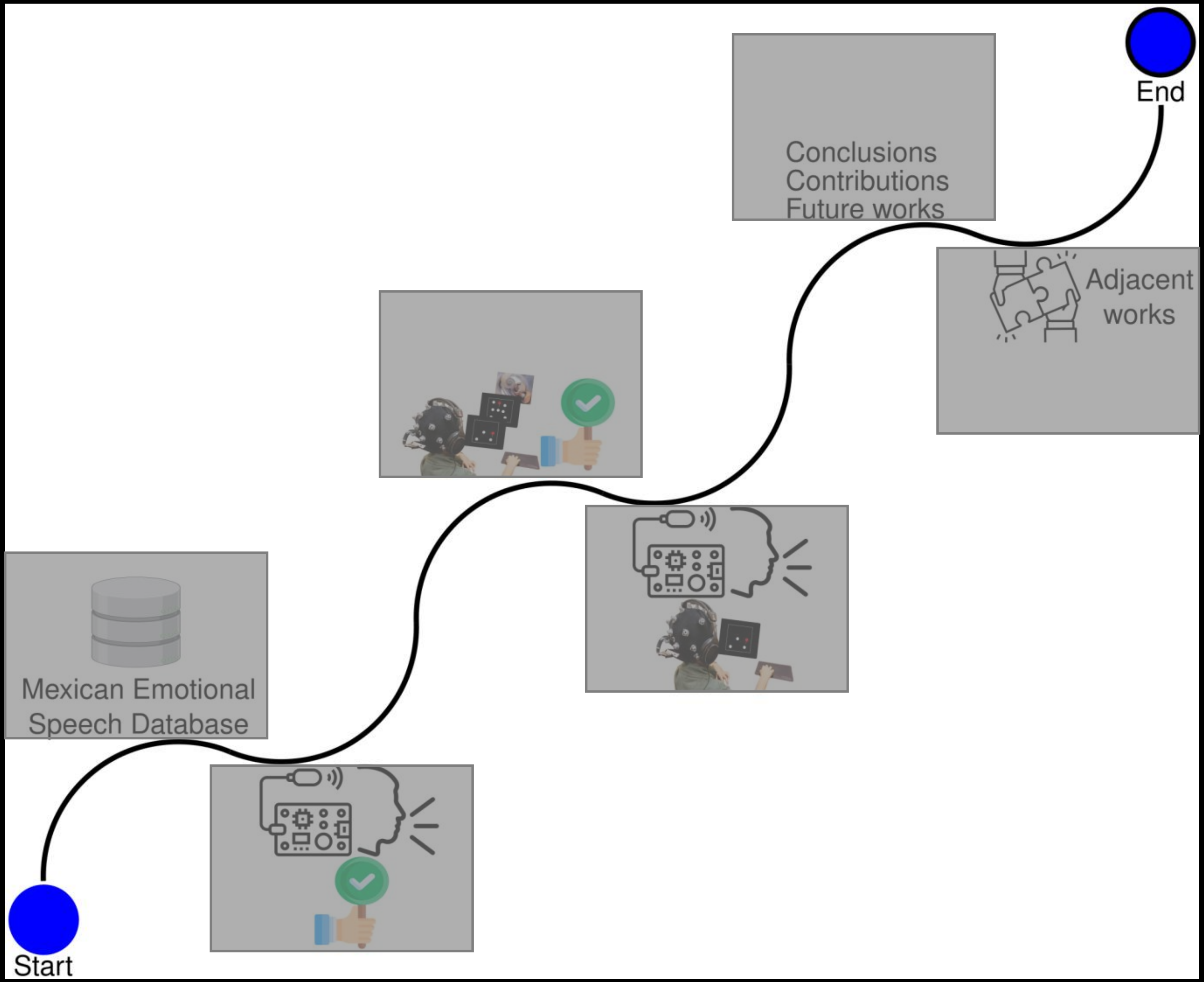
Framework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Conclusions
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Mexican Emotional
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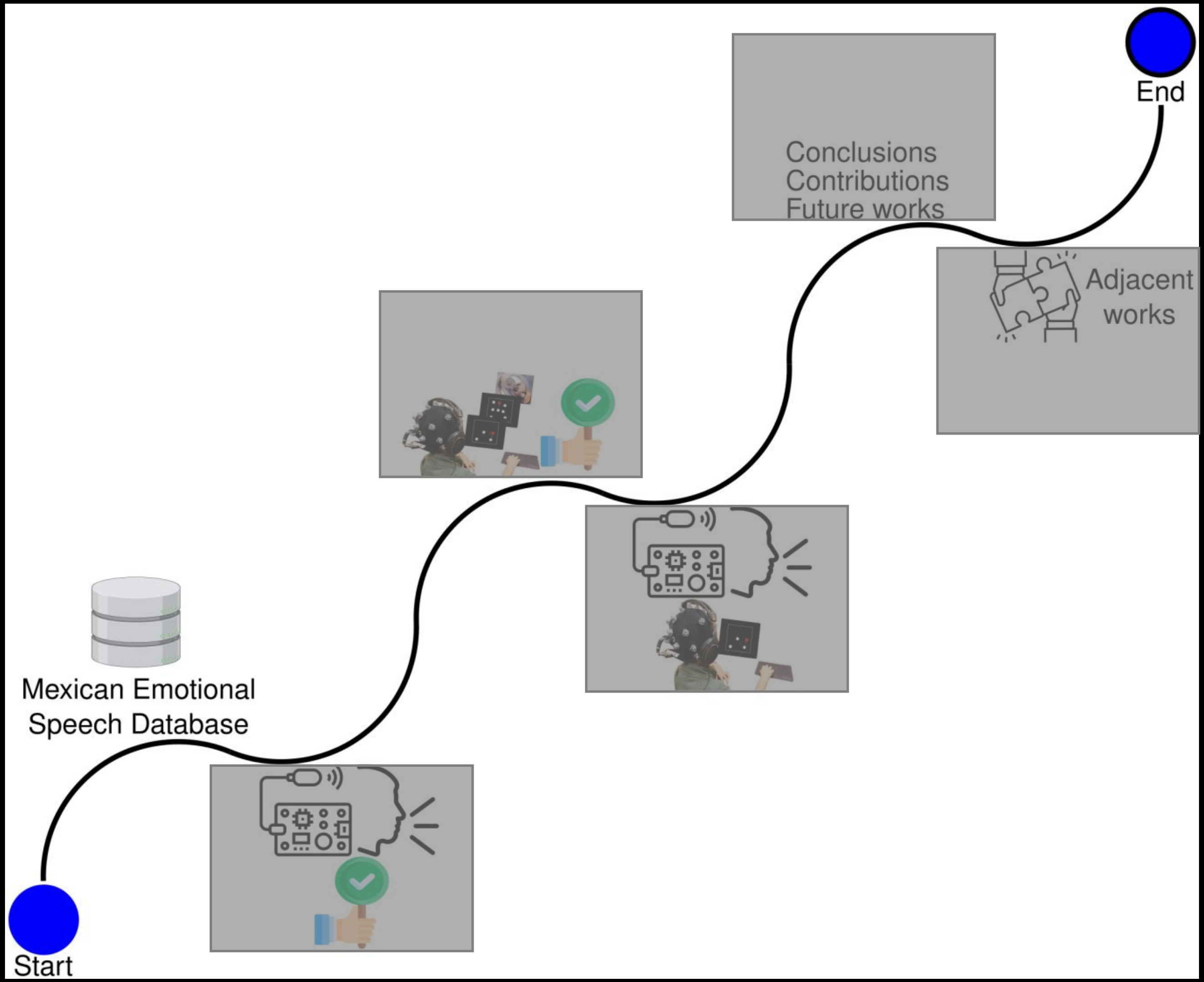

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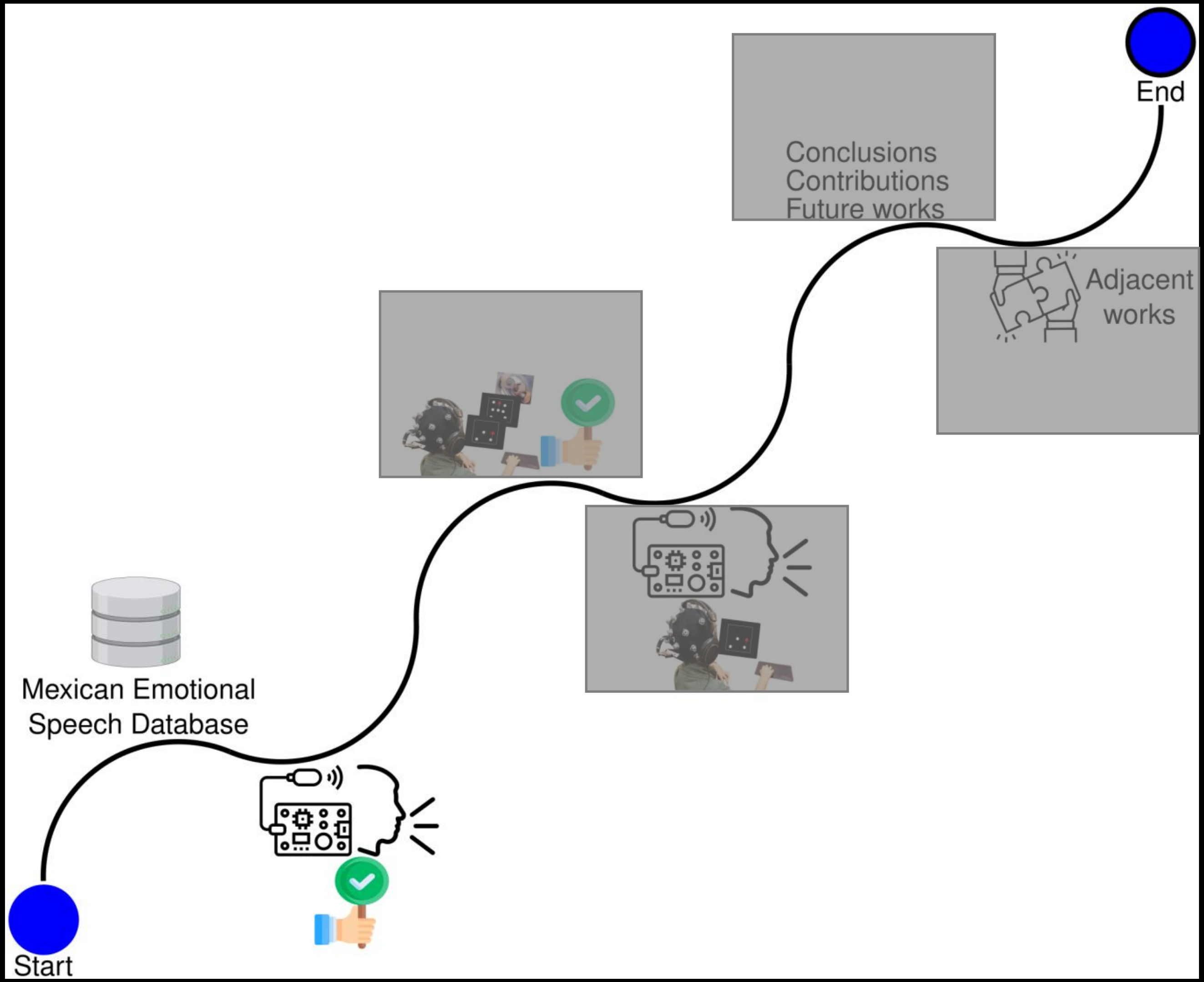
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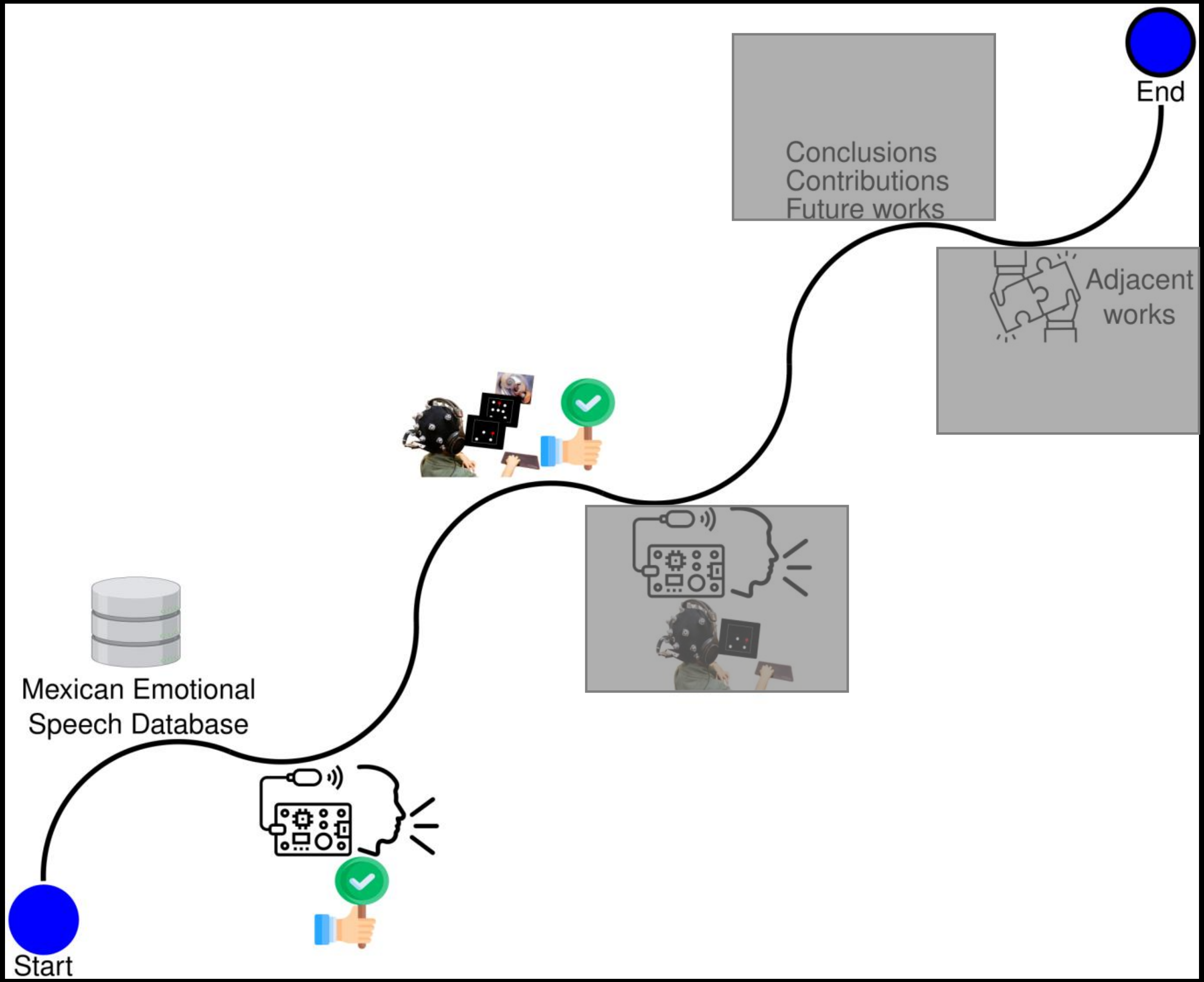

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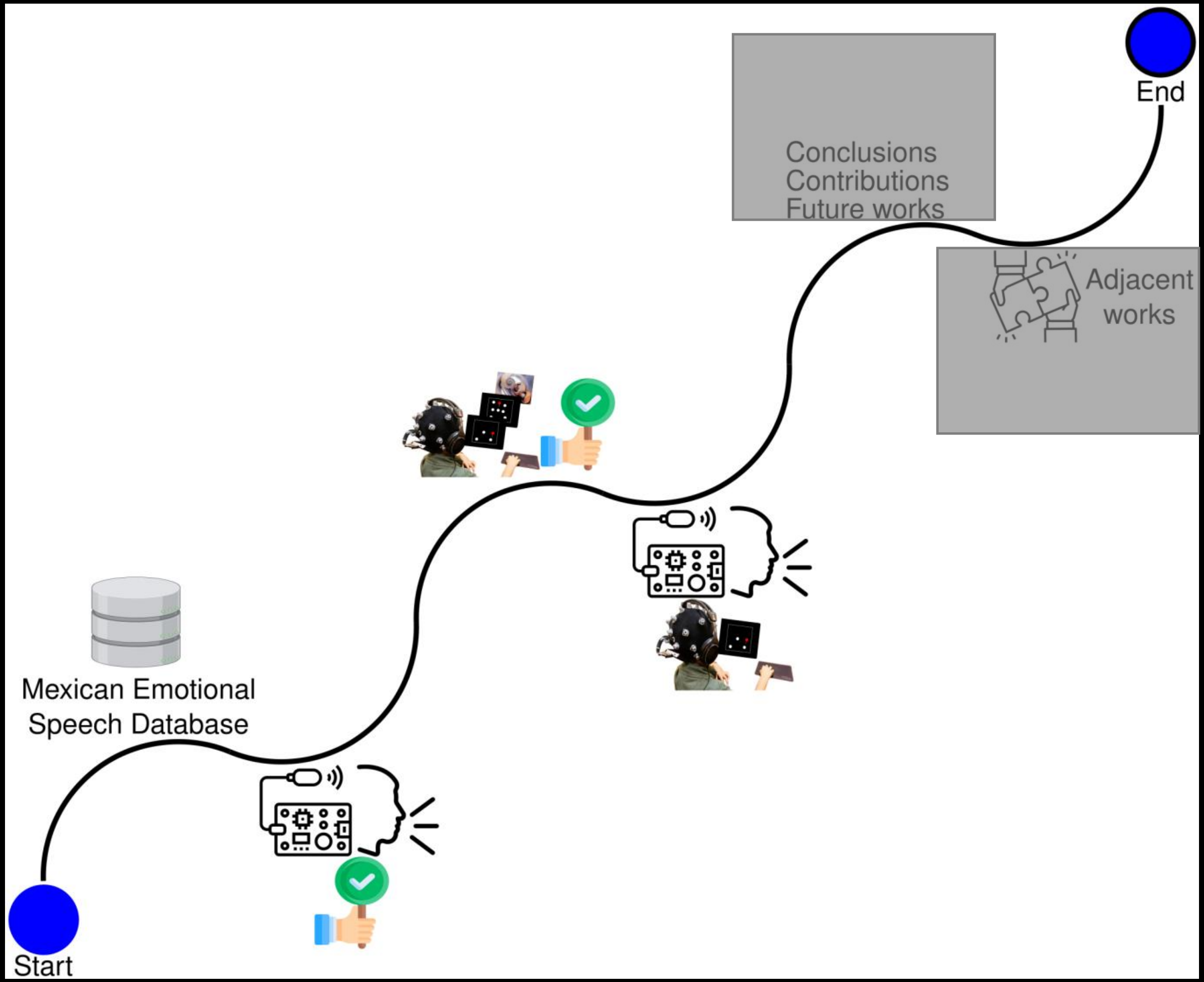

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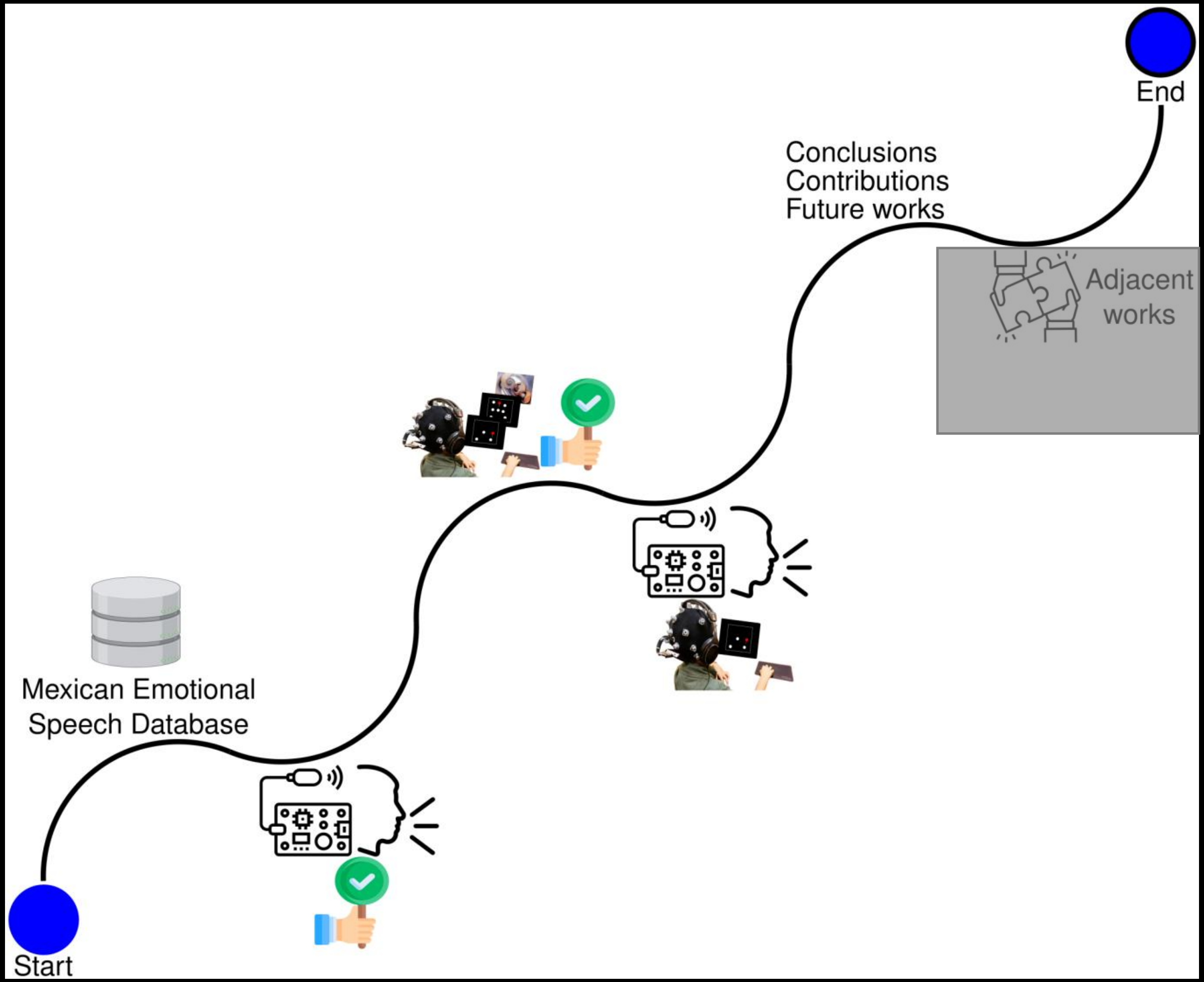
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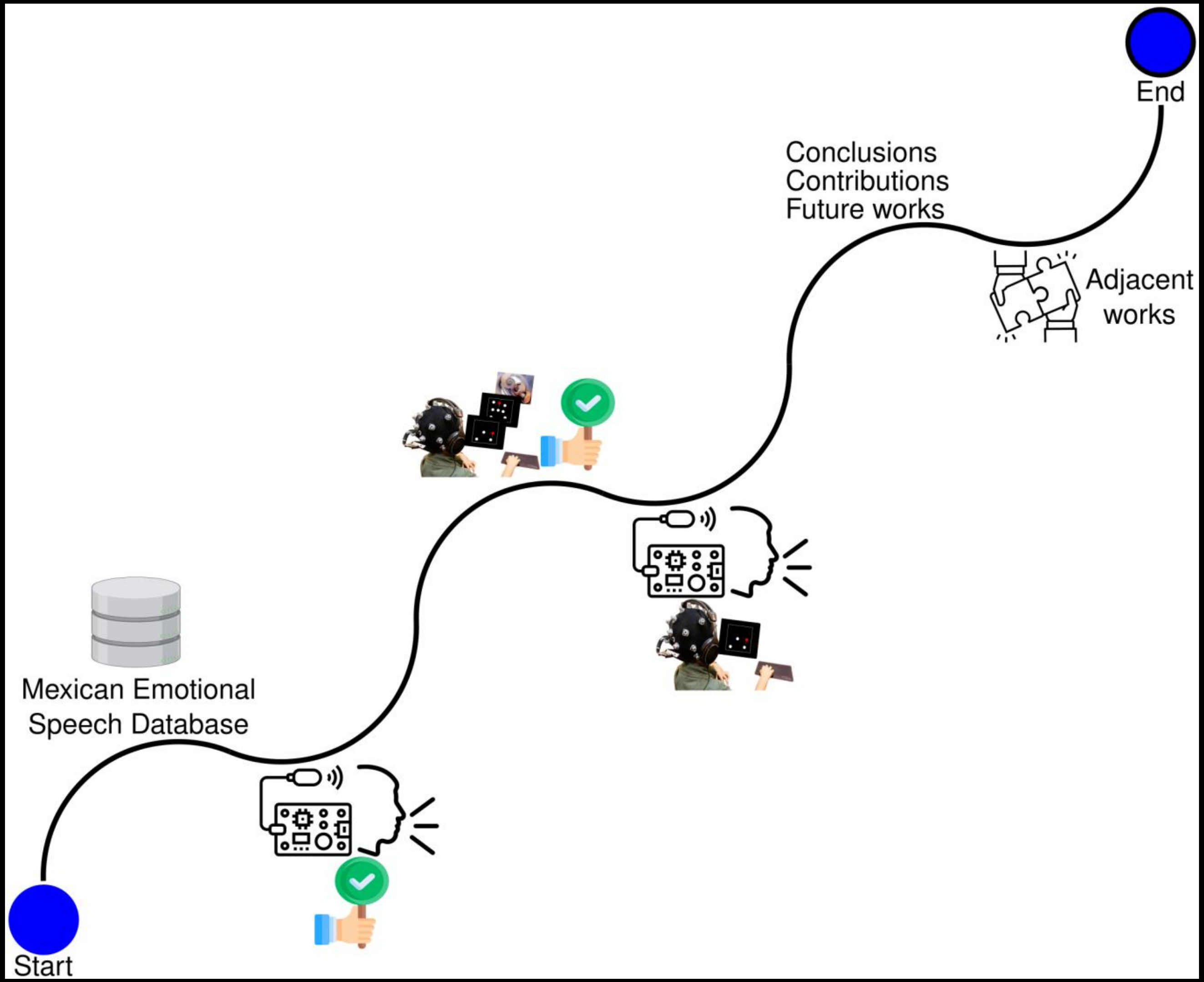
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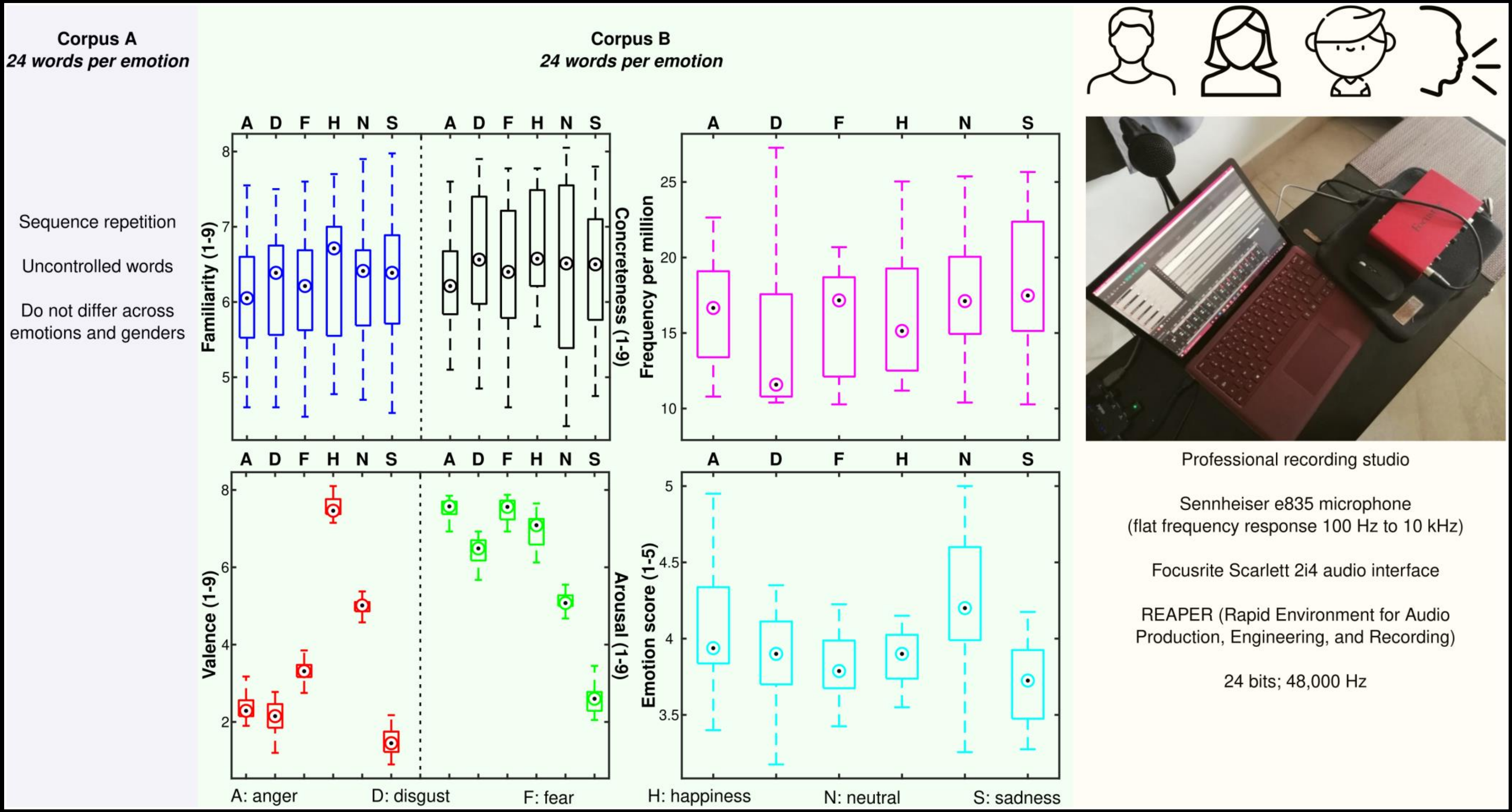

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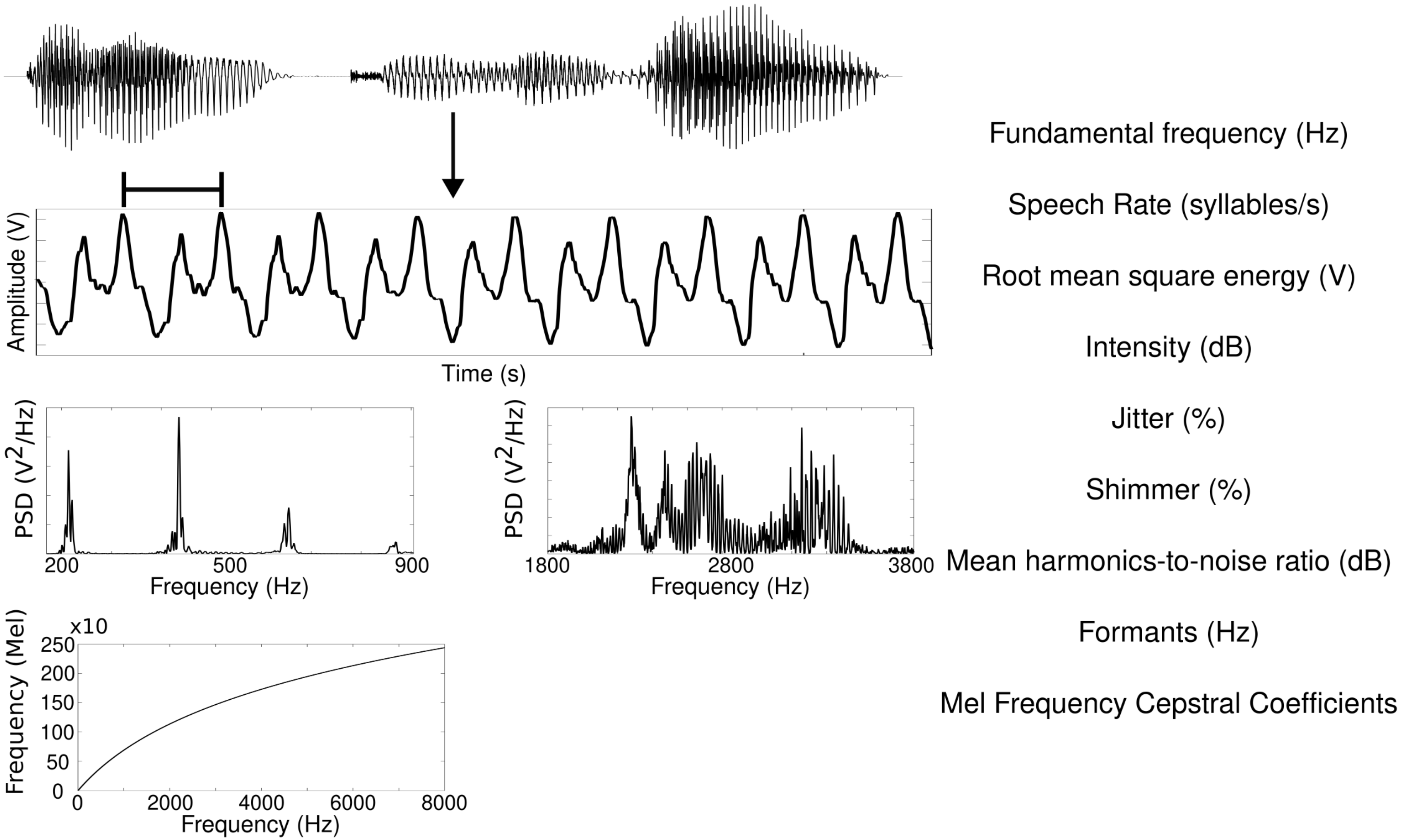

