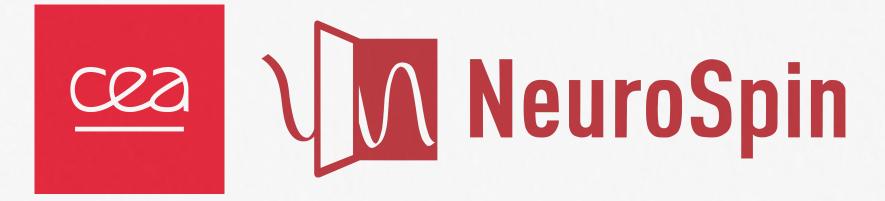
# Neural and representational dynamics of duration processing





LONDON







### Background

### **Temporal distortions**



Marie Montant



Johannes Ziegler



Jenny Coull





CENTRE DE RECHERCHE EN PSYCHOLOGIE & **NEUROSCIENCES** 



Contribution of motor processes to the representation of temporal (order) concepts

### **Duration representation**

### Next steps



Virginie van Wassenhove





Kenneth Kishida



Nathan Faivre





2023 - 2025

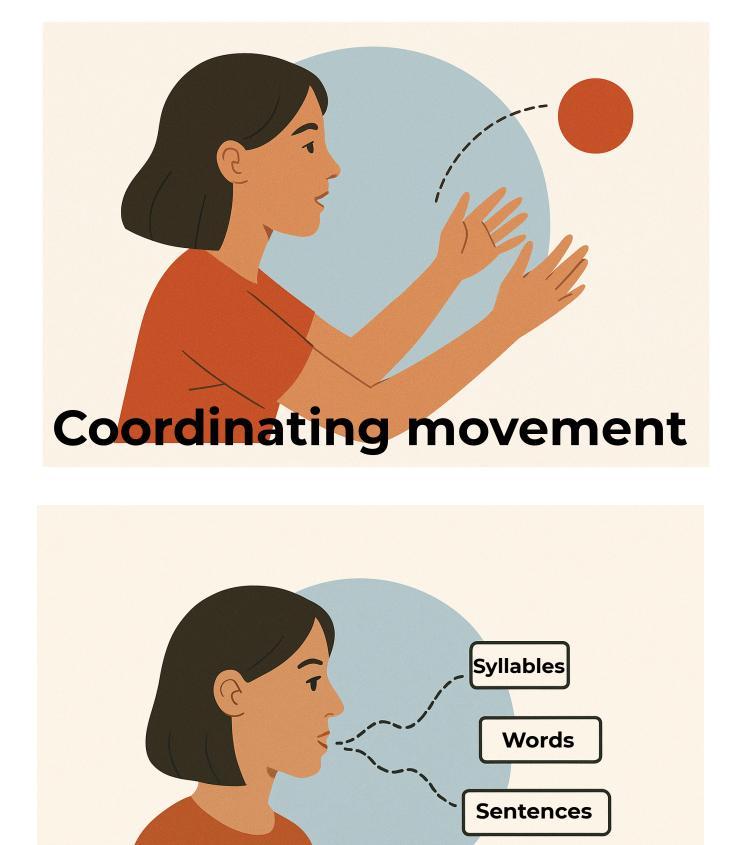


Neural and conceptual representation of subjective duration

Multiscale investigation of the neural and electrochemical correlates of subjective experiences



# **Duration perception**



our environment.

Yet, the precise neural mechanisms involved in subjective duration remain poorly understood.

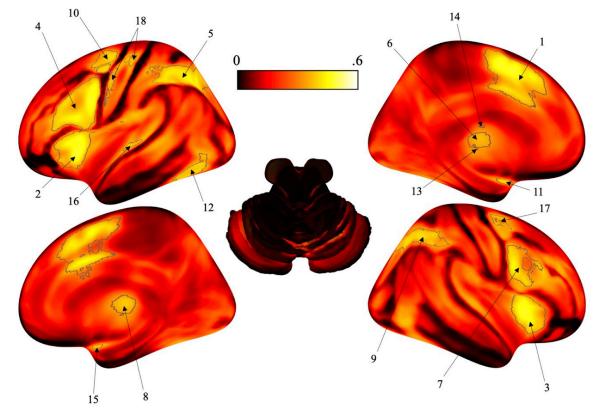
Language understanding

# All our perceptual experiences unfold in time, making the neural representation of time on the sub-second scale a fundamental requisite to perceive, predict, and interact with



### Background

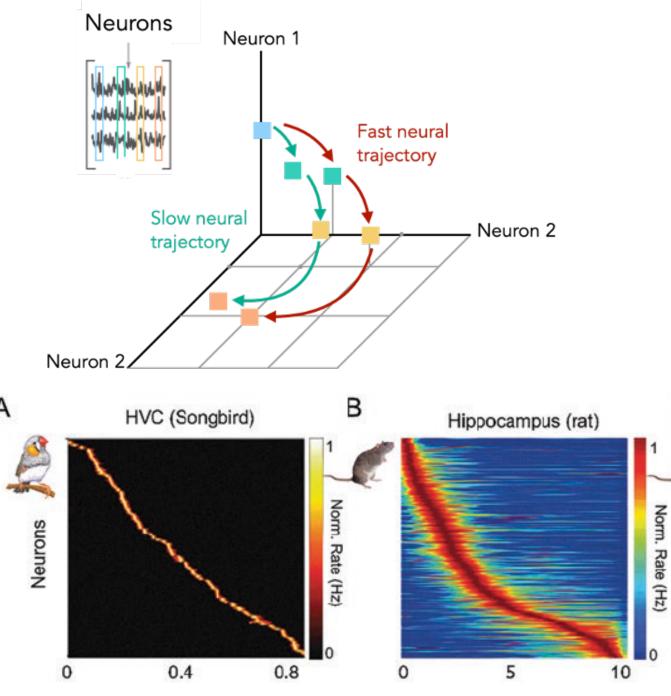
### Several brain areas



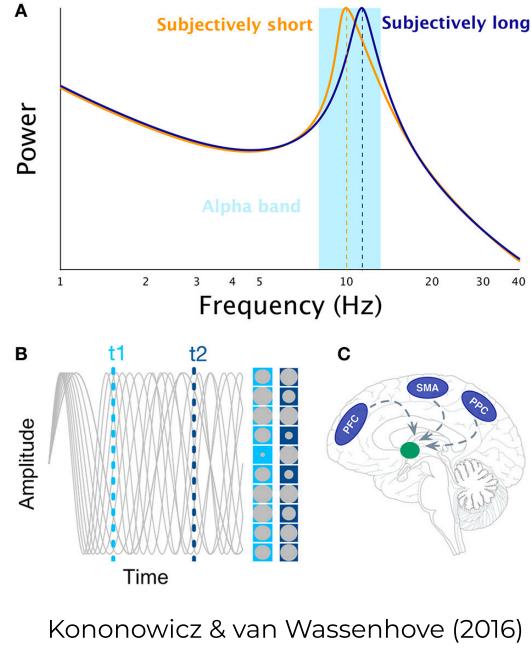
« for anyone conducting a neuroimaging study of time perception, they may consider the probability that any one brain region will be observed in their study. » Mondok & Wiener, 2022

Mondok & Wiener (2022)

# Several mechanisms







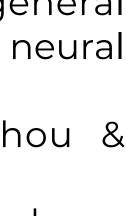
**Cortical areas** (across the frontal, parietal, temporal and occipital lobes) and **subcortical structures** (e.g., thalamus).

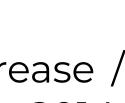
- **Population level dynamics:** timing emerges from general properties of neurons and the inherent dynamics of neural circuits:
- how neural trajectories evolve over time, e(.g., Zhou & Buonomano, Remington et al., 2018; Wang et al., 2018)
- brain oscillations (e.g., theta, alpha, beta; van Wassenhove, 2016 ; Oprisan & Buhusi, 2013)

Single-neuron level: ramping activity: monotonic increase / decrease in firing rate to track elapsed time (Xu et al., 2014; Komura et al., 2001).

**Neurochemical level**: dopamine fluctuations impact duration perception (Sadibolova et al., 2024).







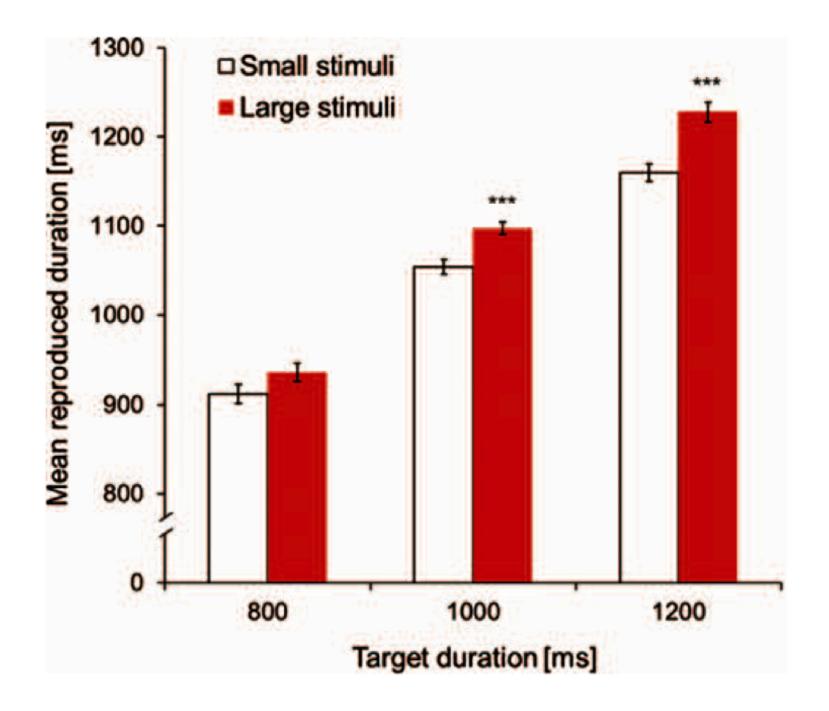




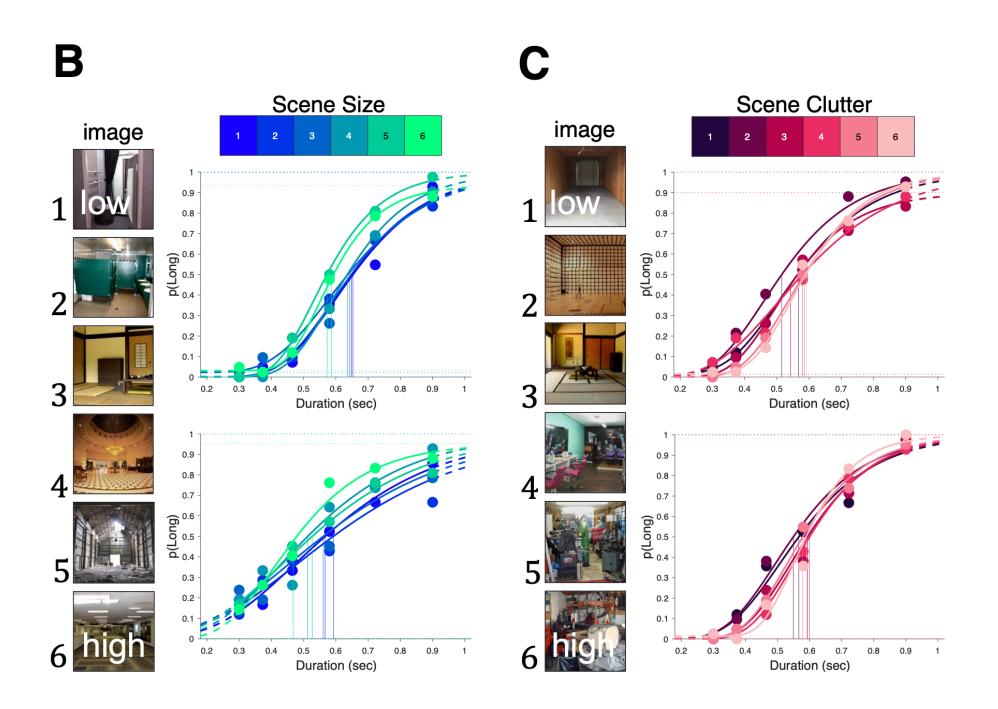
## Subjective duration can be studied objectively: the case of temporal distortions

