

Cognitive fluctuations



How a variability perspective can offer a novel phenotype

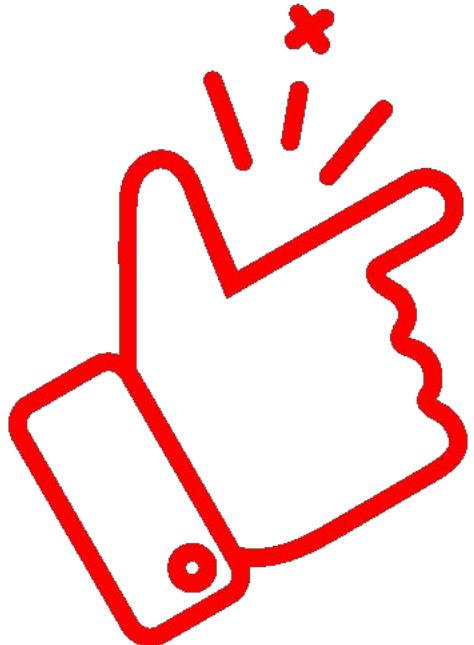
Outline



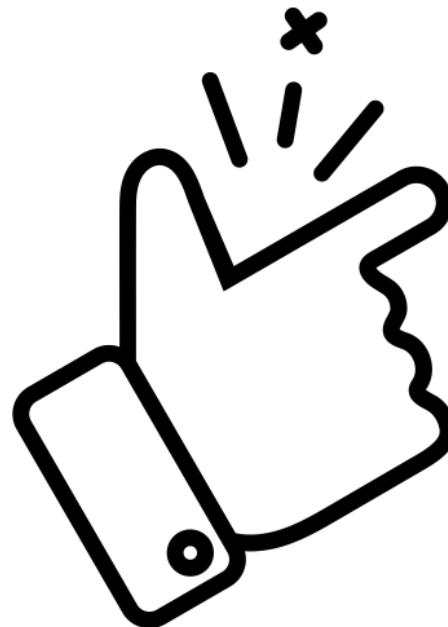
1. Task
2. Variability's importance
3. Goals & findings
4. Future directions