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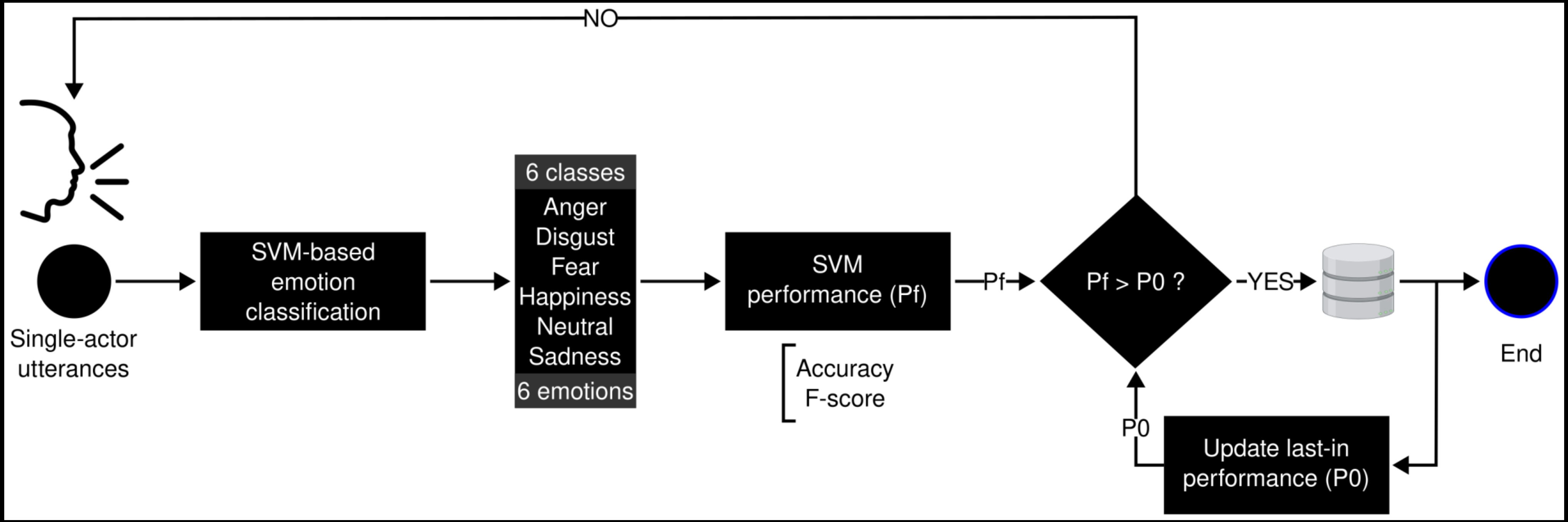

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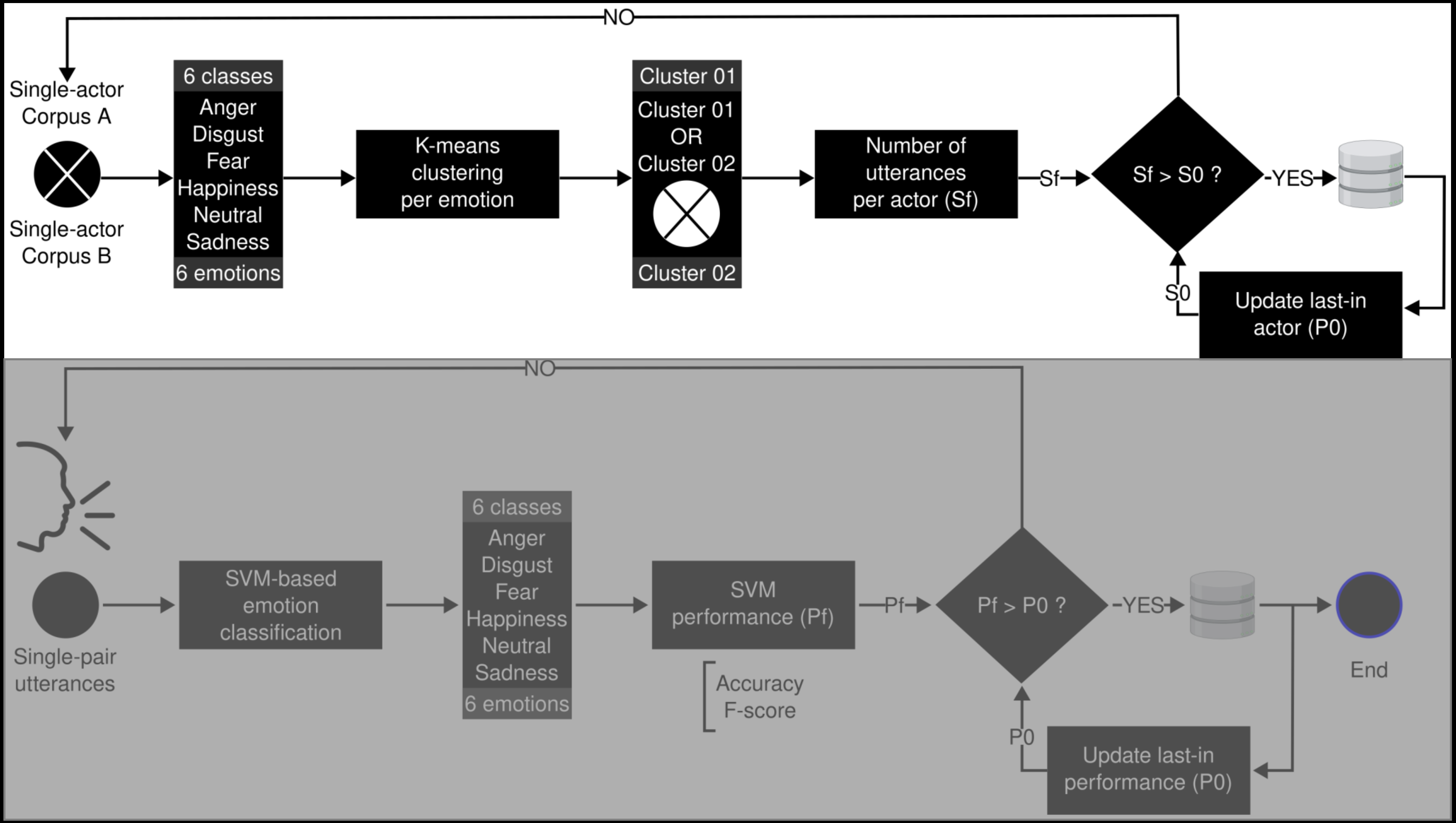

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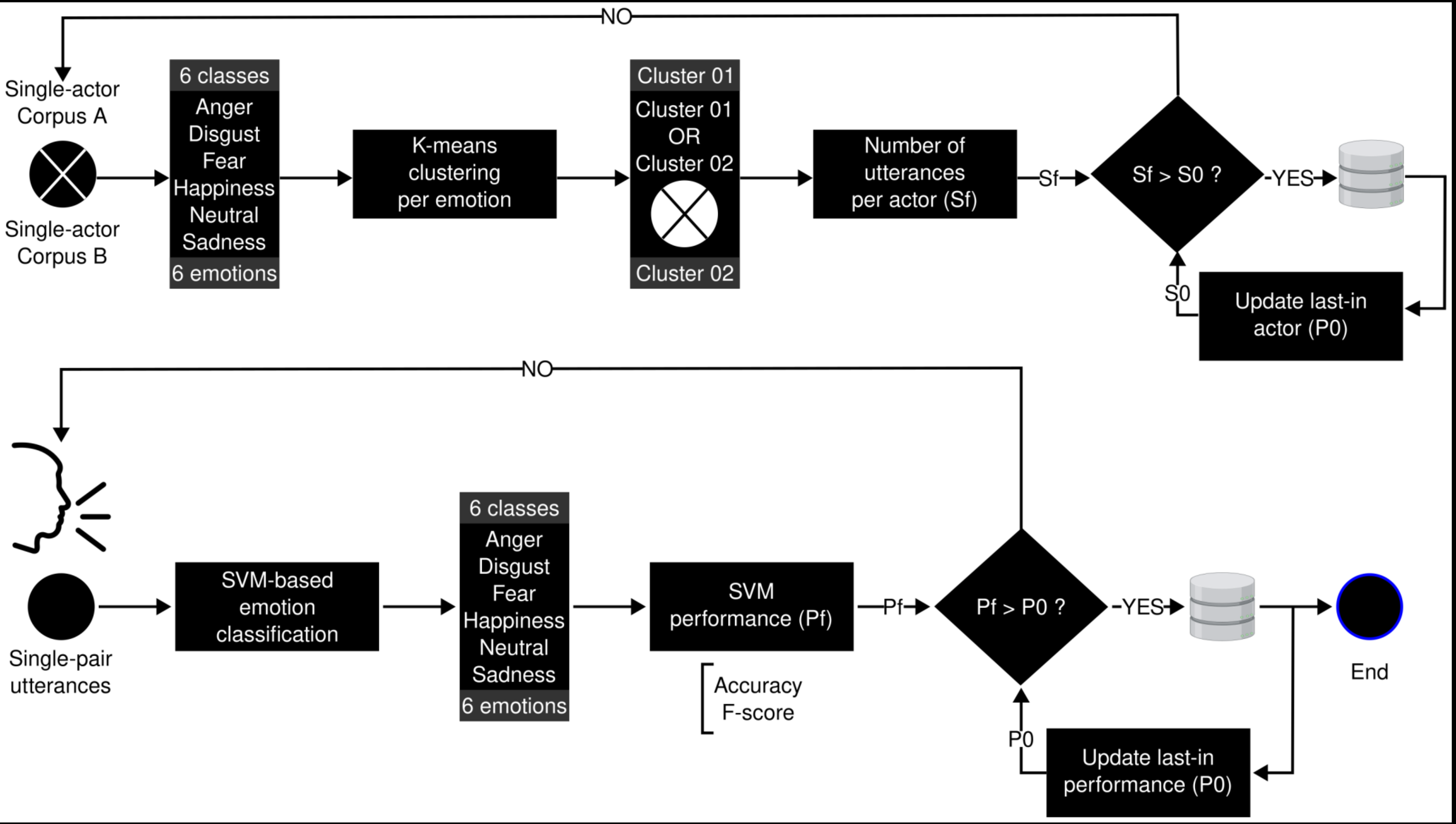

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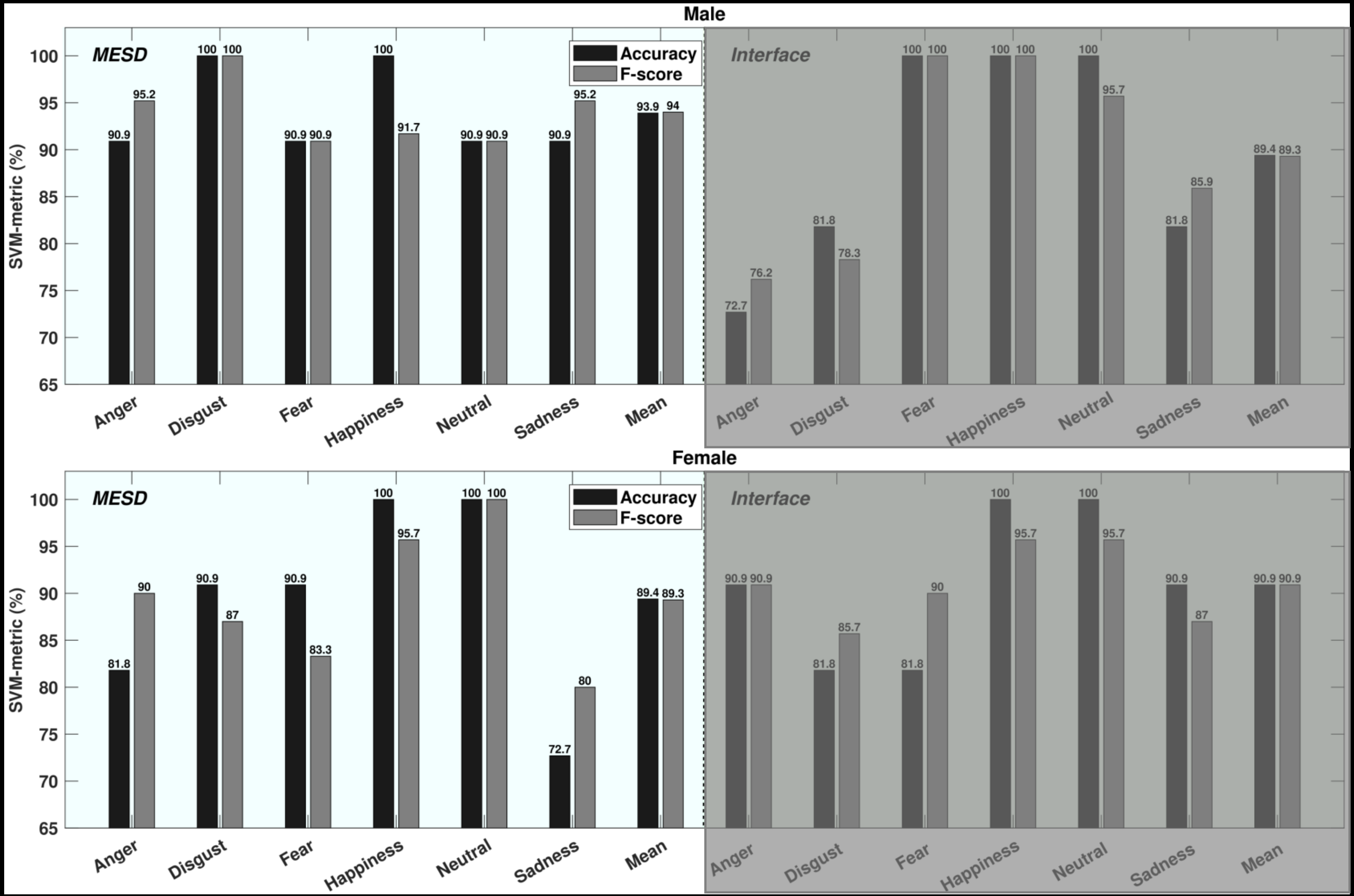

41-47

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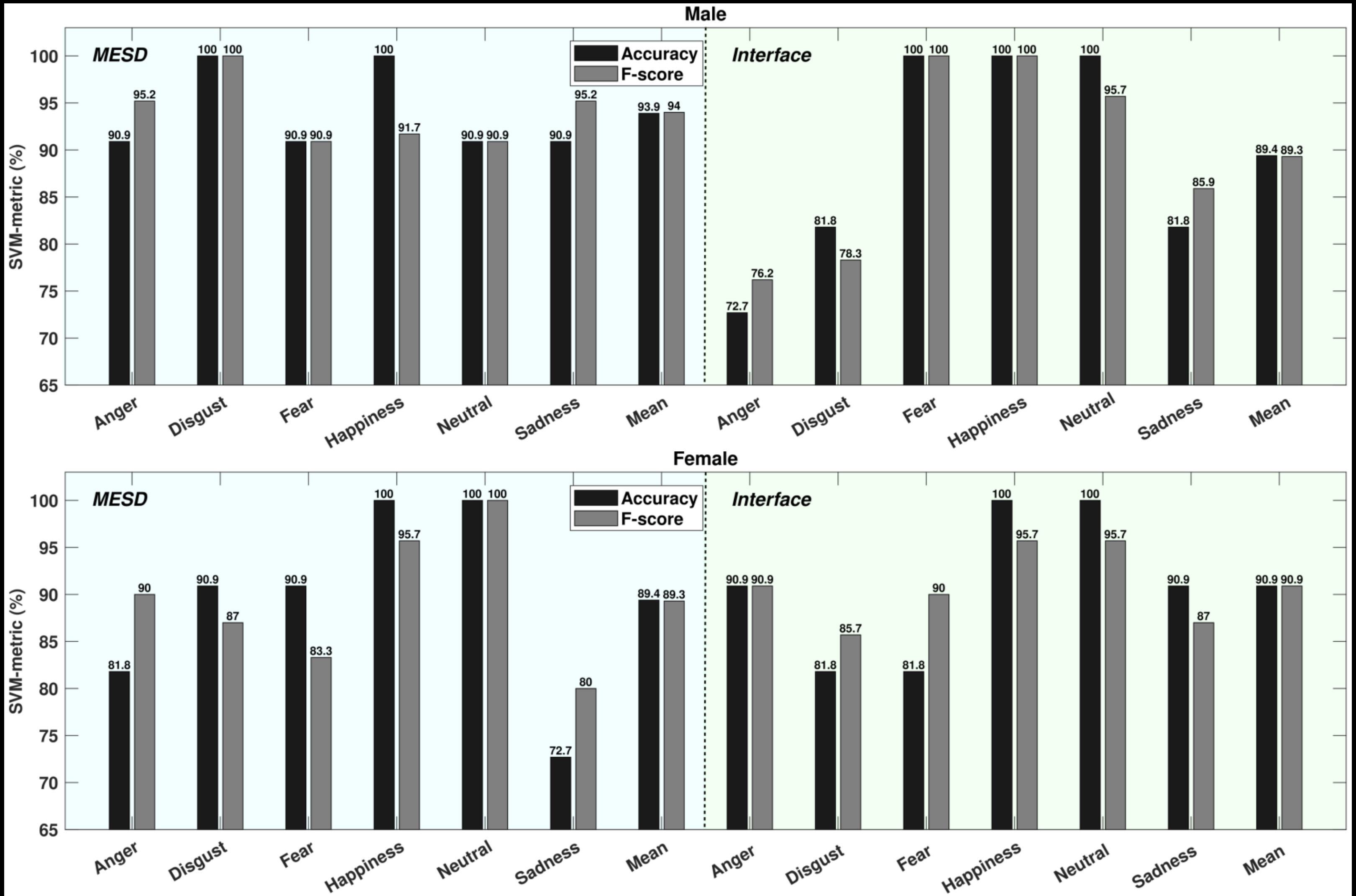

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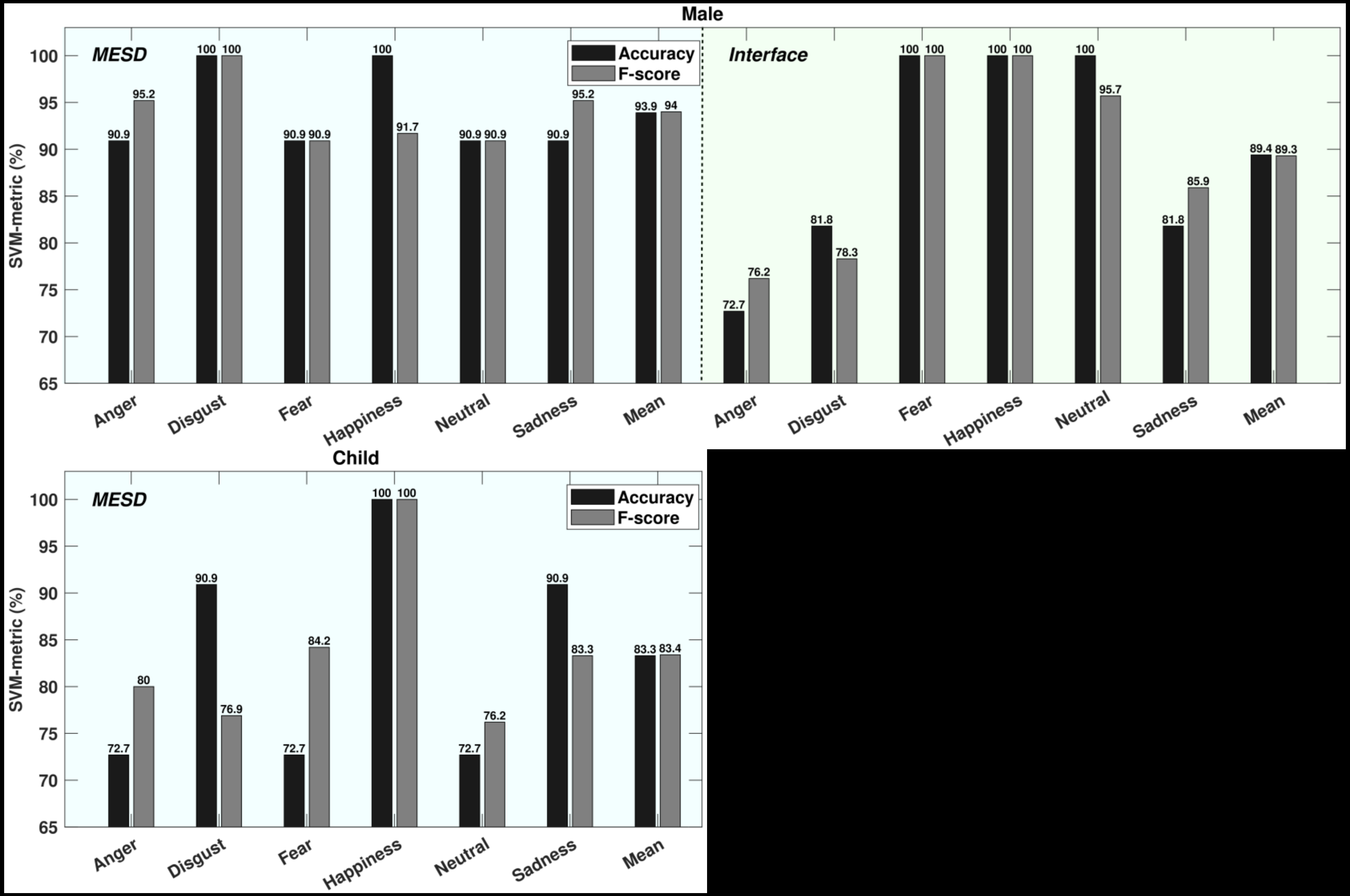

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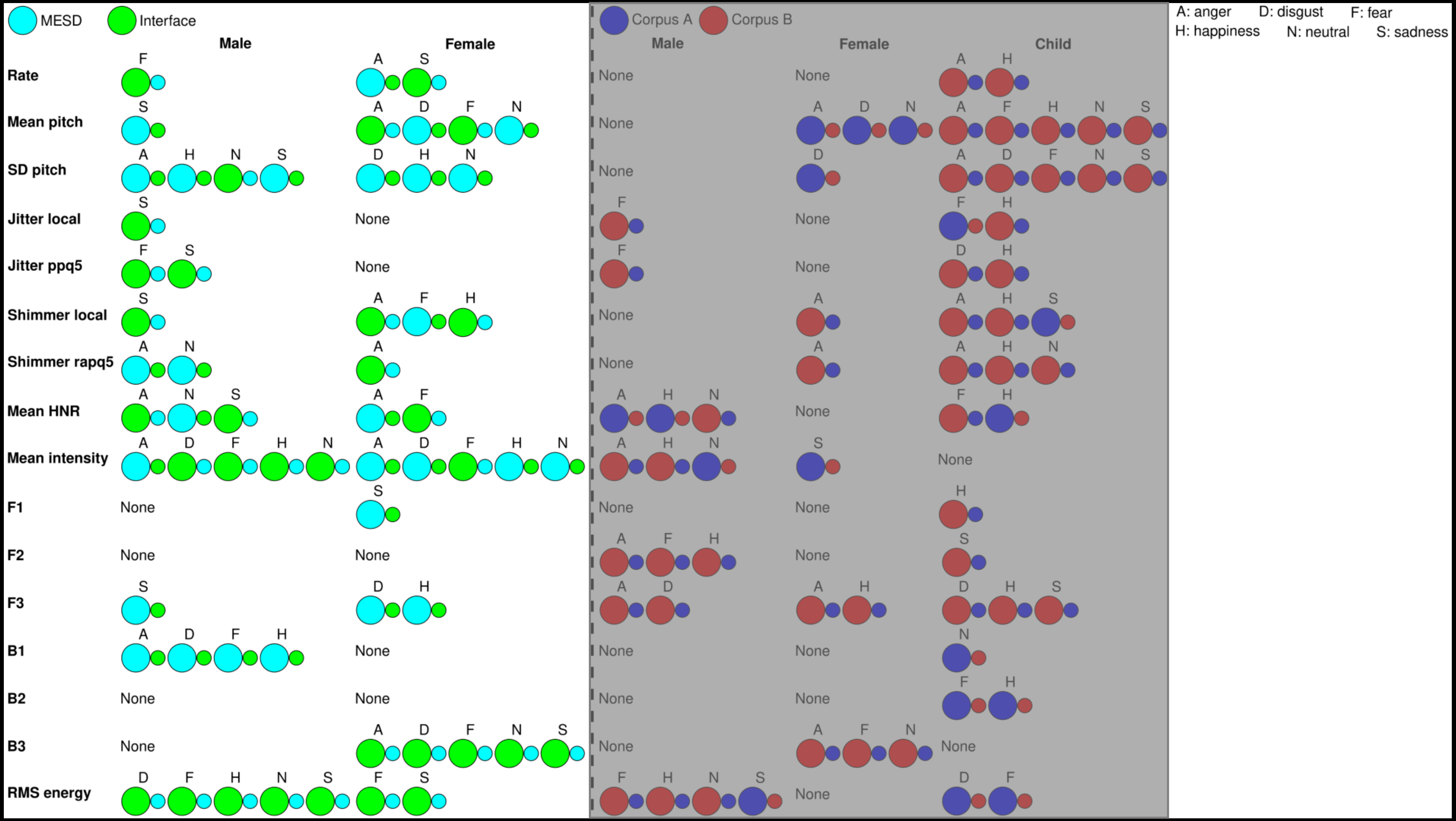

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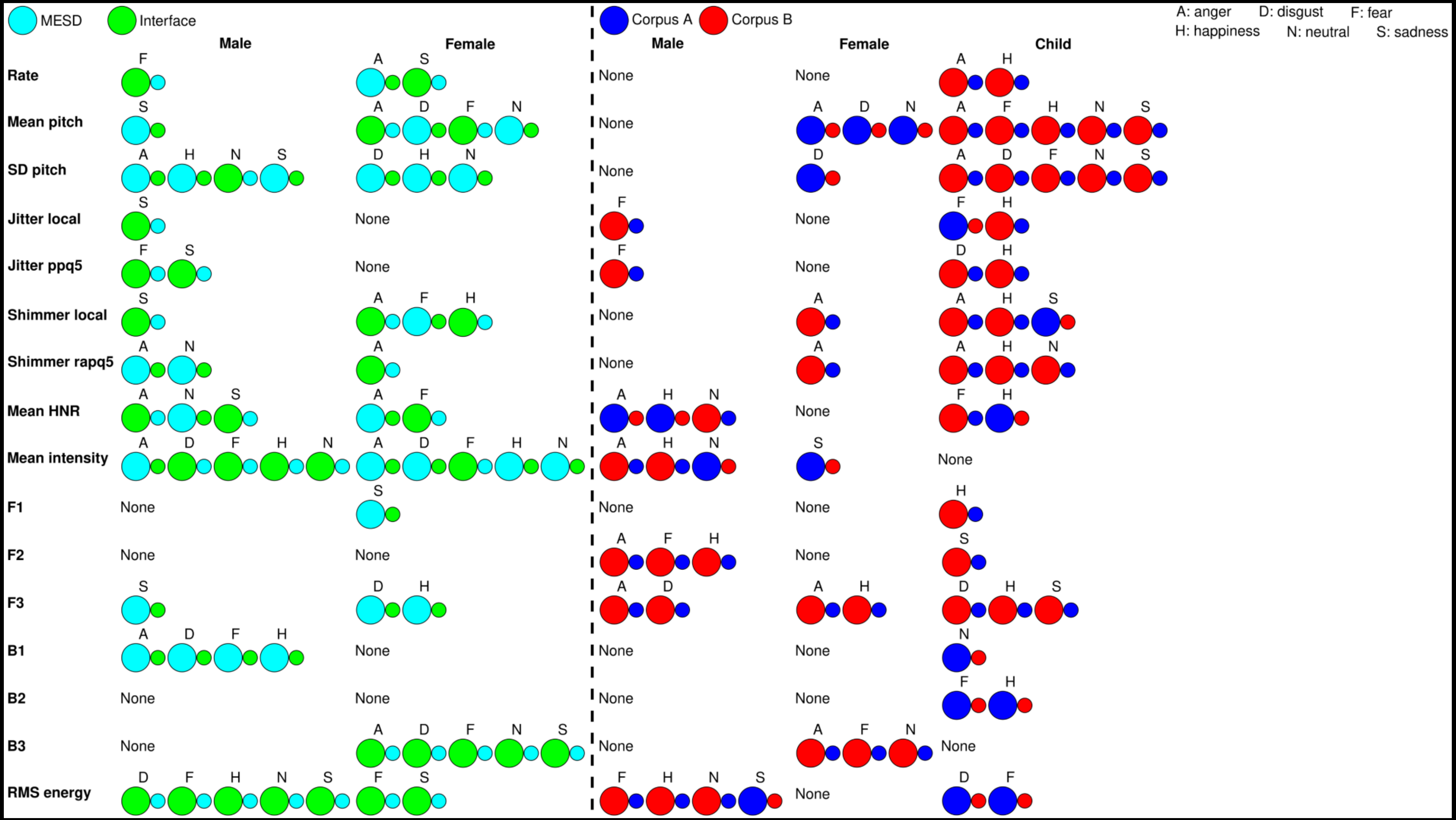

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Mexican Emotional Speech Database

A database for emotional speech, shaped by the Mexican culture was created, that is:

- Competitive compared to a previously-validated database of same language
- Corpus B is controlled for trade-offs between lexicosemantic attributes and emotions to ensure posterior unbiased emotion recognition by listeners

From the database:

- The assessment of emotion recognition by **humans** is necessary to confirm its reliability
- Reliable material to substantiate the **posterior creation of naturalness-reduced emotional prosodies**

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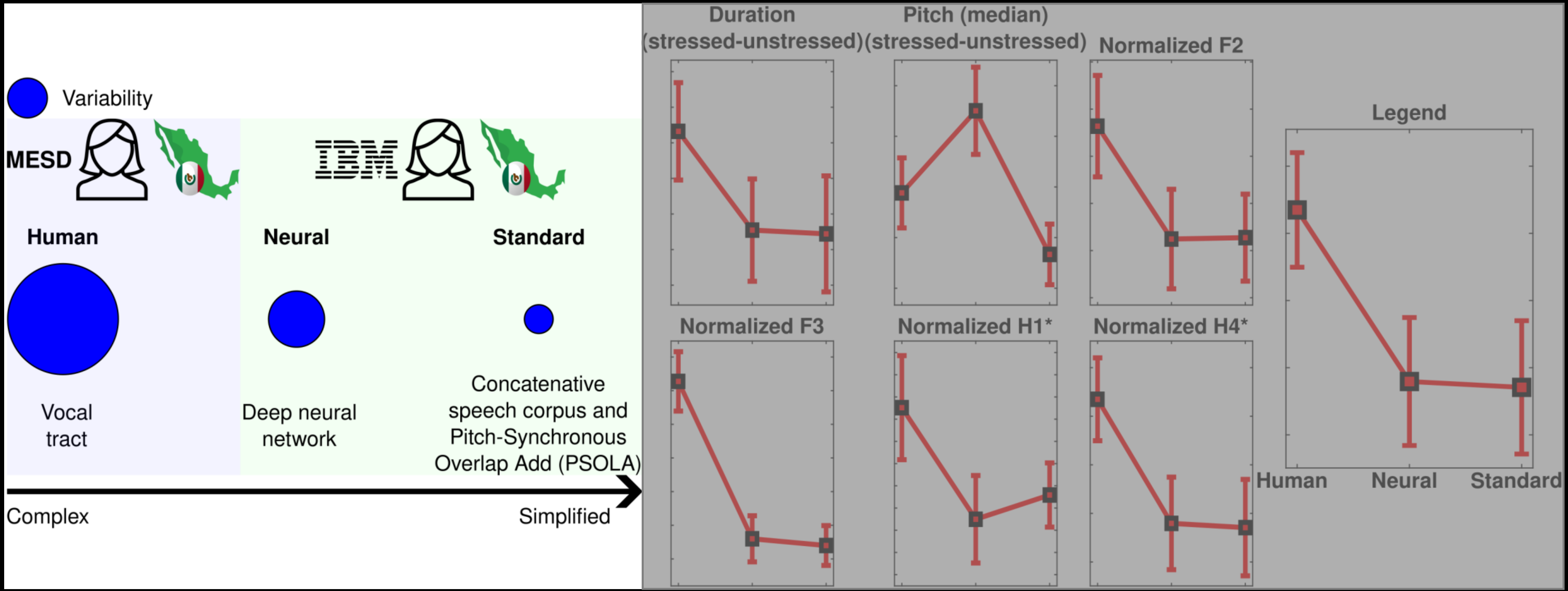
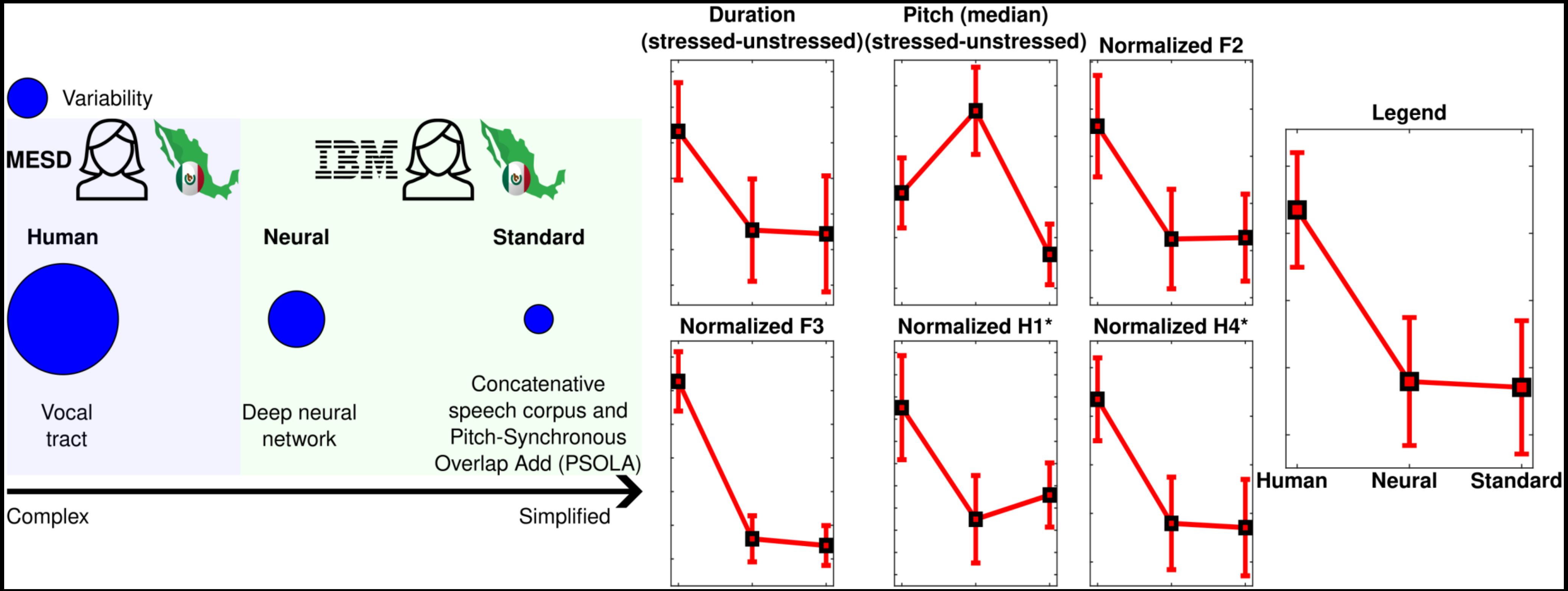
Naturalness-reduced voices: creation