### The physical properties of stimuli:

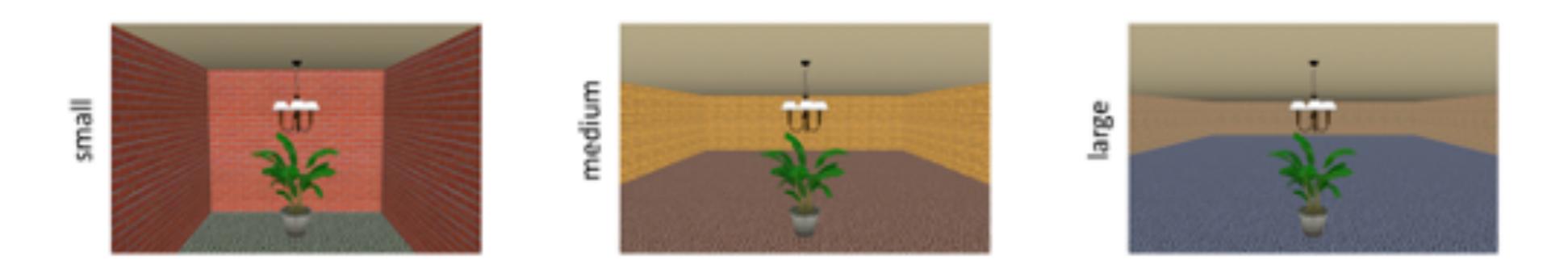
Complexity (e.g., Schiffman & Book, 1974), Color (Aaen-Stockdale et al., 2011) Size (e.g., Rammsayer & Verner, 2014; Xuan et al., 2007) Numerosity (e.g., Dormal et al., 2006) Biological and non biological movement (e.g., Gavazzi et al., 2013 ; Wang & Jiang, 2012) Speed (e.g., Brown, 1995)

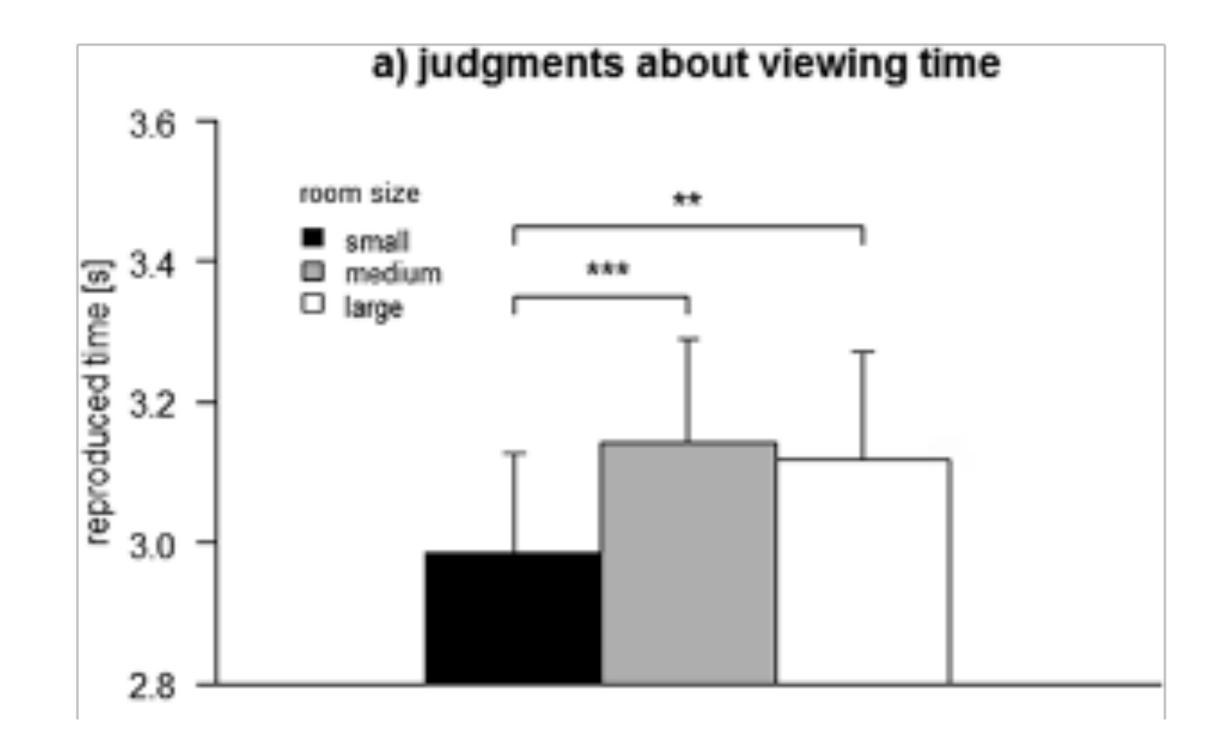


Cognitive load (e.g., Block et al., 2010) Attention (e.g., Zakay & Block, 1994) Emotions (e.g., Droit-Volet & Meck, 2007) Interoceptive states (e.g., Di Liernia et al., 2018) Space (e.g., De Pra et al., 2023) & Environmental constraints (e.g., DeLong, 1981; Riemer et al., 2018; Ma et al., 2024)



Subjects observing differently scaled environments undergo shifts in their experience of time: smaller-scale environments were associated with shorter duration estimates (DeLong, 1981) and larger-scale environments were associated with larger duration estimates (Riemer et al., 2018).





Riemer et al. (2018)

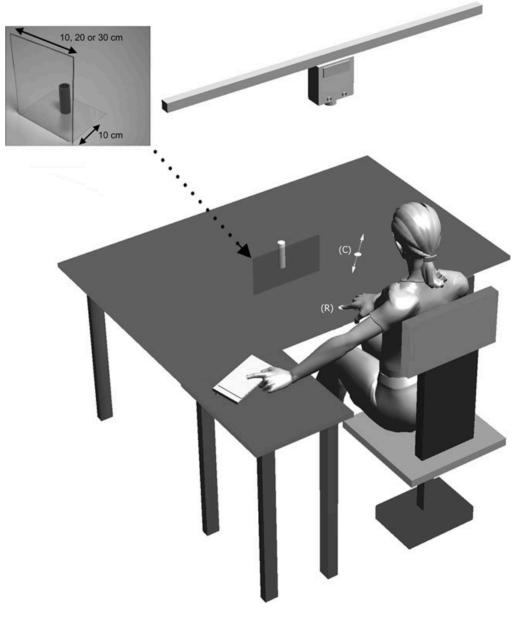


# A Theory of Magnitude (ATOM)

A common neural code in parietal cortex for magnitude (time, space, numerosity). Predicts that larger spatial magnitudes should lead to longer perceived durations (e.g., Walsh, 2003; Bueti and Walsh, 2009).

However, this theory cannot fully explain the results found by Ma et al. (2023).

# **Action constraint theory (ACT)**



slope, size).

For duration perception: overestimation of duration in large environments could be explained by action constraints theory: larger environments involve more potential movements, and thus more time to move through them.

Morgado et al. (2013)

Morgado et al. (2013); Jackson & Cormack (2007); Jeffery et al. (2021); Bueti & Walsh (2009)

For space navigation: postulates that the constraints associated with spatial navigation (e.g., effort, falling risk) influence the perception of space (i.e., distance,



**A.** Can we **replicate** the effect of environment size on duration production in virtual environments?

Testing (more directly) the hypothesis that individuals overestimate durations in larger environments because they involve greater travel times.

# **B.** To investigate the neural basis of such effects.

Which stage of the duration production process is affected by the room size: planification, production? Can we decode (and when?) the room size from the EEG signals?



Matthew Logie



Virginie van Wassenhove





# **Duration production task**

Virtual environments varying in **size** (small vs. large) and **ceiling height** (normal vs. high).

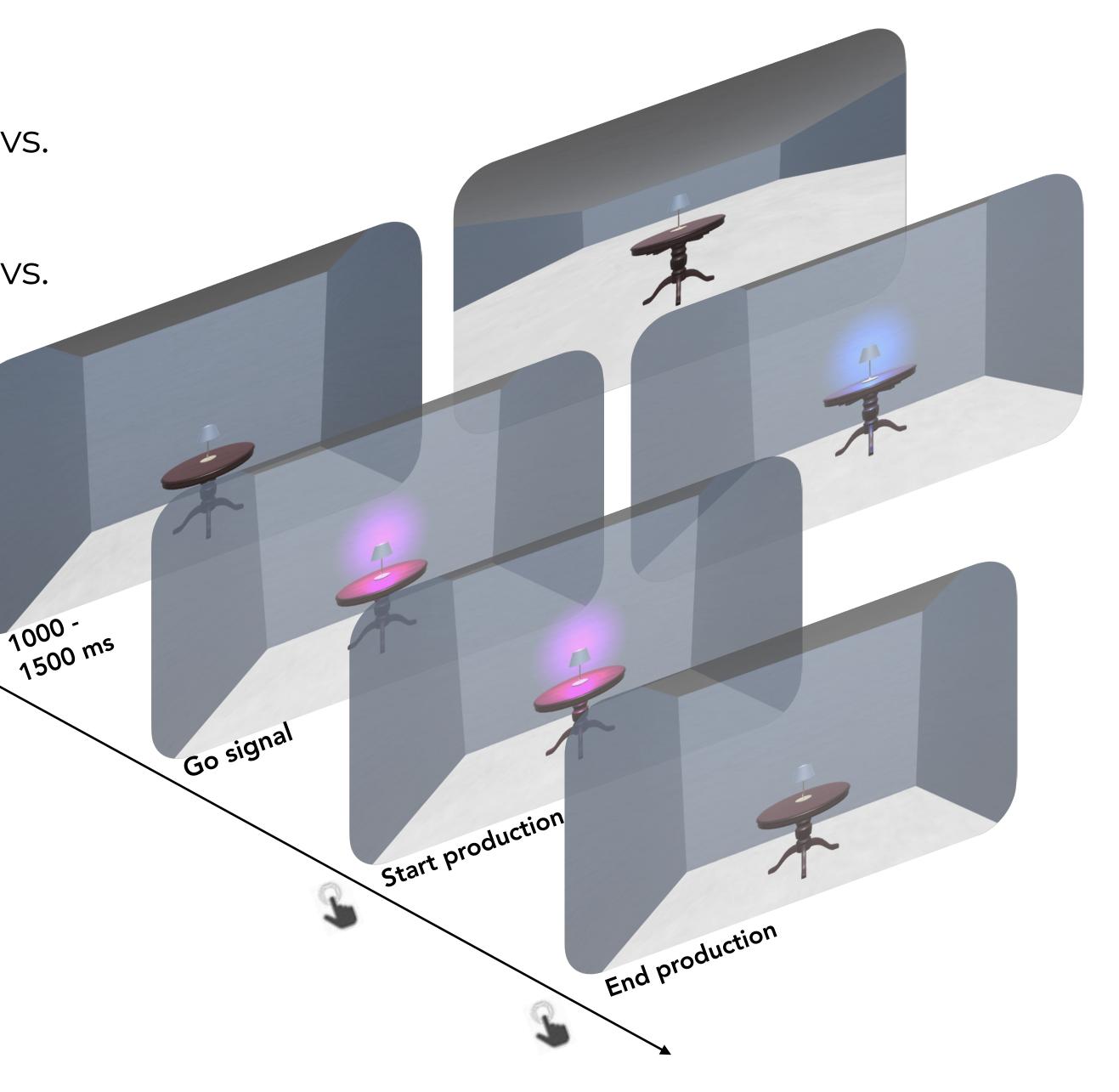
**Short** and **long** duration production (1.45s vs. 2.9s) to avoid counting.