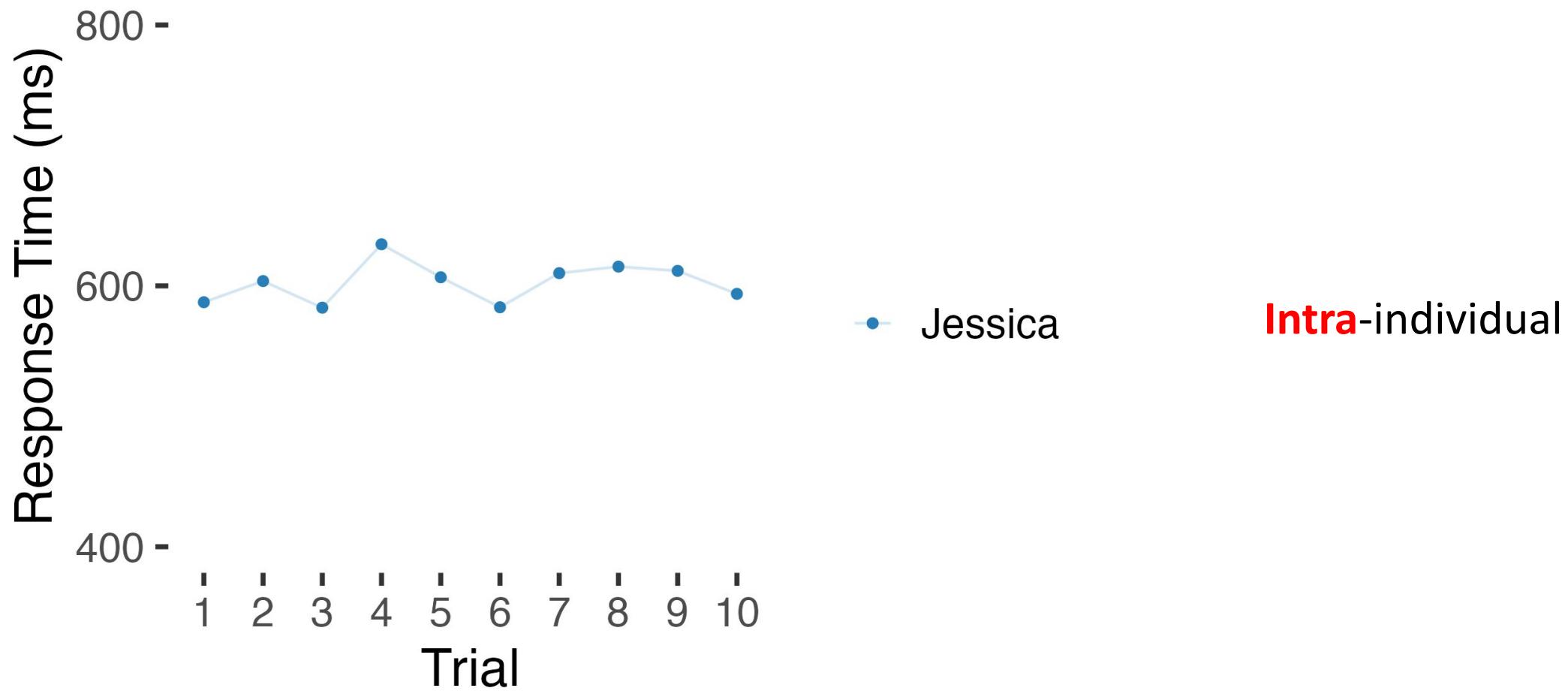
Snapping fingers task

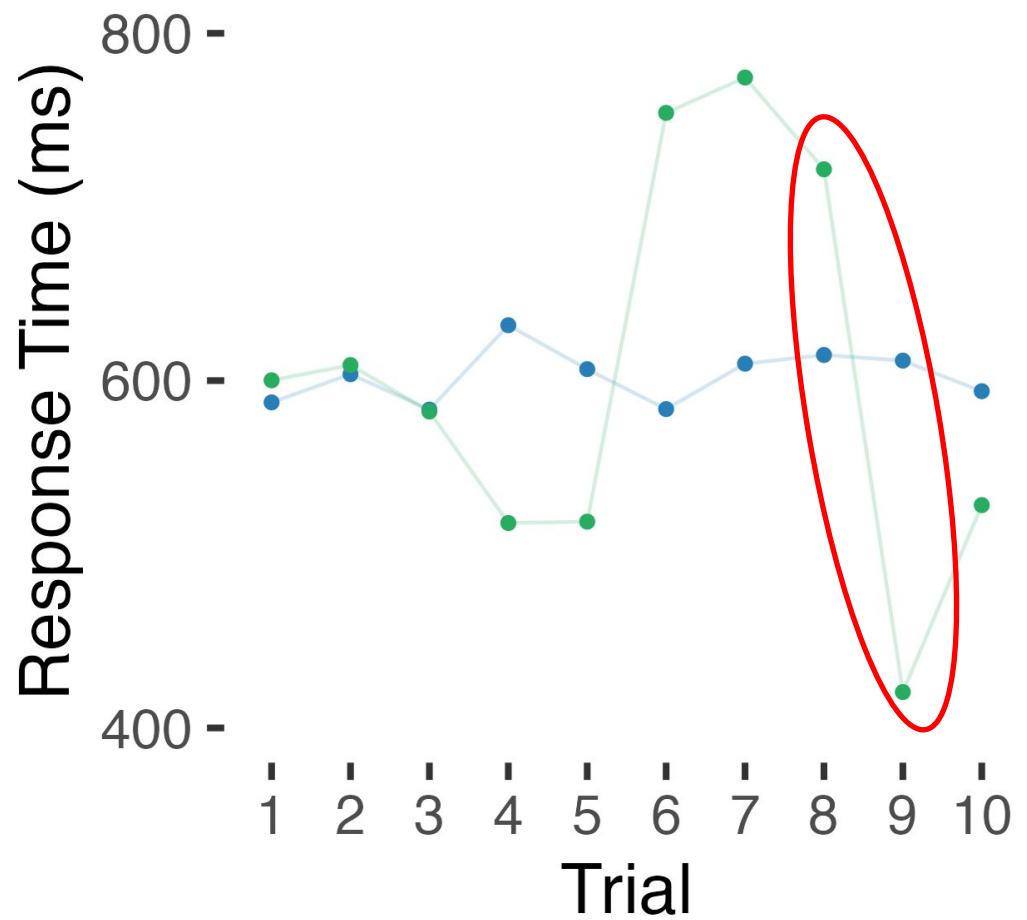
Snap your fingers



Do not respond

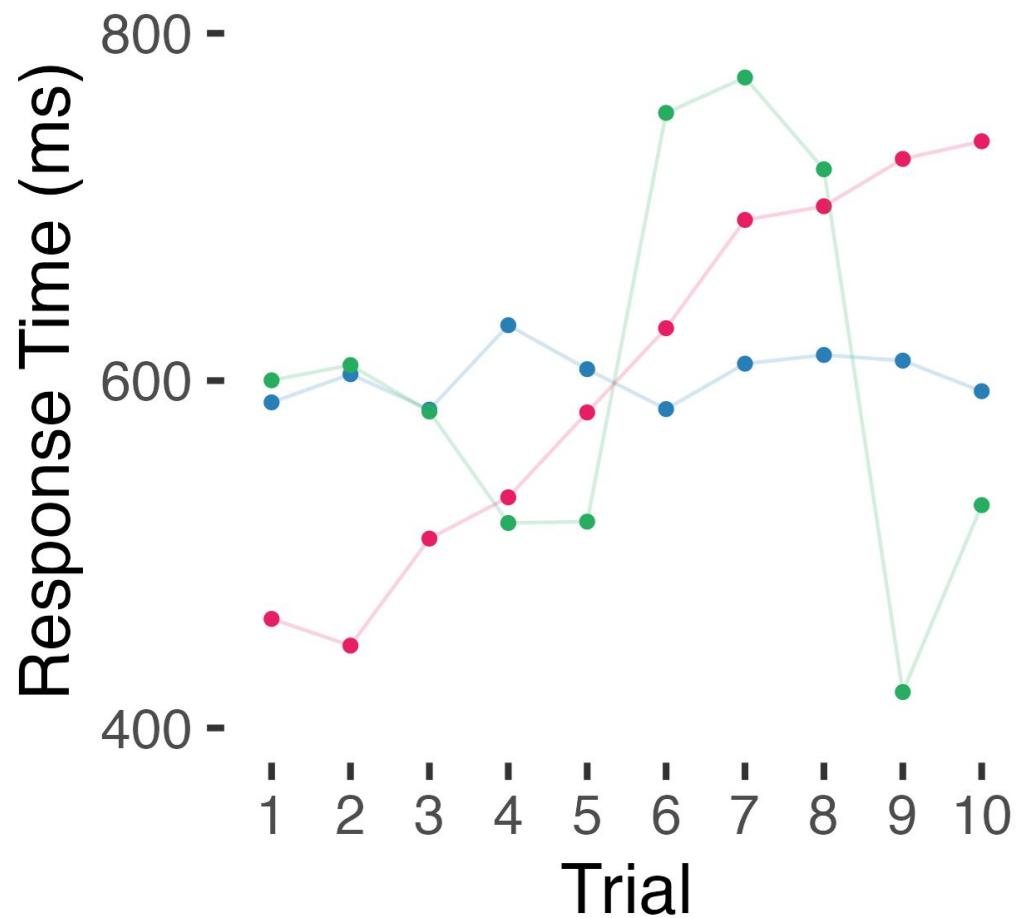






Inter-individual

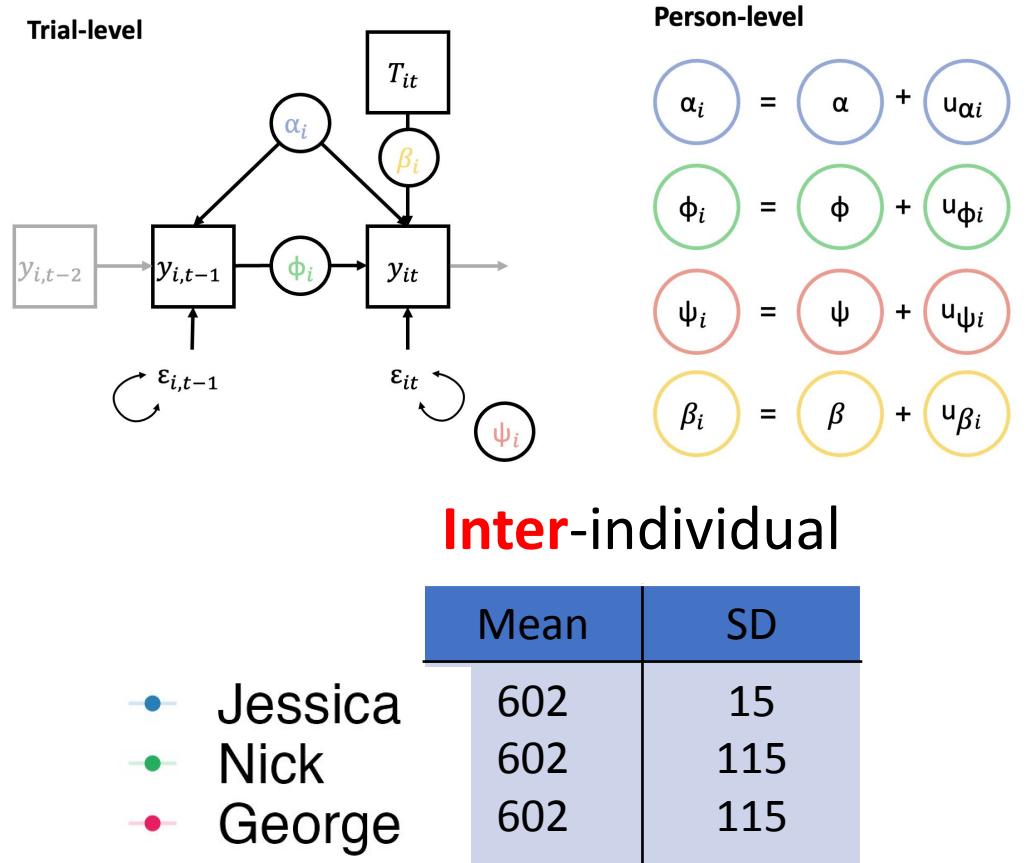
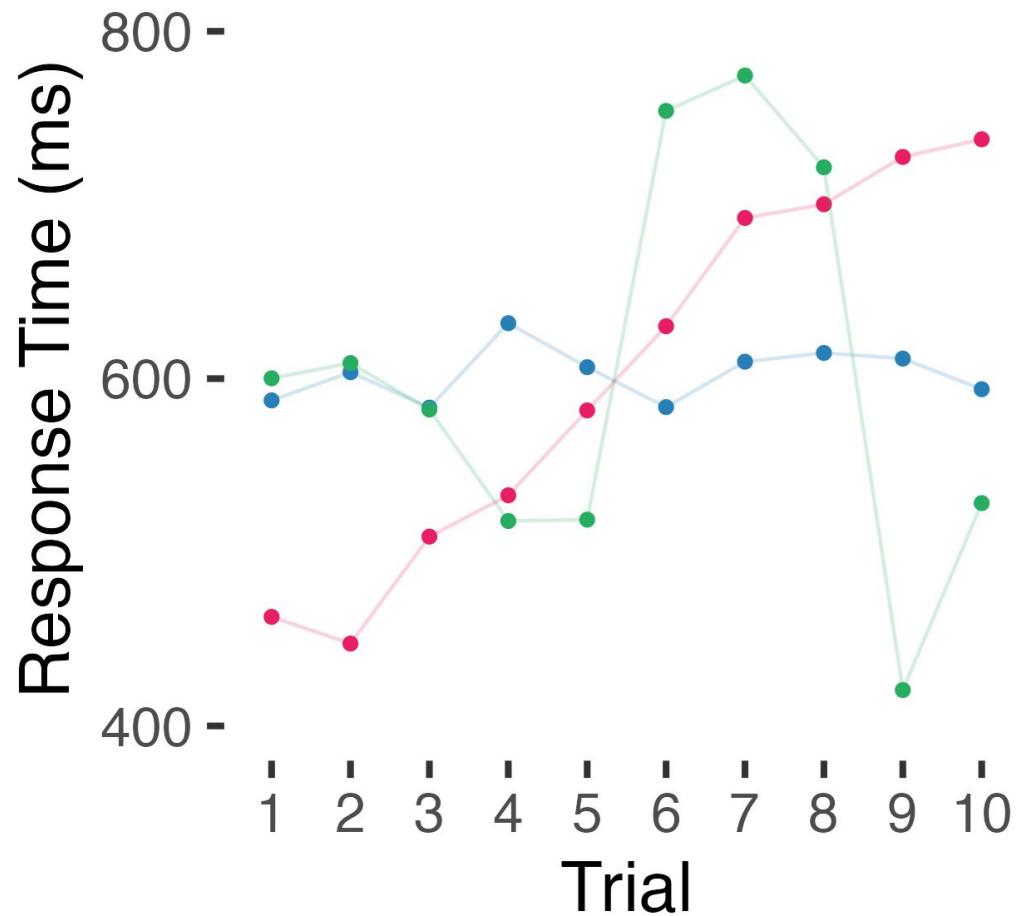
	Mean	SD
Jessica	602	15
Nick	602	115

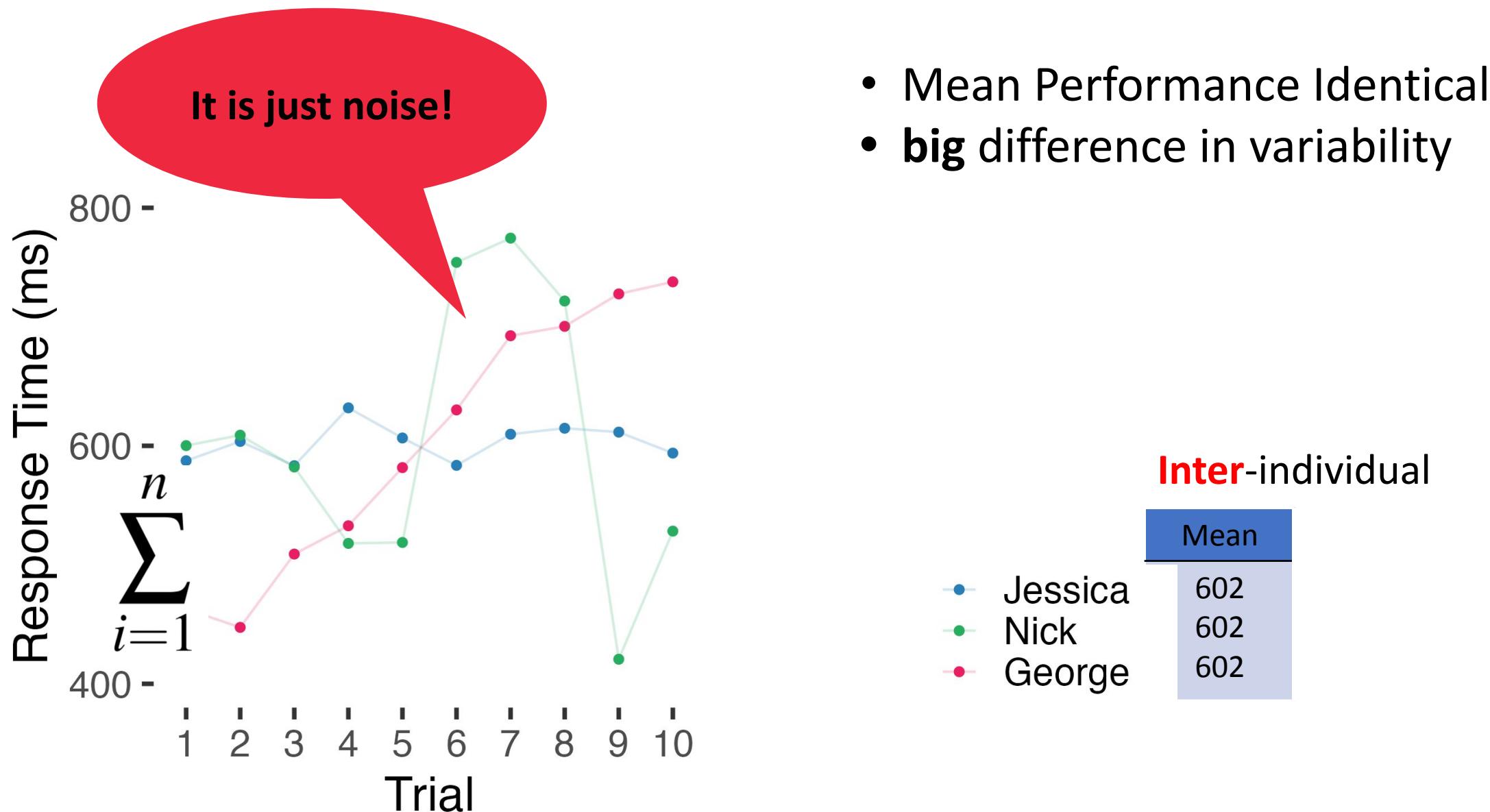


Inter-individual		
Mean	SD	
602	15	
602	115	

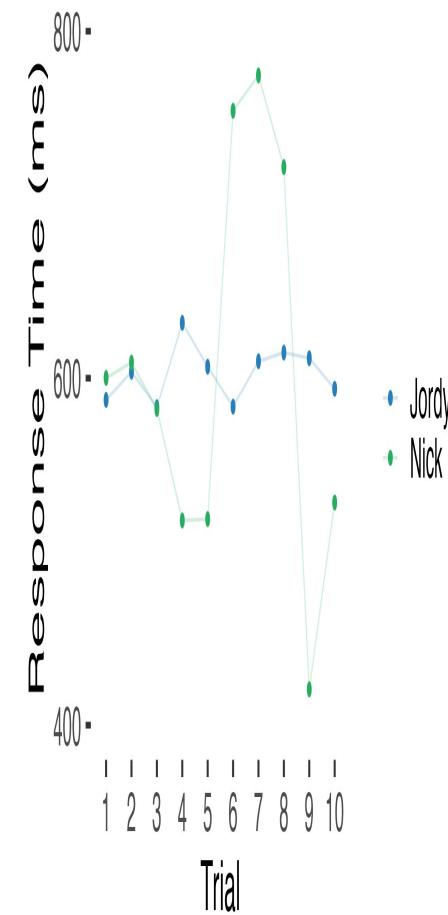
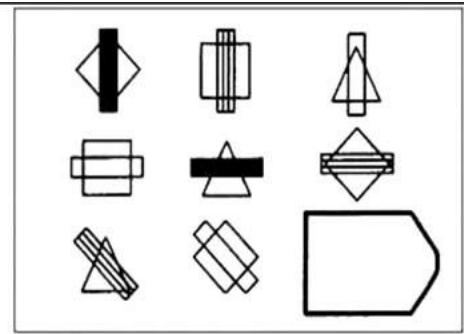
Legend:

- Jessica (Blue)
- Nick (Green)
- George (Pink)

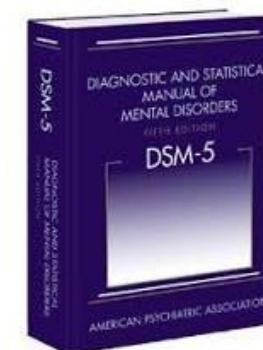




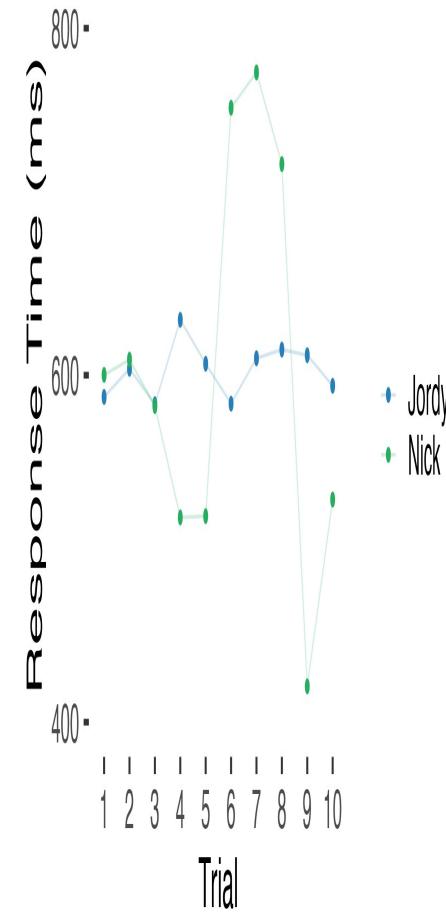
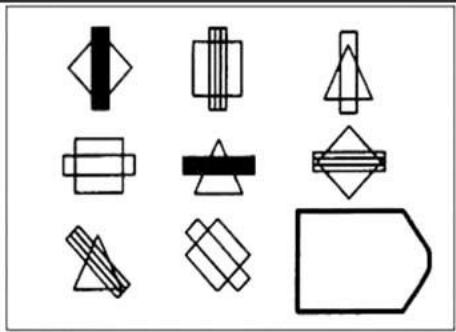
$$\sum_{i=1}^n$$