48-56

Naturalness-reduced voices: creation



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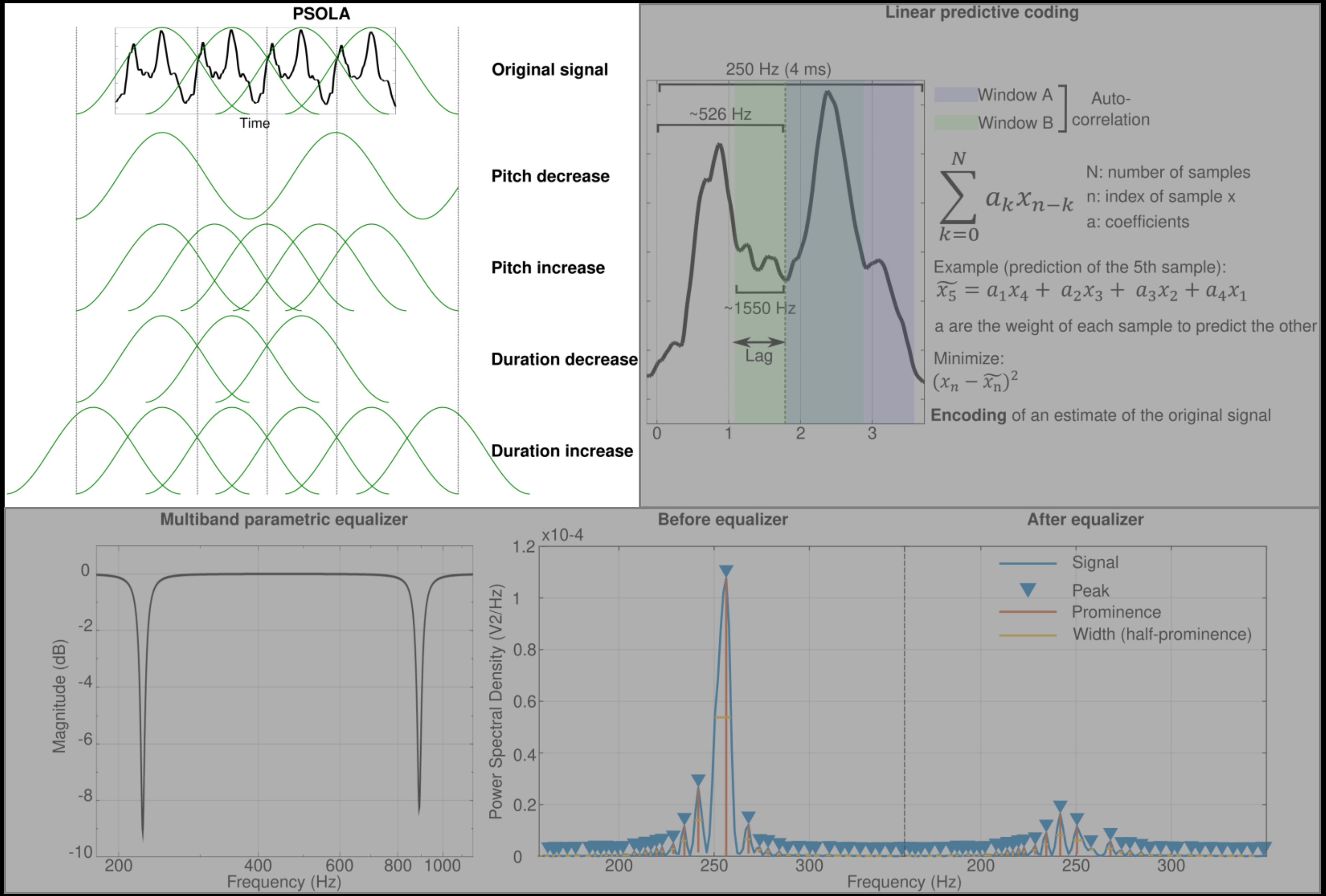

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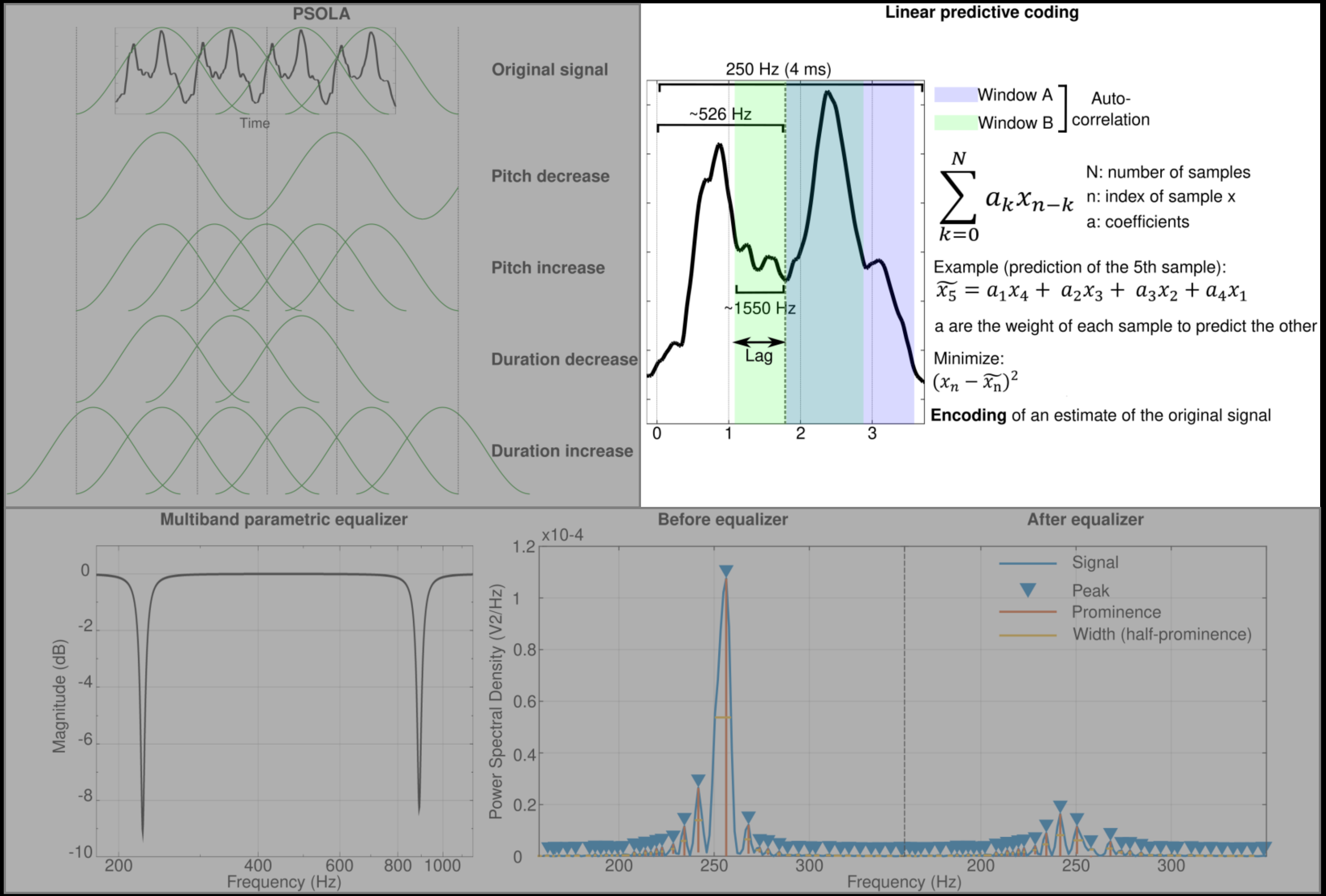

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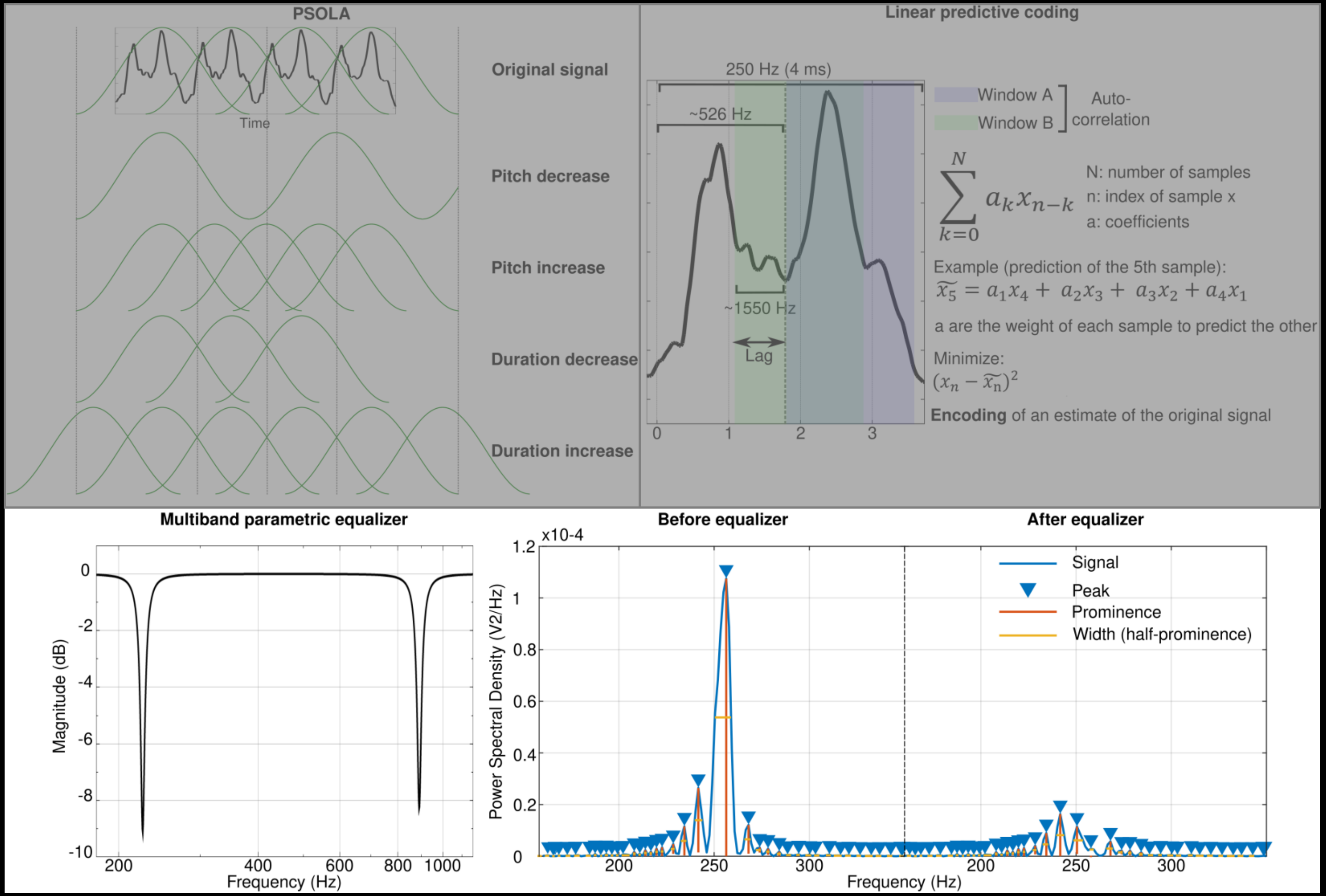

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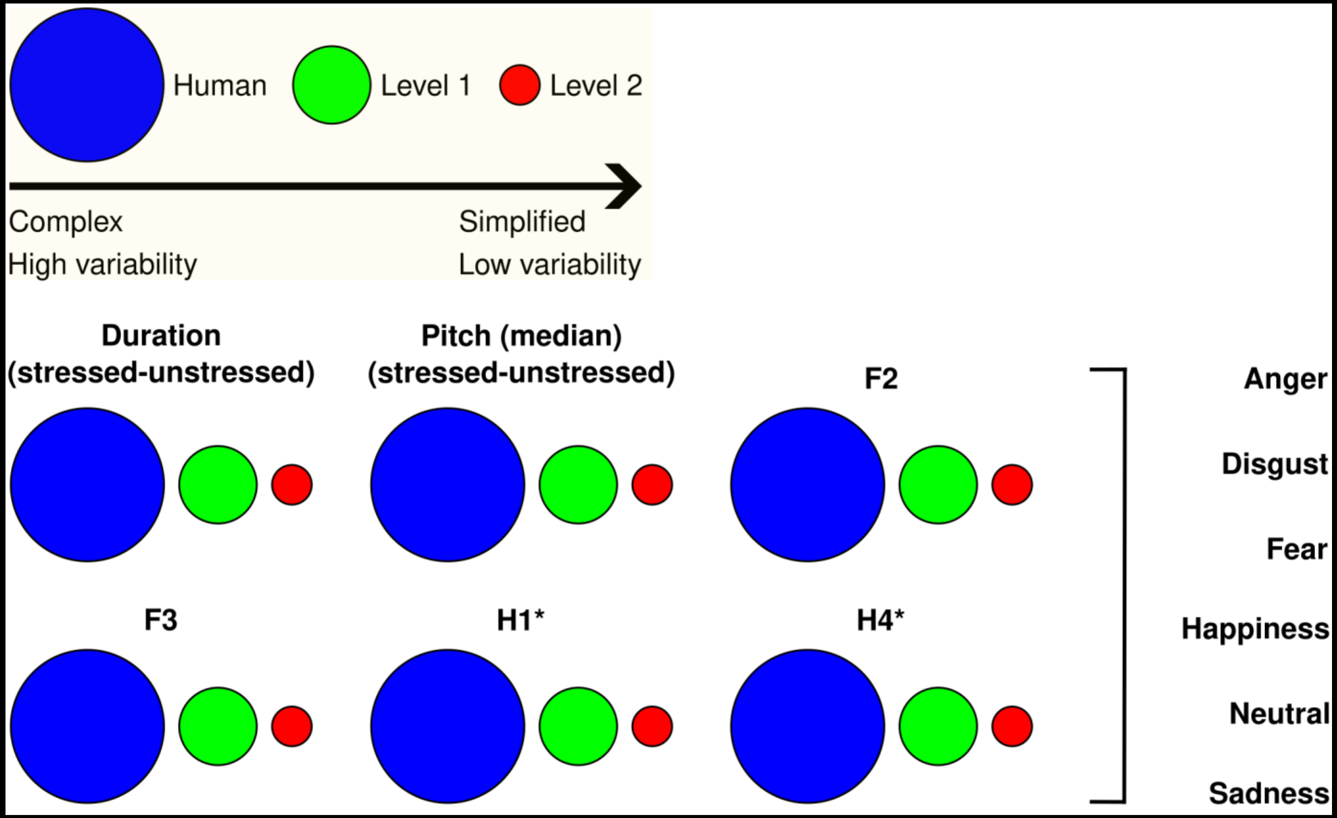

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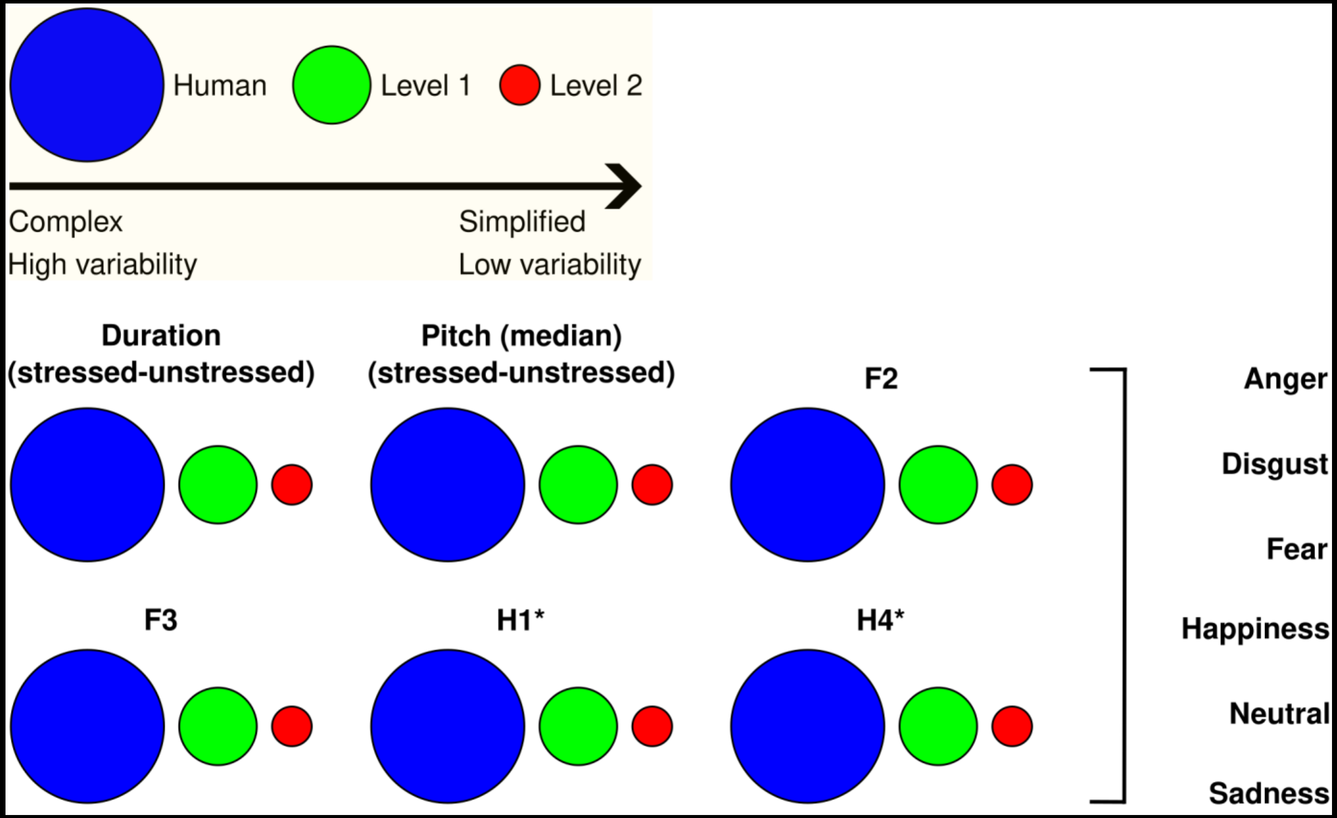

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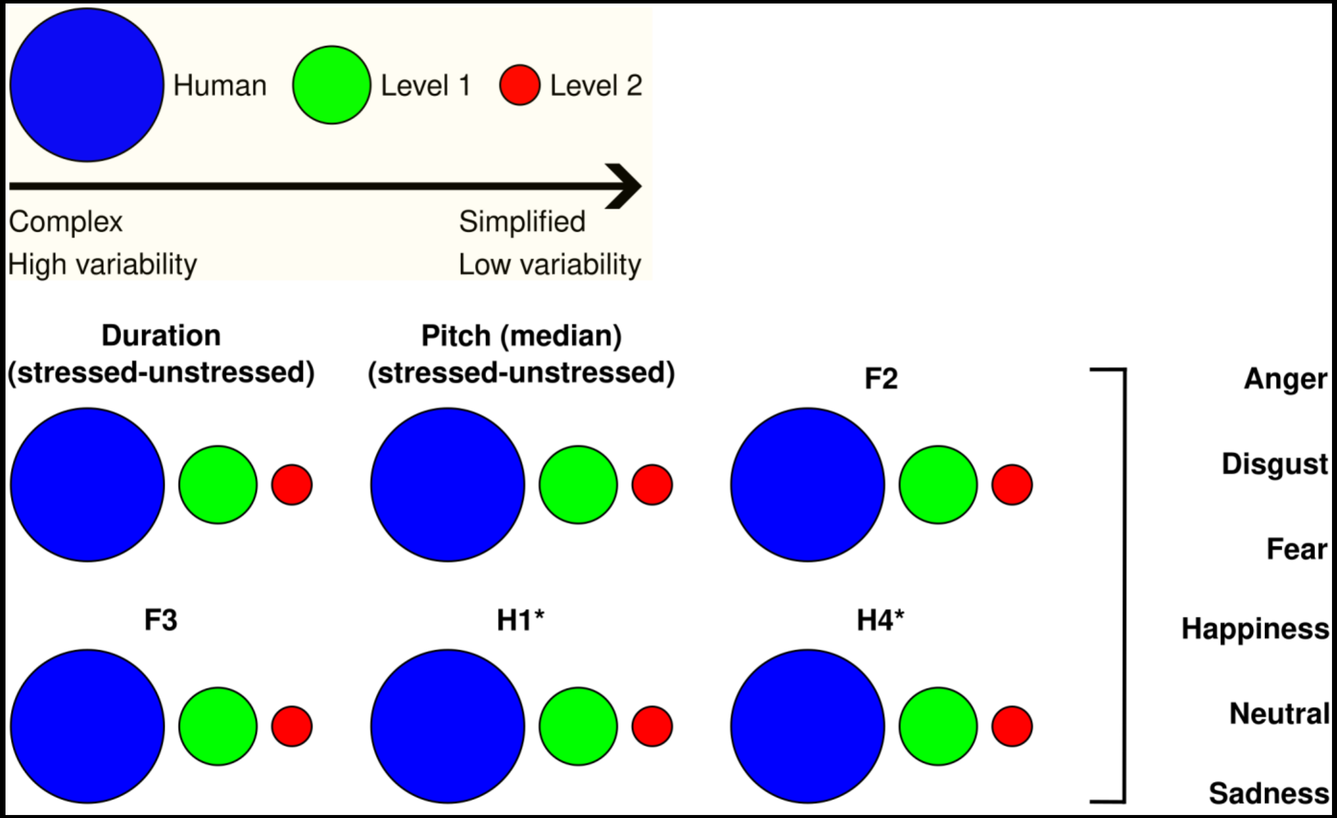

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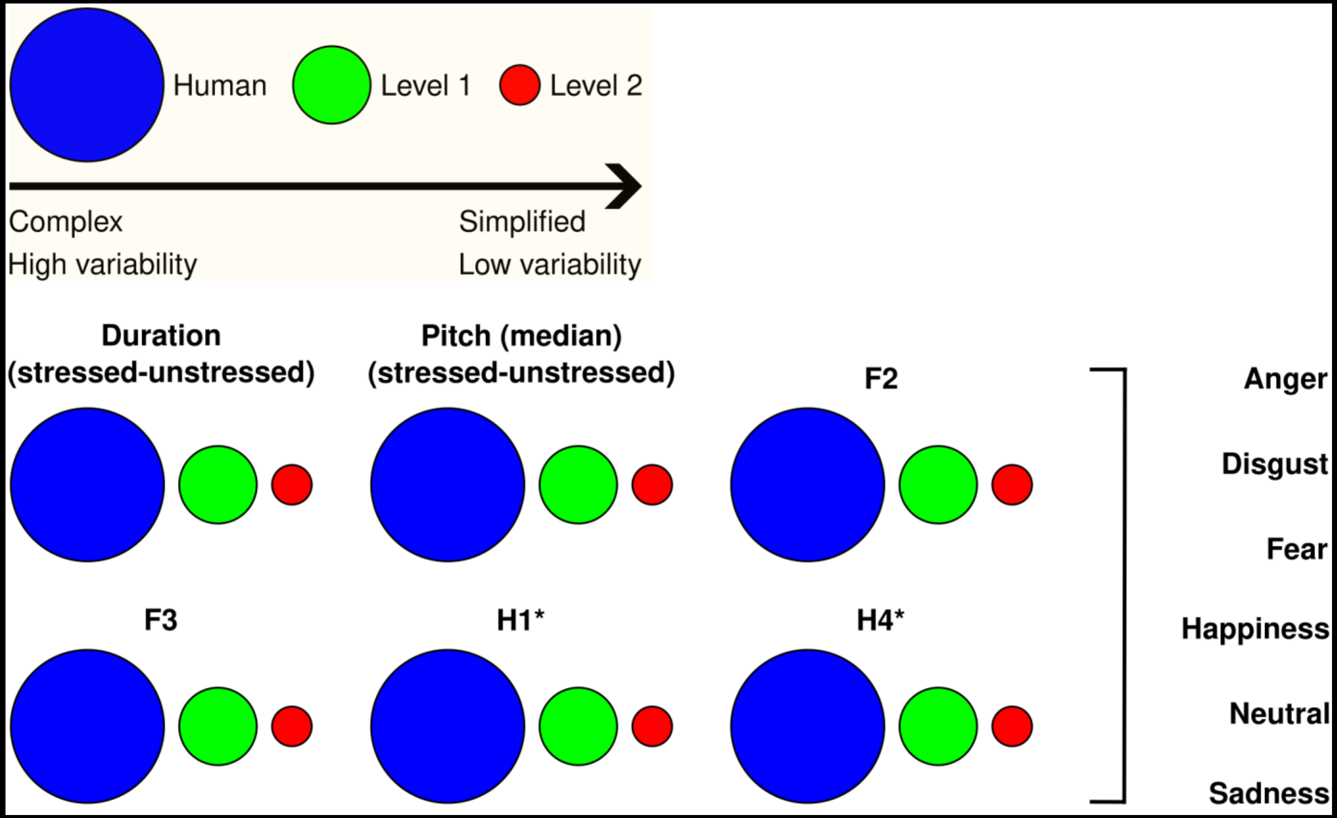

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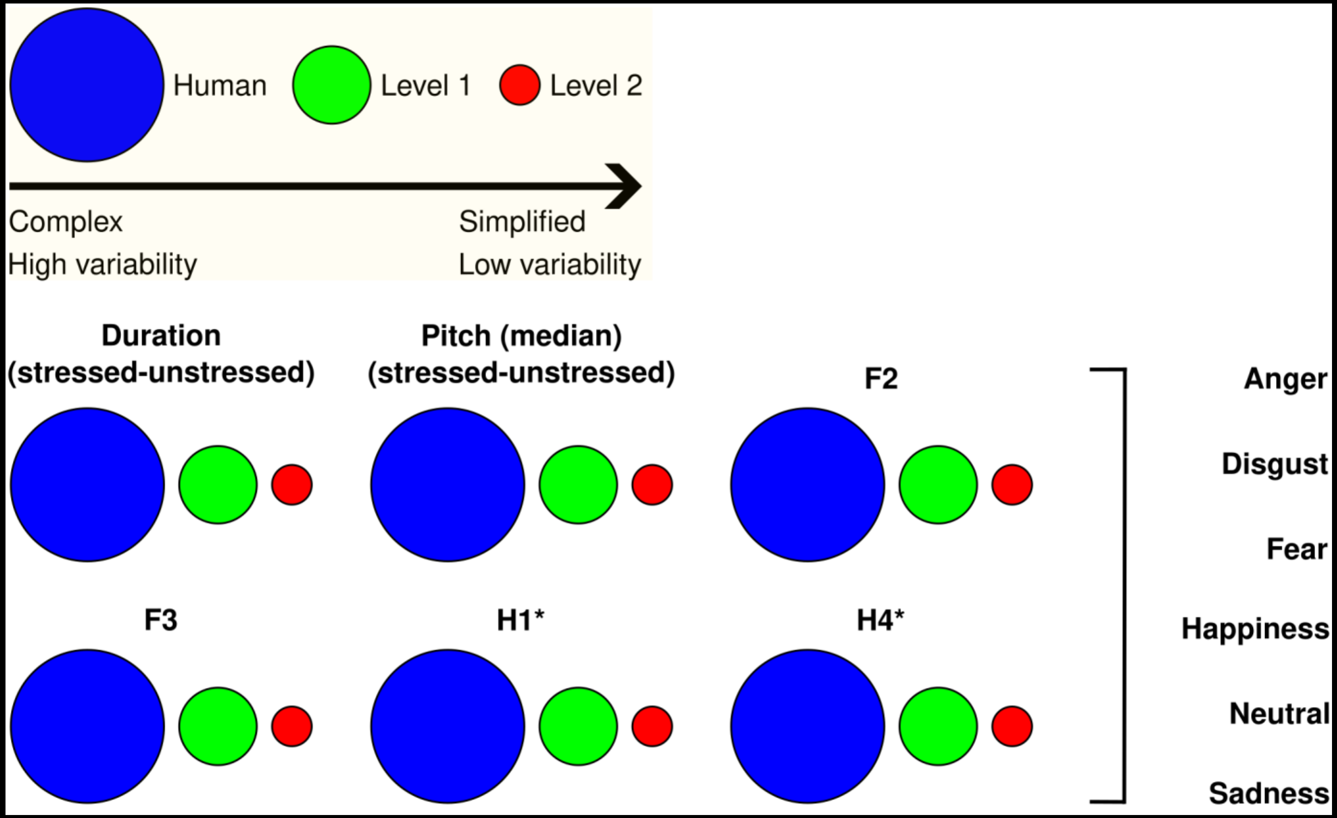