https://robertoostenveld.nl/eeg-combined-with-vr/

### **Duration representation**

### Next steps



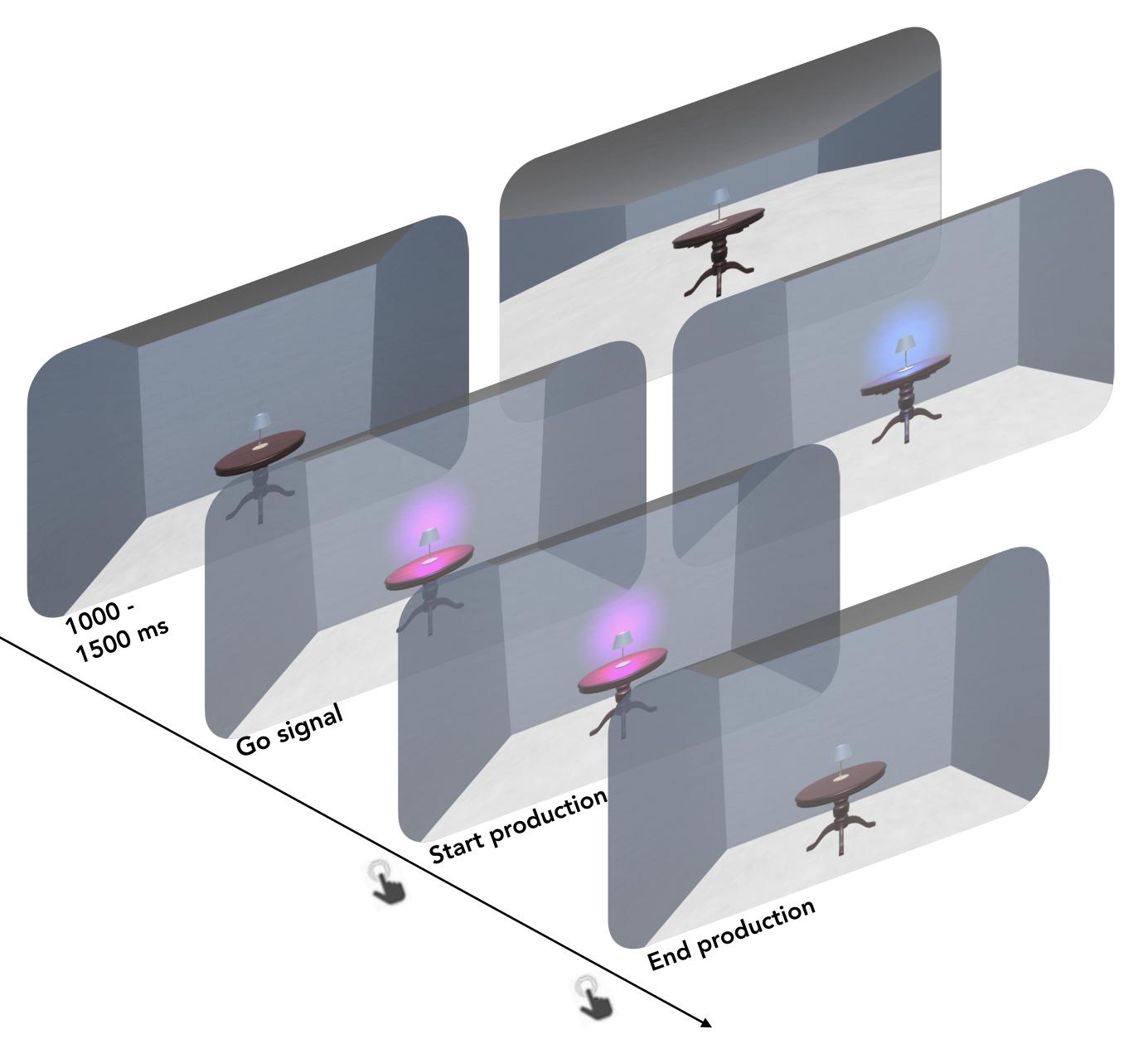


# **Duration production task**

As proposed by the **action constraints theory** (e.g., Morgado and Palluel-Germain, 2015; Jackson & Cormack, 2007; Jackson & Wiley, 2011), participants **should produce longer durations in larger environments** (as these environment involve more

(as these environment involve more movements and/or movements that take more time).

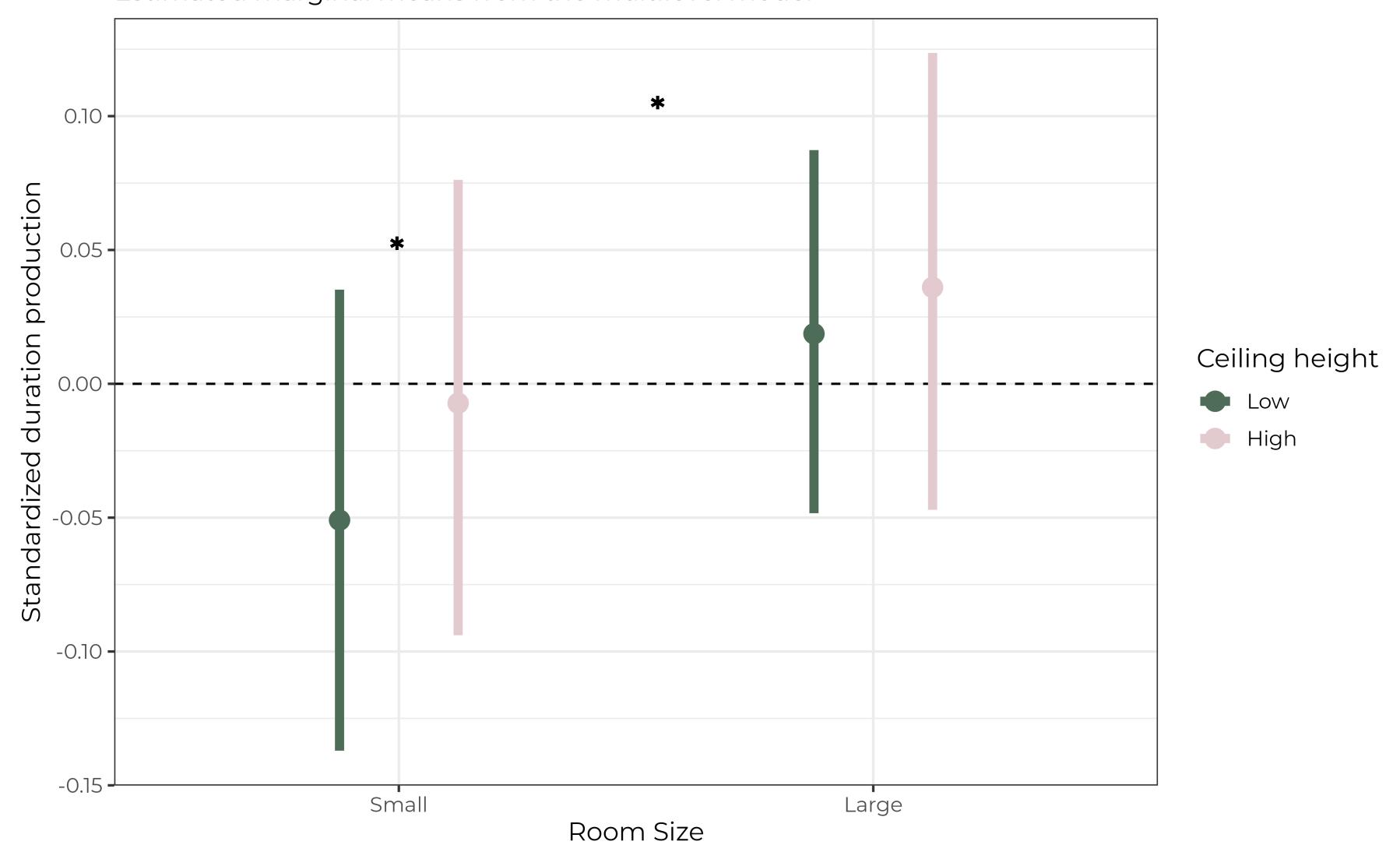
**However**, their temporal production should not be influenced by the height of the ceiling (as it has no impact on travel times in that environment).