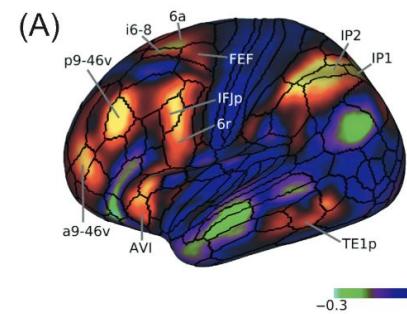
- Interindividual Differences in Mean Performance
 - 1. Clinical/Educational/occupational contexts



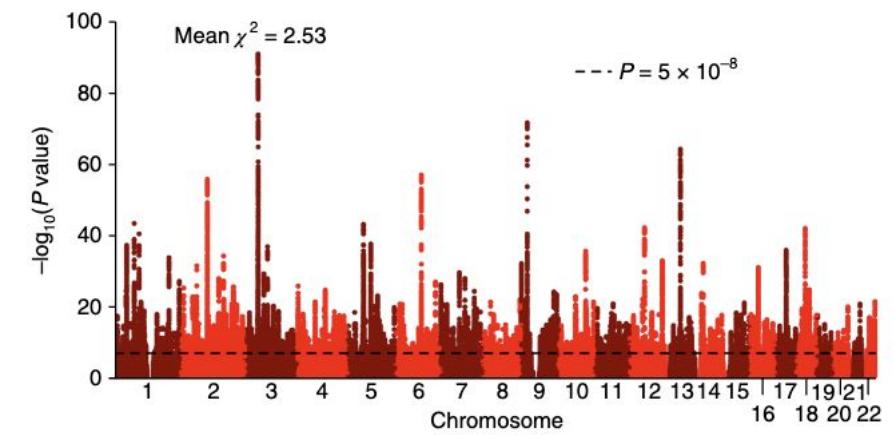
$$\sum_{i=1}^n$$



Duncan et al., 2020

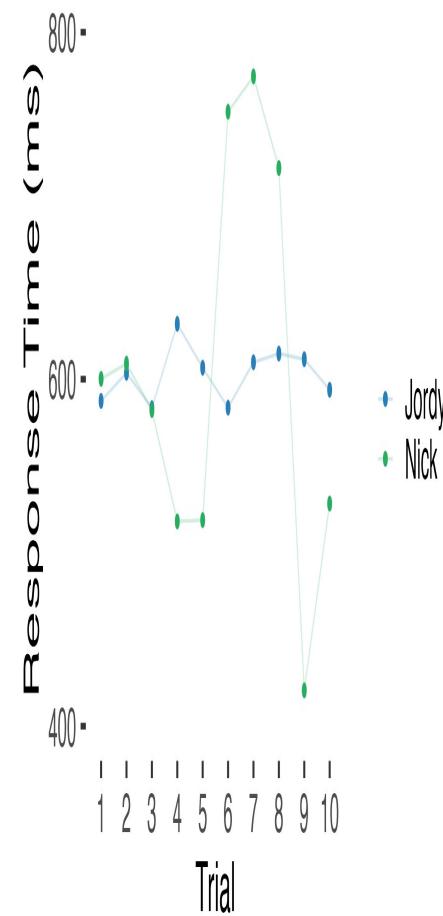
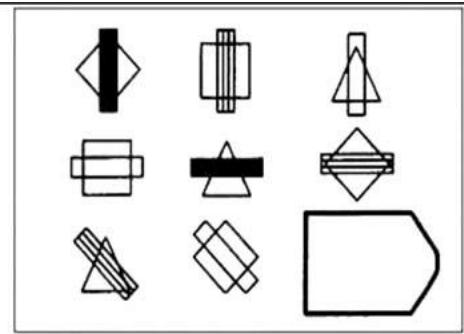


- Interindividual Differences in Mean Performance
 1. Clinical/Educational/occupational contexts
 2. Neural and genetic mechanisms

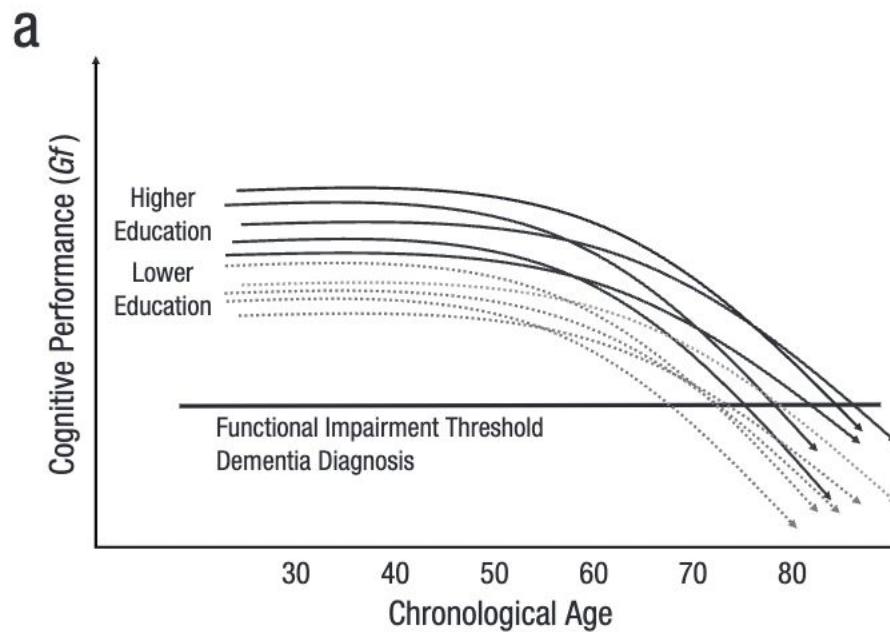


Lee et al., 2018

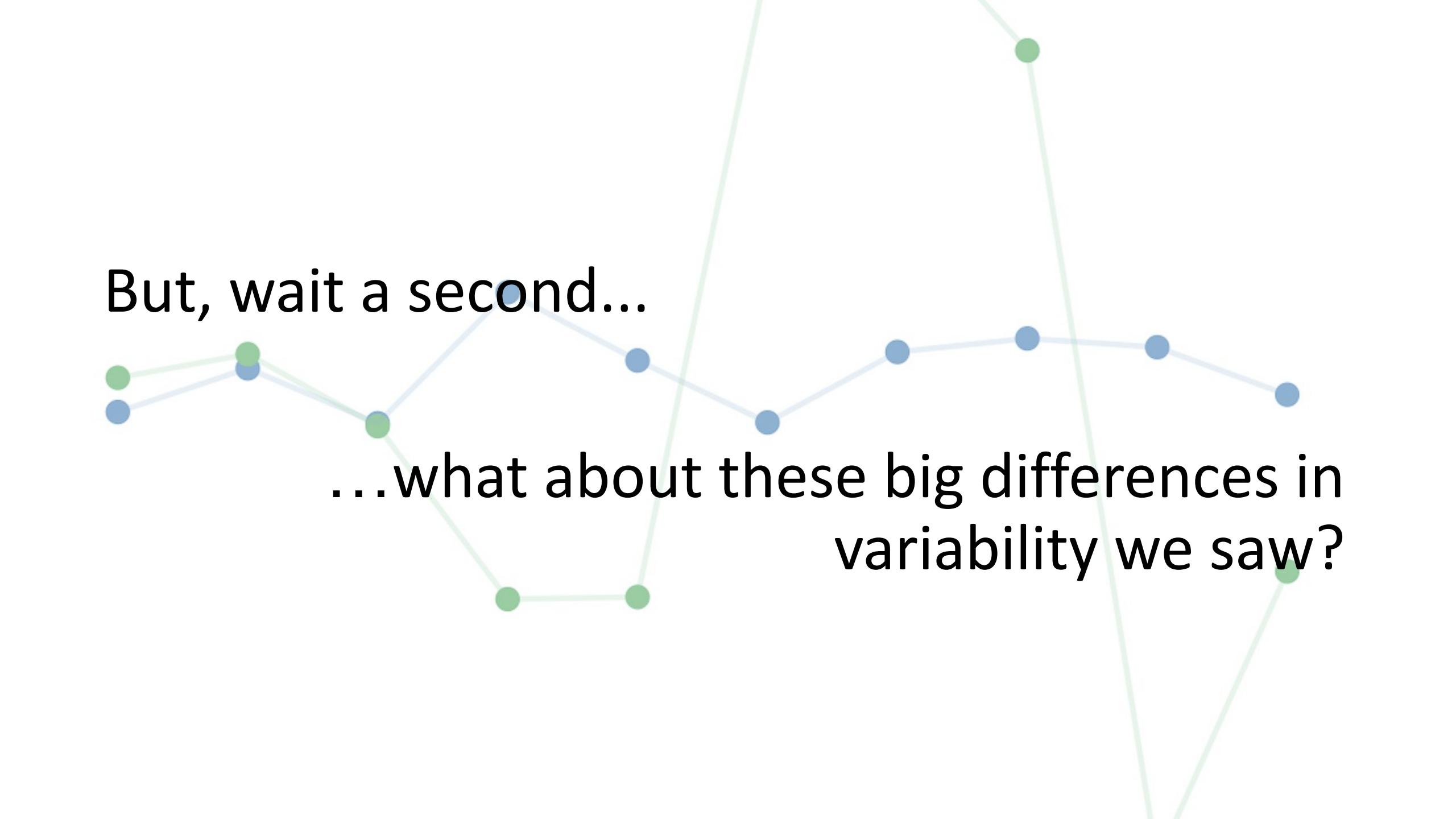
$$\sum_{i=1}^n$$



- Interindividual Differences in Mean Performance
 1. Clinical/Educational/occupational contexts
 2. Neural and genetic mechanisms
 3. Positively predicts important outcomes



Tucker-Drob 2019



But, wait a second...

...what about these big differences in
variability we saw?

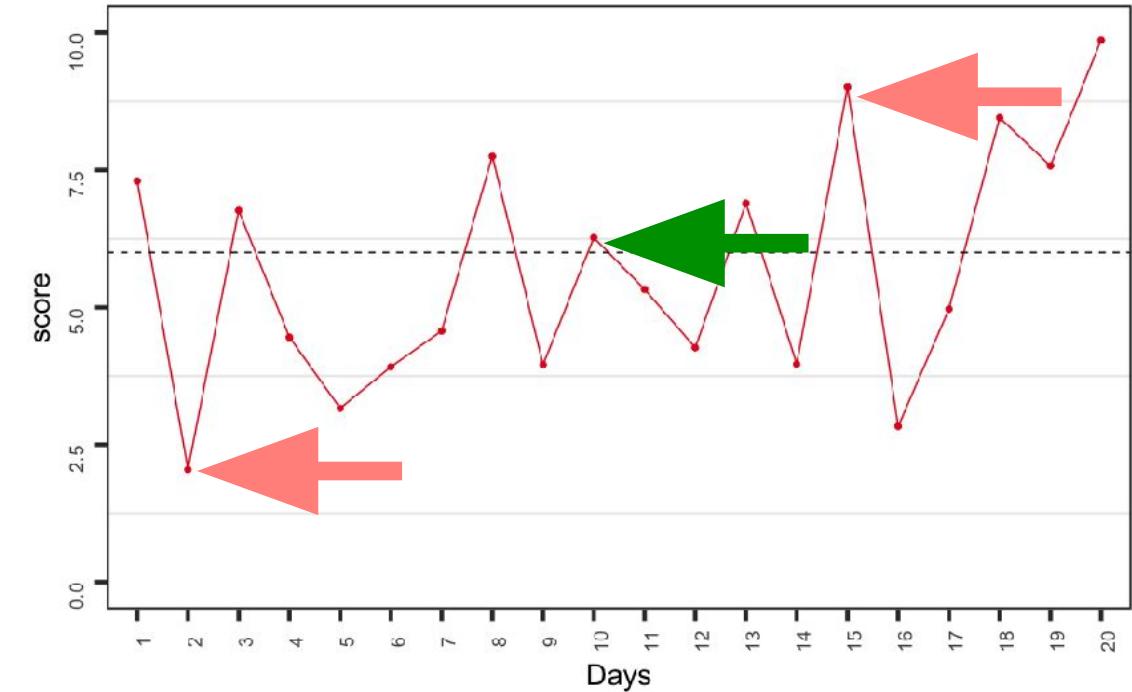
But, wait a second...