✓ **We created simplified acoustic environments for emotional prosodies**

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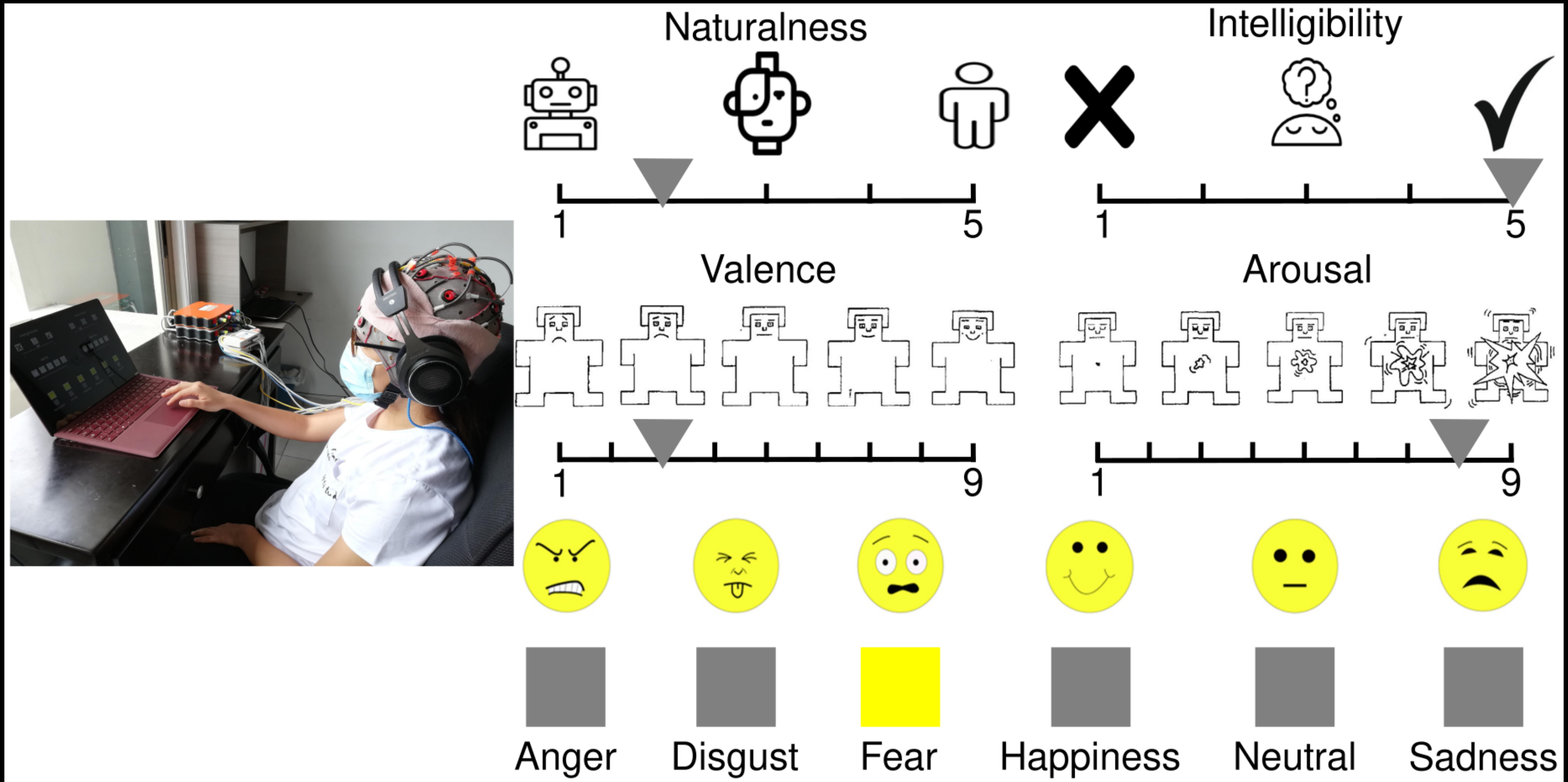
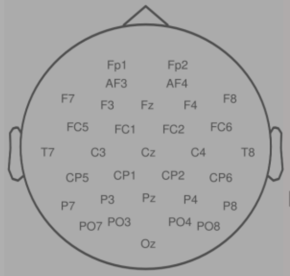
MESD: human perception



57-72

MESD: human perception

Type of data	Data curation
Behavioral	
Qualitative emotions	Accuracy F-score
Quantitative emotions Valence and arousal	Repeated measures ANOVA Emotion and level effects p<0.05 corrected for multiple comparisons (Bonferroni)
Naturalness Intelligibility	

Type of data	Data curation			
	Online	Offline		
Electroencephalography (EEG)	32 channels	Baseline means removal	Butterworth low-pass 8th order 30 Hz	***Analysis of Variance (ANOVA)*** Emotion and level effects
	Expanded 10-20 topography			1000 permutations under data exchangeability
	Sample frequency: 256 Hz	Artifact Subspace Reconstruction (mean: 21/24, sd: 4)		One or more neighboring sensors
	Impedance<5 kOhms		Epoch definition [-0.5 1] s	Cluster-level statistic: sum of statistics
		Bad channels detection and interpolation (mean: 1.8/32, sd: 2)		Maximum cluster-level statistic per iteration
			Baseline correction [-0.5 -0.2] s	p<0.05 corrected for multiple comparisons (Bonferroni)
		Extended Infomax Independent Components Analysis	Single-trial Event-Related Potentials (ERP)	***Inter-Trial Phase Coherence (ITPC)*** Between trials Between participants
	Butterworth bandpass 8th order 0.1-100 Hz	Wavelet-ICA for fixed-sourced artifacts rejection	Linear Discriminant Analysis Beamformer	Morlet wavelet 1 cycle (2 Hz) - 15 cycles (30 Hz)
				ITPC = mean(M[cos(angle) + i sin(angle)] / M)
	Butterworth notch 4th order 60 [58-62] Hz	Reference Electrode Standardization Technique	P200 [0.15 0.25] s Early LPP [0.4 0.7] s Late LPP [0.7 1] s	Significant ITPC compared to baseline (1000 permutations)

MESD: human perception

Type of data	Data curation
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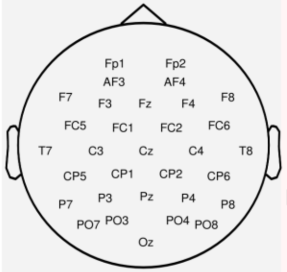
Qualitative emotions	Accuracy F-score
Quantitative emotions ***Valence and arousal*** ***Naturalness*** ***Intelligibility***	Repeated measures ANOVA Emotion and level effects $p<0.05$ corrected for multiple comparisons (Bonferroni)

Type of data	**Data curation**			
Electroencephalography (EEG)	**Online**	**Offline**		
	32 channels Expanded 10-20 topography Sample frequency: 256 Hz Impedance<5 kOhms  Butterworth bandpass 8th order 0.1-100 Hz Butterworth notch 4th order 60 [58-62] Hz	Baseline means removal Artifact Subspace Reconstruction (mean: 21/24, sd: 4) Bad channels detection and interpolation (mean: 1.8/32, sd: 2) Extended Infomax Independent Components Analysis Wavelet-ICA for fixed-sourced artifacts rejection Reference Electrode Standardization Technique	Butterworth low-pass 8th order 30 Hz Epoch definition [-0.5 1] s Baseline correction [-0.5 -0.2] s Single-trial Event-Related Potentials (ERP) Linear Discriminant Analysis Beamformer P200 [0.15 0.25] s Early LPP [0.4 0.7] s Late LPP [0.7 1] s	***Analysis of Variance (ANOVA)*** Emotion and level effects 1000 permutations under data exchangeability One or more neighboring sensors Cluster-level statistic: sum of statistics Maximum cluster-level statistic per iteration $p<0.05$ corrected for multiple comparisons (Bonferroni) ***Inter-Trial Phase Coherence (ITPC)*** Between trials Between participants Morlet wavelet 1 cycle (2 Hz) - 15 cycles (30 Hz) $ITPC = mean(M[cos(angle) + i\ sin(angle)] / M)$ Significant ITPC compared to baseline (1000 permutations)

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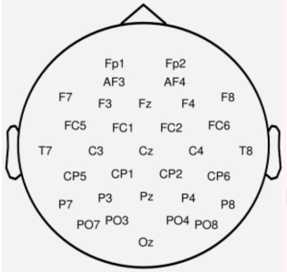
MESD: human perception

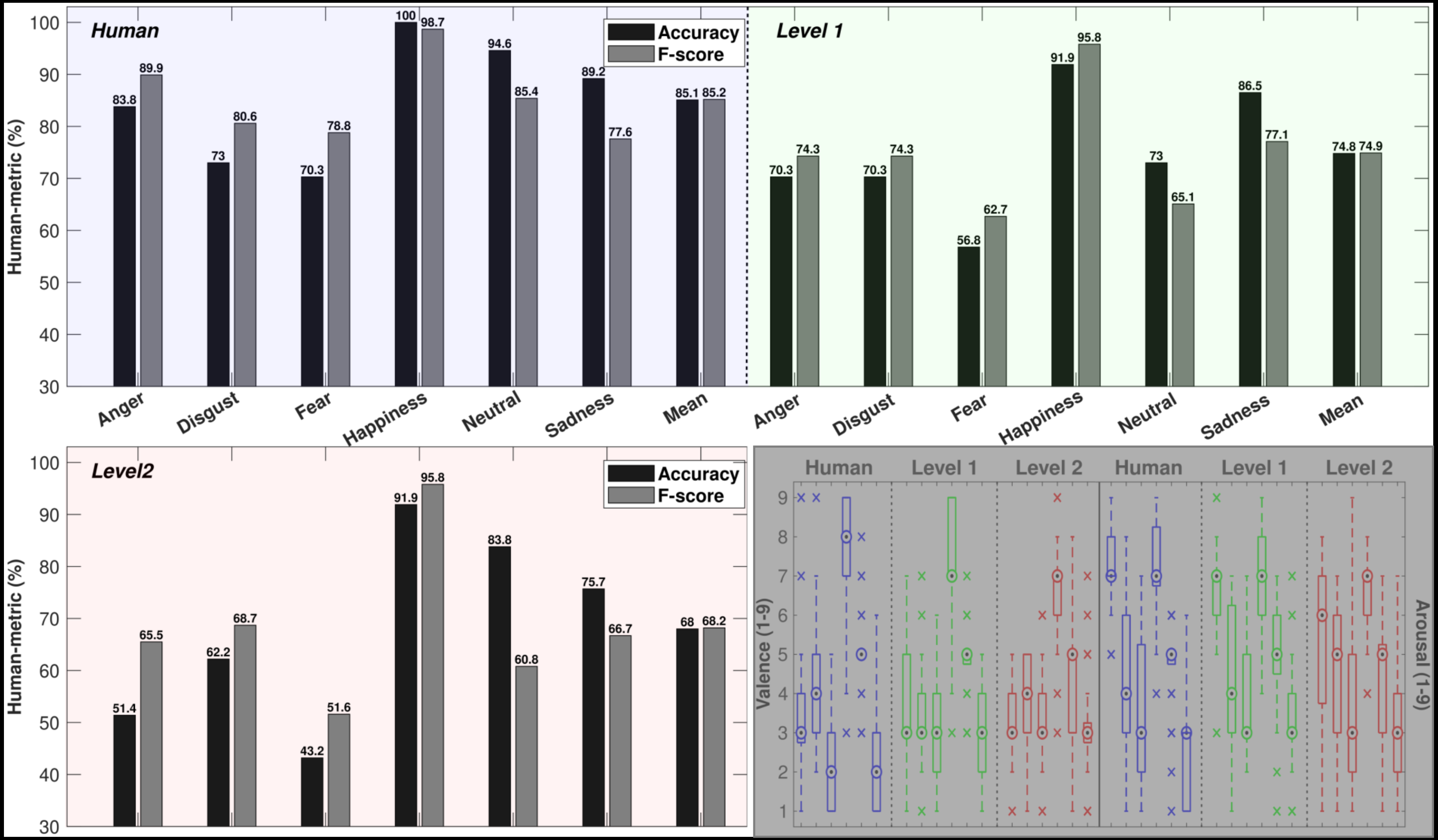
Type of data	Data curation
Behavioral	
Qualitative emotions	Accuracy F-score
Quantitative emotions ***Valence and arousal***	Repeated measures ANOVA Emotion and level effects p<0.05 corrected for multiple comparisons (Bonferroni)
Naturalness ***Intelligibility***	

Type of data	**Data curation**			
Electroencephalography (EEG)	**Online**	**Offline**		
	32 channels Expanded 10-20 topography Sample frequency: 256 Hz Impedance<5 kOhms Butterworth bandpass 8th order 0.1-100 Hz Butterworth notch 4th order 60 [58-62] Hz	Baseline means removal Artifact Subspace Reconstruction (mean: 21/24, sd: 4) Bad channels detection and interpolation (mean: 1.8/32, sd: 2) Extended Infomax Independent Components Analysis Wavelet-ICA for fixed-sourced artifacts rejection Reference Electrode Standardization Technique	Butterworth low-pass 8th order 30 Hz Epoch definition [-0.5 1] s Baseline correction [-0.5 -0.2] s Single-trial Event-Related Potentials (ERP) Linear Discriminant Analysis Beamformer P200 [0.15 0.25] s Early LPP [0.4 0.7] s Late LPP [0.7 1] s	***Analysis of Variance (ANOVA)*** Emotion and level effects 1000 permutations under data exchangeability One or more neighboring sensors Cluster-level statistic: sum of statistics Maximum cluster-level statistic per iteration p<0.05 corrected for multiple comparisons (Bonferroni)
				Inter-Trial Phase Coherence (ITPC) Between trials Between participants Morlet wavelet 1 cycle (2 Hz) - 15 cycles (30 Hz) ITPC = mean(M[cos(angle) + i sin(angle)] / M) Significant ITPC compared to baseline (1000 permutations)



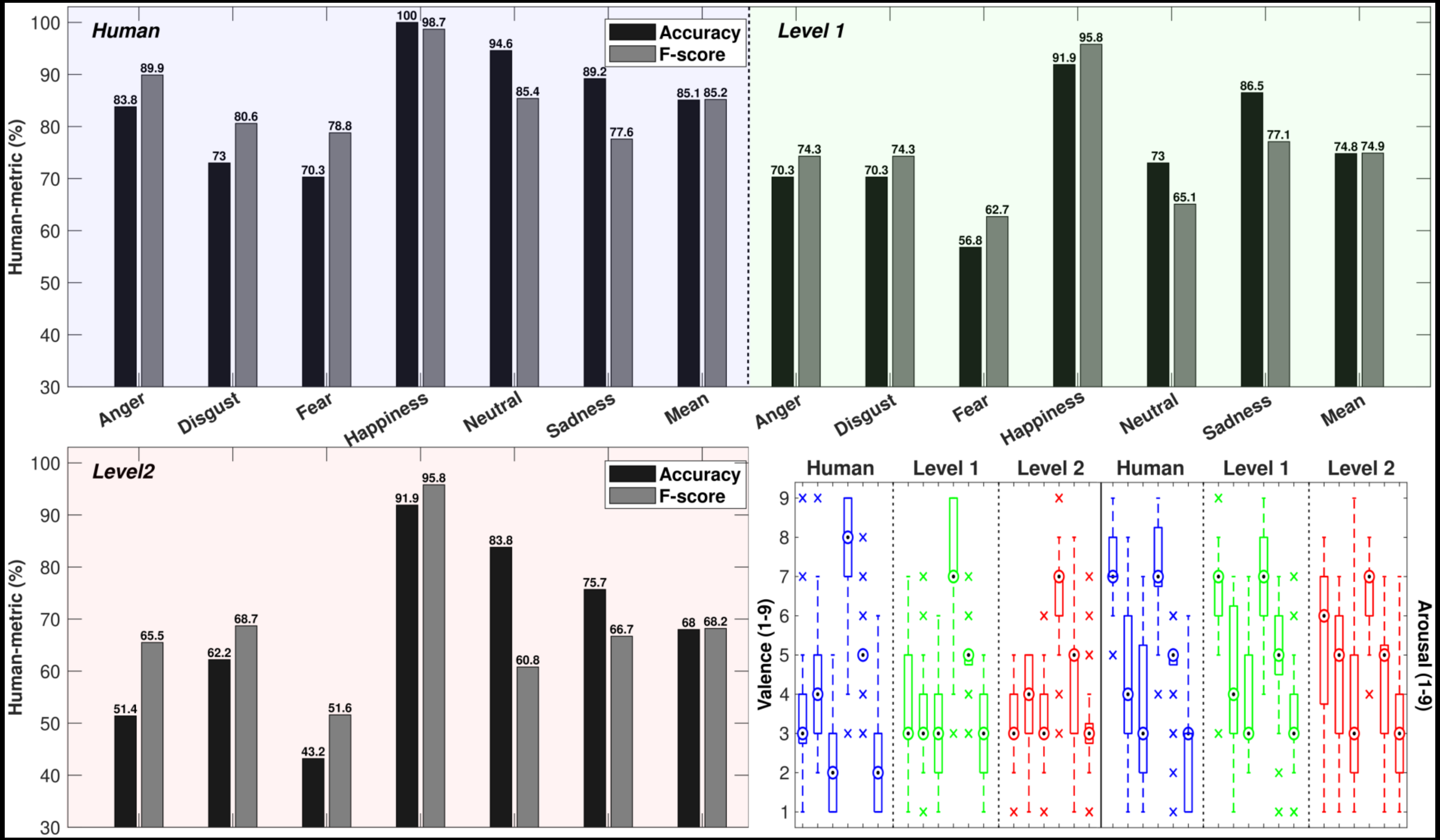
57-72

MESD: human perception



73-80

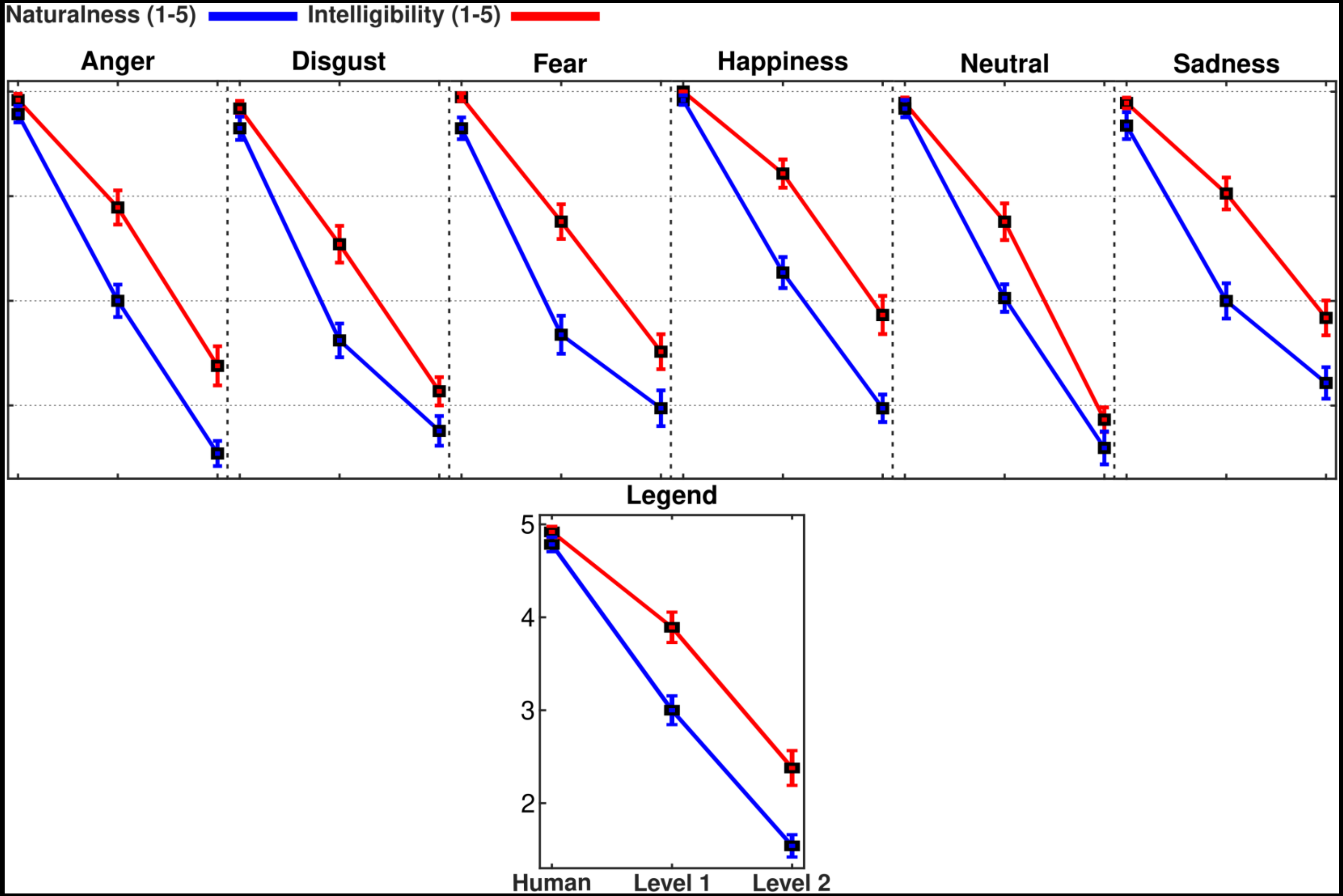
MESD: human perception



Overview
Introduction
Framework
MESD
Naturalness
Creation
Validation
Outcome
Highlights
Paradigm
Emotion ASD
Conclusions
Endorsement
Future
Adjacent work
References

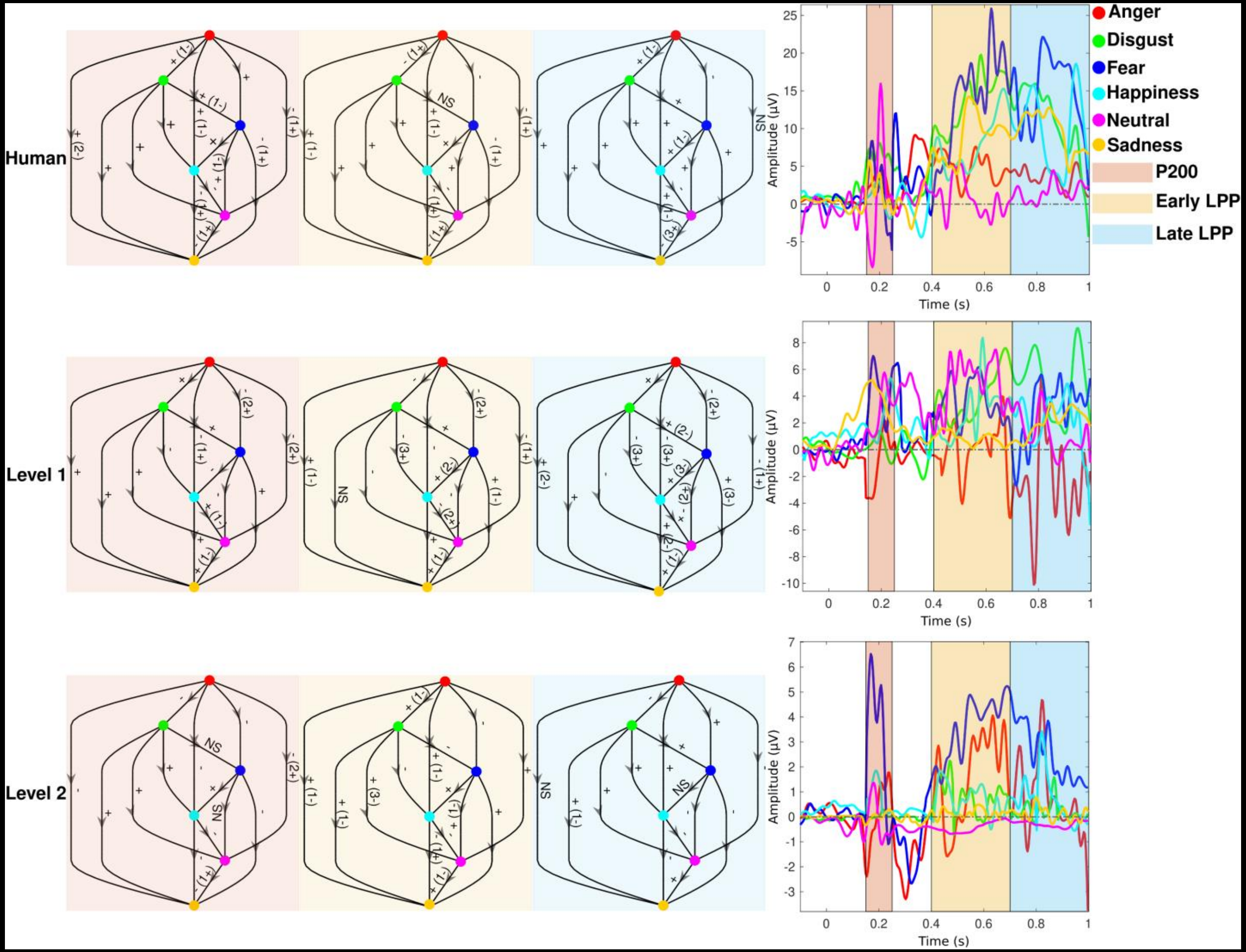
73-80

MESD: human perception



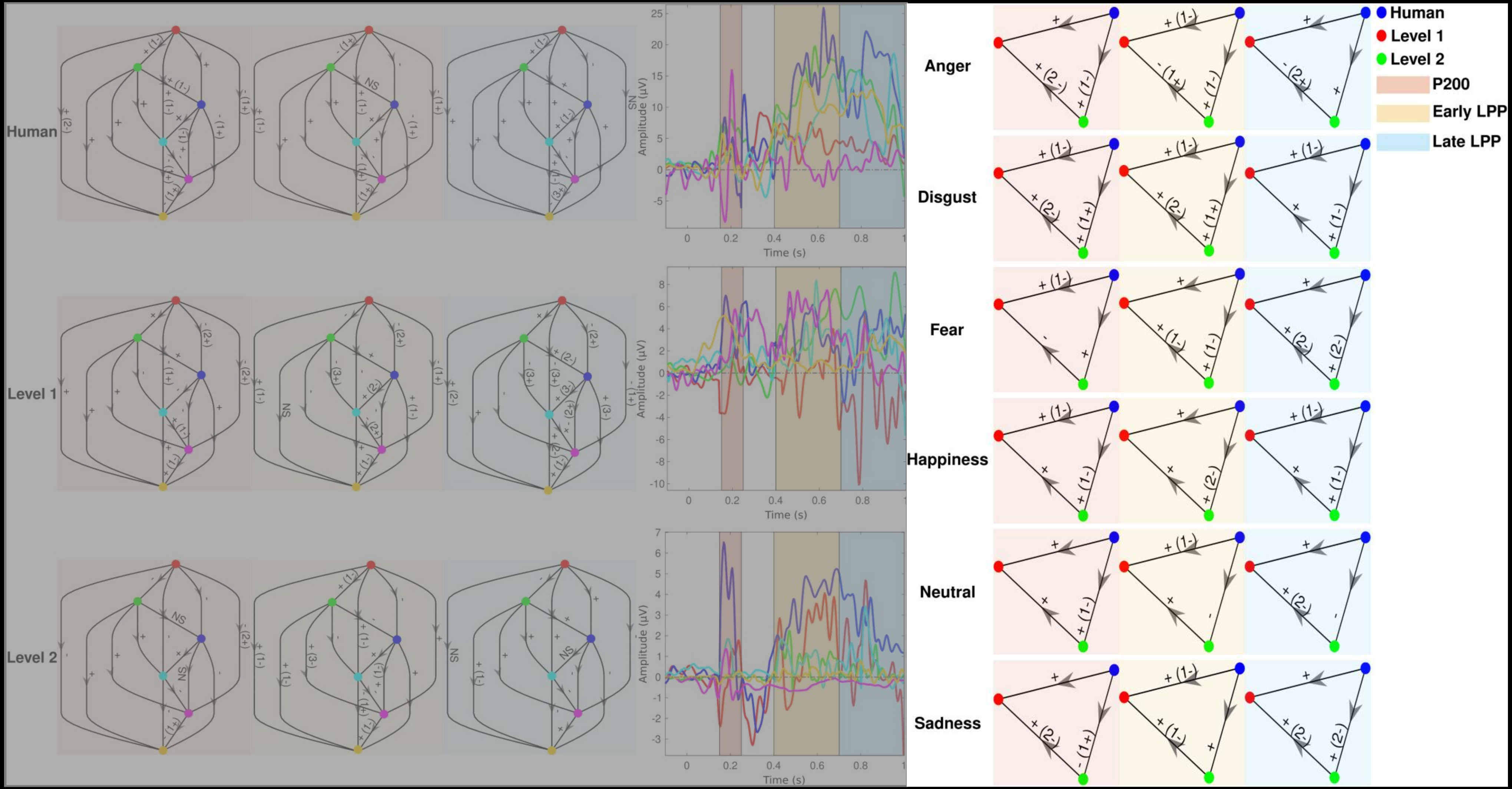
73-80

MESD: human perception



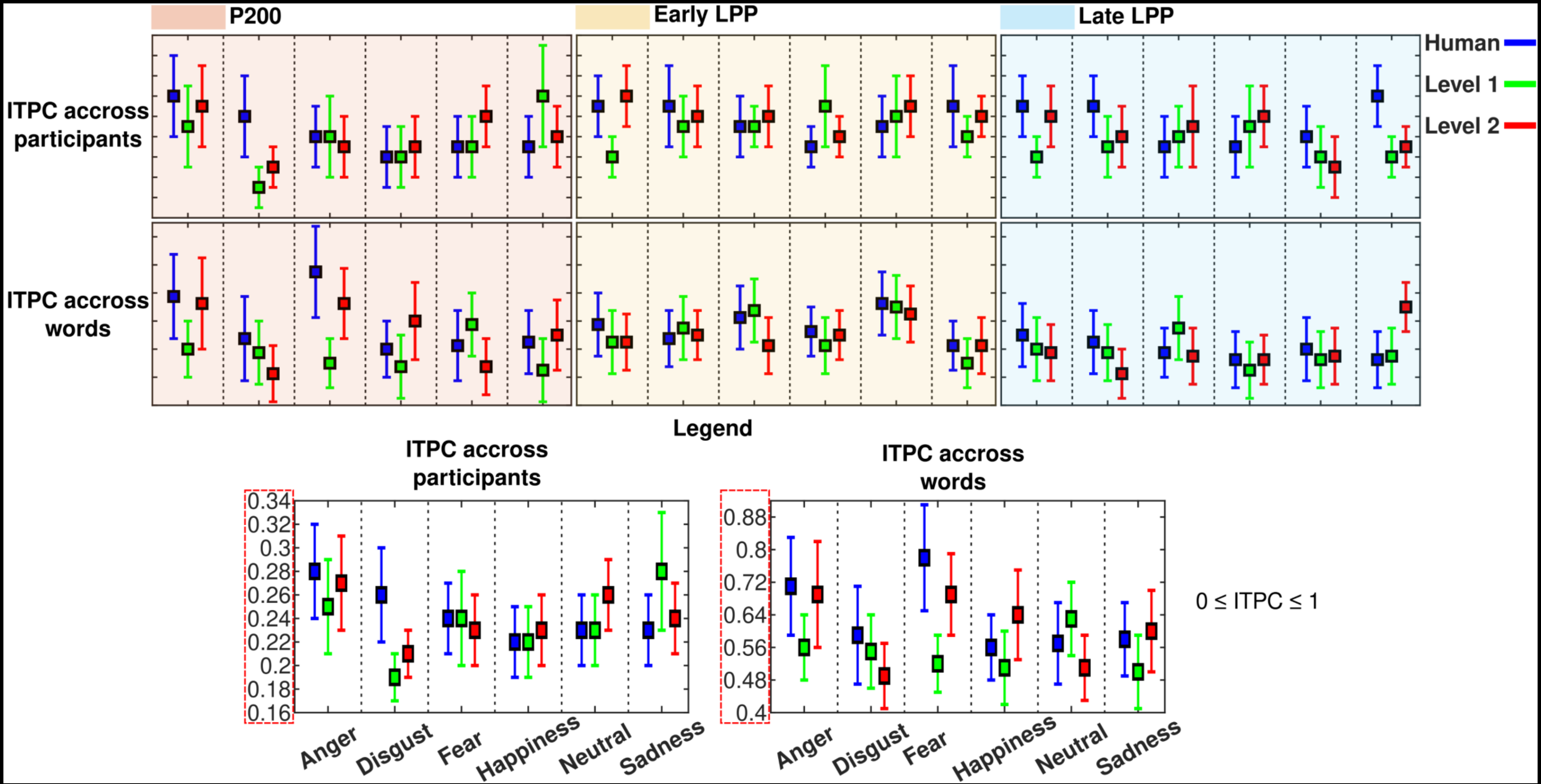
73-80

MESD: human perception



73-80

MESD: human perception



73-80

Human and naturalness-reduced voices

Naturalness-reduced voices were created:

- From high to low **variability** of acoustic features: Human > Level 1 > Level 2
- From which **emotional prosodies are recognized**, assessed by behavioral and electrophysiological markers
- Differential early and late patterns of neuronal activity while naturalness reduces highlight different processes for perception

Human voices previously recorded:

- Allow **emotional prosody recognition**, as assessed by behavioral and electrophysiological markers

Validity of MESD's word corpus:

- High coherence for emotion processing **between words** for every emotion (high ITPC)

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Human and naturalness-reduced voices

From the complemented database (human and naturalness-reduced voices):

- The assessment of emotion recognition by **children** is necessary
- The validation of an experimental paradigm is necessary, that allows to assess both:
  - (a) precision-weighting mechanisms for perception
  - (b) emotional prosodies' recognition

Two studies have been implemented:

I. Validation of an experimental paradigm to assess perception by children (TD and ASD)
   - ❑ Human voices only

II. Assessment of perception by TD and ASD children (and of repeatability of previously emphasized experimental framework)
   - ❑ Human and naturalness-reduced voices