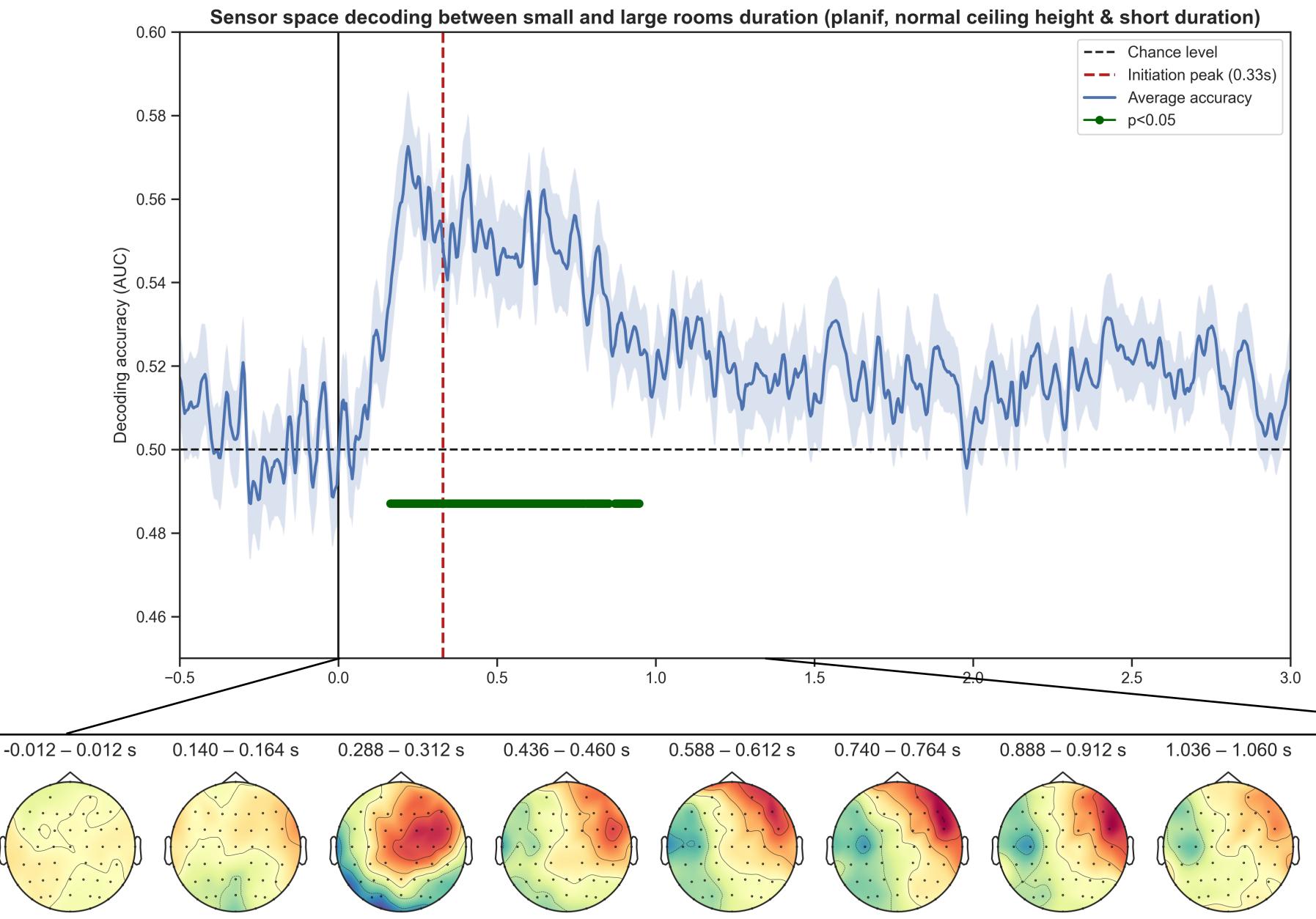
### **Duration representation**

### Next steps

### Effect of room size and ceiling height on standardized duration production (N=28)



Estimated marginal means from the multilevel model



### Next steps

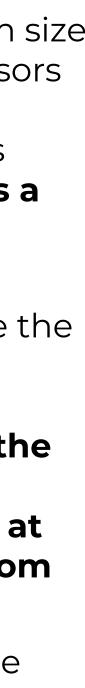
Decoding accuracy for room size over time using all EEG sensors relative to the GO signal. Decoding performance was assessed using ROC AUC as a metric and 4-fold crossvalidation.

Topographic maps illustrate the spatial distribution of the sensors' contributions to decoding accuracy, that is, **the** relative weight of each electrode across the scalp at different time intervals (from **Os to 1.4s).** 

Statistical significance of the decoding accuracy was assessed using a cluster-based permutation test.

1.336 – 1.360 s

1.188 – 1.212 s



# Discussion

Participants produced longer durations in larger and higher-ceiling environments.

Decoding analyses further revealed that both the size and height can be decoded as early as 200ms after the GO signal, (around the first button press), suggesting that the spatial features are taken into to account during the planification of duration production.

While results are broadly consistent with the magnitude theory — the idea that larger spatial magnitudes bias our perception of other magnitudes like time. But they're not fully consistent with the environmental constraint theory. Further work is needed to tease apart these explanations.

# Next analytical steps

Can we decode/predict the precision of duration production through time?

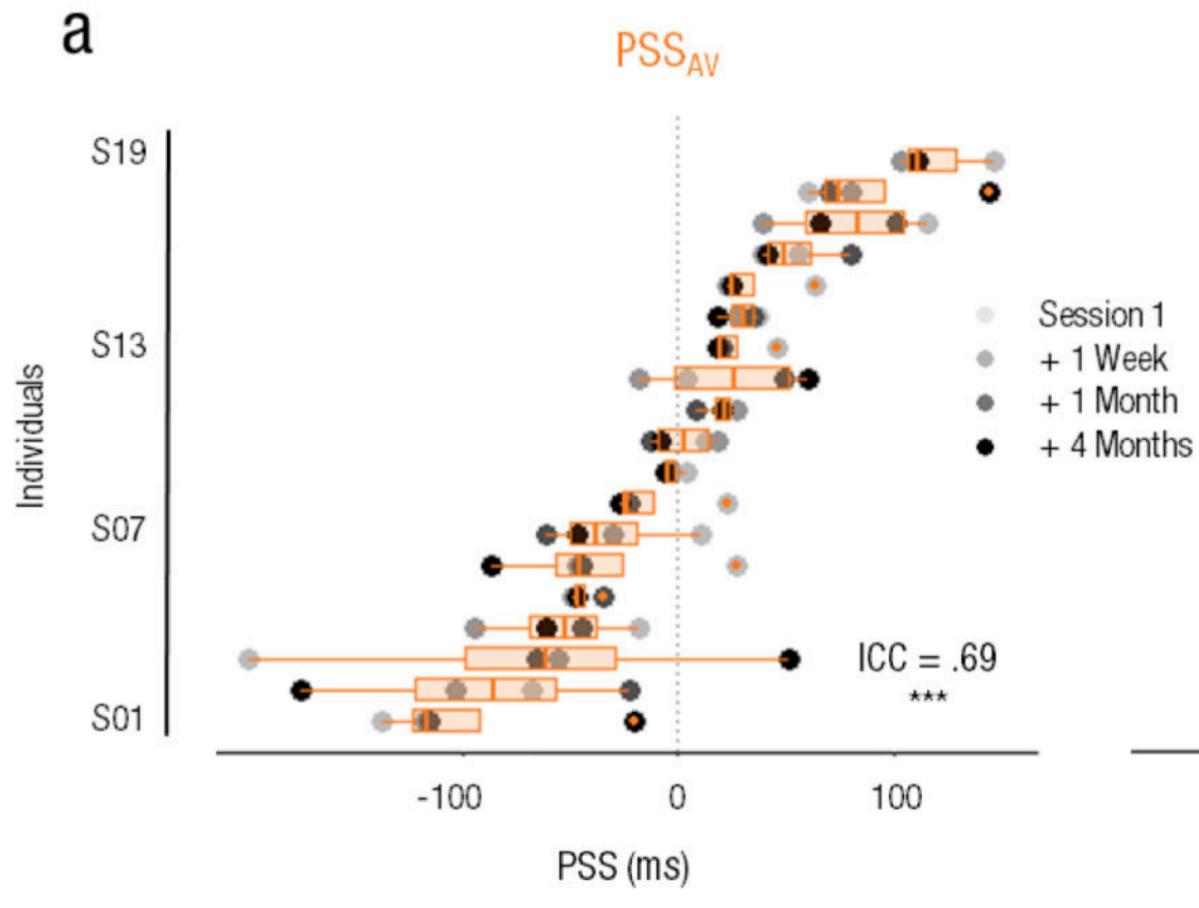
Time-frequency analysis: testing if the room size / height influence oscillatory power, and if yes, how?





# Investigating the (geometrical) structure of duration representations

### Within- and between-individual variability



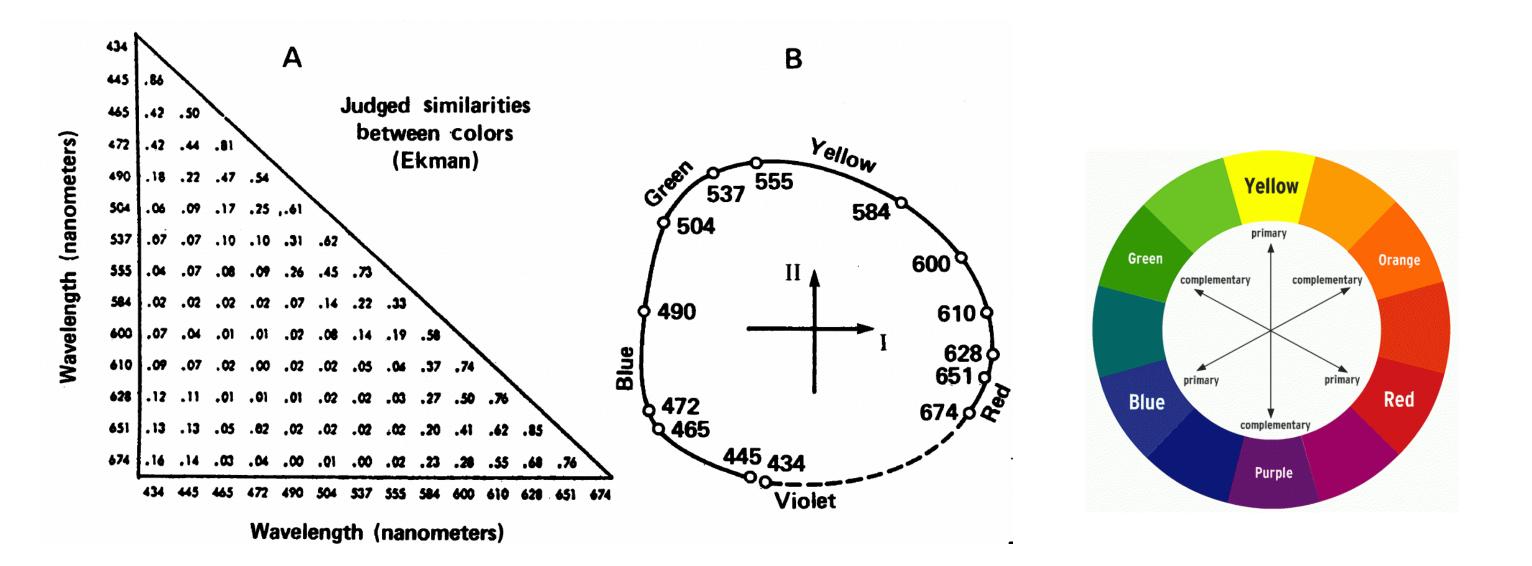
Grabot & van Wassenhove (2017)

What is the underlying structure of duration representation?

Are there stable geometrical principles that shape this organisation at both the conceptual and neural levels?

# Investigating the (geometrical) structure of duration representations

"Analogously in psychology, a law that is invariant across perceptual dimensions, modalities, individuals, and species may be attainable only by formulating that law with respect to the appropriate abstract psychological space."



Edelman (1995; 1998); Edelman & Duvdevani-Bar (1997); Shepard (1980); Shepard & Chipman (1970); Shepard et al. (1975).

### Second-Order Isomorphism of Internal Representations: Shapes of States<sup>1</sup>

ROGER N. SHEPARD

Stanford University

AND

SUSAN CHIPMAN

Harvard University

The key idea is to take into account the relational structure of neural/subjective experiences, and to relate it across domains (e.g., brain, cognition) and individuals.