...what about these big differences in variability we saw?

And are they meaningful...?

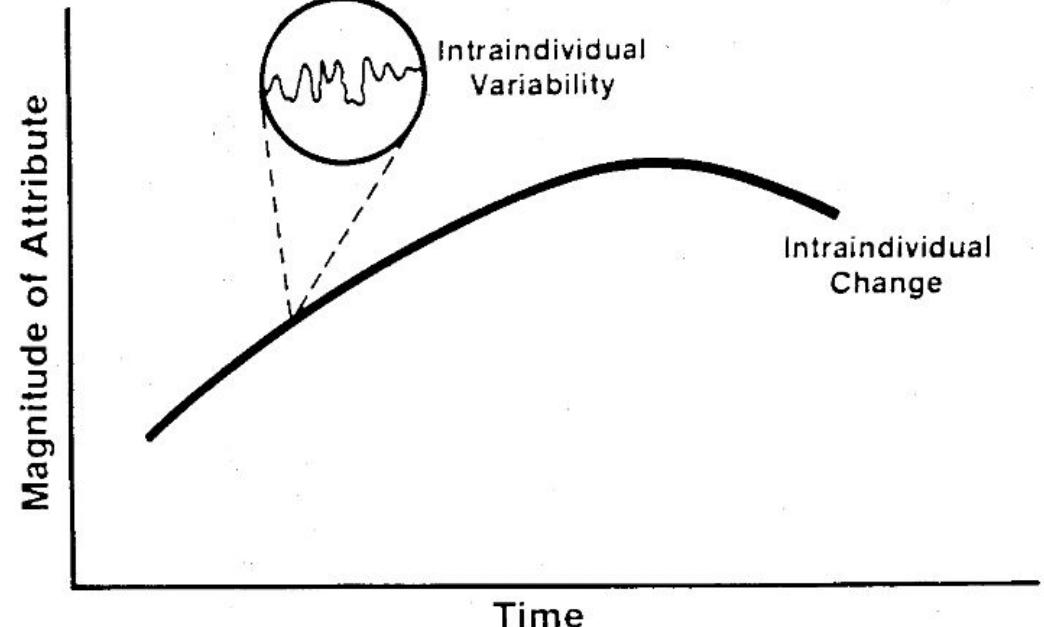
Why is variability important?

- A neglected source of individual differences
- Variability can lead to mis-stratification with lifelong consequences
- Variability is likely a sensitive, early marker of atypical development



Why is variability important?

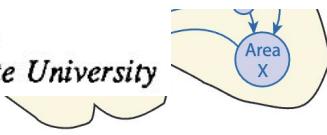
- An urgent need to better understand *adaptive* versus *maladaptive* variability
- Crucial function in learning
 - Songbirds
 - Humans (Wu et al., 2013)



The Warp and the Woof of the Developmental Fabric

John R. Nesselroade
The Pennsylvania State University

respiratory muscles



general, much less variability in behavior than do organisms. Indeed, variability, inconsistency, and specific unpredictability of behavior have long been recognized as the chief molar distinctions between organisms and inorganic machines. Clearly a character-



Patterns of Change: Measurement in Relation to State-Dimension, Trait Change, Lability, and Process Concepts

RAYMOND B. CATTELL
University of Illinois

FINAL REPORT

SHORT PERIOD FLUCTUATIONS IN INTELLIGENCE

"unity" and what is meant by "functional". The results illustrated how fluid intelligence (as well as other attributes of intellectual test behavior) varies functionally within persons and also represents a stable pattern of performances that distinguishes one person from another. This kind of finding could have considerable value in several fields of psychology.

Fiske & Rice, 1955

INTRA-INDIVIDUAL RESPONSE VARIABILITY¹

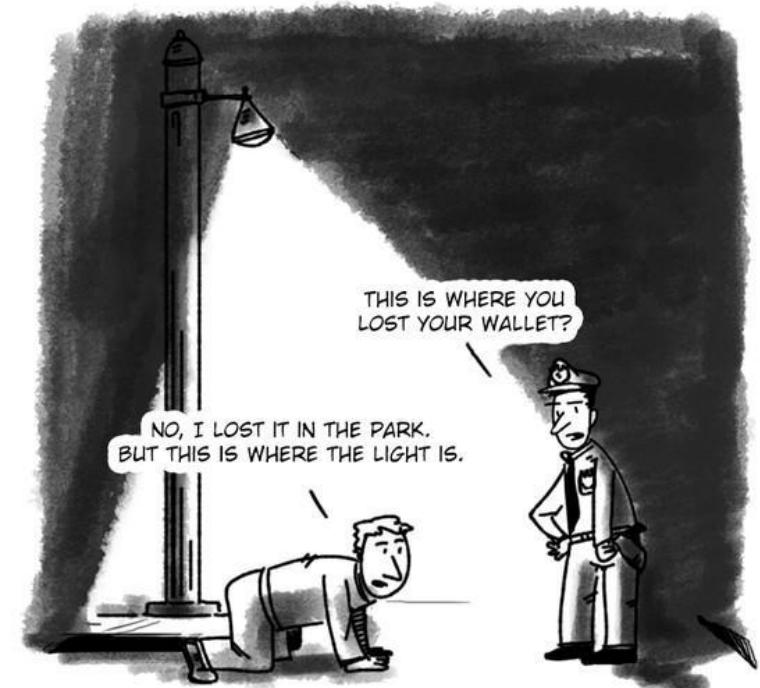
DONALD W. FISKE AND LAURA RICE^{2,3}

University of Chicago

The problem of intra-individual variability has not been subjected to systematic conceptualization.

Why has variability ignored?

1. Limits in data
2. Limits on quantification



Why has variability ignored?

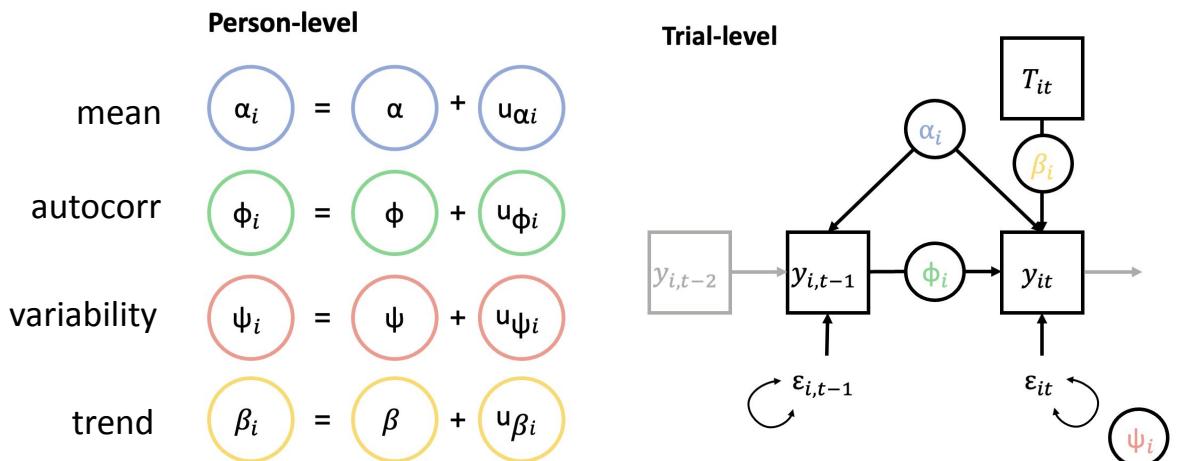
1. Limits in data

- Dense, time series data



2. Limits on quantification

- Novel modeling techniques
(Dynamic SEM)



McNeish & Hamaker, 2020

Aims:

3 fundamental properties of cognitive variability

1. Ubiquity

do we find cognitive variability in each task?

2. Structure

how are individual differences in variability across tasks related?

3. Discrimination

is variability a distinct concept from mean performance?





Judd & Klingberg, 2021

Methods – Sample

- A math training app
- 6-8 year old children (n = 2608)
- 11 tasks with 7,204,127 trials

Mathematics (~50%)	Working Memory (~20%)
Rotation (~20%)	Non-verbal reasoning (~10%)

Methods – Sample

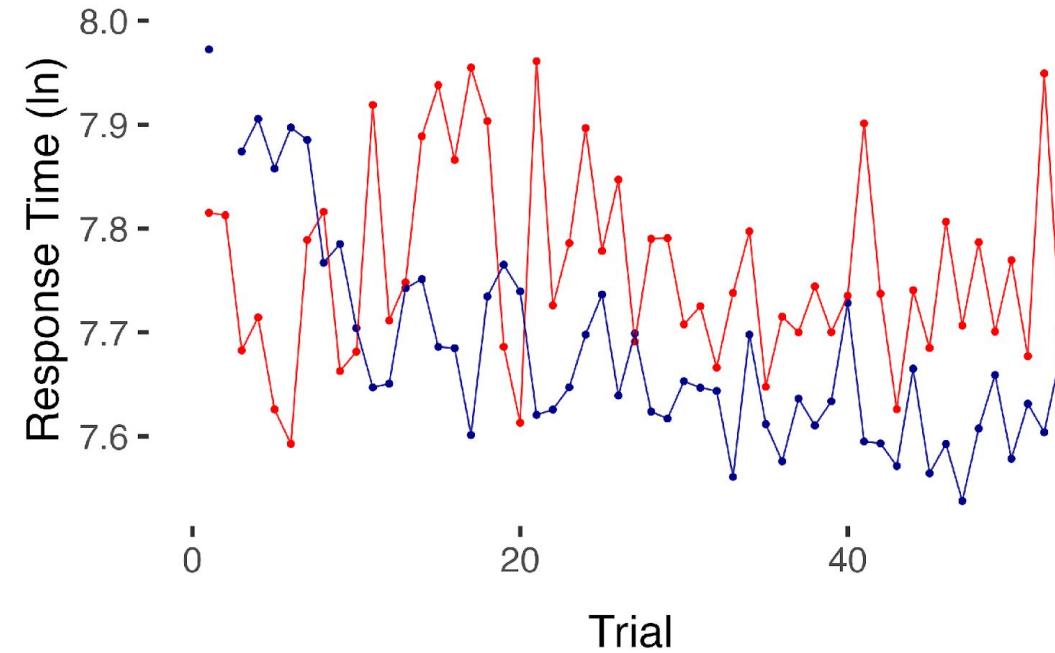
Mathematics (~50%)	Working Memory (~20%)
Rotation (~20%)	Non-verbal reasoning (~10%)

“tangram”

Methods – Sample

- Cognitive Variability = Response time of correct trials
- Mean performance = Average level of a child

$$\psi_i = \psi + u\psi_i$$



Results – Ubiquity

- Model fit comparison (dDIC)
- Found meaningful inter-individual differences in intra-individual variability across all 11 tasks