Human and naturalness-reduced voices

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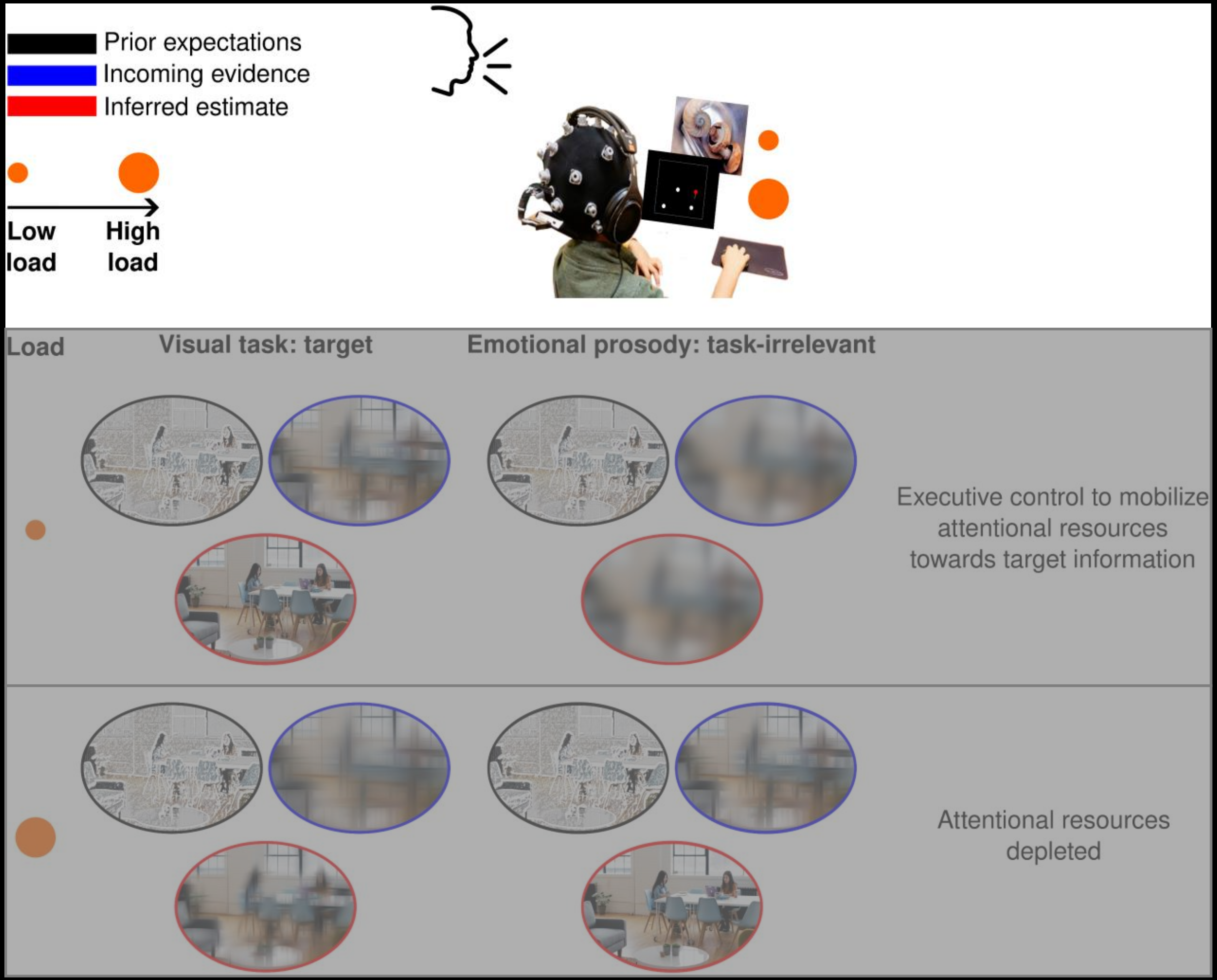
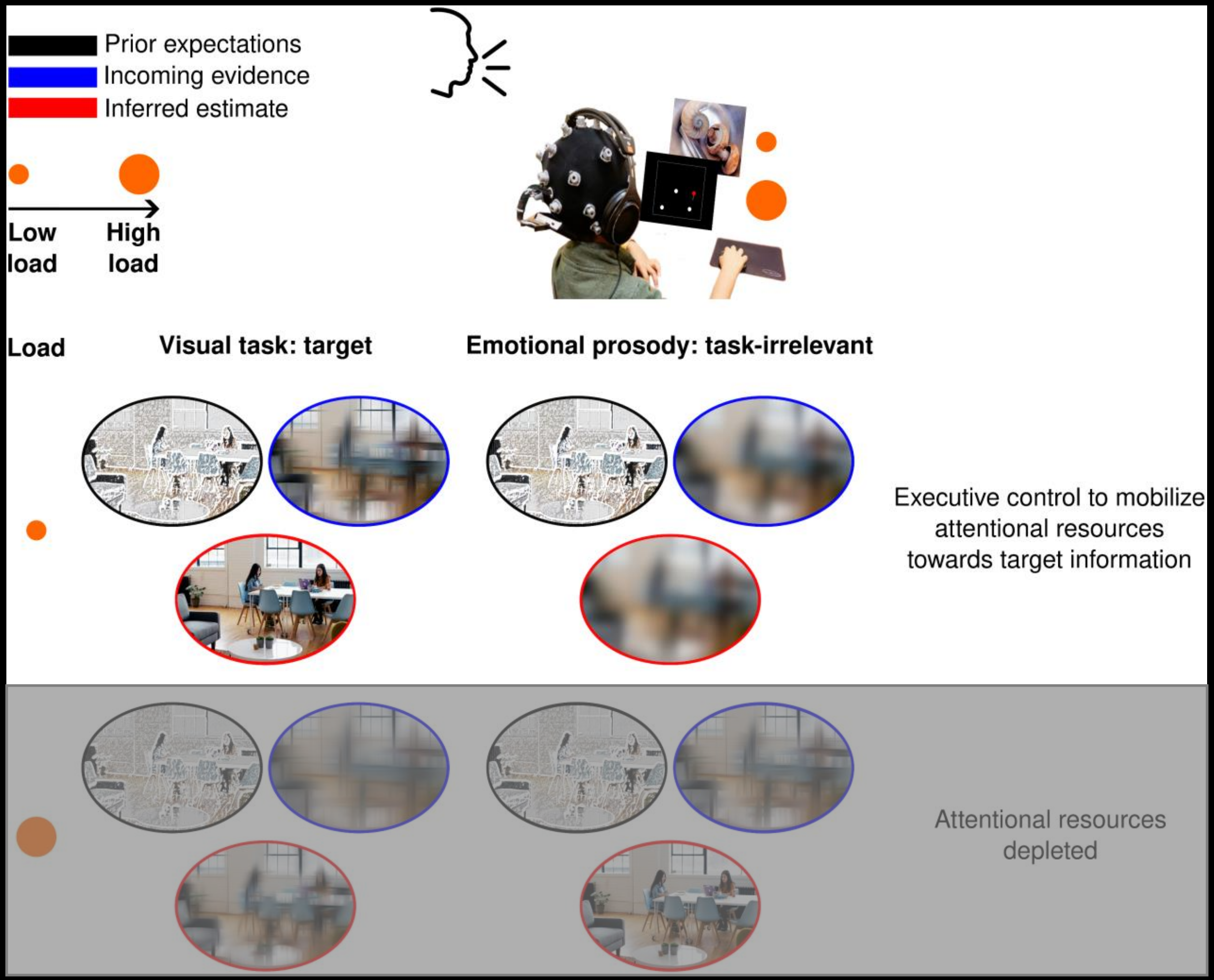
Perception by children: task and sample



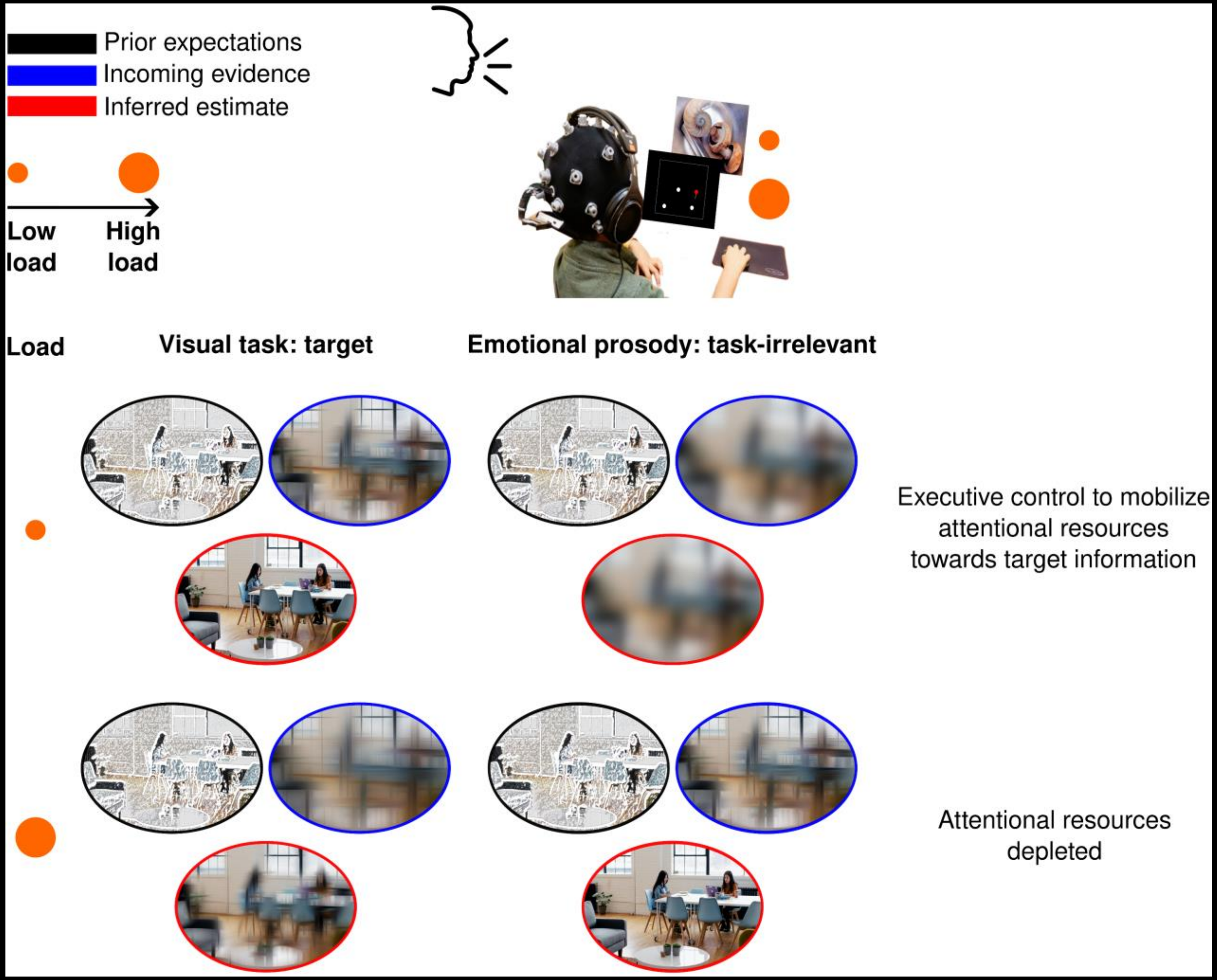
81-86

Perception by children: task and sample



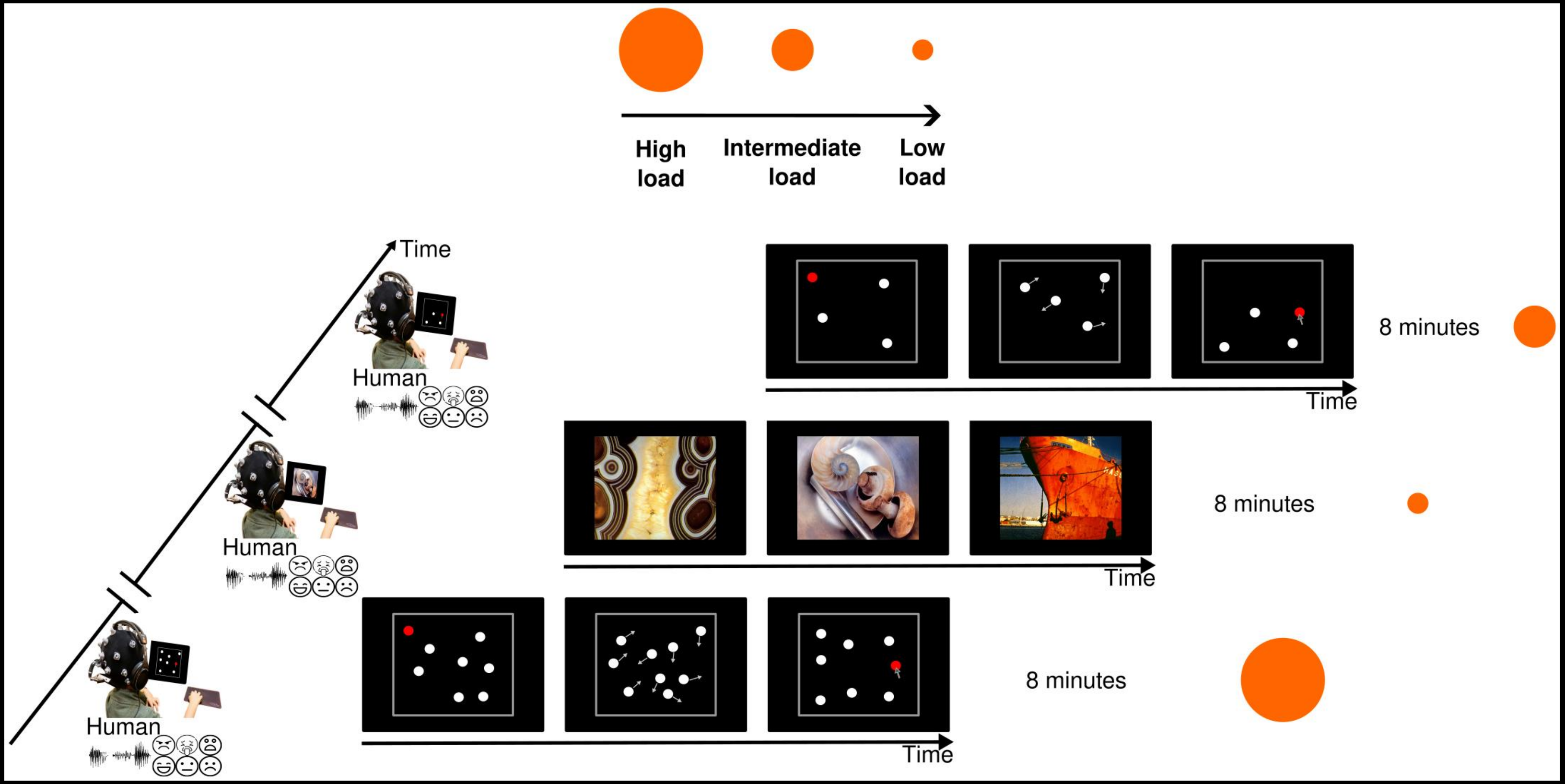
81-86

Perception by children: task and sample



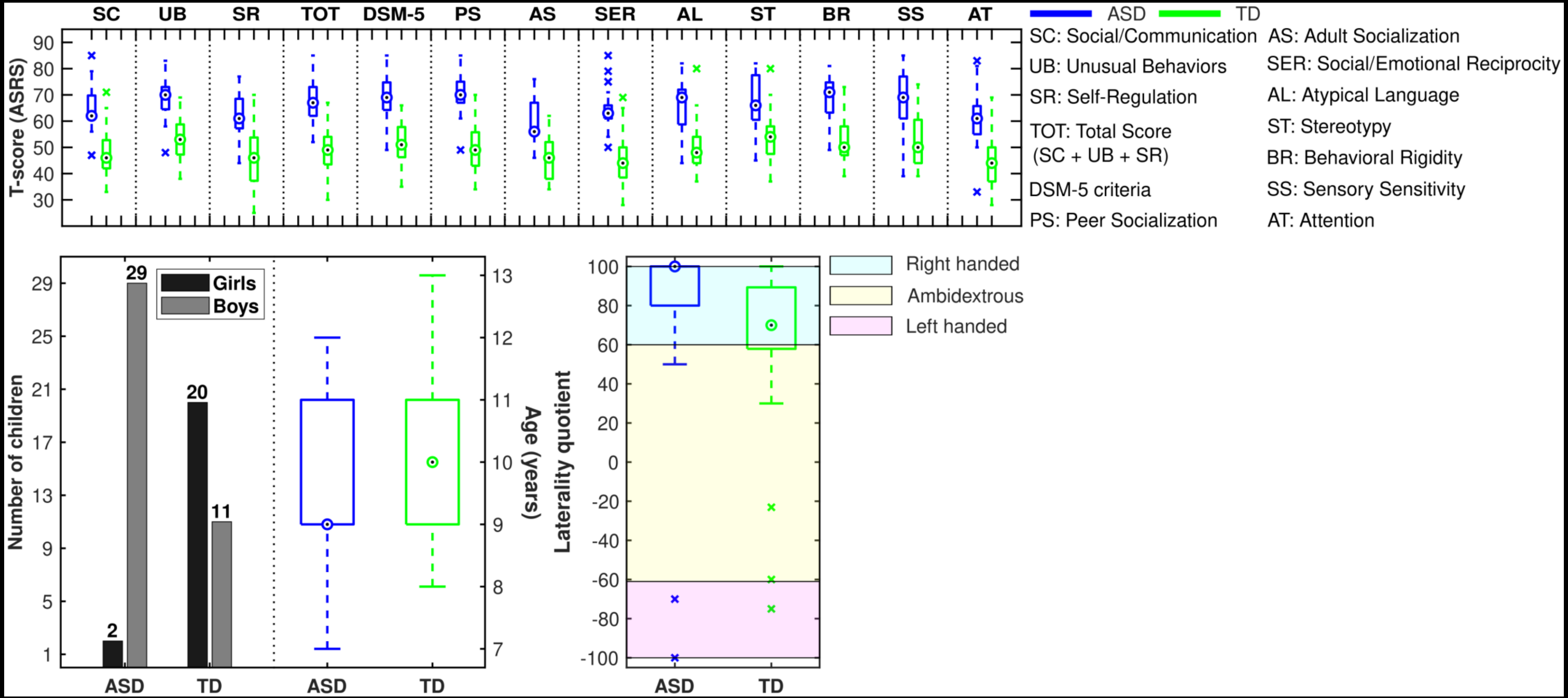
81-86

Perception by children: task and sample



81-86

Perception by children: task and sample



81-86

Perception by children: markers

Type of data | **Data curation**

Behavioral

Correct/incorrect responses on MOT

Tracking capacity (m')

Rate of correct guess

$p = \boxed{n/d}\left(m/n + d/2\right)$

$m = n\left(dp - d/2\right)$

m is in range: $[-d/2 \quad d/2]$

$m' = -1 + \left(2(m - \min(m)) / \max(m) - \min(m)\right)$

m' is in range [-1 1]

p: proportion of correct responses
n: the number of targets
d: number of discs
m: number of targets correctly tracked after correction

min(m) = -2 when d = 4
min(m) = -4 when d = 8
max(m) = 2 when d = 4
max(m) = 4 when d = 8

Analysis of Variance (ANOVA)
Group and condition effects

p<0.05 corrected for multiple comparisons (post-hoc Tukey)

Bayesian ANOVA
In case of null result

Evidence in favor of the null hypothesis (BF01)

Type of data | **Data curation**

Electroencephalography (EEG)

Online

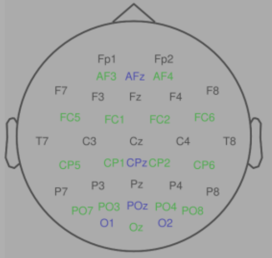
17 channels

Expanded 10-20 topography

Sample frequency: 256 Hz

Impedance<10 kOhms

ASD
TD
ASD and TD



Offline

Average referencing

Baseline means removal

Butterworth bandpass 6th order 0.1-100 Hz

Line noise removal 60 Hz - Cleanline

Artifact Subspace Reconstruction (mean: 22.5/24, sd: 4.8)

Bad channels detection and interpolation (mean: 3.4/32, sd: 2.1, 1.1/24, sd: 1)

Extended Infomax Independent Components Analysis

ICLabel for fixed-sourced artifacts rejection (<70% brain, mean: 1.77, sd: 2)

Epoch definition [-1.1 2] s

Time-locked to auditory stimuli

ERSP extraction Morlet wavelet

3 to 67.5 cycles 4 to 90 Hz

Baseline [-1.1 -1] s

Significant ERSP compared to baseline (1000 permutations)

Analysis of Variance (ANOVA)
Emotion and condition effects

1000 permutations under data exchangeability

One or more neighboring sensors

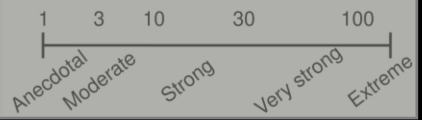
Cluster-level statistic: sum of statistics

Maximum cluster-level statistic per iteration

p<0.05 corrected for multiple comparisons (Bonferroni)

Bayesian ANOVA
In case of null result

Evidence in favor of the null hypothesis (BF01)



87-90

Perception by children: markers

Type of data

Behavioral

Correct/incorrect responses on MOT

Data curation

Tracking capacity (m')

Rate of correct guess

$$p = \boxed{\frac{n}{d}}\left(\frac{m}{n} + \frac{d}{2}\right)$$

$$m = n\left(dp - \frac{d}{2}\right)$$

m is in range: $\left[-\frac{d}{2} \;\; \frac{d}{2}\right]$

$$m' = -1 + \left(\frac{2(m - \min(m))}{\max(m) - \min(m)}\right)$$

m' is in range [-1 1]

p: proportion of correct responses
n: the number of targets
d: number of discs
m: number of targets correctly tracked after correction

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Analysis of Variance (ANOVA)
Group and condition effects

p<0.05 corrected for multiple comparisons (post-hoc Tukey)

Bayesian ANOVA
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Evidence in favor of the null hypothesis (BF01)

Type of data

Electroencephalography (EEG)

Data curation

Online

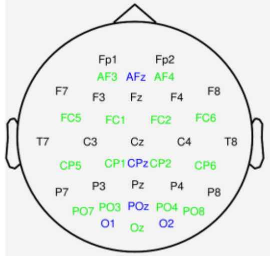
17 channels

Expanded 10-20 topography

Sample frequency: 256 Hz

Impedance<10 kOhms

ASD
TD
ASD and TD



Offline

Average referencing

Baseline means removal

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1000 permutations under data exchangeability

One or more neighboring sensors

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Maximum cluster-level statistic per iteration

p<0.05 corrected for multiple comparisons (Bonferroni)

Bayesian ANOVA
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Evidence in favor of the null hypothesis (BF01)

1 3 10 30 100

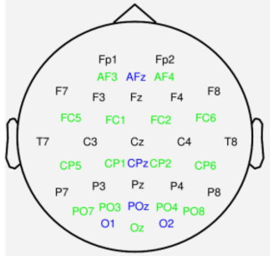
Anecdotal Moderate Strong Very strong Extreme

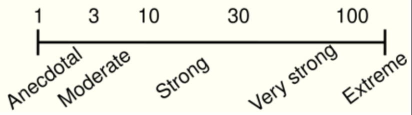
87-90

Perception by children: markers

Type of data	Data curation			
Behavioral ***Correct/incorrect responses on MOT***	Tracking capacity (m')	Rate of correct guess $p = \boxed{n/_d}\left(m/_n + d/_2\right)$ $m = n(dp - d/_2)$ m is in range: $[-d/_2 \;\; d/_2]$ $m' = -1 + \left(2(m - \min(m))/_{\max(m) - \min(m)}\right)$ m' is in range [-1 1]	p: proportion of correct responses n: the number of targets d: number of discs m: number of targets correctly tracked after correction min(m) = -2 when d = 4 min(m) = -4 when d = 8 max(m) = 2 when d = 4 max(m) = 4 when d = 8	***Analysis of Variance (ANOVA)*** Group and condition effects p<0.05 corrected for multiple comparisons (post-hoc Tukey) ***Bayesian ANOVA*** In case of null result Evidence in favor of the null hypothesis (BF01)

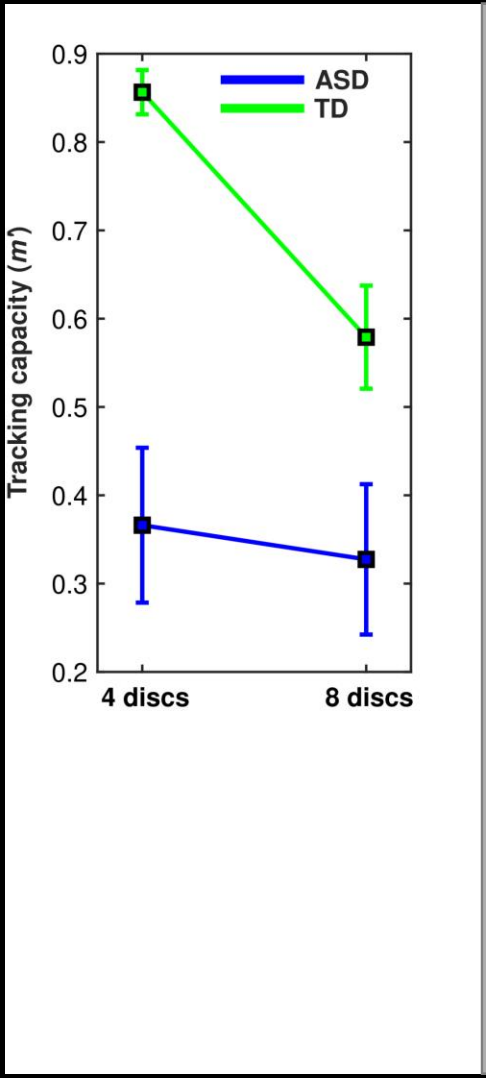
Type of data	Data curation			
	Online	**Offline**		
Electroencephalography (EEG)	17 channels Expanded 10-20 topography Sample frequency: 256 Hz Impedance<10 kOhms ASD TD $\boxed{\text{ASD and TD}}$	Average referencing Baseline means removal Butterworth bandpass 6th order 0.1-100 Hz Line noise removal 60 Hz - Cleanline Artifact Subspace Reconstruction (mean: 22.5/24, sd: 4.8) Bad channels detection and interpolation (mean: 3.4/32, sd: 2.1, 1.1/24, sd: 1) Extended Infomax Independent Components Analysis ICLabel for fixed-sourced artifacts rejection (<70% brain, mean: 1.77, sd: 2)	Epoch definition [-1.1 2] s Time-locked to auditory stimuli ERSP extraction Morlet wavelet 3 to 67.5 cycles 4 to 90 Hz Baseline [-1.1 -1] s Significant ERSP compared to baseline (1000 permutations)	***Analysis of Variance (ANOVA)*** Emotion and condition effects 1000 permutations under data exchangeability One or more neighboring sensors Cluster-level statistic: sum of statistics Maximum cluster-level statistic per iteration p<0.05 corrected for multiple comparisons (Bonferroni) ***Bayesian ANOVA*** In case of null result Evidence in favor of the null hypothesis (BF01)

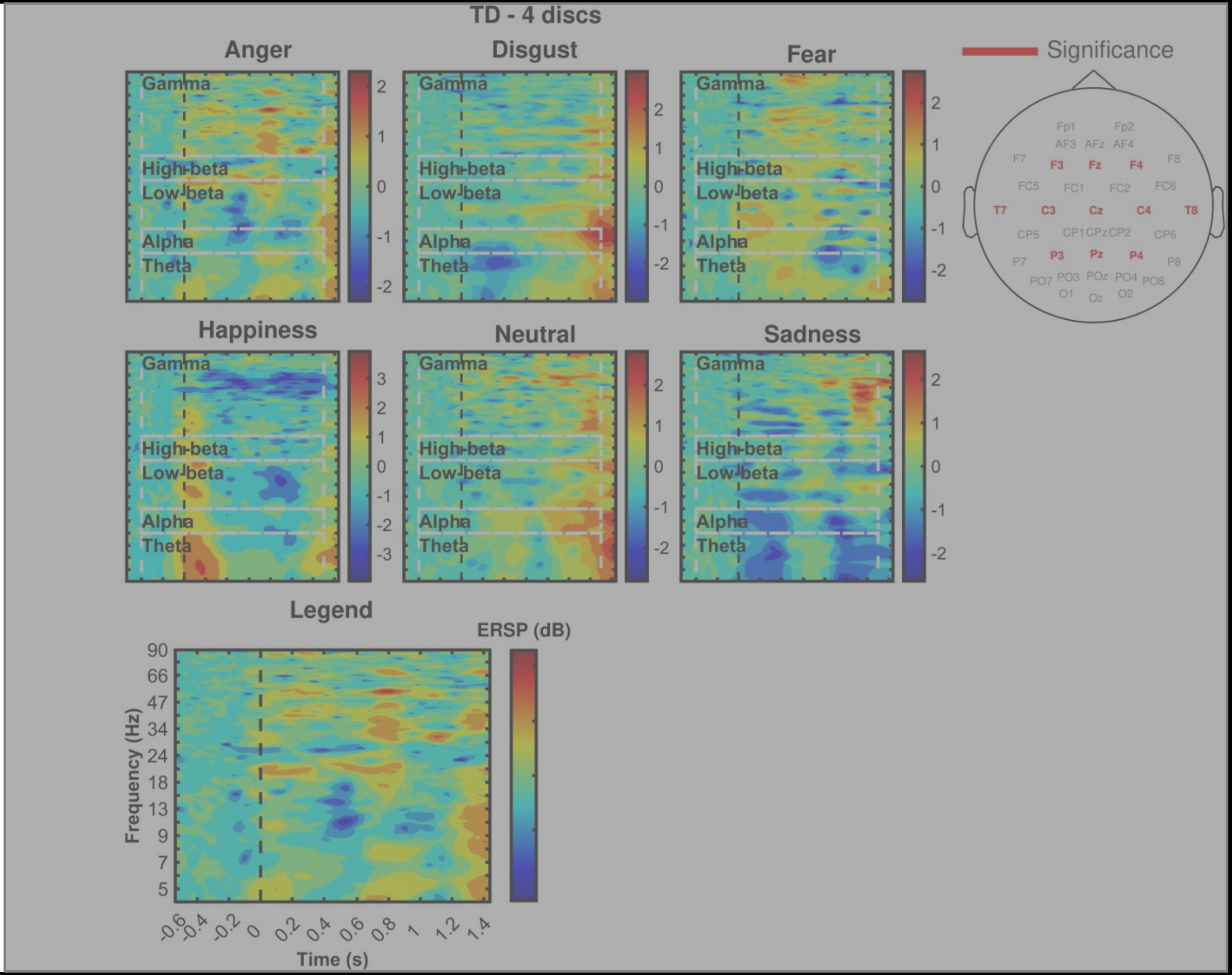




87-90

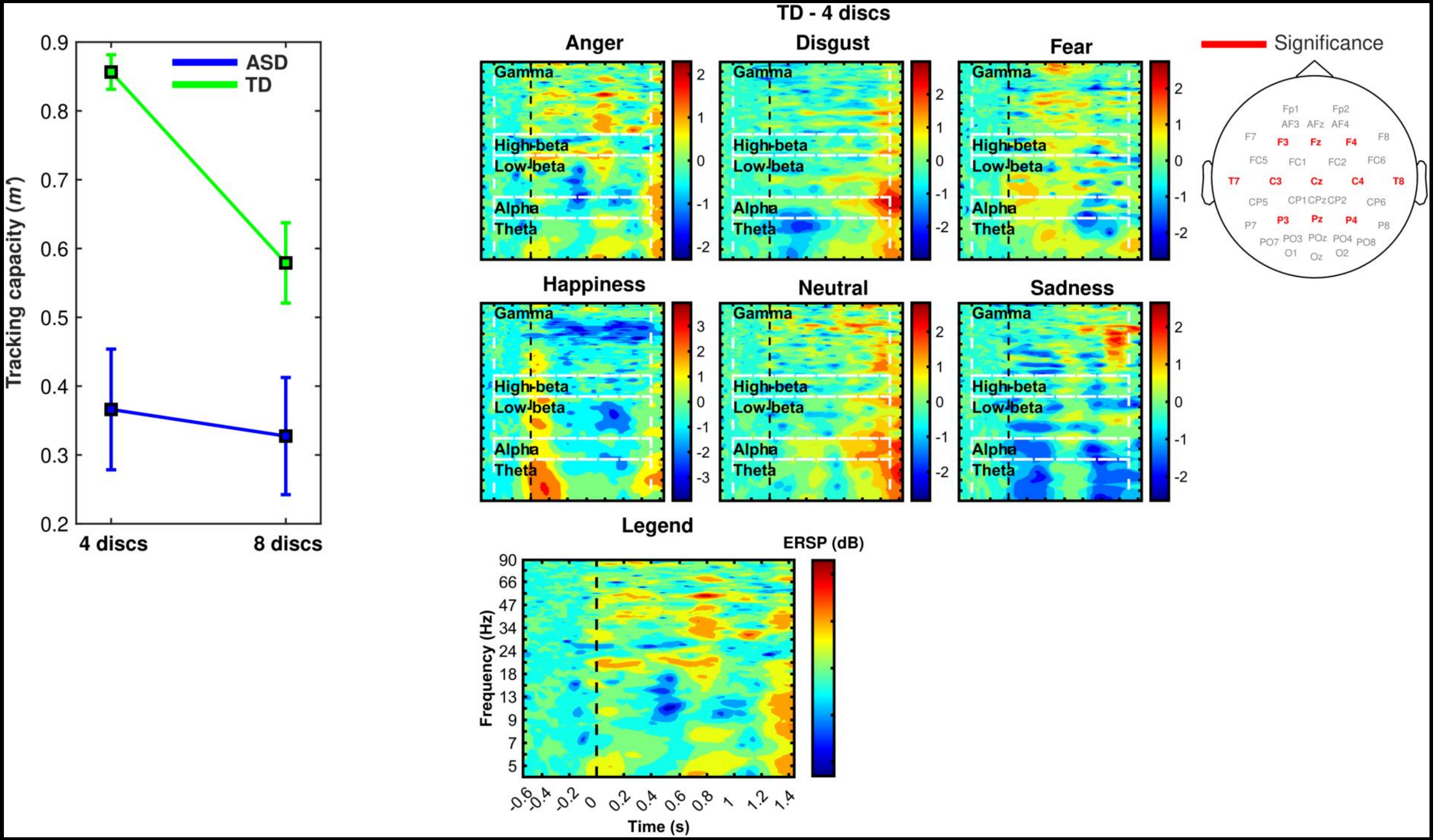
Medium load: emotion recognition by TD





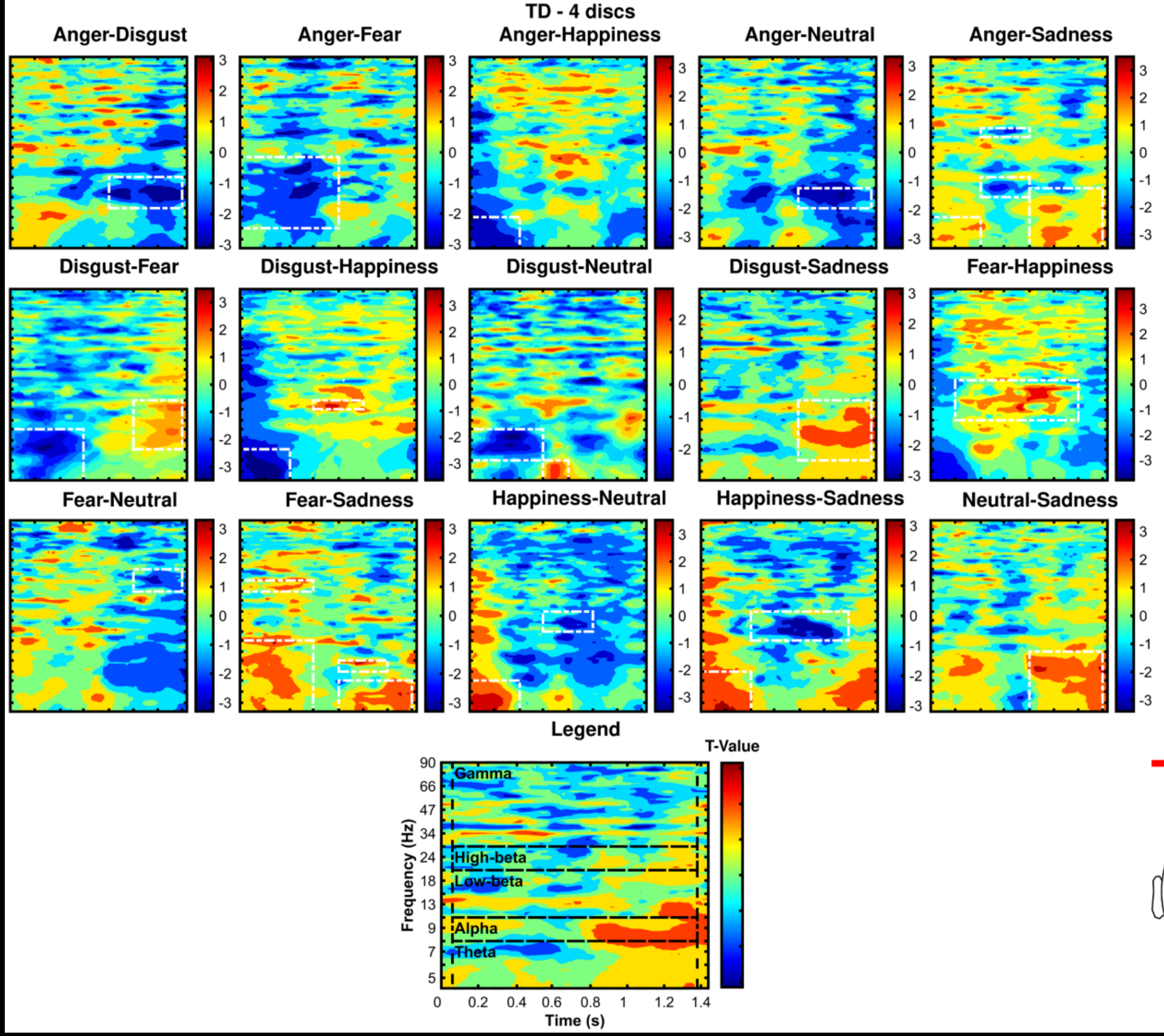
91-97

Medium load: emotion recognition by TD



91-97

Medium load: emotion recognition by TD



Other significant results

Load*Emotion - TD	Frequency: 13-18 Hz, Time: 0.3-0.8 s
Emotion effect IAPS - TD	Frequency: 13-16 Hz, Time: 0.4-0.7 s
Anger-Happiness	Frequency: 13-20 Hz, Time: 0.3-0.7 s