# Investigating the (geometrical) structure of duration representations

Inspired by work from Shepard (1982) and others. The pitch helix "explains" why tones separated by an octave sound similar despite the pitch distance (height vs. chroma).

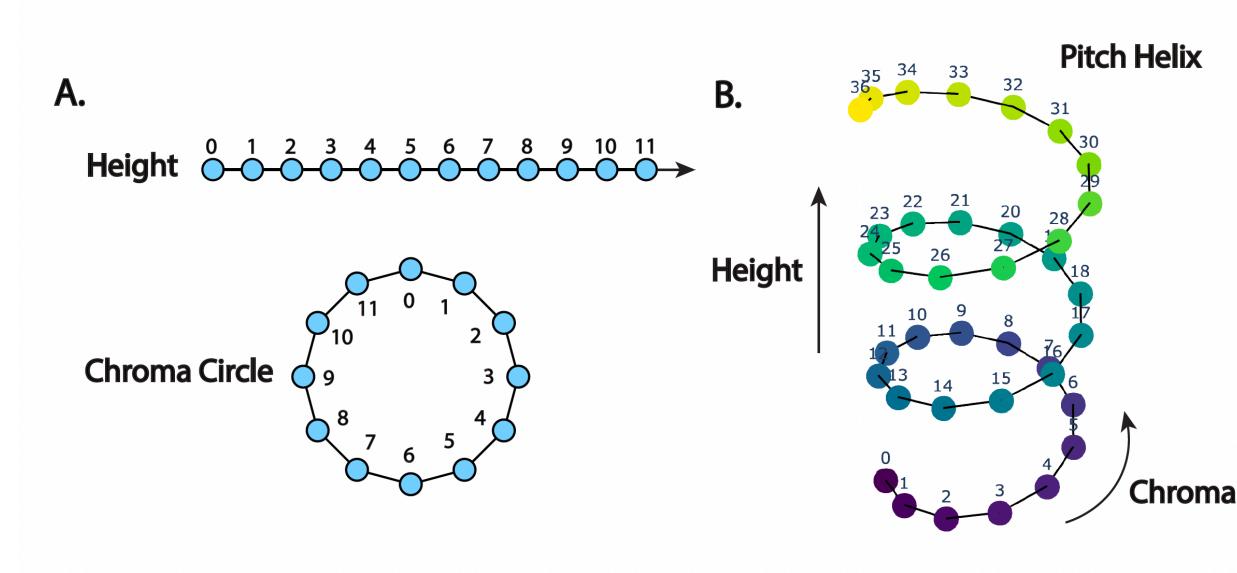
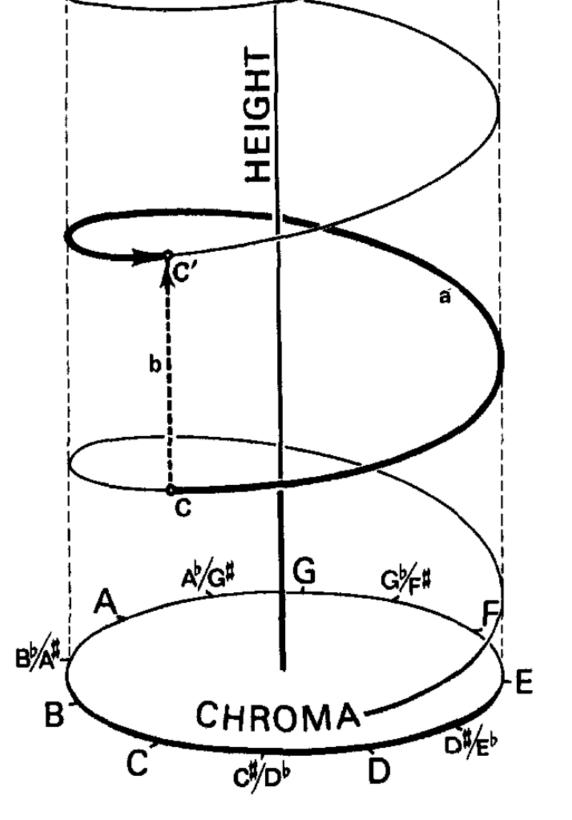
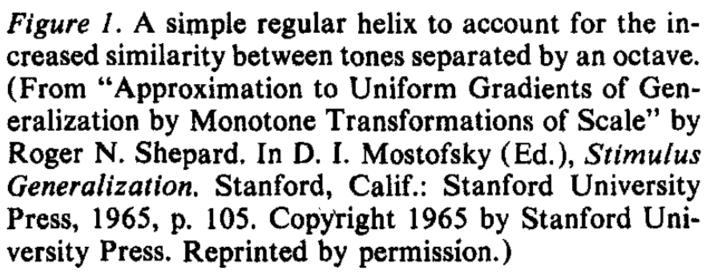


Fig. 1 The pitch helix representation and its underlying components, namely, the pitch height line and the chroma circle.

Marjieh et al., (2024); Kriegerkorte et al. (2008).







# **Objectives**

- Characterizing the structure (shape) of duration representations by comparing different models (i.e., hypotheses) about this structure, using RSA. For example, durations could be 'mentally organised' in a linear or logarithmic fashion, or according to a 'power-law', or in more exotic forms.
- Relating behavioral and EEG representations, and relating these representations with classical EEG markers of duration processing (e.g., theta, alpha, beta frequency bands).
- Finally, if time perception is known to show a lot of variability both within and across individuals, a third objective is to explore whether there might still be shared structure across people

Identify shared geometric principles underlying duration representations, and to explore how these principles manifest both within individuals and across individuals.

### Next steps



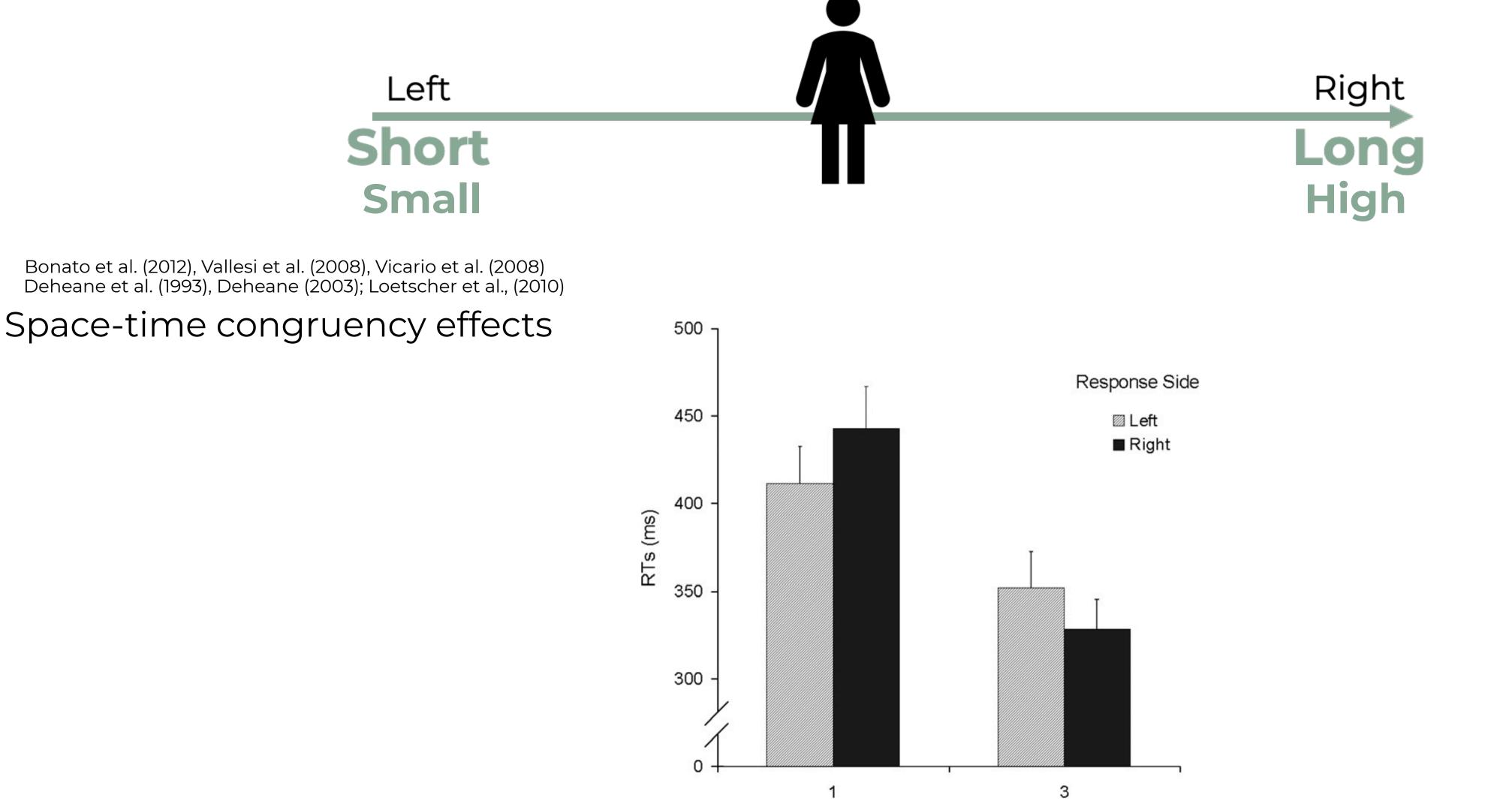


Ladislas Nalborczyk Virginie van Wassenhove



# Investigating the (geometrical) structure of duration representation

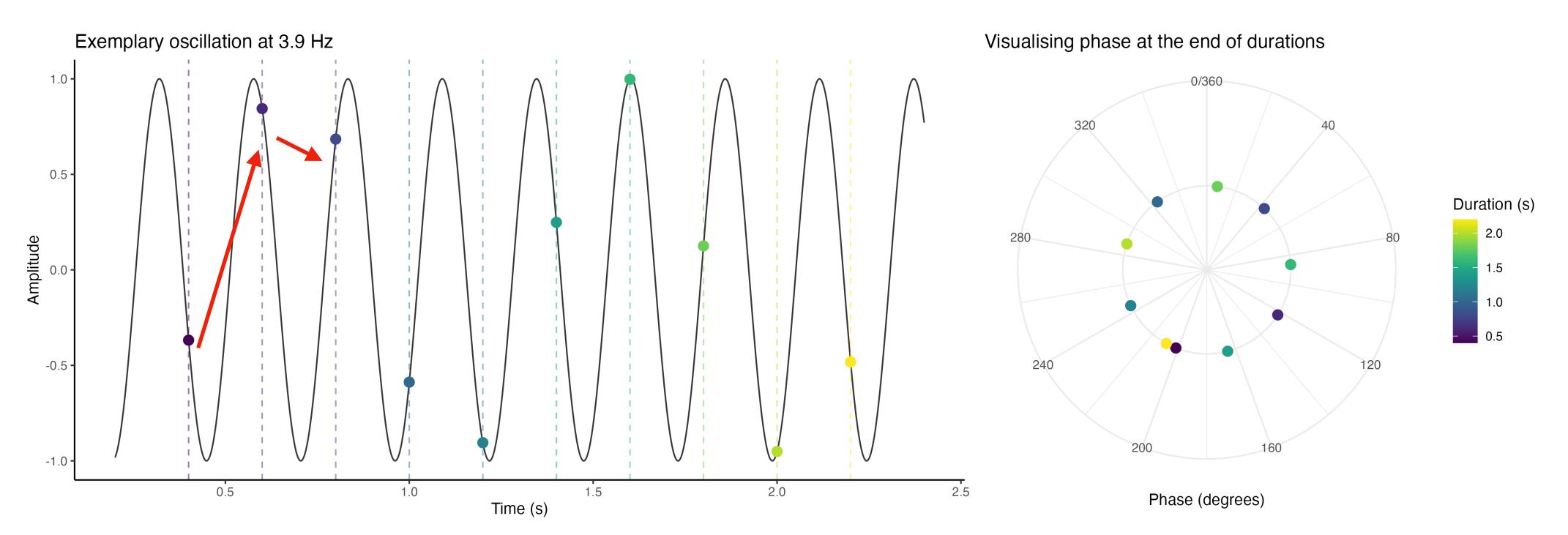
1-D representation of magnitudes: Mental timeline / Mental number line:



# **Constraints for the structure of duration representations**

For durations, we need a representation that account for the **monotonic arrangement of durations** (from short to long durations), the **Weber-like effects** (compression of larger durations relative to shorter durations), and allow for the possibility of "octave-like" relations.