Model 1 (full model)

$$\alpha_i = \alpha + u_{\alpha i}$$

$$\phi_i = \phi + u_{\phi i}$$

$$\psi_i = \psi + u_{\psi i}$$

$$\beta_i = \beta + u_{\beta i}$$



Model 2 (no variability parameter)

$$\alpha_i = \alpha + u_{\alpha i}$$

$$\phi_i = \phi + u_{\phi i}$$

$$\psi_i = \psi + \text{no } u_{\psi i}$$

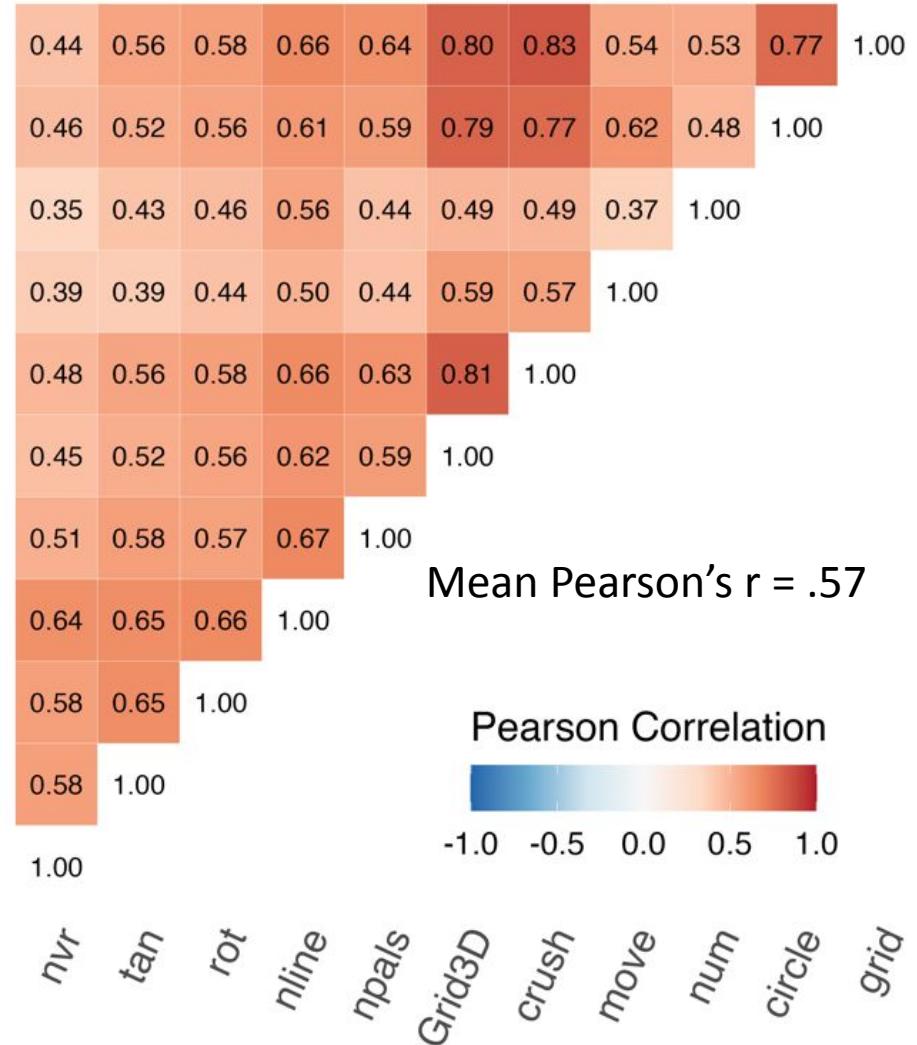
$$\beta_i = \beta + u_{\beta i}$$



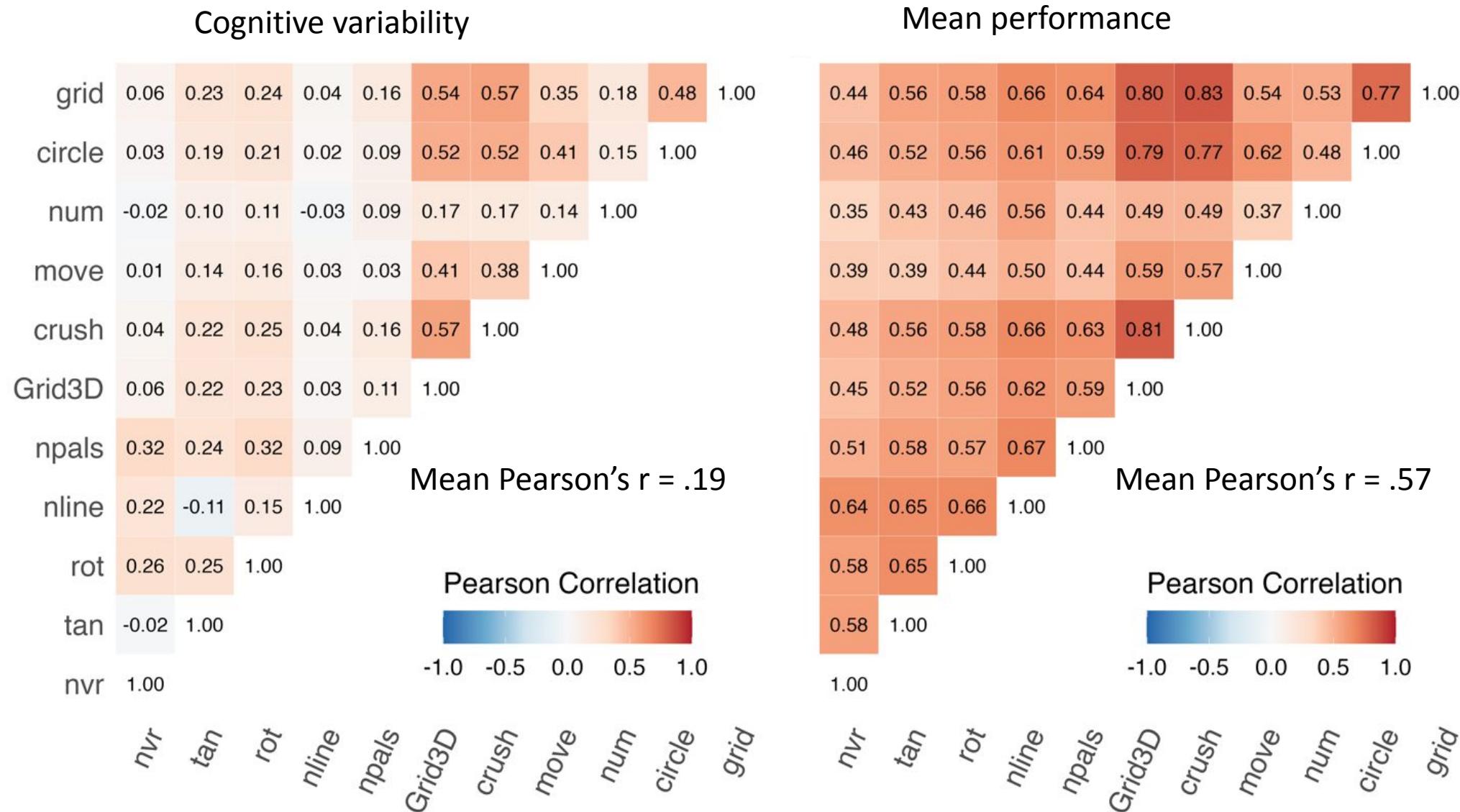
Results – Structure

Cognitive variability

Mean performance

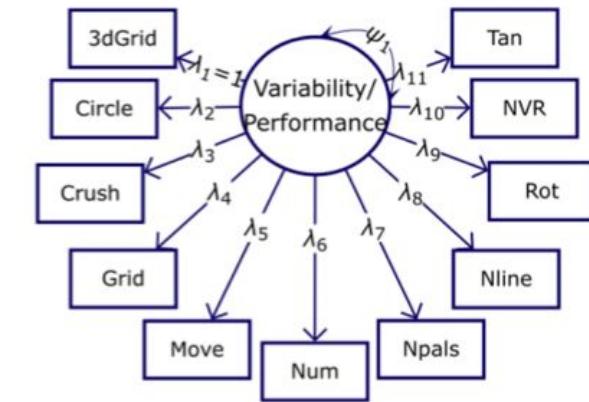


Results – Structure



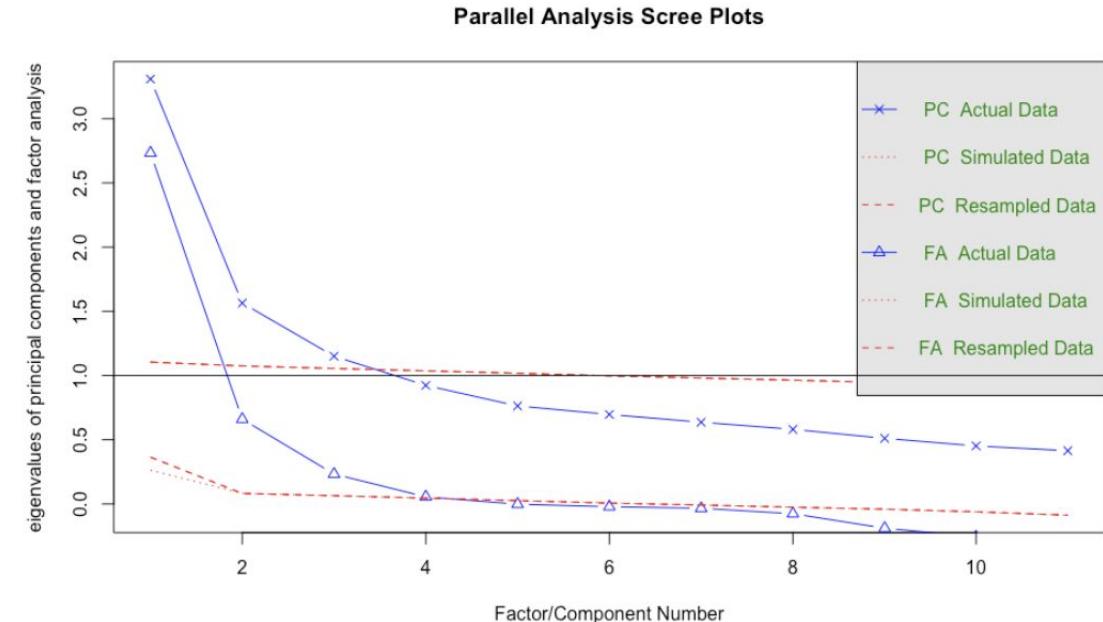
Results – Structure

- We used confirmatory factor analysis
- None of our *a priori* models fit variability well



Shifted to an exploratory factor analysis

- 3-factor solution

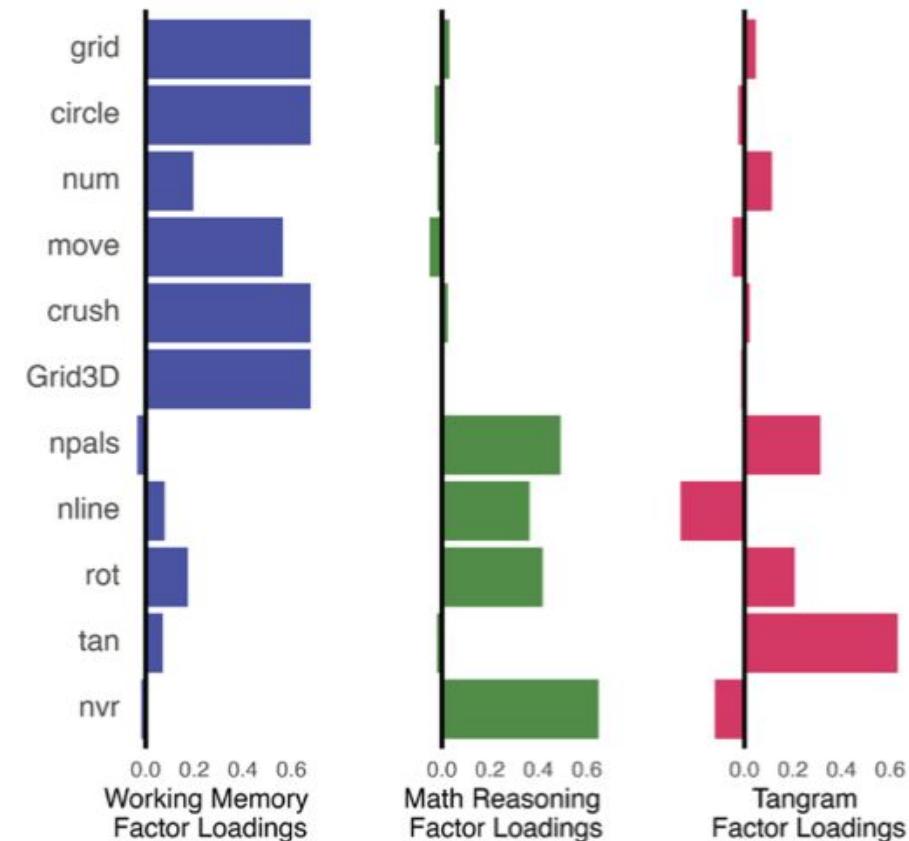


Results – Structure

- We used confirmatory factor analysis
- None of our *a priori* models fit variability well

Shifted to an exploratory factor analysis

- 3-factor solution
 1. Working memory (22%)
 2. Math-reasoning (9%)
 3. Tangram (6%)