Null results

	Tracking capacity (m')	**BF_{01}**
Insensitivity to cognitive load in ASD	*4 discs vs 8 discs - ASD*	4.60 Moderate
	ERSP	
	Emotion effect 8 discs - TD	34.23 Very strong
Insensitivity to cognitive load in ASD	*Emotion effect 4 discs - ASD*	4.33 Moderate
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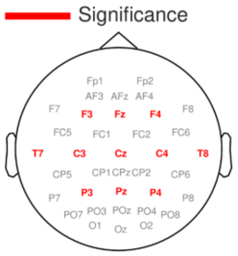

91-97

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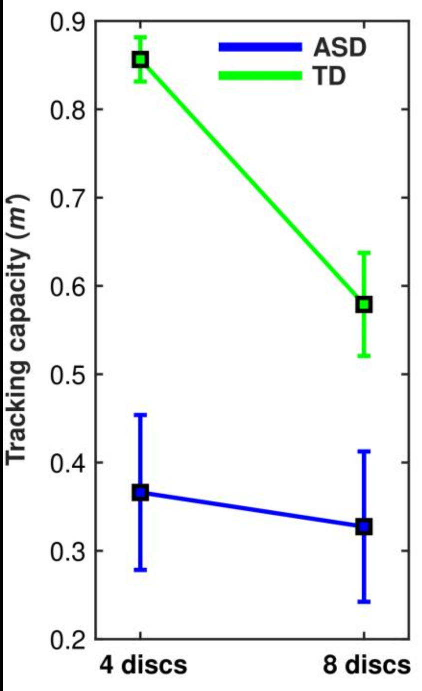

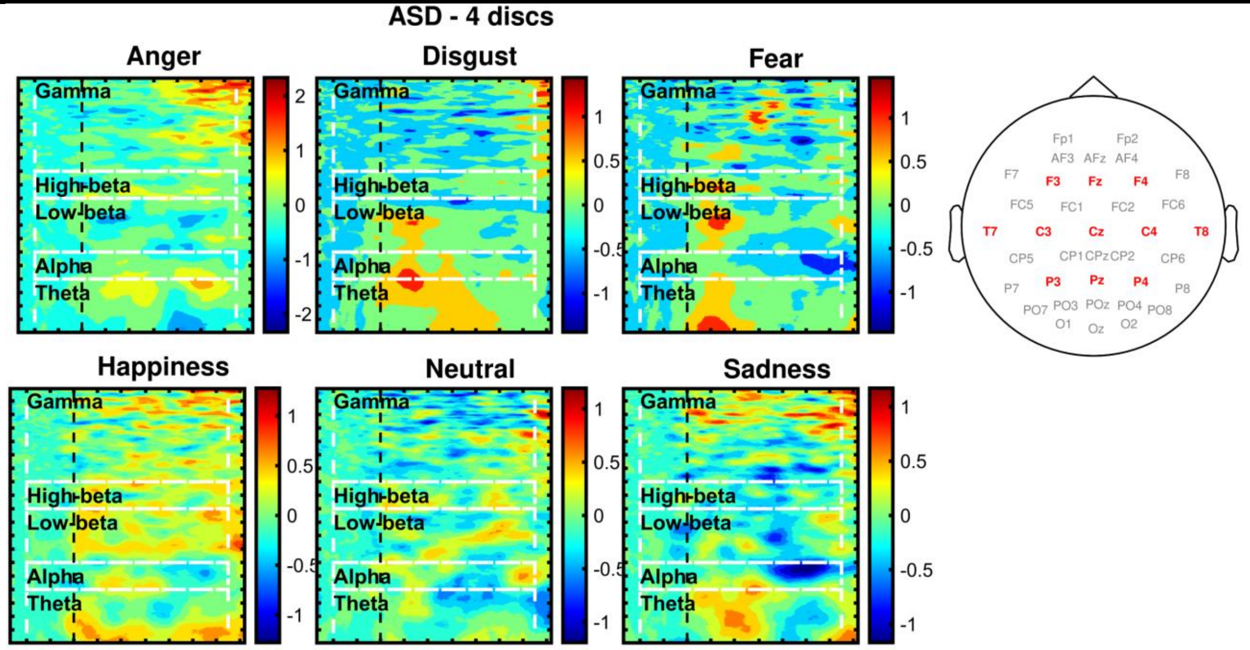

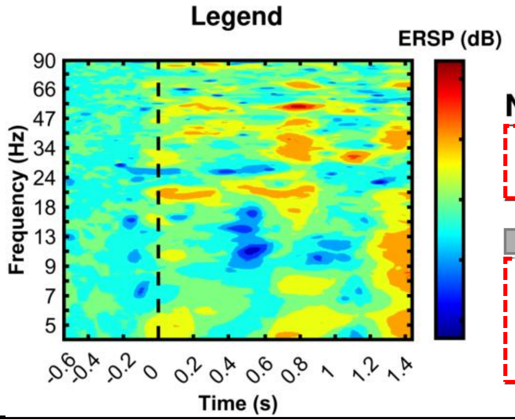

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91-97

A validated paradigm to assess perception

Mechanisms for perception:

- **Emotions are recognized by TD children** while listening to human voices
  - **Medium load (4 discs)** is optimal to process emotional prosodies

- Both the tracking capacity and ERSP are insensitive to cognitive load in ASD
- ASD children have lower tracking capacity than TD:
  - Consistent with the **overestimation of environmental variability** and **steady overweighting of sensory inputs**. Clear the path for **the next study**

- Altered neuronal processing of emotional prosodies in ASD while listening to human voices. No emotion recognition

From the complemented database (human and naturalness-reduced voices):

- The perception of **naturalness-reduced** emotional prosodies by children is necessary

- **4 discs** to assess precision-weighting mechanisms by behavioral markers

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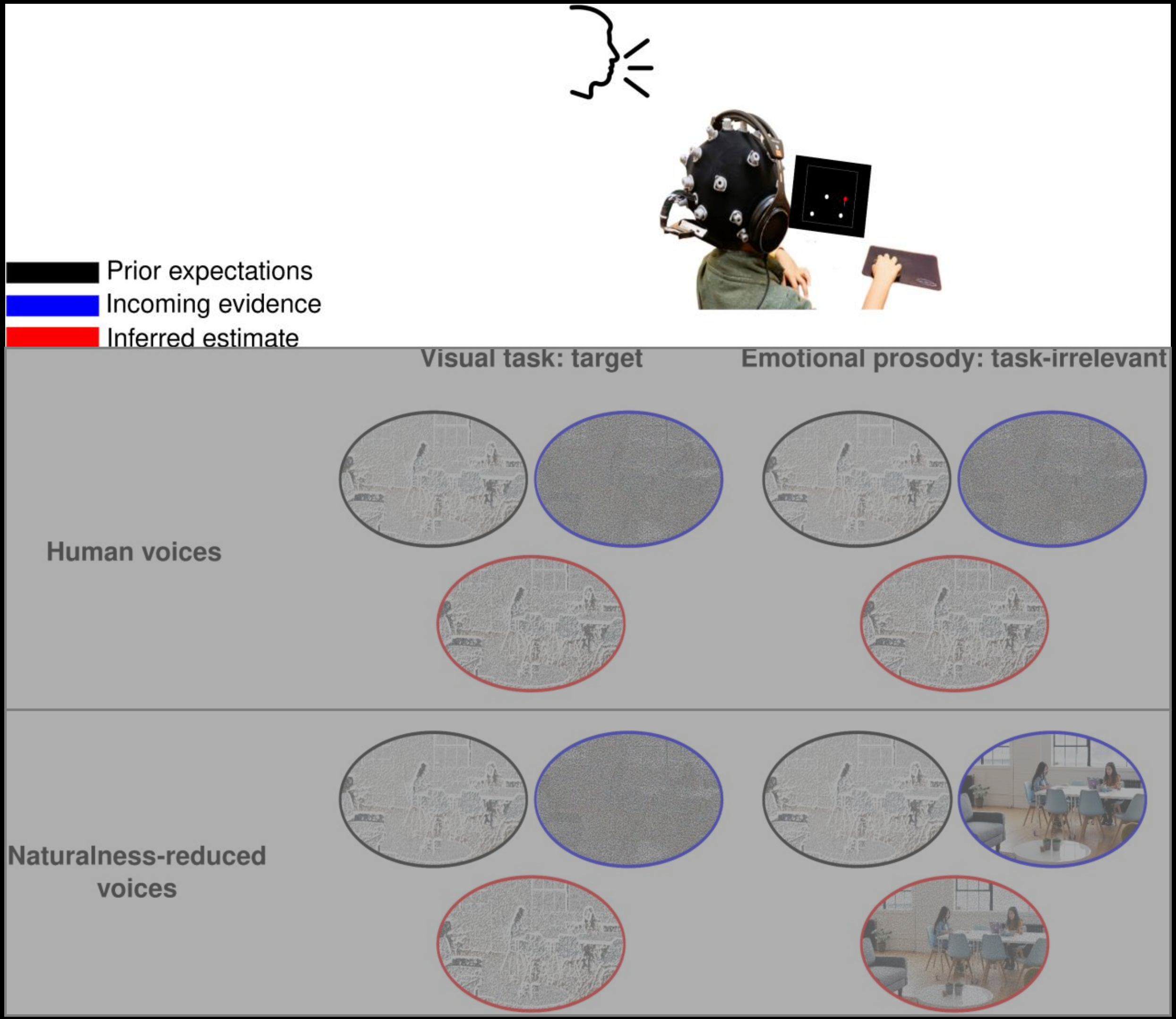
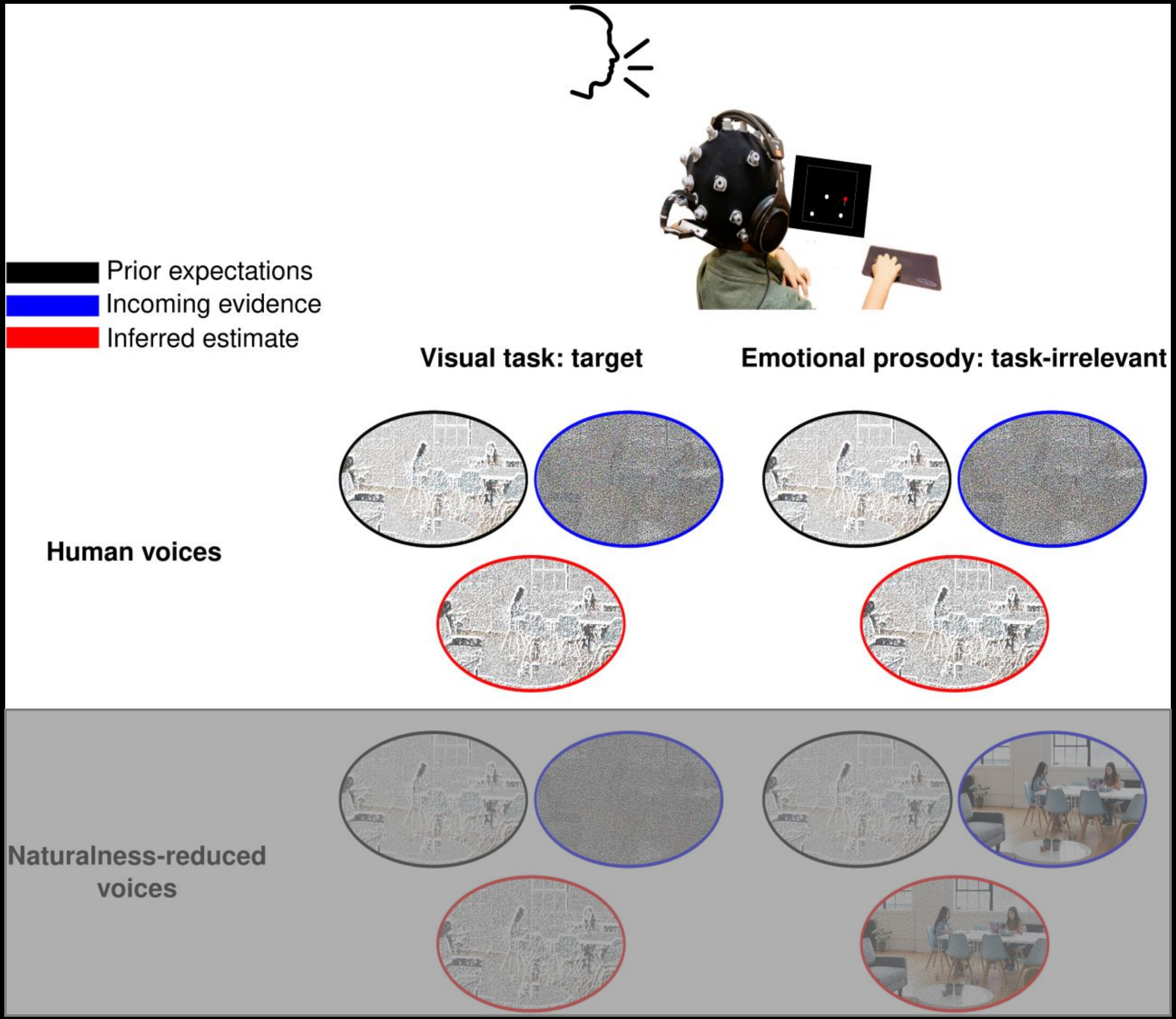
Naturalness reduction: perception ASD and TD



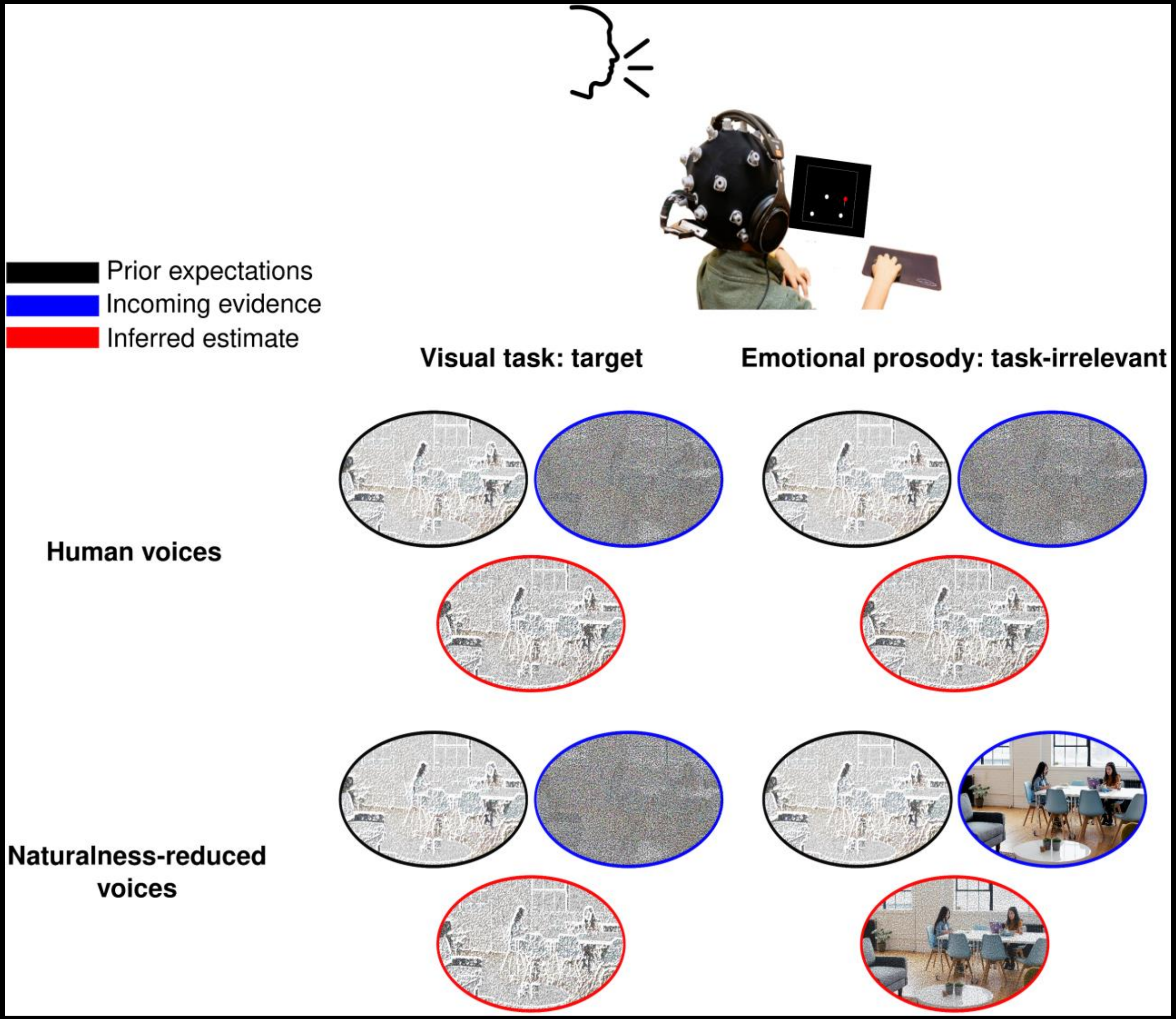
98-99

Naturalness reduction: perception ASD and TD



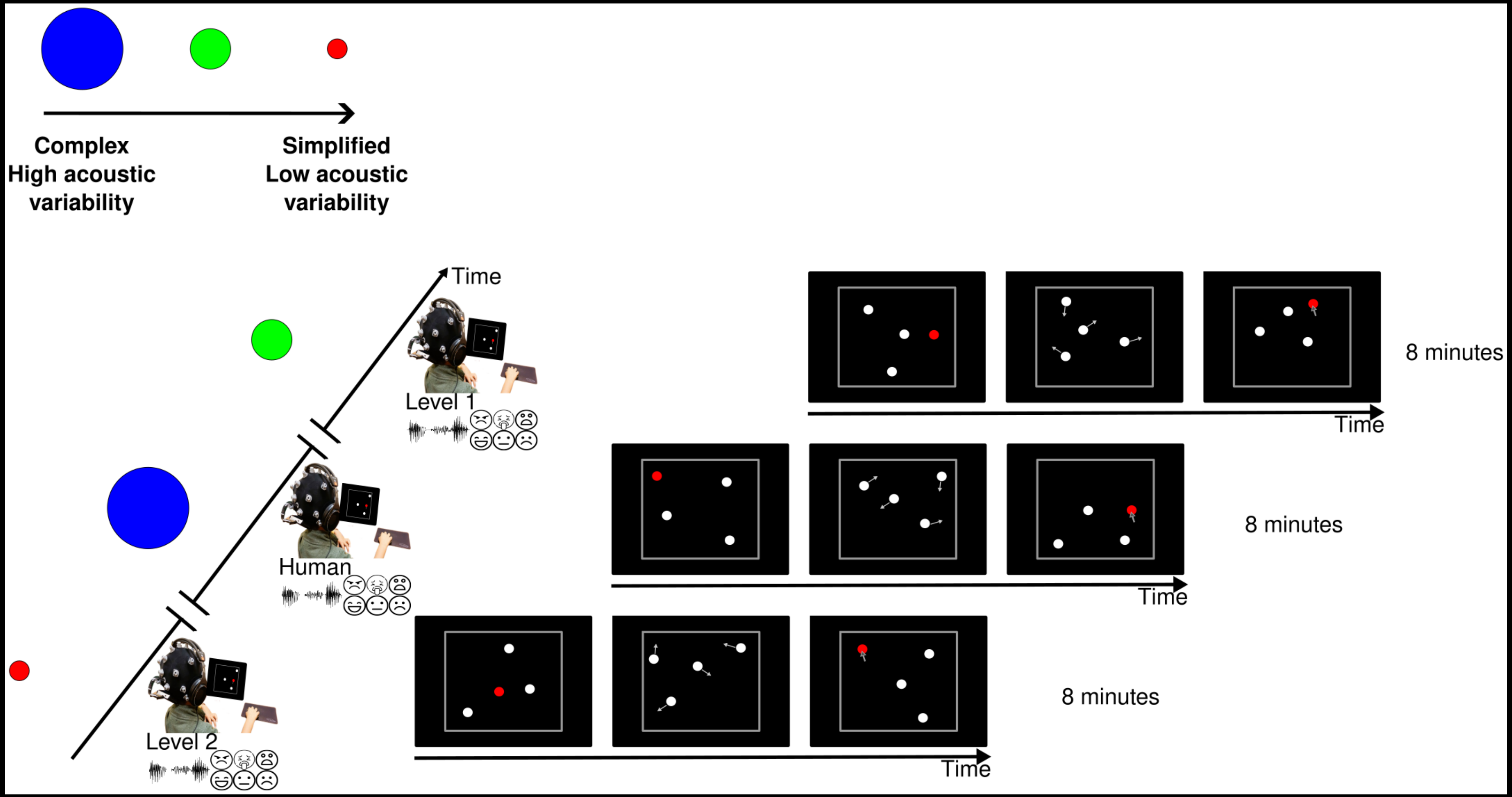
98-99

Naturalness reduction: perception ASD and TD



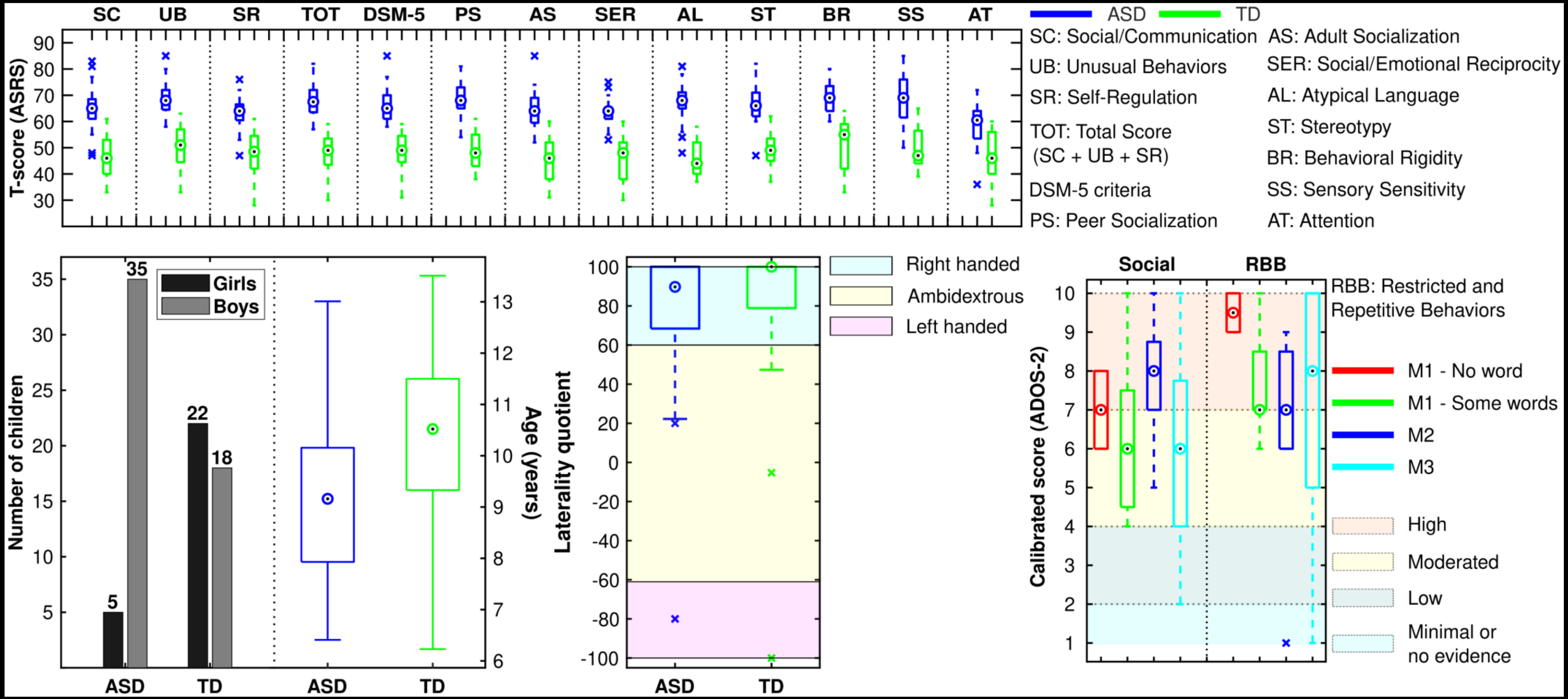
98-99

Naturalness reduction: perception ASD and TD



98-99

Naturalness reduction: perception ASD and TD

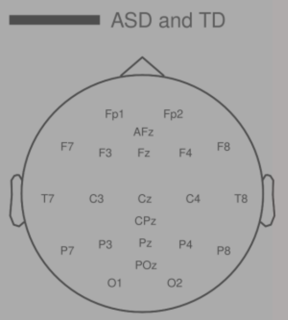


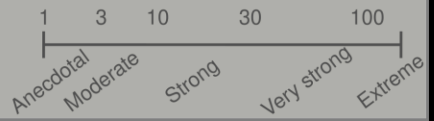
98-99

Perception by ASD and TD: markers

Type of data	Data curation			Statistics
Behavioral ***Correct/incorrect responses on MOT***	Tracking capacity (m)	Rate of correct guess $p = \boxed{n/d}(m/n + d/2)$ $m = n(dp - d/2)$ m is in range: $[-d/2 \;\; d/2]$ [-2 2]	p: proportion of correct responses n: the number of targets d: number of discs m: number of targets correctly tracked after correction	***Analysis of Variance (ANOVA)*** Group and condition effects p<0.05 ***Bayesian ANOVA*** In case of null result Evidence in favor of the null hypothesis (BF01)

Type of data	Data curation: Online	Data curation: Offline		Statistics
Electroencephalography (EEG)	22 channels Expanded 10-20 topography Sample frequency: 500 Hz Impedance<10 kOhms	Average referencing Baseline means removal High-pass; transition band [0.25 0.75] Hz, stopband attenuation: 80 dB - clean_rawdata function Line noise removal 60 Hz - Cleanline Artifact Subspace Reconstruction (mean: 23/24, sd: 3.2) Bad channels detection and interpolation (mean: 1.7/22, sd: 1.4) Extended Infomax Independent Components Analysis ICLabel for fixed-sourced artifacts rejection (<70% brain, mean: 1.90, sd: 2.2)	Epoch definition [-1.1 2] s Time-locked to auditory stimuli ERSP extraction Morlet wavelet 3 to 67.5 cycles 4 to 90 Hz Baseline [-1.1 -1] s Significant ERSP compared to baseline (1000 permutations)	***Analysis of Variance (ANOVA)*** Emotion and condition effects 1000 permutations under data exchangeability One or more neighboring sensors Cluster-level statistic: sum of statistics Maximum cluster-level statistic per iteration p<0.05 corrected for multiple comparisons (Bonferroni) ***Bayesian ANOVA*** In case of null result Evidence in favor of the null hypothesis (BF01)





87-90

Perception by ASD and TD: markers

Type of data

Behavioral

Correct/incorrect responses on MOT

Data curation

Tracking capacity (m)

Rate of correct guess

$$p = \boxed{n/d}\,(m/n + d/2)$$

$$m = n(dp - d/2)$$

m is in range: $[-d/2 \;\; d/2]$

[-2 2]

p: proportion of correct responses
n: the number of targets
d: number of discs
m: number of targets correctly tracked after correction

Analysis of Variance (ANOVA)
Group and condition effects

$p<0.05$

Bayesian ANOVA
In case of null result

Evidence in favor of the null hypothesis (BF01)

Type of data

Electroencephalography (EEG)

Data curation

Online

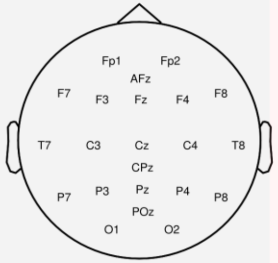
22 channels

Expanded 10-20 topography

Sample frequency: 500 Hz

Impedance<10 kOhms

ASD and TD



Offline

Average referencing

Baseline means removal

High-pass; transition band [0.25 0.75] Hz, stopband attenuation: 80 dB - clean_rawdata function

Line noise removal 60 Hz - Cleanline

Artifact Subspace Reconstruction (mean: 23/24, sd: 3.2)

Bad channels detection and interpolation (mean: 1.7/22, sd: 1.4)

Extended Infomax Independent Components Analysis

ICLabel for fixed-sourced artifacts rejection (<70% brain, mean: 1.90, sd: 2.2)

Epoch definition [-1.1 2] s

Time-locked to auditory stimuli

ERSP extraction Morlet wavelet

3 to 67.5 cycles
4 to 90 Hz

Baseline [-1.1 -1] s

Significant ERSP compared to baseline (1000 permutations)