For instance, we know oscillations are crucial for timing durations (Oprisan & Buhusi, 2013). Thus, durations that share oscillatory properties (e.g., phase at the end of the duration) may be judged as more similar to each other than what would be predicted by a simple linear or logarithmic model.



what if the mental representation of duration forms not a line or a curve in 1 or 2 dimensions, but more complex shape in 3 dimensions?





# Behavioral and electrophysiological investigation of duration representation

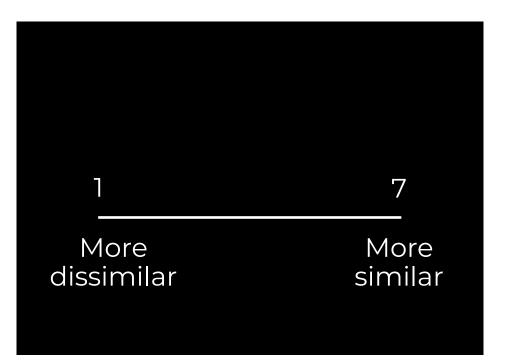


# Session 1 - Similarity judgment task

10 durations [0.4 : 2.2 : 0.2], 34 participants 4 blocks









### Similarity judgment

# Behavioral and electrophysiological investigation of duration representation



# **Session 2 - Oddball detection task (EEG recordings)**

10 durations [0.4 : 2.2 : 0.2], 30 participants (ongoing) 10 blocks







### ITI 700ms +/- 10%



- 80% standards durations, 20% oddball durations (short and long), 940 trials



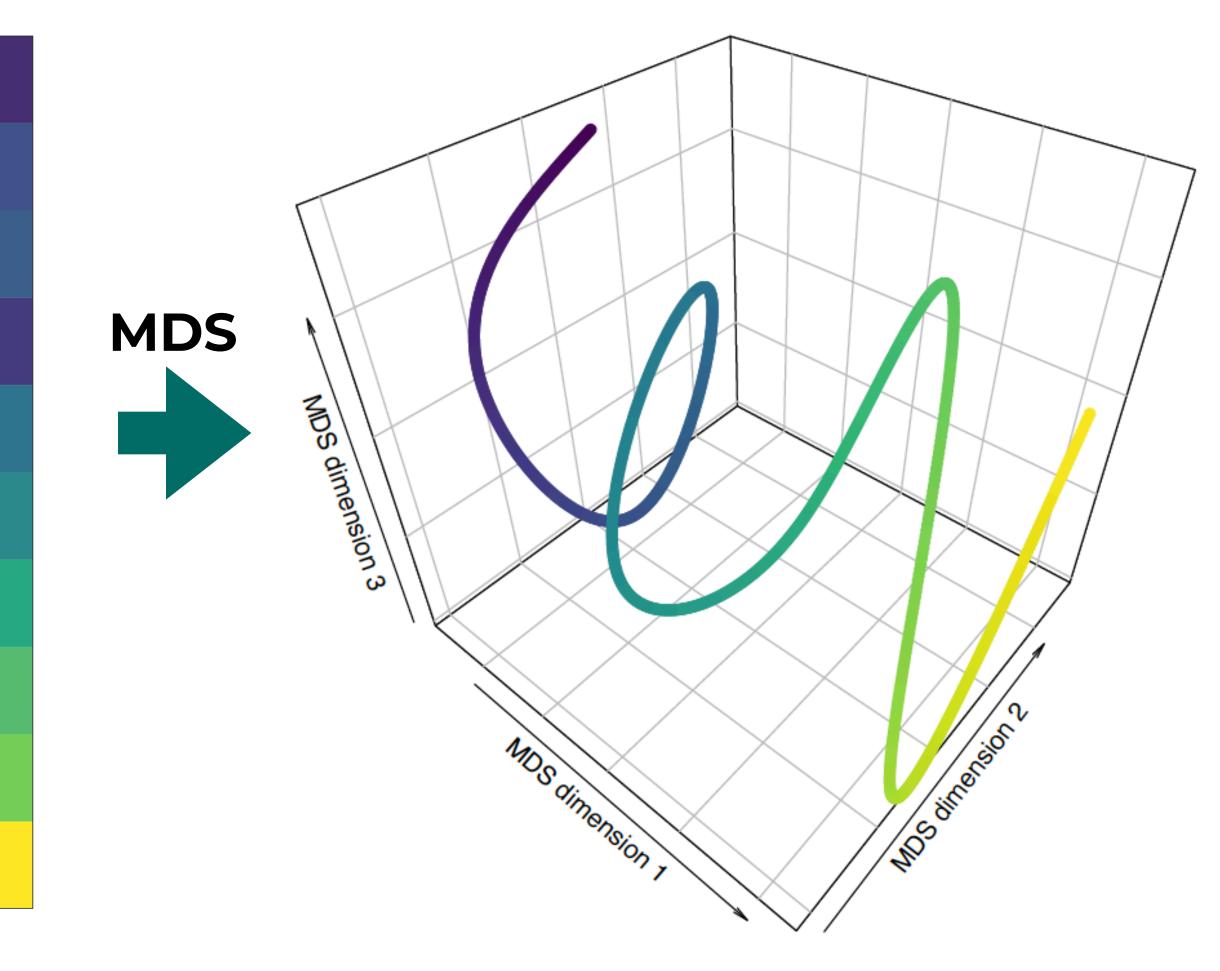


# Visualizing the representational structure implied by subjective similarity ratings

### Dissimilarity matrix

Average normalised dissimilarity ratings (1 - normalised similarity)

2.2 <b>-</b>	0.88	0.67	0.72	0.46	0.42	0.33	0.17	0.08	0.21	0.12
2-	0.83	0.67	0.5	0.58	0.33	0.38	0.33	0.11	0.17	0.25
1.8 <b>-</b>	0.71	0.67	0.54	0.5	0.38	0.17	0.25	0.12	0.17	0.29
1.6-	0.67	0.61	0.42	0.38	0.38	0.29	0.12	0.12	0.25	0.17
Second duration (s)	0.54	0.54	0.46	0.42	0.42	0.25	0.12	0.25	0.46	0.38
Second du	0.54	0.42	0.39	0.21	0.17	0.17	0.21	0.38	0.42	0.46
1 -	0.58	0.33	0.29	0.08	0.12	0.33	0.38	0.46	0.67	0.58
0.8 <b>-</b>	0.38	0.12	0.08	0.21	0.33	0.38	0.5	0.5	0.62	0.67
0.6 <b>-</b>	0.12	0.01	0.12	0.28	0.33	0.5	0.67	0.5	0.71	0.75
0.4 <b>-</b>	0.01	0.04	0.33	0.29	0.5	0.54	0.67	0.92	0.96	0.96
	0.4	0.6	0.8	1	1.2 First dur	1.4 ation (s)	1.6	1.8	2	2.2



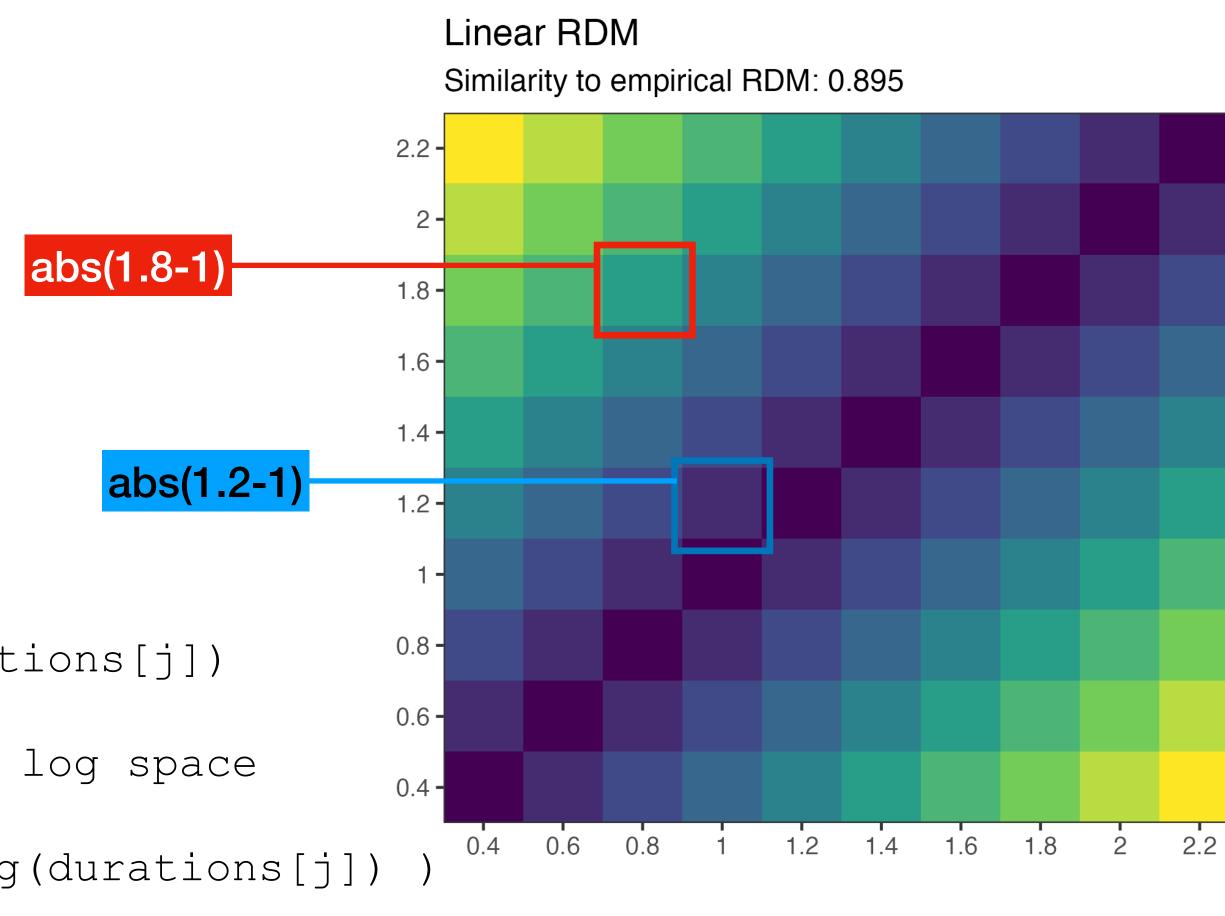
# **Building theoretical RDMs**

Each element of the RDM contains the similarity predicted by each model.