Results – Discrimination

- Unique from mean performance
 1. The within-task DSEM parameters

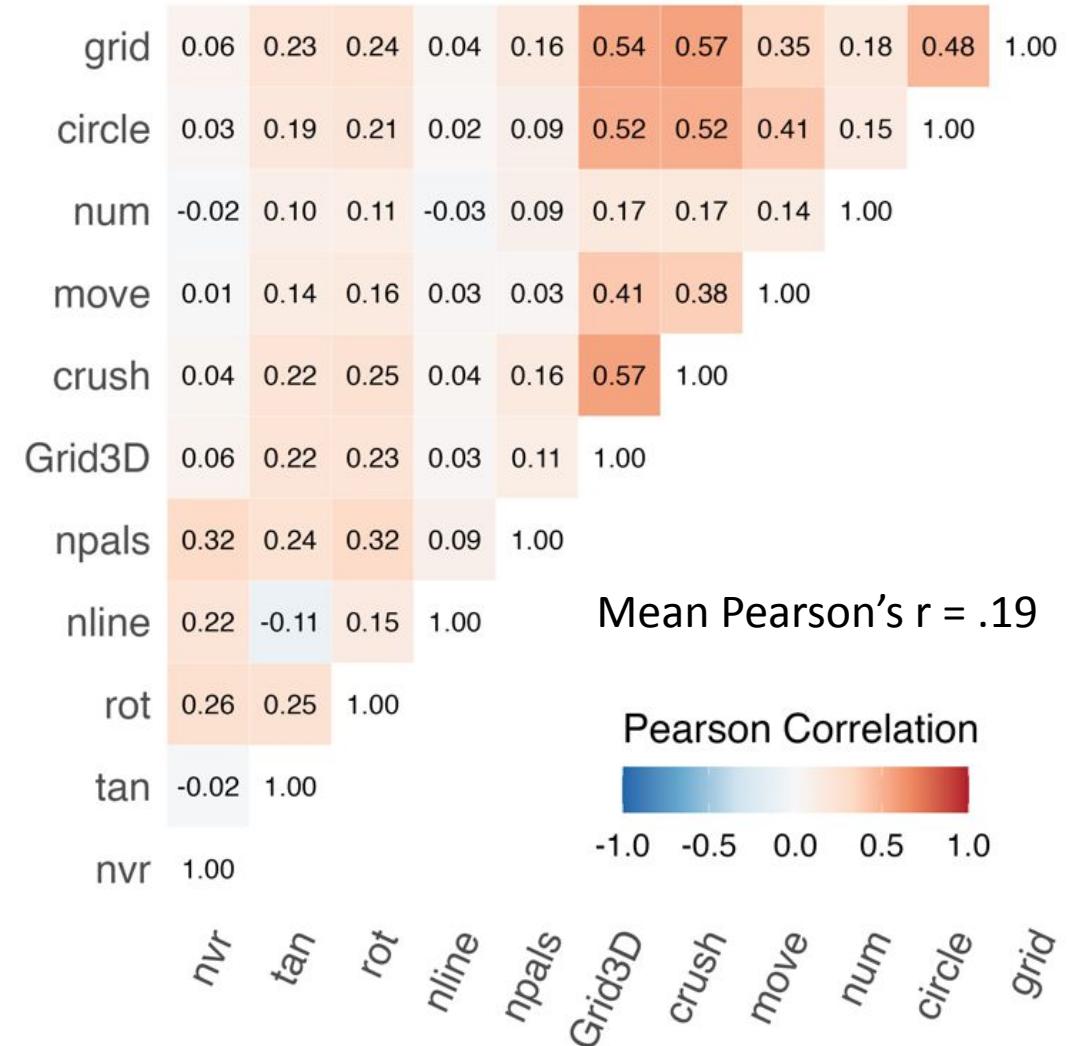
Person-level

$$\begin{array}{l} \text{mean} \quad \alpha_i = \alpha + u_{\alpha i} \\ \text{phi} \quad \phi_i = \phi + u_{\phi i} \\ \text{var} \quad \psi_i = \psi + u_{\psi i} \\ \text{trend} \quad \psi_i = \psi + u_{\psi i} \end{array}$$



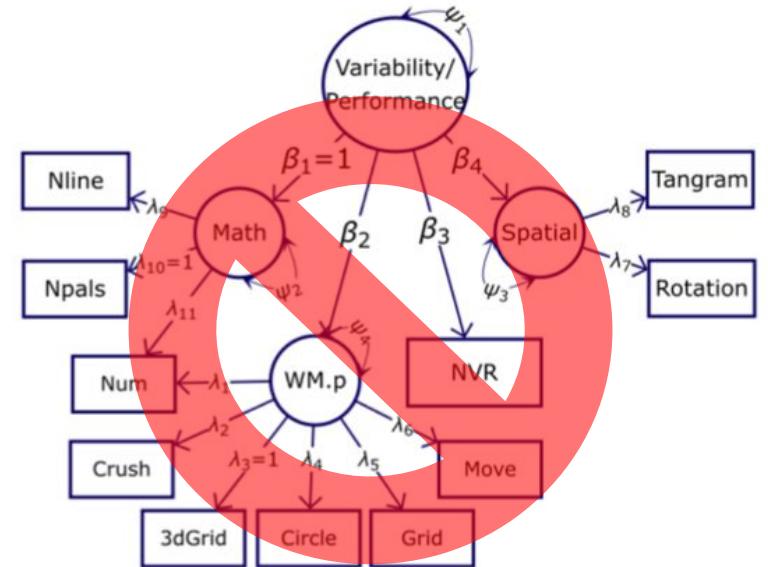
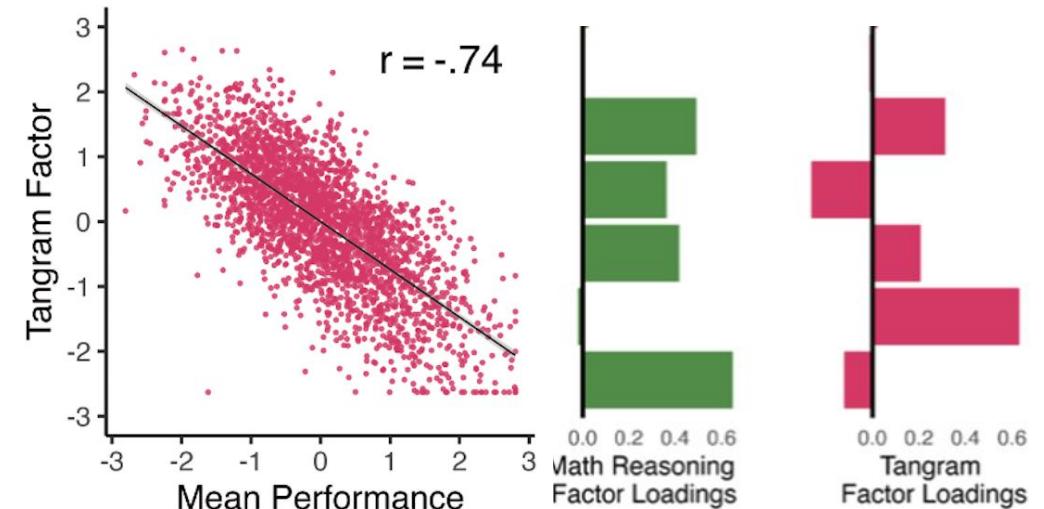
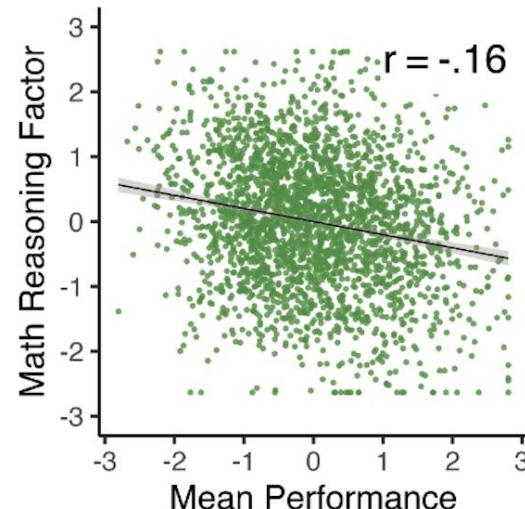
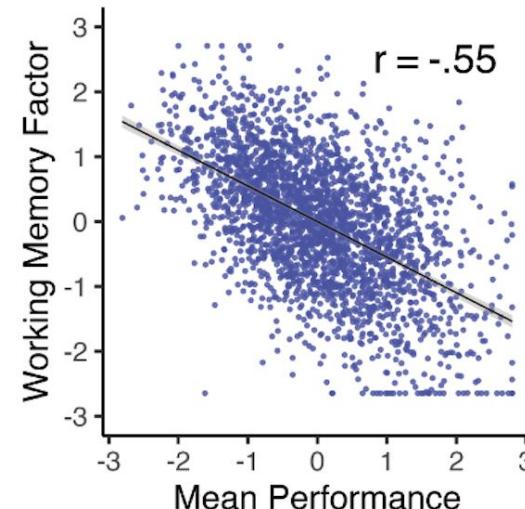
Results – Discrimination

- Unique from mean performance
 1. The within-task DSEM parameters
 2. Weak correlations across tasks



Results – Discrimination

- Unique from mean performance
 1. The within-task DSEM parameters
 2. Weak correlations across tasks
 3. Factor structure
 4. EFA correlations with mean performance

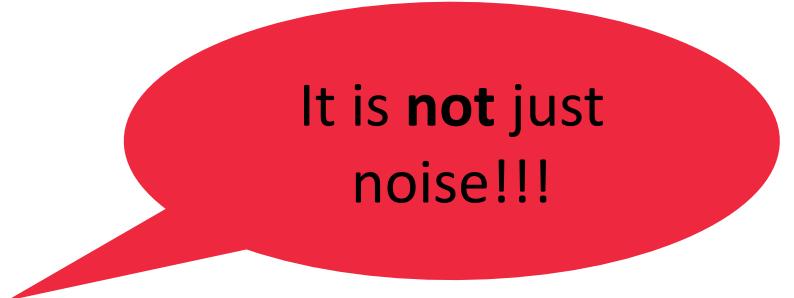


Take home messages

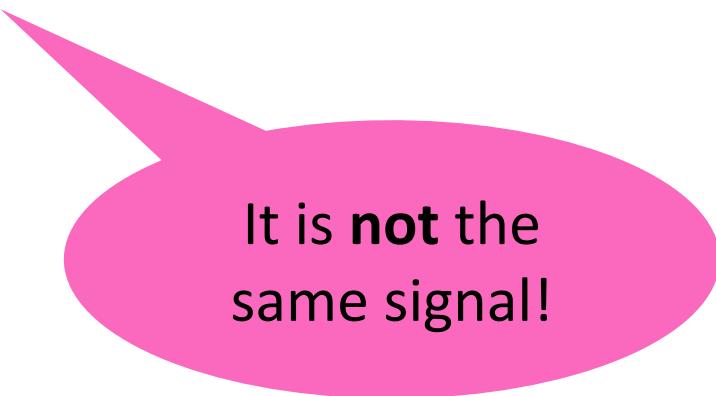
1. There is *meaningful* interindividual variability across all tasks studied
2. Cognitive variability has a unique structure
3. Distinct from mean performance

Take home messages

1. There is *meaningful* interindividual variability across all tasks studied
2. Cognitive variability has a unique structure
3. Distinct from mean performance



It is **not** just noise!!!



It is **not** the same signal!