Analysis of Variance (ANOVA)
Emotion and condition effects

1000 permutations under data exchangeability

One or more neighboring sensors

Cluster-level statistic: sum of statistics

Maximum cluster-level statistic per iteration

p<0.05 corrected for multiple comparisons (Bonferroni)

Bayesian ANOVA
In case of null result

Evidence in favor of the null hypothesis (BF01)

1 3 10 30 100

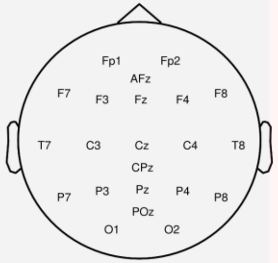
Anecdotal Moderate Strong Very strong Extreme

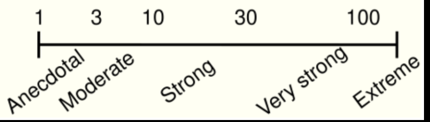
87-90

Perception by ASD and TD: markers

Type of data	Data curation			
Behavioral ***Correct/incorrect responses on MOT***	Tracking capacity (m)	Rate of correct guess $p = \boxed{n/_d}\,(m/_n + d/_2)$ $m = n(dp - d/_2)$ m is in range: $[-d/_2 \;\; d/_2]$ [-2 2]	p: proportion of correct responses n: the number of targets d: number of discs m: number of targets correctly tracked after correction	***Analysis of Variance (ANOVA)*** Group and condition effects $p<0.05$ ***Bayesian ANOVA*** In case of null result Evidence in favor of the null hypothesis (BF01)

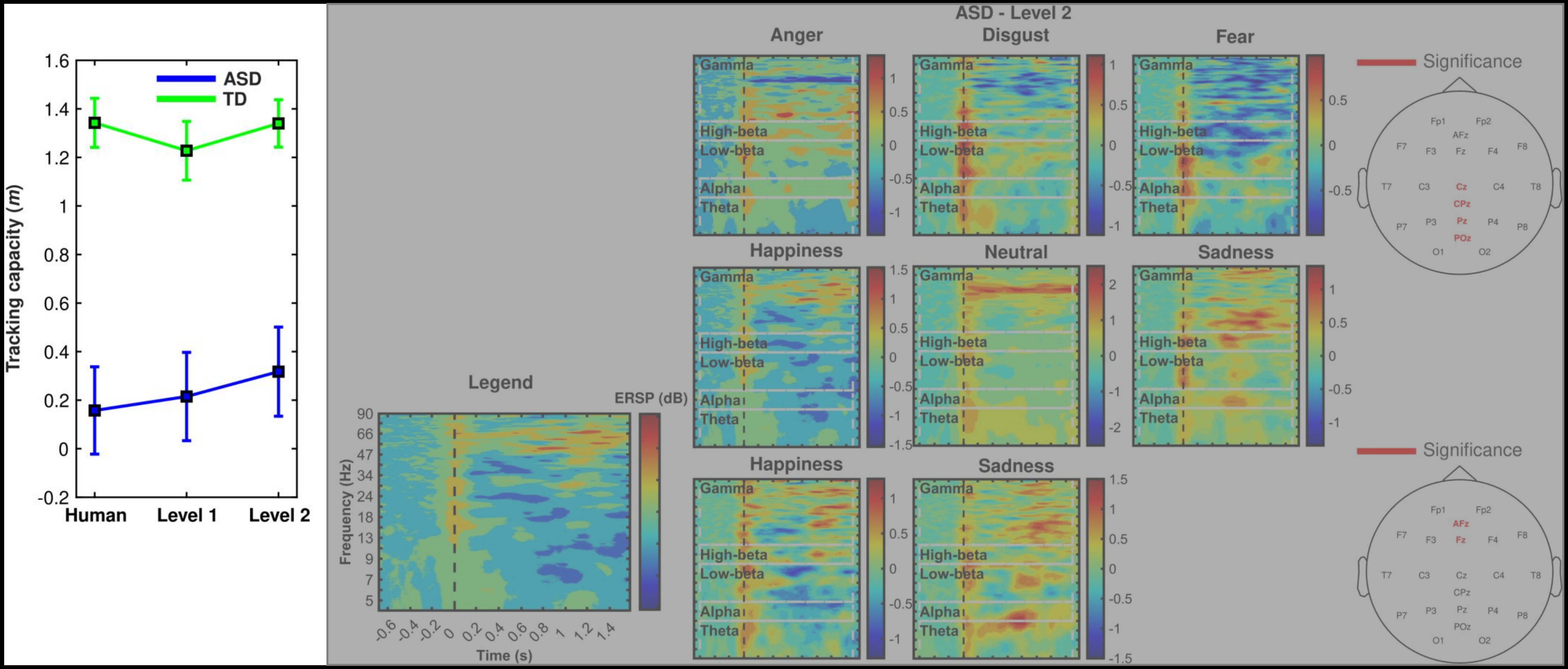
Type of data	Data curation			
	Online	**Offline**		
Electroencephalography (EEG)	22 channels Expanded 10-20 topography Sample frequency: 500 Hz Impedance<10 kOhms ASD and TD	Average referencing Baseline means removal High-pass; transition band [0.25 0.75] Hz, stopband attenuation: 80 dB - clean_rawdata function Line noise removal 60 Hz - Cleanline Artifact Subspace Reconstruction (mean: 23/24, sd: 3.2) Bad channels detection and interpolation (mean: 1.7/22, sd: 1.4) Extended Infomax Independent Components Analysis ICLabel for fixed-sourced artifacts rejection (<70% brain, mean: 1.90, sd: 2.2)	Epoch definition [-1.1 2] s Time-locked to auditory stimuli ERSP extraction Morlet wavelet 3 to 67.5 cycles 4 to 90 Hz Baseline [-1.1 -1] s Significant ERSP compared to baseline (1000 permutations)	***Analysis of Variance (ANOVA)*** Emotion and condition effects 1000 permutations under data exchangeability One or more neighboring sensors Cluster-level statistic: sum of statistics Maximum cluster-level statistic per iteration $p<0.05$ corrected for multiple comparisons (Bonferroni) ***Bayesian ANOVA*** In case of null result Evidence in favor of the null hypothesis (BF01)





87-90

Level 2: emotion recognition by ASD



100-110

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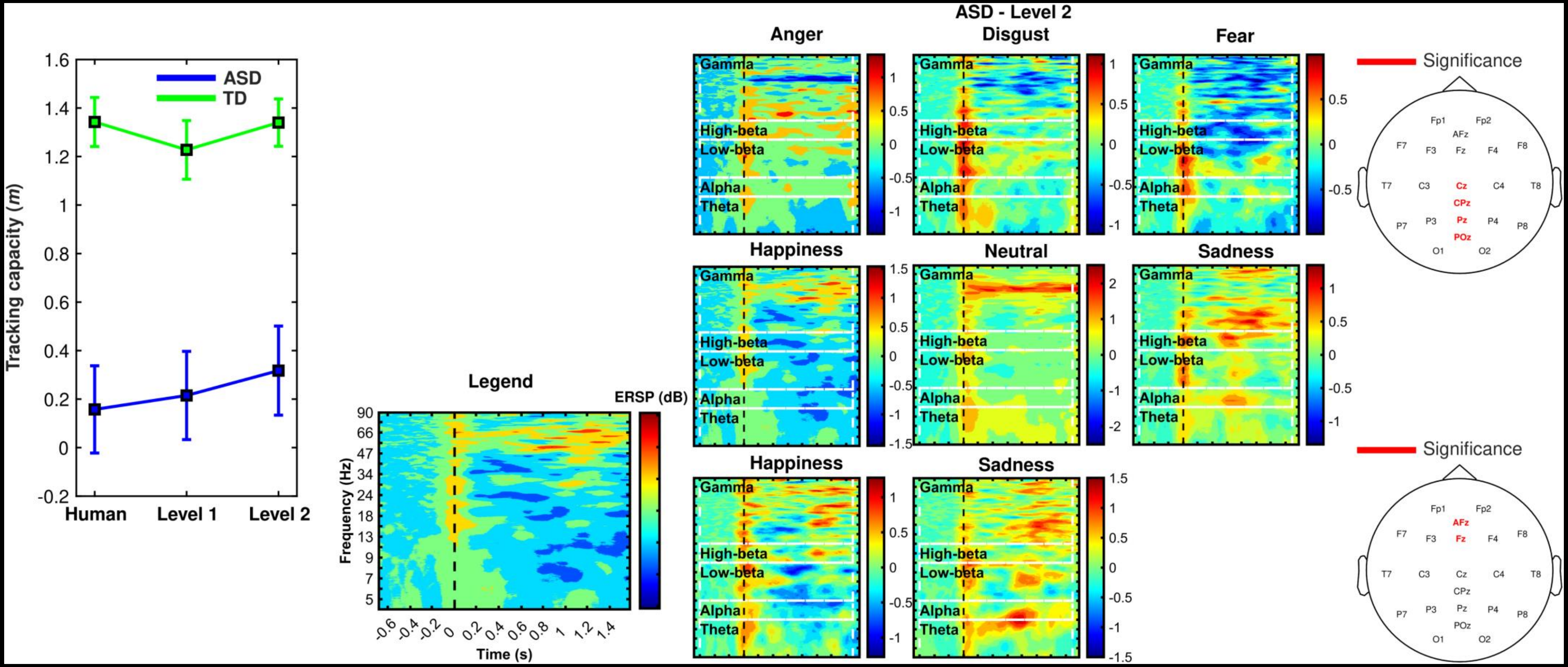

100-110

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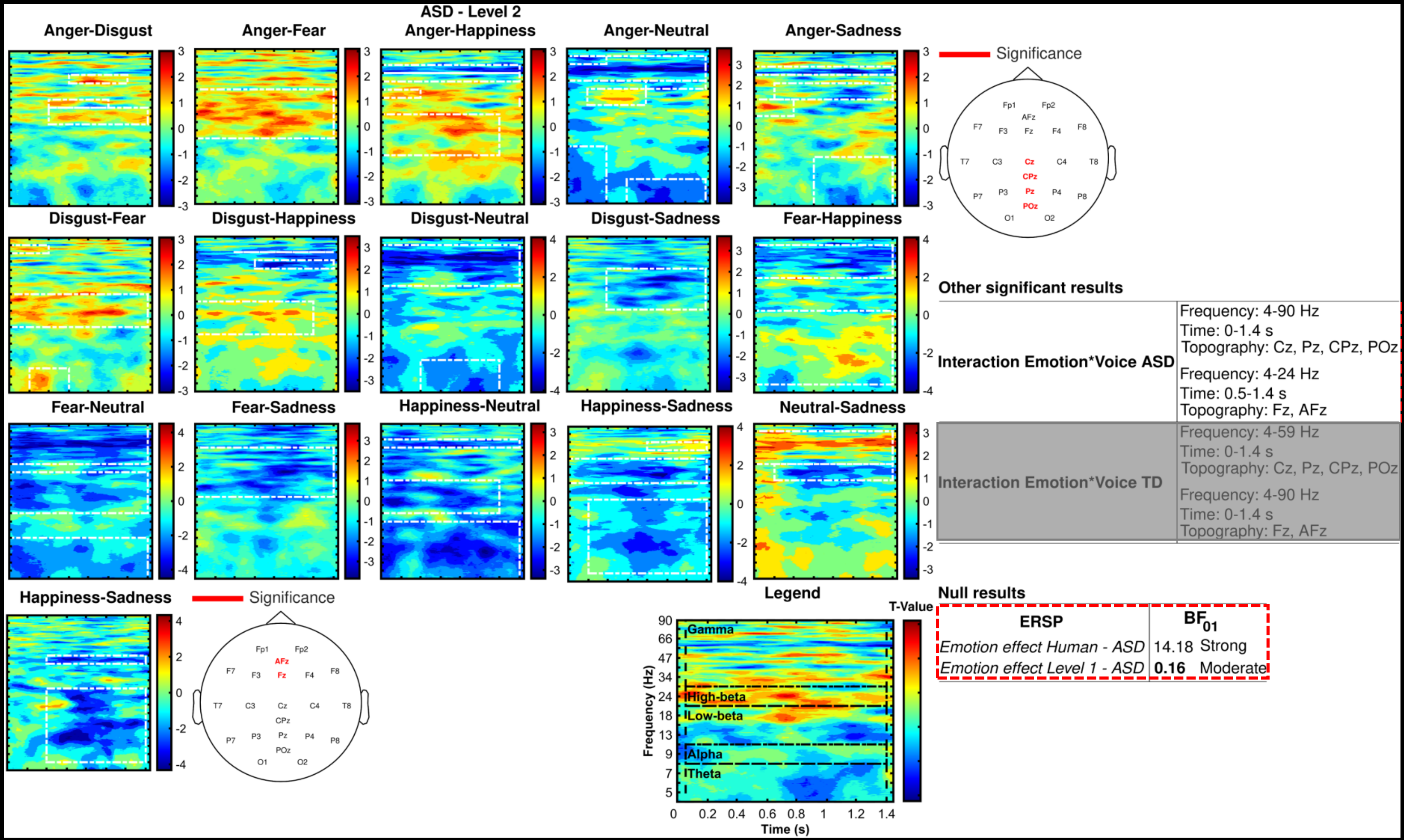


Other significant results

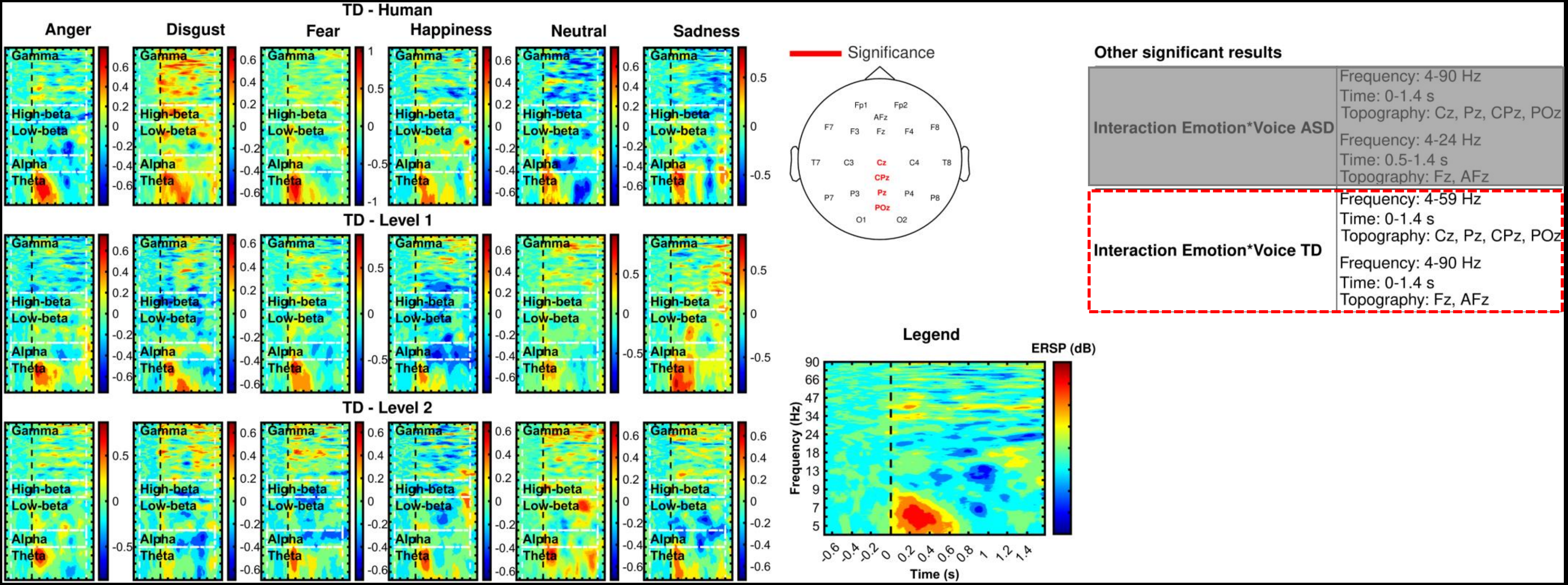
Interaction Emotion*Voice ASD	Frequency: 4-90 Hz Time: 0-1.4 s Topography: Cz, Pz, CPz, POz
	Frequency: 4-24 Hz Time: 0.5-1.4 s Topography: Fz, AFz
Interaction Emotion*Voice TD	Frequency: 4-59 Hz Time: 0-1.4 s Topography: Cz, Pz, CPz, POz
	Frequency: 4-90 Hz Time: 0-1.4 s Topography: Fz, AFz

Null results

ERSP	**BF_{01}**	
Emotion effect Human - ASD	14.18	Strong
Emotion effect Level 1 - ASD	**0.16**	Moderate

100-110

Level 2: emotion recognition by ASD



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- Naturalness
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  - Overview
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  - Outcome
  - Highlights
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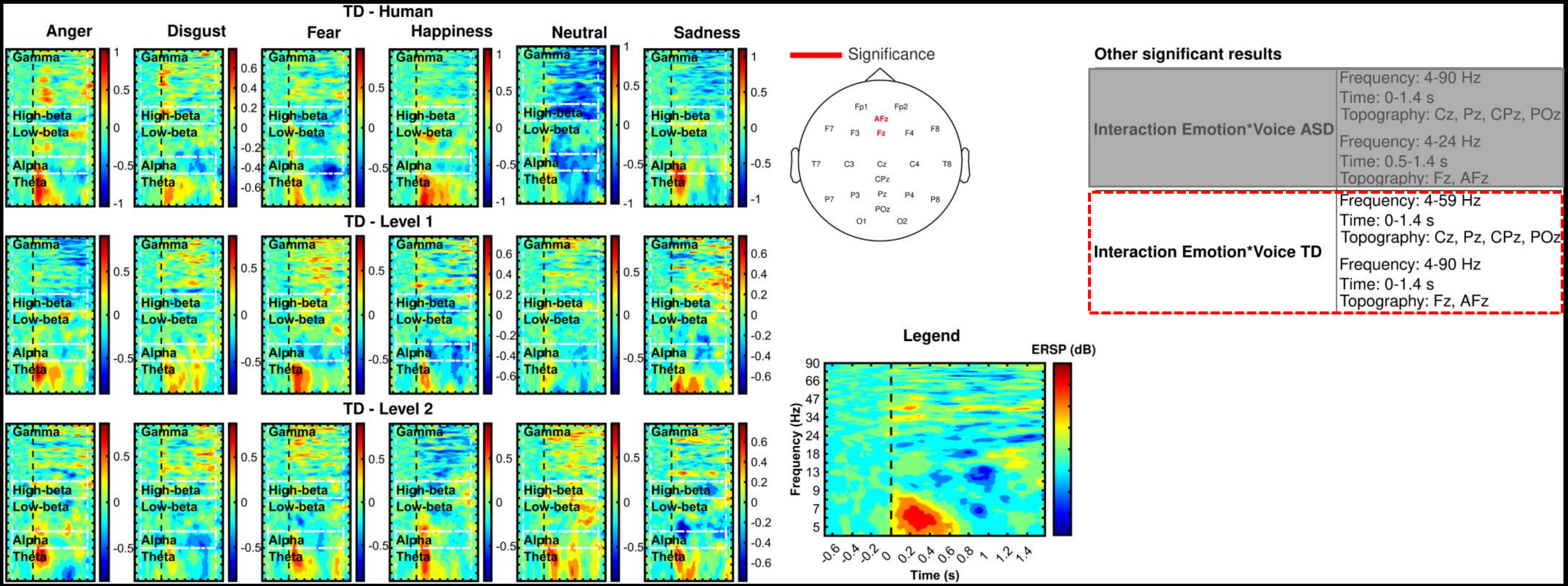

100-110

Optimization of the acoustic environment

Mechanisms for perception:

- **Emotions are recognized by TD children** while listening to both human and naturalness-reduced voices
  - Nevertheless, different mechanisms for perception are involved (emotion*voice)

- ASD children have **lower tracking capacity** than TD
- **ASD children recognize emotion while listening to Level 2**
  - Recognition of acoustic hierarchical scales (fine-grained)

About naturalness-reduced voices for ASD:

- **More reliable (near to discrete) acoustic variations** within words while conserving unique profiles of emotions

- Require the accurate encoding of acoustic variations

- Perception adapted to autistic mechanisms

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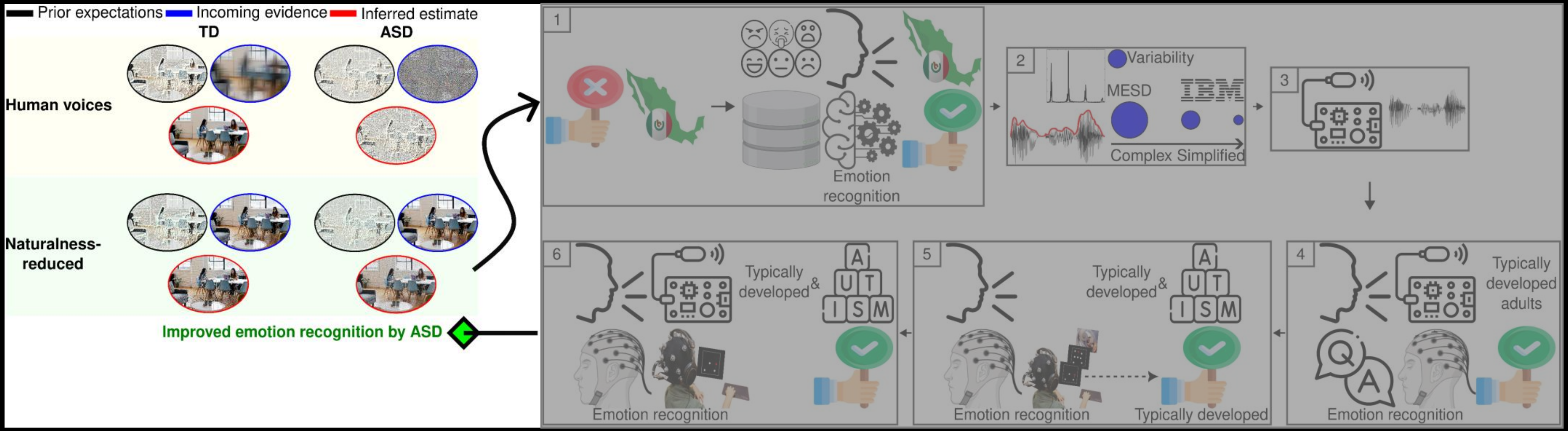
Take-home message



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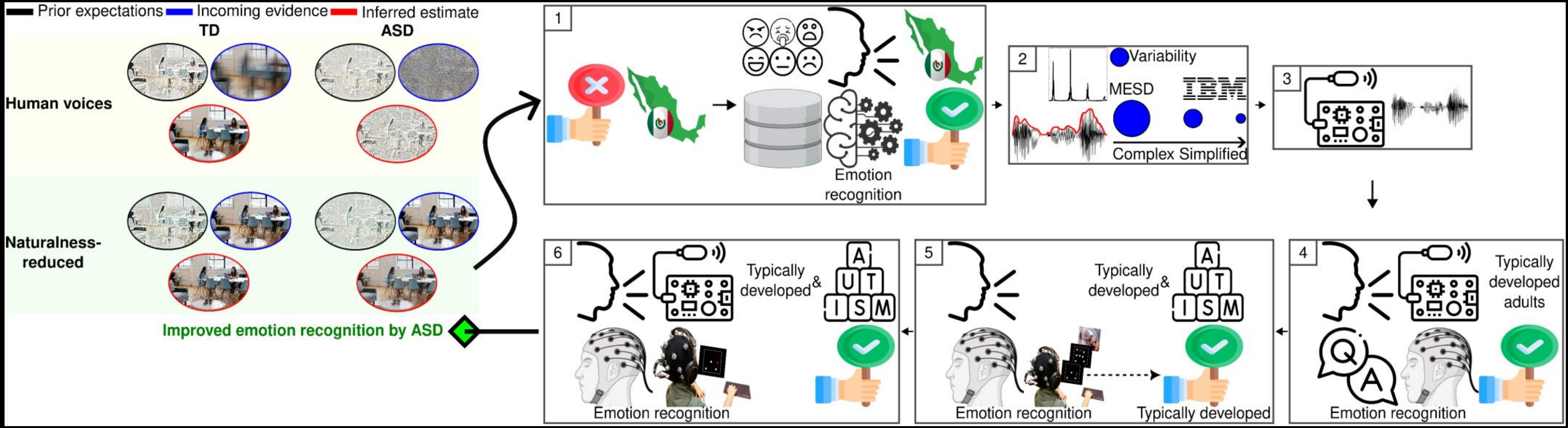
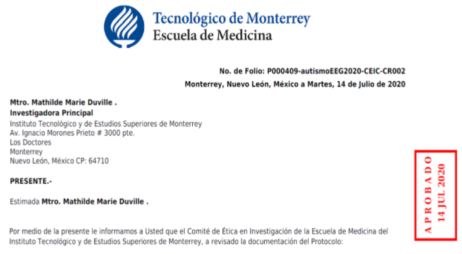


Contributions



Acoustic engineering | Experimental paradigm | Clinical setting

Design, validation, implementation


Tecnológico de Monterrey
Escuela de Medicina

No. de Folio: P000409-autismoEEG2020-CEIC-CR002
Monterrey, Nuevo León, México a Martes, 14 de Julio de 2020

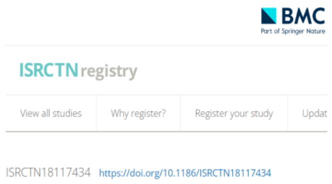
Mtro. Mathilde Marie Duville .
Investigadora Principal
Instituto Tecnológico y de Estudios Superiores de Monterrey
Av. Ignacio Morones Prieto # 3000 pte.
Los Doctores
Monterrey
Nuevo León, México CP: 64710

PRESENTE.-

Estimada Mtro. Mathilde Marie Duville .

Por medio de la presente le informamos a Usted que el Comité de Ética en Investigación de la Escuela de Medicina del Instituto Tecnológico y de Estudios Superiores de Monterrey, a revisado la documentación del Protocolo:

APROBADO
14 JUL 2020



Open access data

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[2] M. M. Duville, L. M. Alonso-Valerdi, and D. I. Ibarra-Zarate, "Mexican Emotional Speech Database Based on Semantic, Frequency, Familiarity, Concreteness, and Cultural Shaping of Affective Prosody," *Data*, vol. 6, no. 12, p. 130, Dec. 2021, doi: 10.3390/data6120130.

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[4] M. M. Duville, D. I. Ibarra-Zarate, and L. M. Alonso-Valerdi, "Autistic traits shape neuronal oscillations during emotion perception under attentional load modulation," *Sci Rep*, vol. 13, no. 1, p. 8178, May 2023, doi: 10.1038/s41598-023-35013-x.

[5] M. M. Duville *et al.*, "Perception of task-irrelevant affective prosody by typically developed and diagnosed children with Autism Spectrum Disorder under attentional loads: electroencephalographic and behavioural data," *Data in Brief*, vol. 48, p. 109057, Mar. 2023, doi: 10.1016/j.dib.2023.109057.

[6] M. M. Duville, L. M. Alonso-Valerdi, and D. I. Ibarra-Zarate, "Improved emotion recognition under reduced acoustic variability of speech in autism," *Under review*, 2023.

[7] M. M. Duville, L. M. Alonso-Valerdi, and D. I. Ibarra-Zarate, "Electroencephalographic Correlate of Mexican Spanish Emotional Speech Processing in Autism Spectrum Disorder: To a Social Story and Robot-Based Intervention," *Front. Hum. Neurosci.*, vol. 15, p. 626146, Feb. 2021, doi: 10.3389/fnhum.2021.626146.

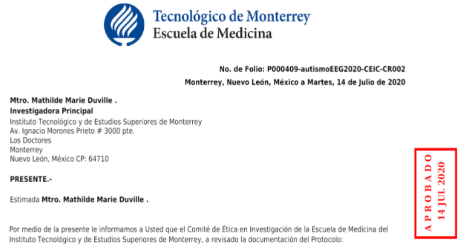
Contributions

Acoustic engineering

Experimental paradigm

Clinical setting

Design, validation, implementation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Por medio de la presente le informamos a Usted que el Comité de Ética en Investigación de la Escuela de Medicina del Instituto Tecnológico y de Estudios Superiores de Monterrey, a revisado la documentación del Protocolo:

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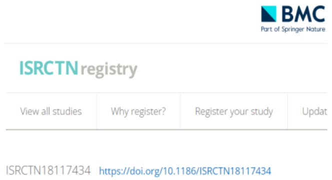

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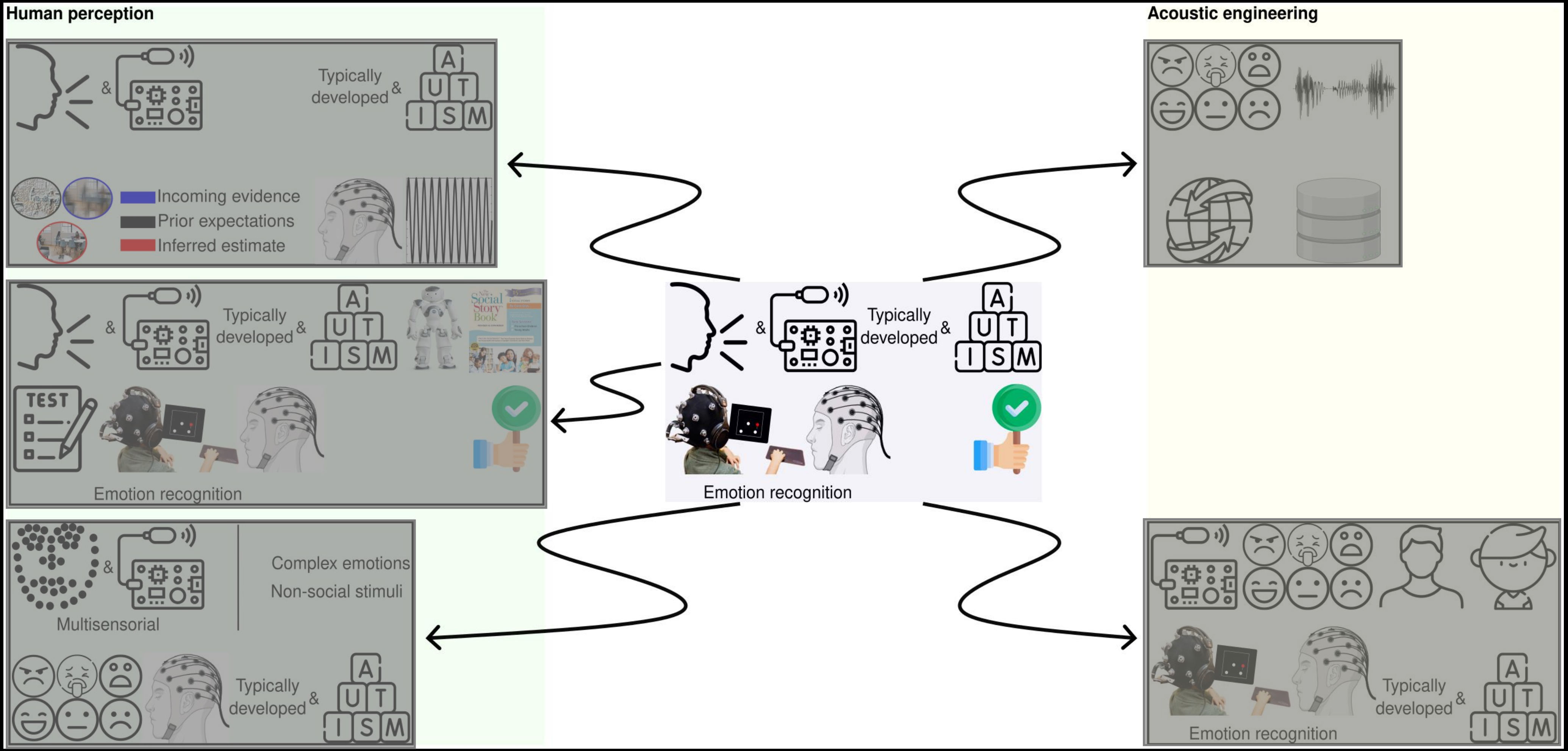
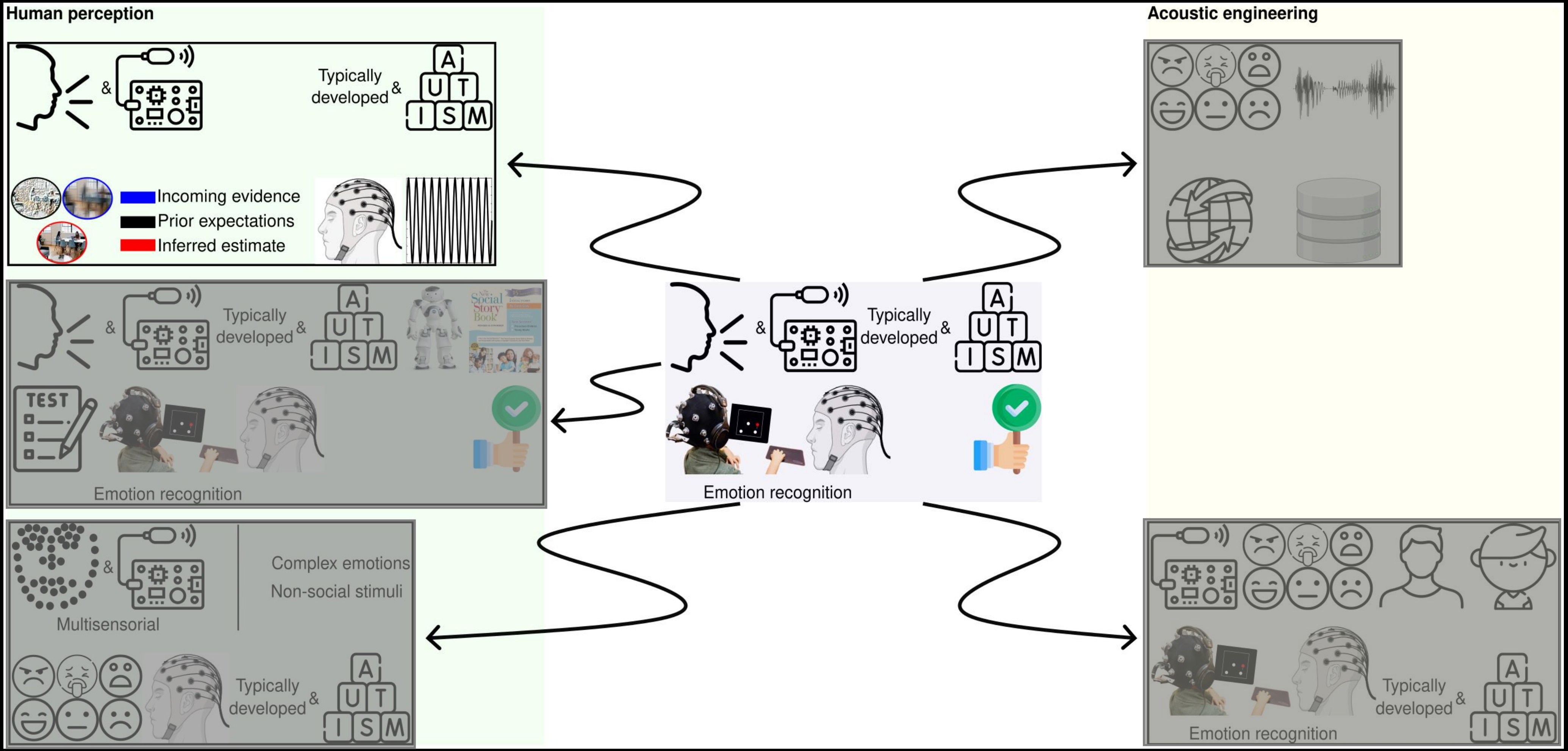
Work opportunities