For example, for the linear model, each element of the RDM simply contains the (absolute) difference of durations (in seconds).

# linear model: absolute difference rdm linear[i, j] <- abs(durations[i] - durations[j])</pre> # logarithmic model: absolute difference in log space rdm log[i, j] <- abs(log(durations[i]) - log(durations[j])</pre> # power-law model

rdm power[i, j] <- abs(durations[i]^alpha - durations[j]^alpha)</pre>



$$S = k \cdot I^{\alpha}$$

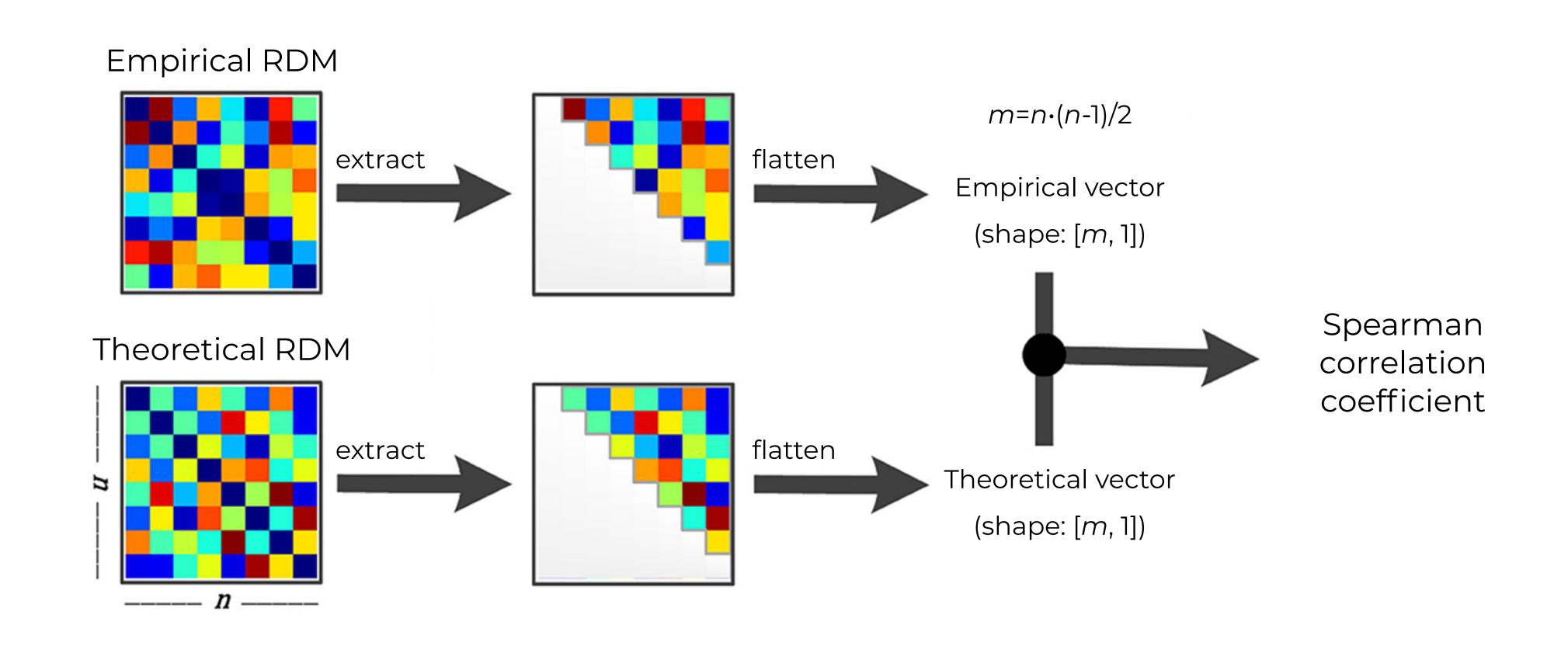
Note that alpha is optimised for the power-law model (cf. next slides).





# Quantifying similarity between subjective similarity judgments and theoretical models

Representational dissimilarity matrices (RDMs) of shape *n*•*n* (for *n* durations)



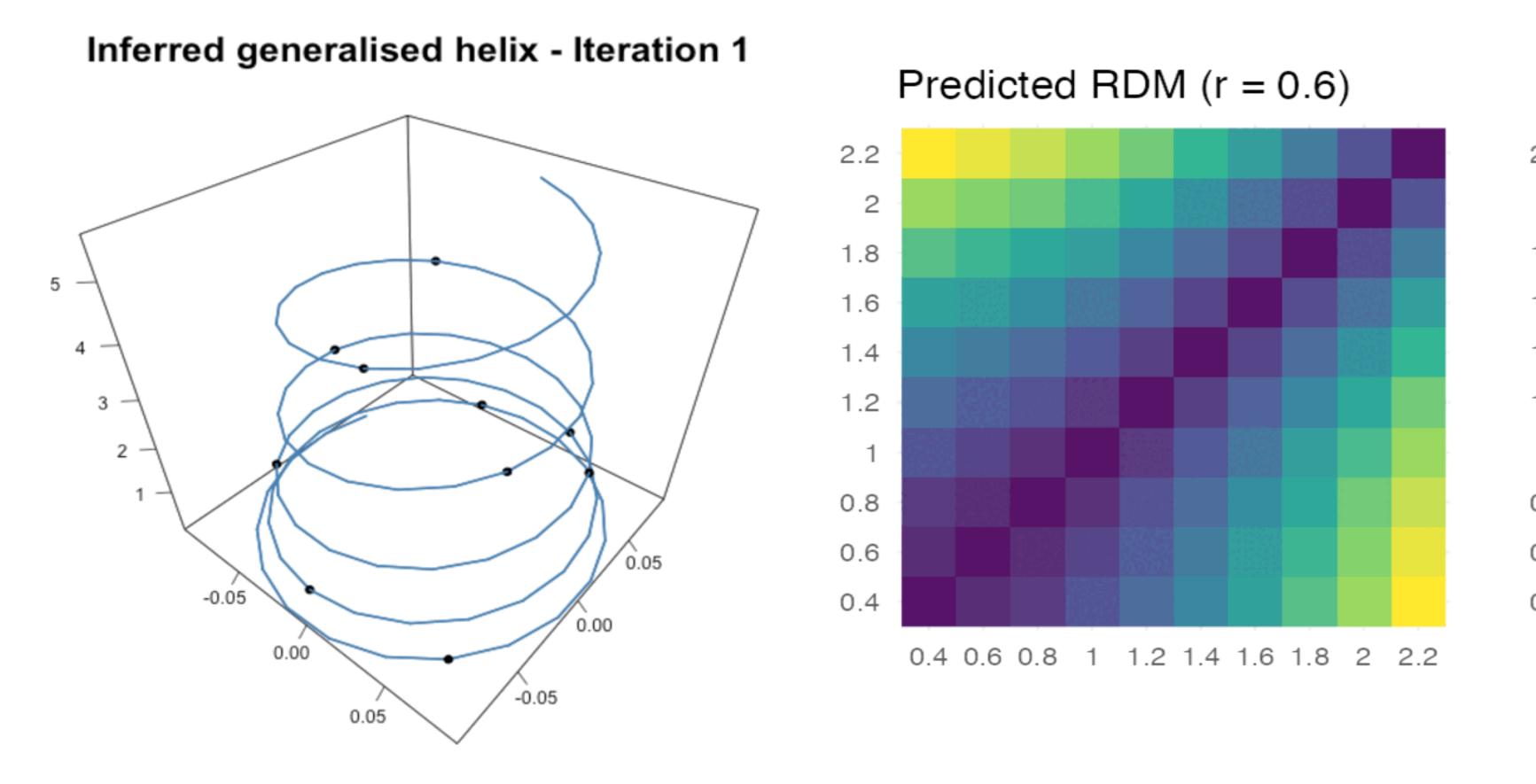




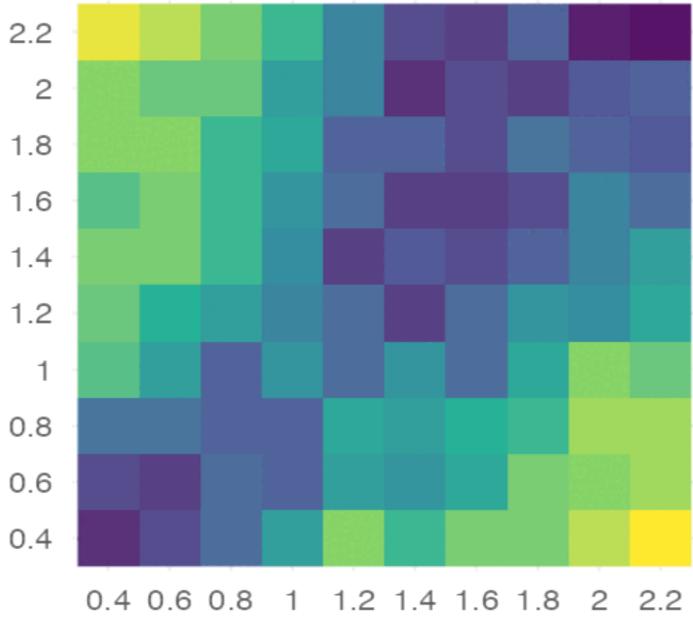
# **Optimisation steps**

We initialise parameters values randomly

We look for the parameter values of the helix (left) that **maximise the correlation** between the theoretical RDM (middle) and the empirical RDM (subjective similarity ratings, right)