Take home messages

Interindividual Differences
in Cognitive Variability Are
Ubiquitous and Distinct
From Mean Performance in
a Battery of Eleven Tasks

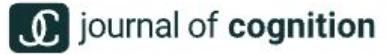
1. There is *meaningful* interindividual variability across all tasks studied
 2. Cognitive variability has a unique structure
 3. Distinct from mean performance
-
- We are very limited in our ability to figure out exactly *what* these task-specific factors are
 - Specific age range with swedish sample

NICHOLAS JUDD 

MICHAEL ARISTODEMOU 

TORKEL KLINGBERG 

ROGIER KIEVIT 

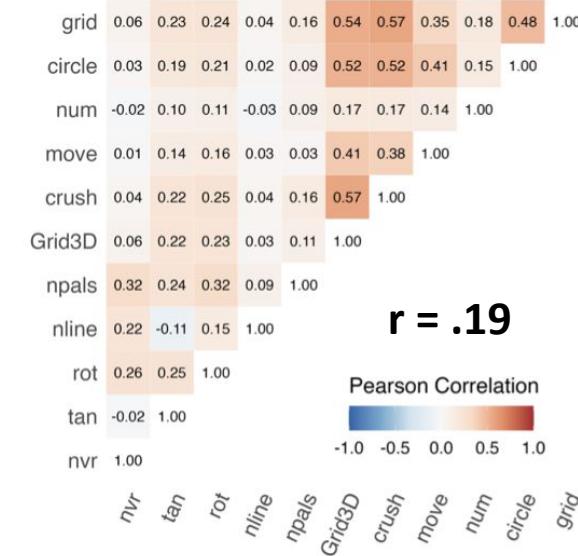


Future – Avenues

- Potentially a phenotypically differentiating tool
- Identifying influences of global and task-specific causes
- How the mean relates to variability
 - Learning processes
 - Explore vs Exploit

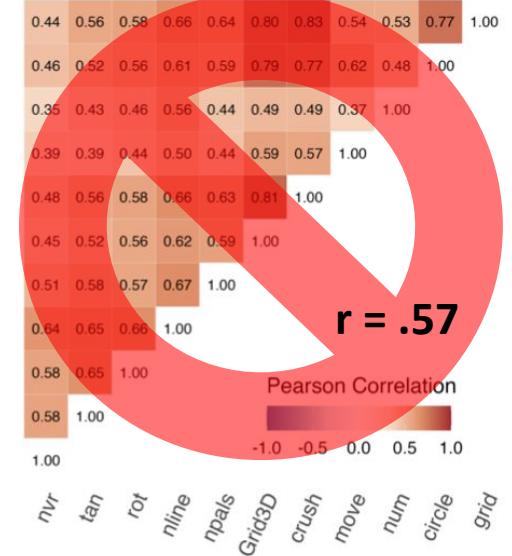


Variability



$r = .19$

Mean

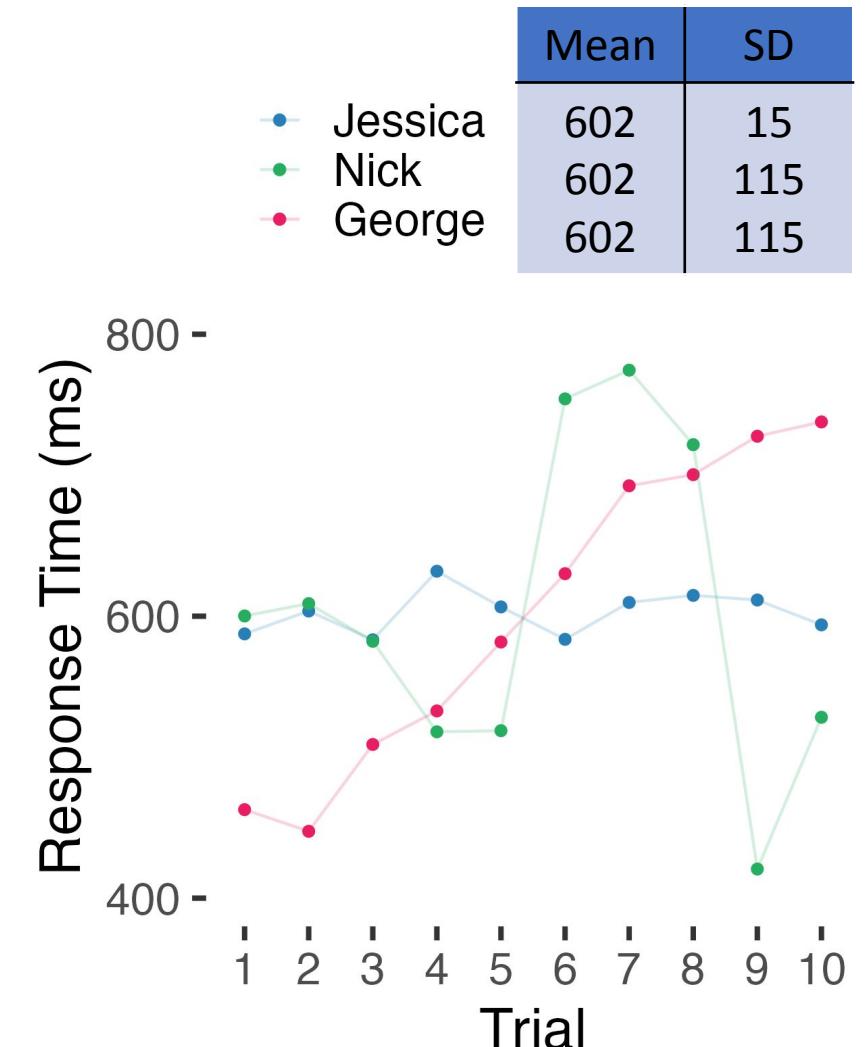


$r = .57$

why psychometrics is important to me

- Bridge from theory to estimand
- It gets us closer to what we want to measure
- Which gets us a *bit closer* to ‘the truth’

It is a fundamental way to make
your empirical science better.



Thank you for your attention

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<https://njudd.com/cognitive-fluctuations/>