111-114

Work opportunities



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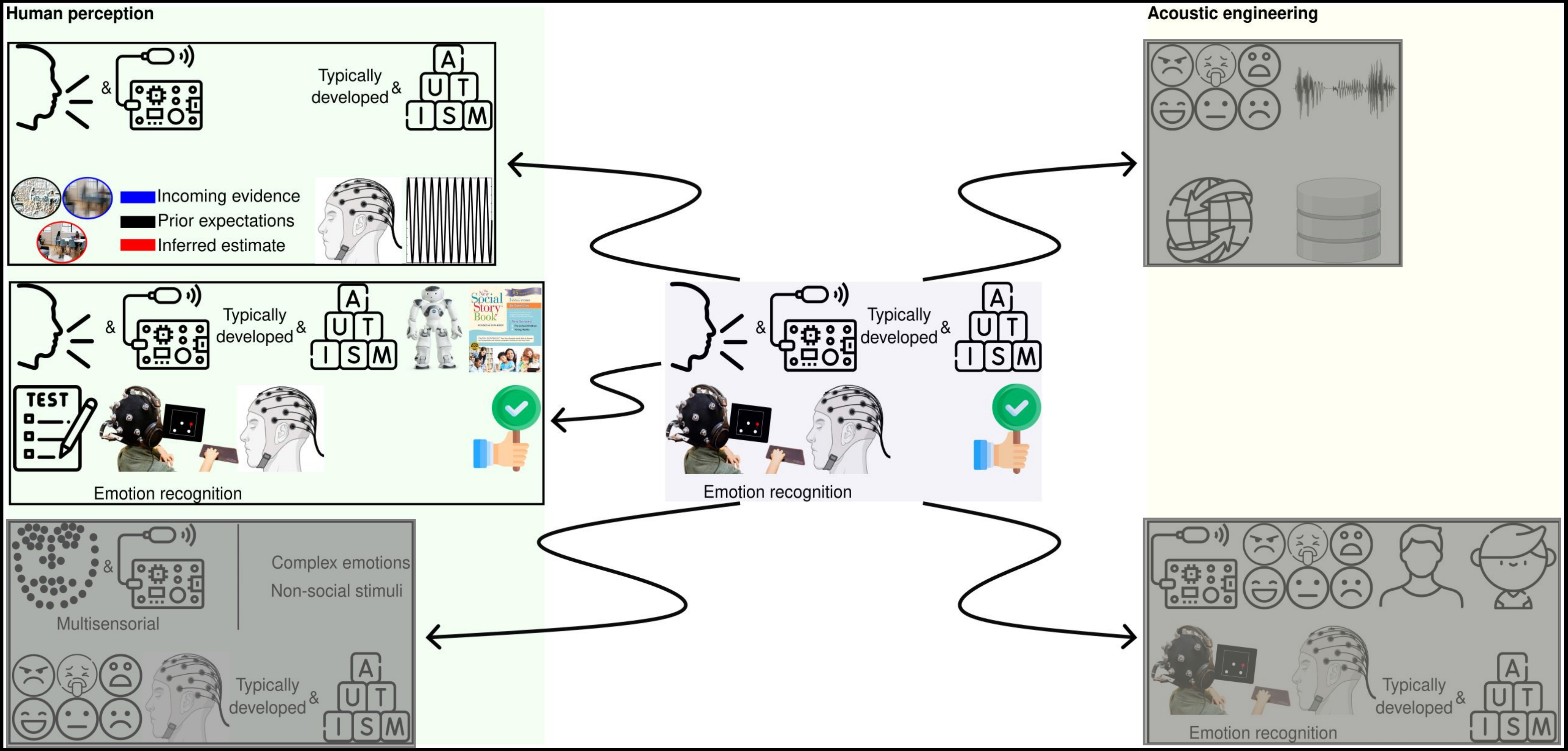

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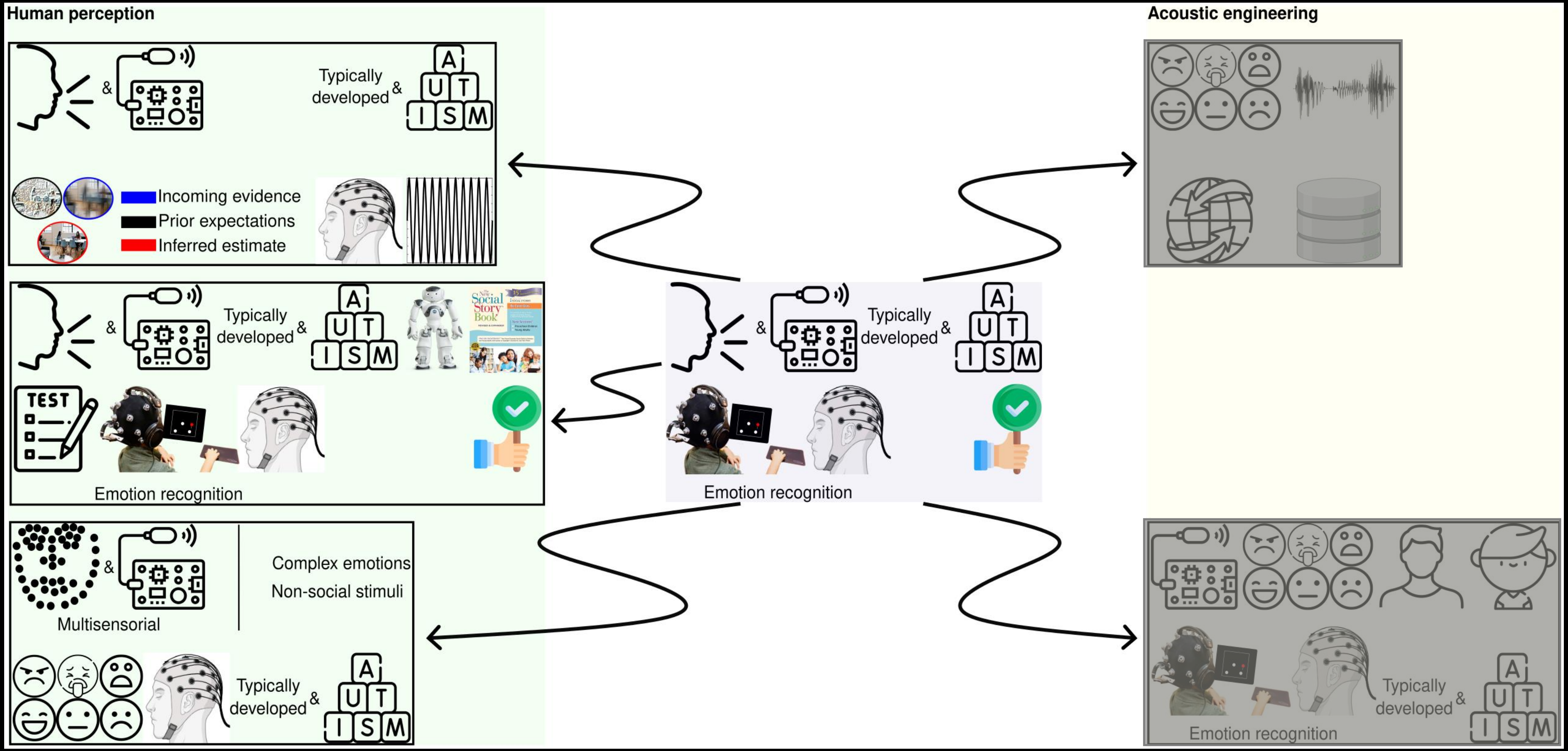

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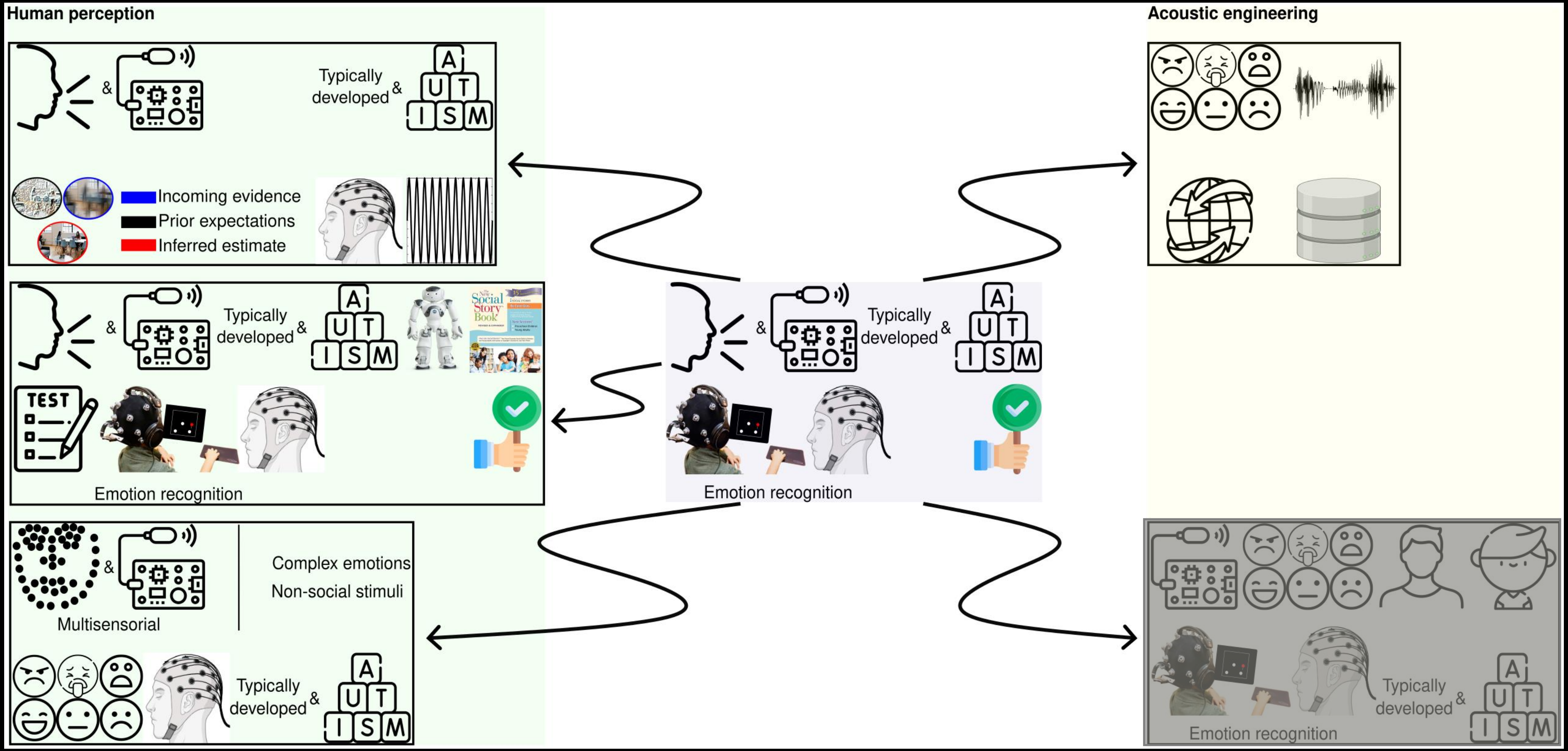

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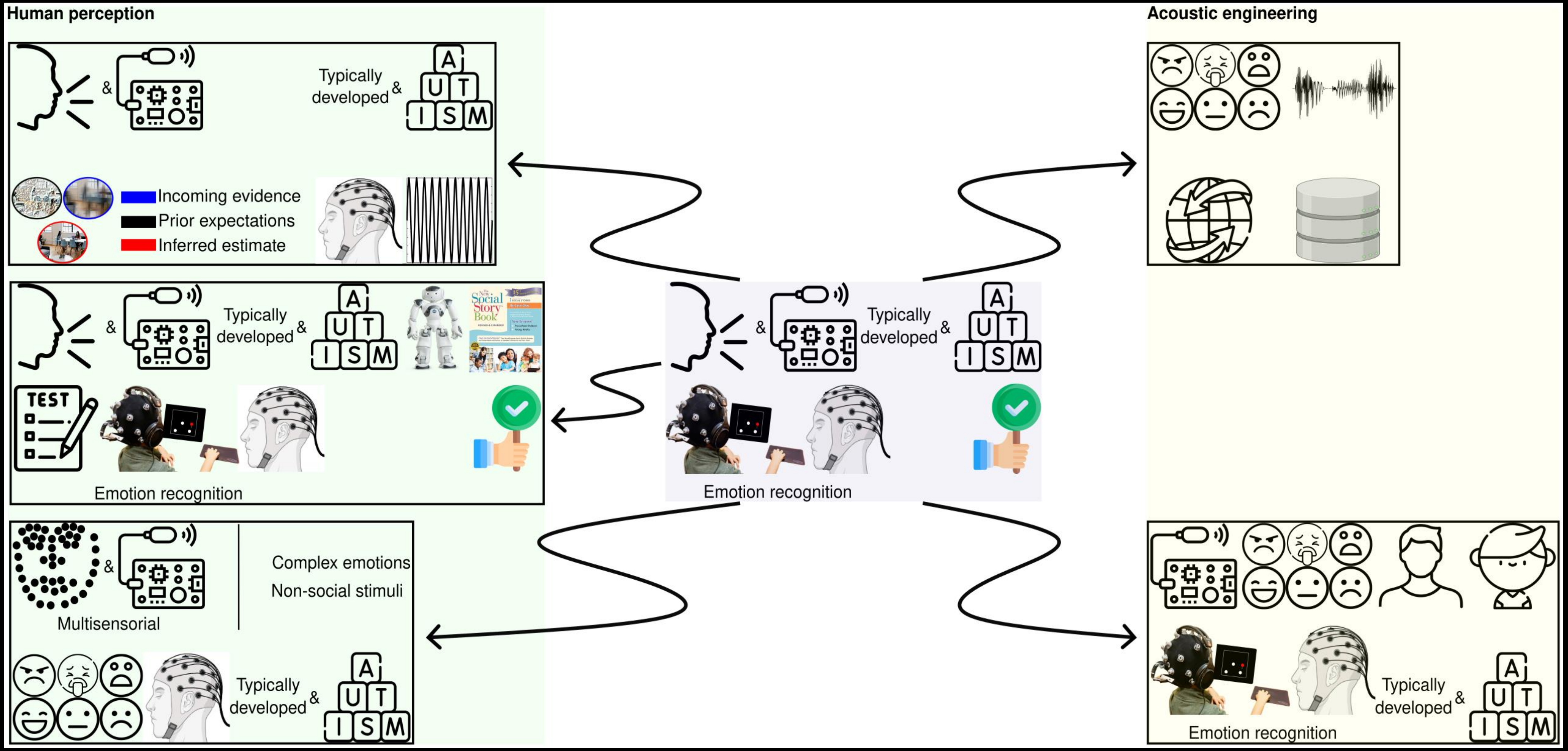
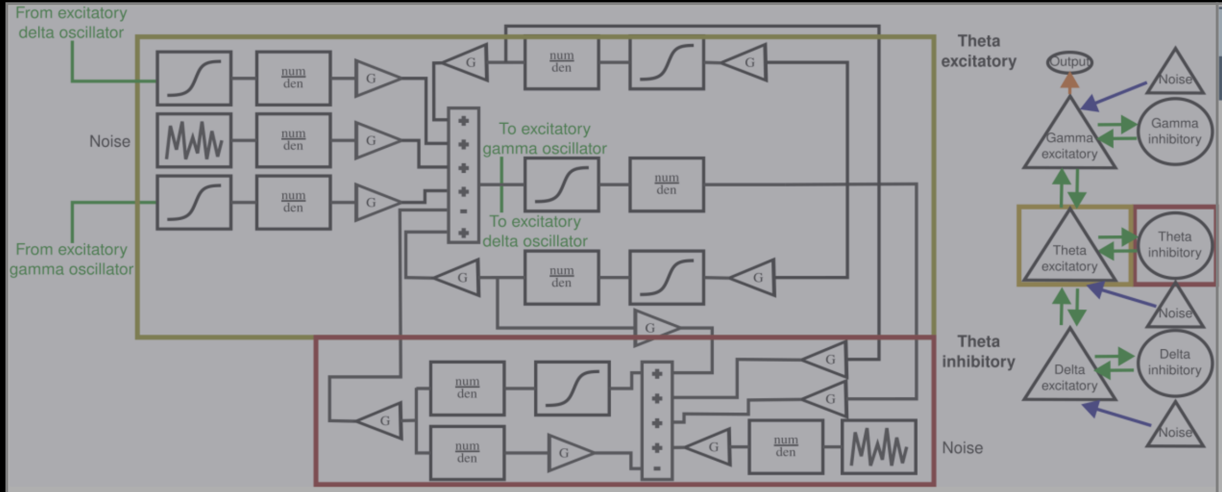
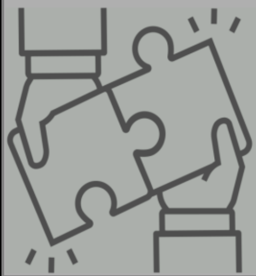


111-114

Other works completed during my PhD





Systematic review

[8] M. M. Duville, Y. Pérez, R. Hugues-Gudiño, N. E. Naal-Ruiz, L. M. Alonso-Valerdi, and D. I. Ibarra-Zarate, "Systematic Review: Emotion Recognition Based on Electrophysiological Patterns for Emotion Regulation Detection," *Applied Sciences*, vol. 13, no. 12, p. 6896, Jun. 2023, doi: 10.3390/app13126896.

Statistical framework
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[9] N. E. Naal-Ruiz, L. Hyunkook, A. Gonzalez, R. Gonzalez, M. M. Duville, L. M. Alonso-Valerdi, and D. I. Ibarra-Zarate, "Towards the neurophysiological characterization of immersive attributes in auditory events," *AES 2023 International Conference on Spatial and Immersive Audio (August 2023)*, p. 51, 2023.

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- **Adjacent work**
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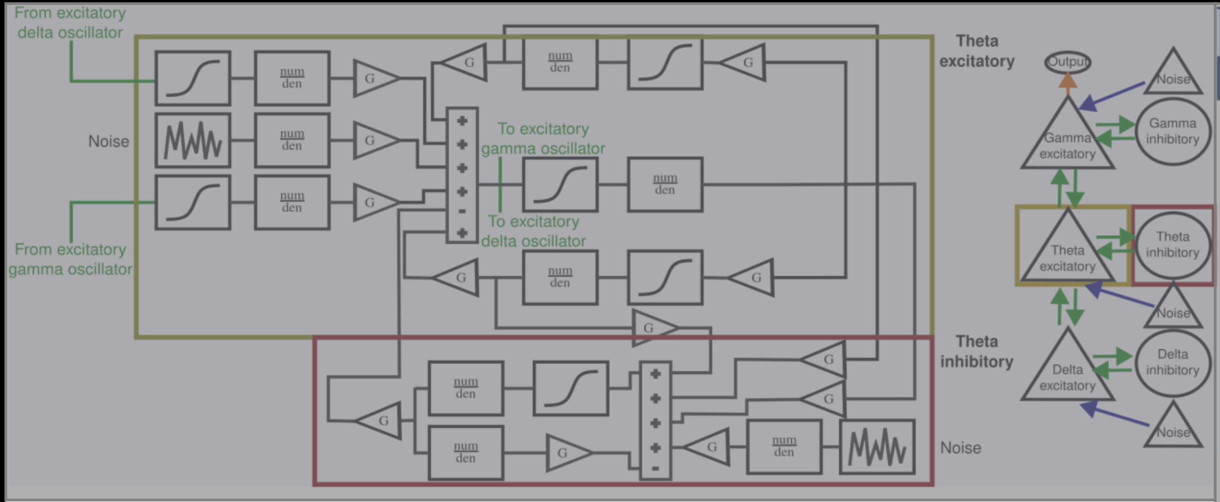
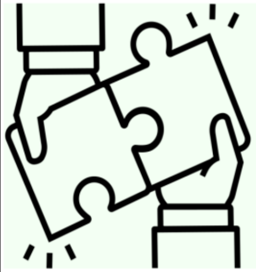
115-117

Other works completed during my PhD

NeuroTechs

CONAHCYT





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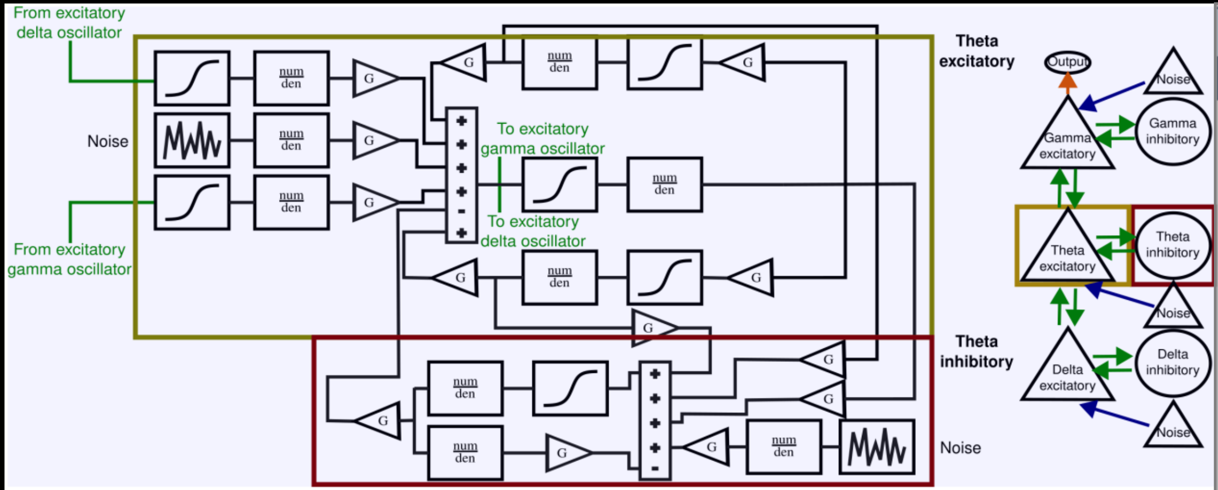

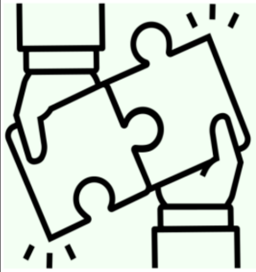

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La Dra. Valeria Nanclares-Nogués
Oficialmente certificada como formadora en ADI-R y ADOS-2
Certifica que

Mathilde Marie Duville

Obtiene la acreditación en la Formación Clínica del Instrumento Diagnóstico

Escala de Observación para el Diagnóstico de Autismo – 2a Edición
Autism Diagnostic Observation Schedule-2nd Edition (ADOS-2)

Valeria Nanclares-Nogués, Psy.D.
9, 10 y 11 de Diciembre, 2022
Habiendo completado una carga horaria de: 22 horas

Valeria Nanclares-Nogués, Psy.D.
Especialista en TEA y Trastornos del Neurodesarrollo
Creando puentes entre paciente, familia y comunidad

arena
Atención Integral del Autismo

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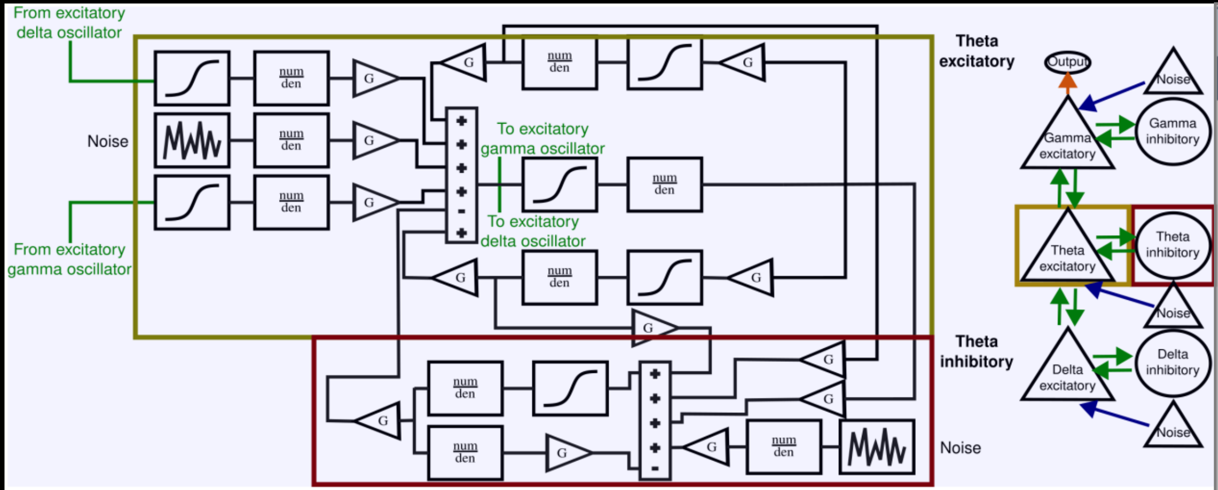

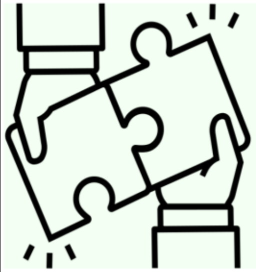

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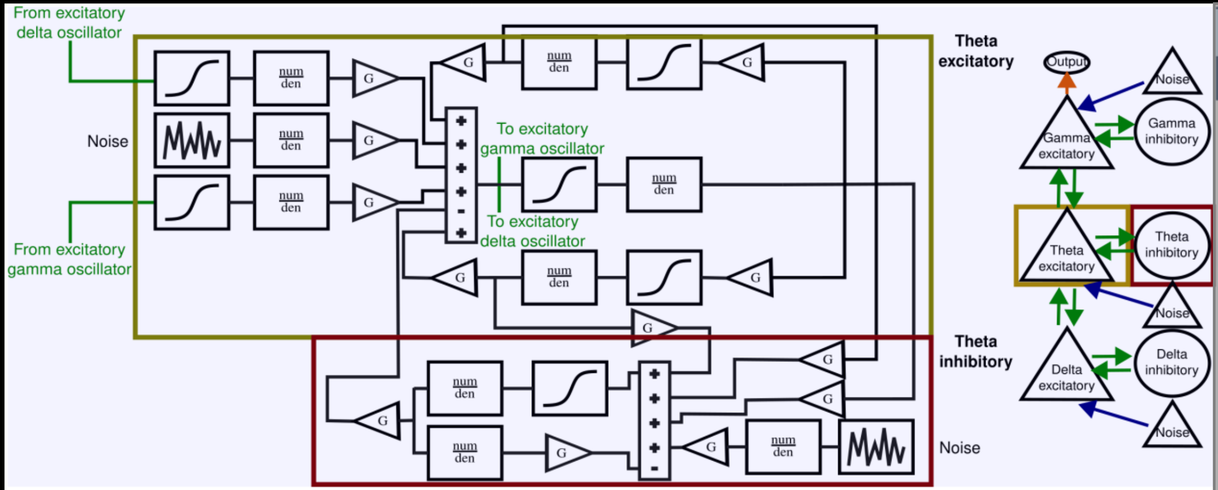

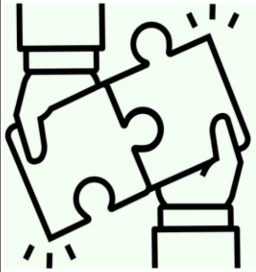

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[9] N. E. Naal-Ruiz, L. Hyunkook, A. Gonzalez, R. Gonzalez, M. M. Duville, L. M. Alonso-Valerdi, and D. I. Ibarra-Zarate, "Towards the neurophysiological characterization of immersive attributes in auditory events," *AES 2023 International* Conference on Spatial and Immersive Audio (August 2023), p. 51, 2023.

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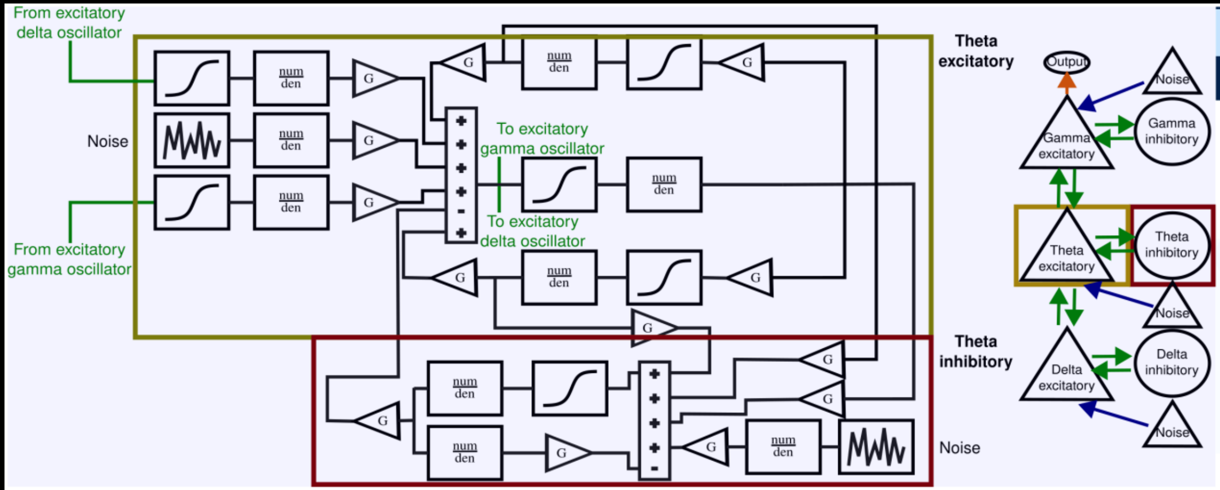

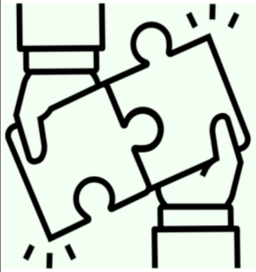

Systematic review

[8] M. M. Duville, Y. Pérez, R. Hugues-Gudiño, N. E. Naal-Ruiz, L. M. Alonso-Valerdi, and D. I. Ibarra-Zarate, "Systematic Review: Emotion Recognition Based on Electrophysiological Patterns for Emotion Regulation Detection," *Applied Sciences*, vol. 13, no. 12, p. 6896, Jun. 2023, doi: 10.3390/app13126896.

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La Dra. Valeria Nanclares-Nogués
Oficialmente certificada como formadora en ADI-R y ADOS-2
Certifica que

Mathilde Marie Duville

Obtiene la acreditación en la Formación Clínica del Instrumento Diagnóstico

Escala de Observación para el Diagnóstico de Autismo – 2a Edición
Autism Diagnostic Observation Schedule-2nd Edition (ADOS-2)

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9, 10 y 11 de Diciembre, 2022
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