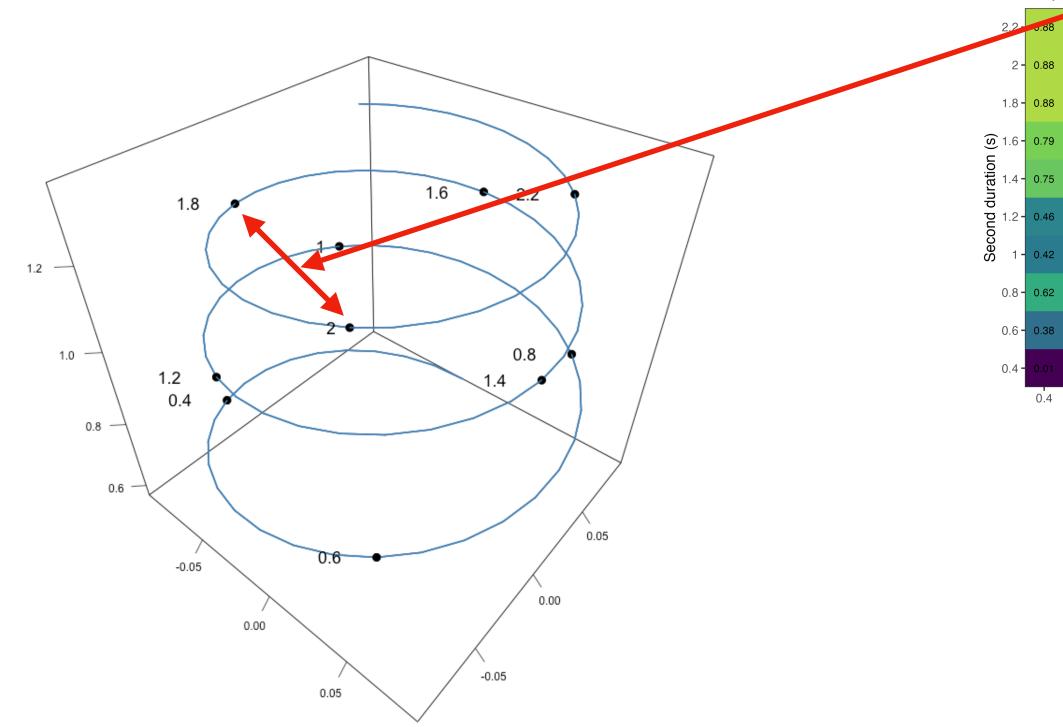


Empirical RDM



# **Exemplary behavioral results (1 participant)**

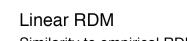
- The helix RDM is best fitting the empirical — RDM, but with 3 free parameters.
- The power-law model is very good as well, with only 1 free parameter.

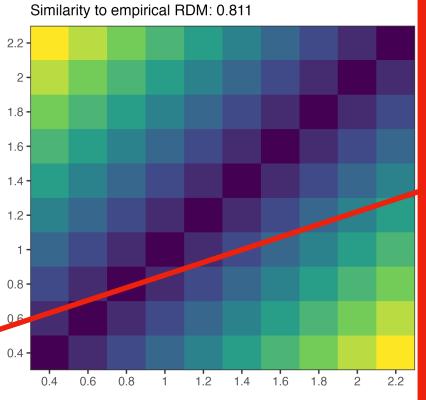


### **Duration representation**

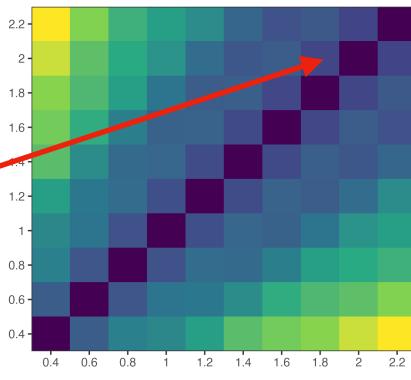
### Next steps



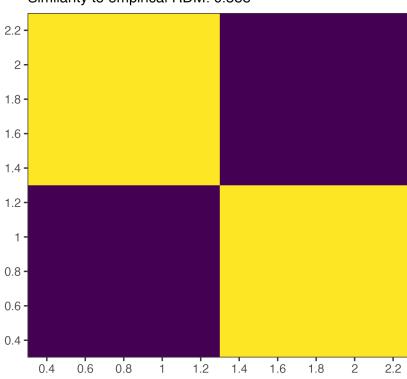




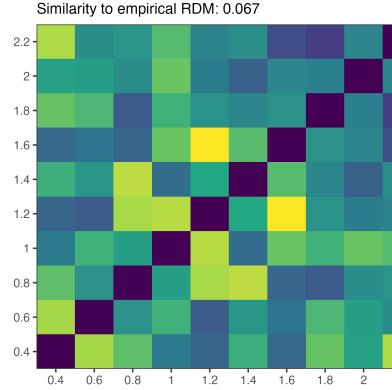
Generalised helix RDM Similarity to empirical RDM: 0.904



### **Binary RDM** Similarity to empirical RDM: 0.588



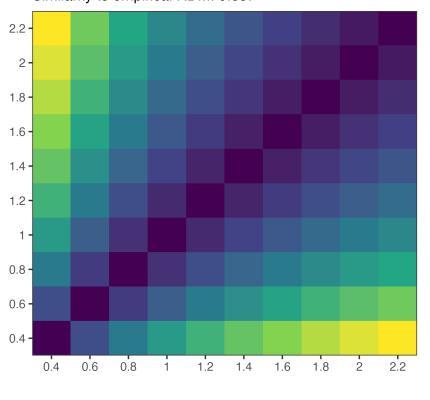
### Random RDM



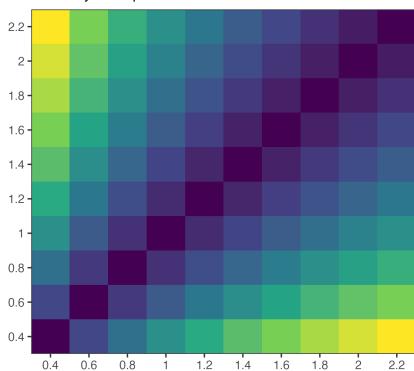
### Empirical RD

0.75	0.71	0.54	0.42	0.33	0.38	0.46	0.17	0.08
0.71	0.62	0.5	0.38	0.08	0.12	0.17	0.12	0.08
0.71	0.46	0.5	0.33	0.21	0.17	0.17	0.25	0.12
0.67	0.54	0.33	0.42	0.12	0.38	0.25	0.33	0.08
0.67	0.33	0.29	0.12	0.08	0.21	0.33	0.38	0.29
0.54	0.46	0.12	0.04	0.21	0.17	0.29	0.62	0.5
0.17	0.21	0.29	0.25	0.46	0.38	0.5	0.67	0.71
0.12	0.25	0.25	0.29	0.42	0.5	0.54	0.75	0.71
0.17	0.12	0.33	0.58	0.58	0.67	0.62	0.75	0.83
0.25	0.33	0.46	0.58	0.62	0.88	0.88	0.92	1
0.6 0.8 1 1.2 1.4 1.6 1.8 2 2.2 First duration (s)								

Logarithmic RDM Similarity to empirical RDM: 0.887











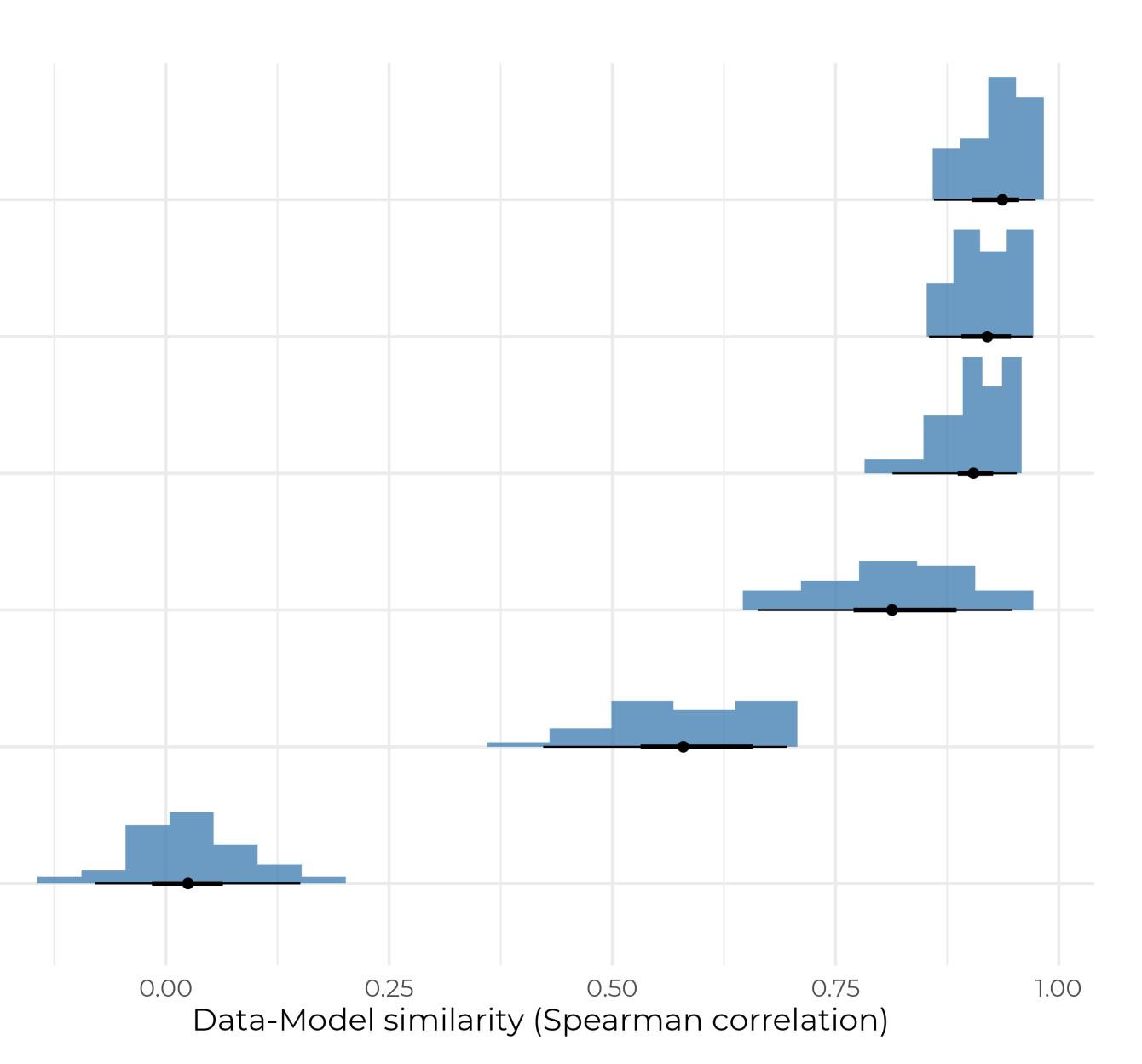


# **Group-level behavioural results (N=34)**

be	verage group-level correlation etween each theoretical RDM and the <b>npirical RDM</b>	Helix –
-	The helix RDM is best fitting the empirical RDM.	Power-law -
-	The power-law model is very good as well, with only I free parameter, followed by the logarithmic model (simplest good model, with no free parameter).	Logarithmic –
		Linear –
-	The random RDM (control) shows no correlation at all, but the binary RDM explains a significant portion of the empirical RDM.	Binary -

Random

### **Duration representation**





# **Preliminary conclusions & next steps**

Duration representation is best explained by nonlinear models — in particular, by the generalised helix, followed by the power-law and logarithmic models.

Relation between RDMs parameters and EEG signals?

Full RSA of EEG data with theoretical RDMs and inter-individual variability analyses.

# Multiscale Investigation of the Neural and electrochemical correlates of Duration perception (MIND)

ACCESS ERC: Understand how dopamine dynamics interact with neural activity to shape subjective time (using voltammetry and intracranial recordings).

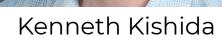








Nathan Faivre









# Thank you