<https://lifespancognitivedynamics.com>



Rogier
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Eleni
Zimianiti

Michael
Aristodemou

Lea
Michel

Sam Parsons

Nick Judd

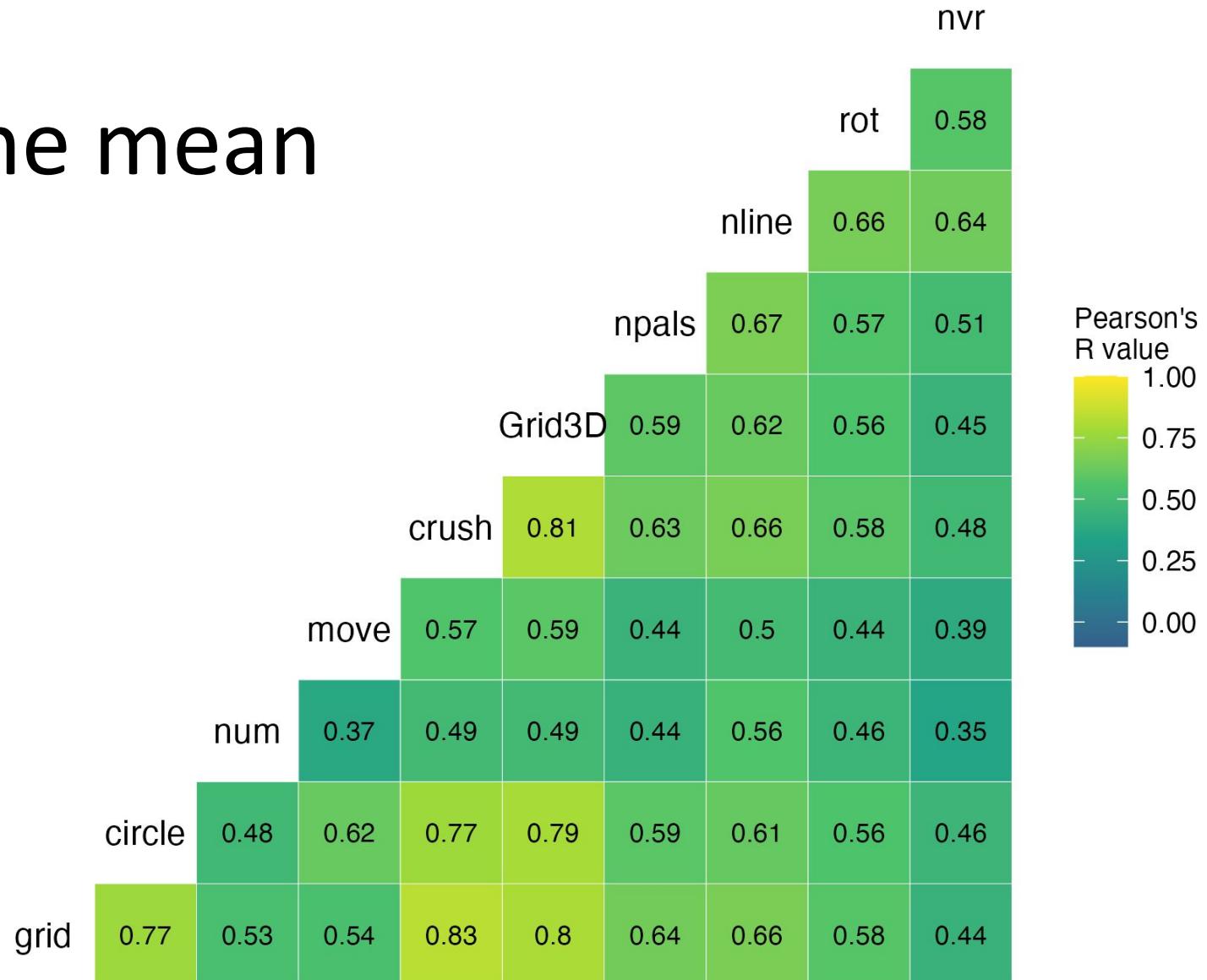
Emma
Meeussen

Sophie
Hofman

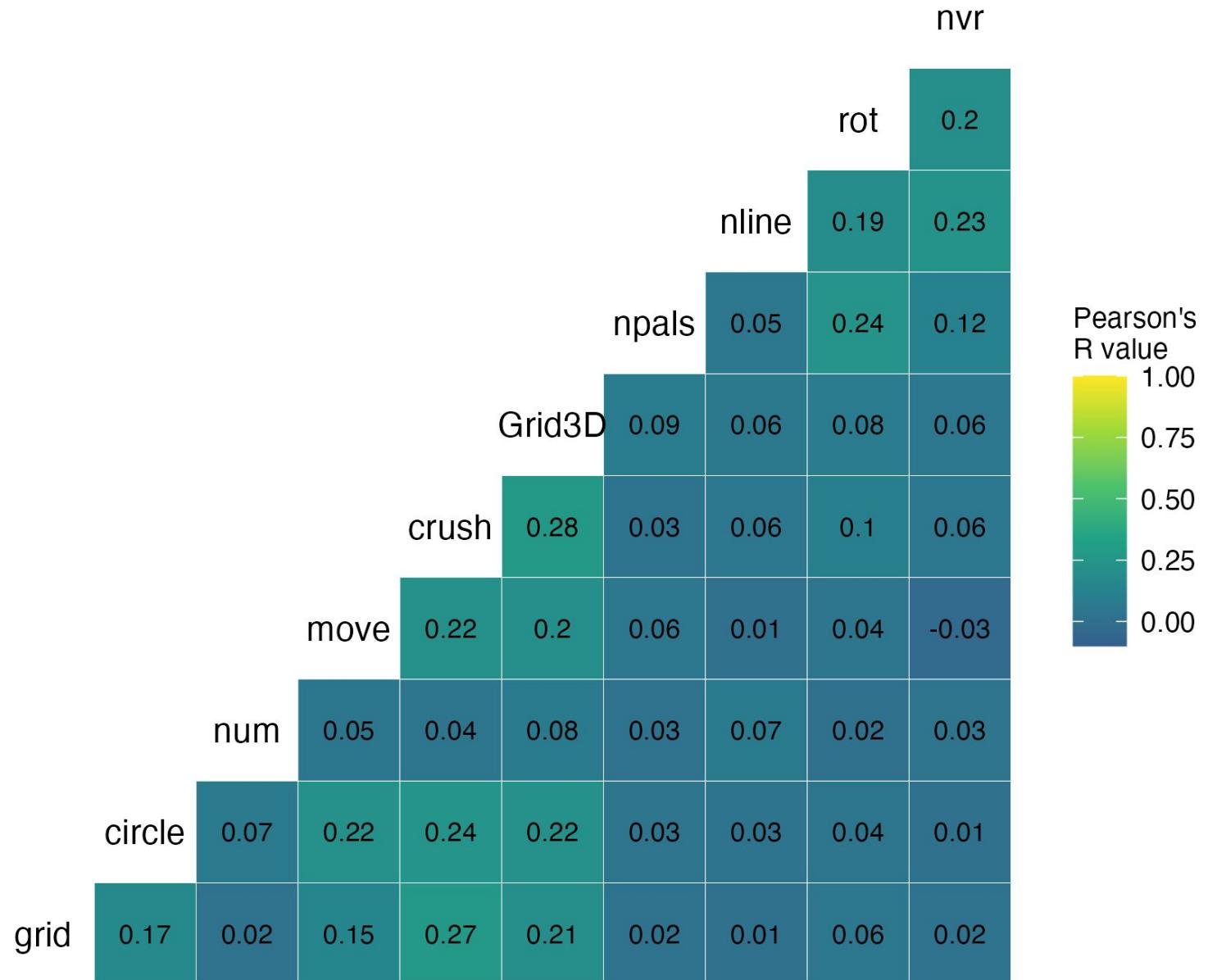
Bonus slides

Performance Correlations

Response time mean



RT Inertia Correlations



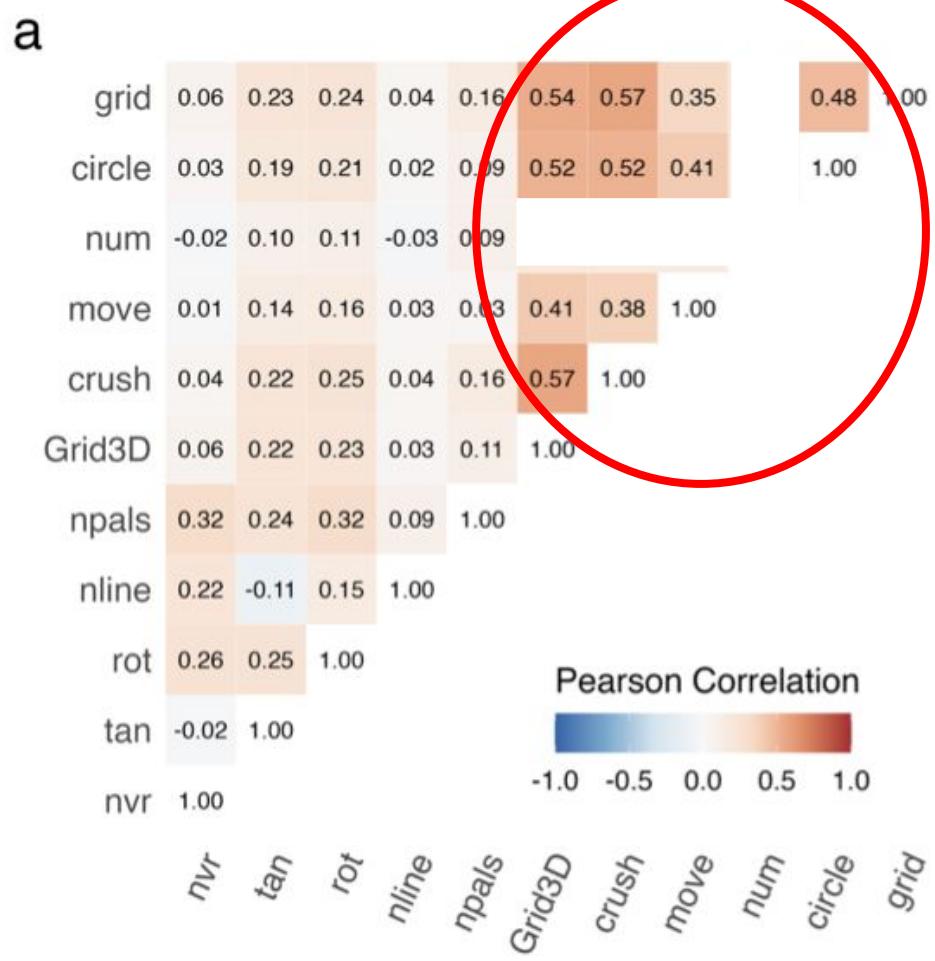
Reliability

- The variability parameter was also reliable within tasks (>.9)

Supplementary Table 2: Trial variance reliability estimations.

Task	# subs	# Trials	Avg # trials	tv_rel.5	tv_rel.7	tv_rel.9
WM_3dgrid (3DGrid)	2608	203738	78.12	0.981	0.988	0.992
WM_circle (circle)	2608	155878	59.77	0.978	0.986	0.99
WM_crush (crush)	2608	243511	93.37	0.985	0.991	0.995
WM_grid (grid)	2608	430708	165.15	0.99	0.994	0.996
WM_moving (move)	2569	85640	33.34	0.971	0.98	0.986
WM_numbers (num)	2591	98300	37.94	0.952	0.972	0.984
Npals	2608	2398463	919.66	0.961	0.981	0.992
Numberline (nline)	2608	1833909	703.19	0.933	0.966	0.981
Non-verbal reasoning (nvr)	2608	548101	210.16	0.761	0.865	0.917
Rotation (rot)	2608	1032751	395.99	0.929	0.964	0.983
Tangram (tan)	2608	173128	66.38	0.593	0.76	0.858

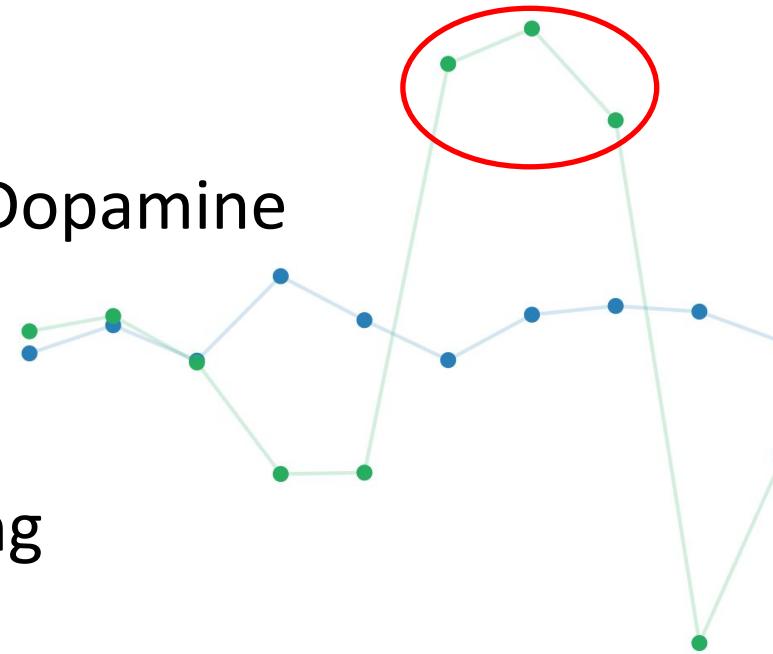
(Du & Wang, 2018)



What causes of variability?

Global causes

- (in)Attention
- Norepinephrine/Dopamine
- Fatigue
- Affect
- Sensory processing



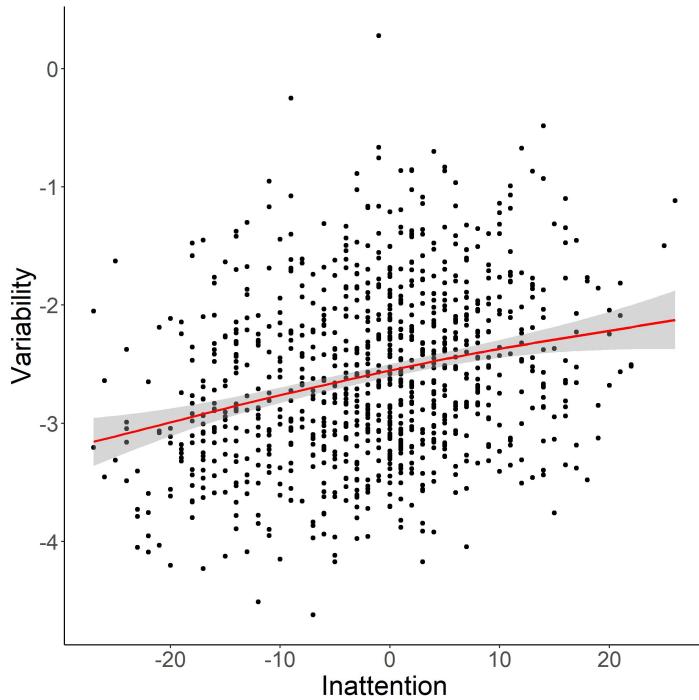
Local causes

- Differential strategies
- Task expertise

(in)Attention



- Increased frequency of lapses
- RT variability is a marker for ADHD
 - Hyperactivity
 - Inattention
- Variability was found to be predictive of inattention symptoms yet *not* hyperactivity ($n = 1121$ children)
- Attentiveness was found to modulate variability

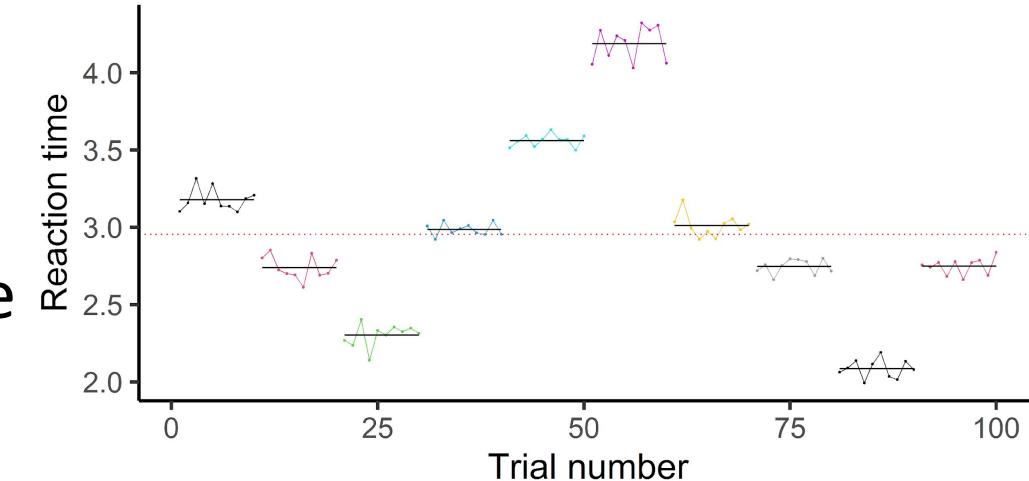


Kofler *et. al.*, 2013

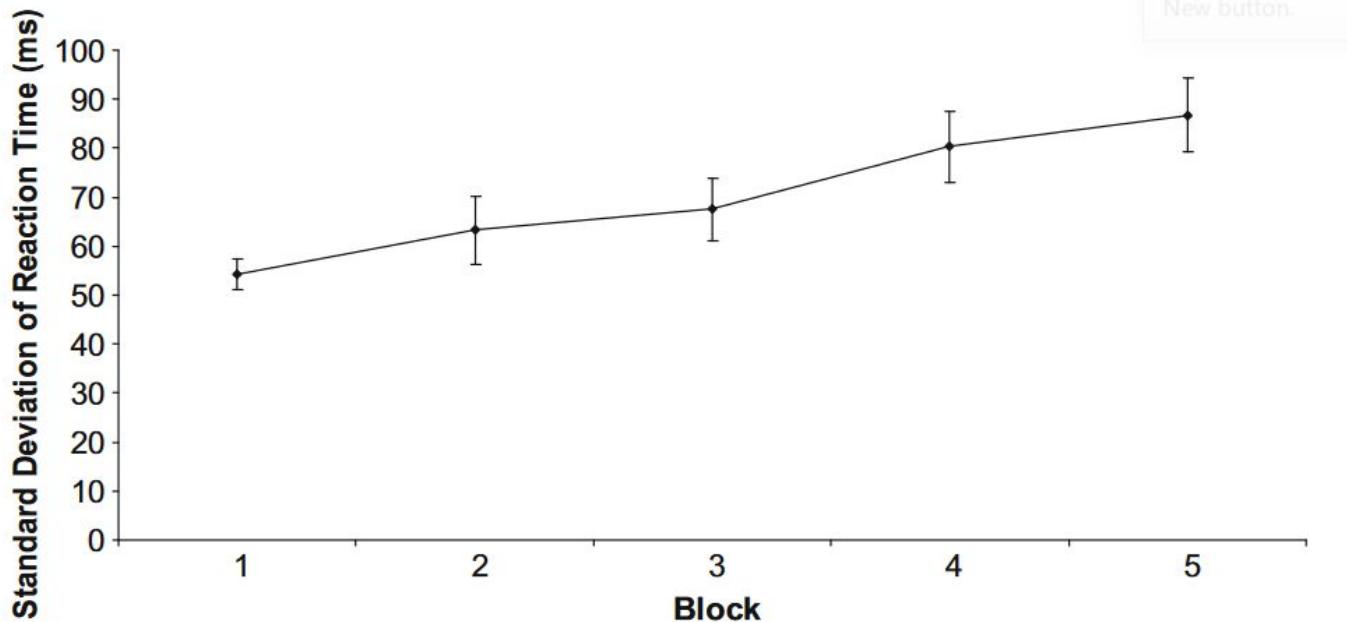
Aristodemou *et. al.*, 2023

Fatigue

- We know sleep deprivation leads to worse cognitive functioning (Bruin et al., 2017)



- Fatigue has been linked to variability
 - Trial level
 - Day level



Unsworth & Robison, 2016
Galeano-Keiner et al., 2021
Könen, Dirk & Schmiedek, 2014

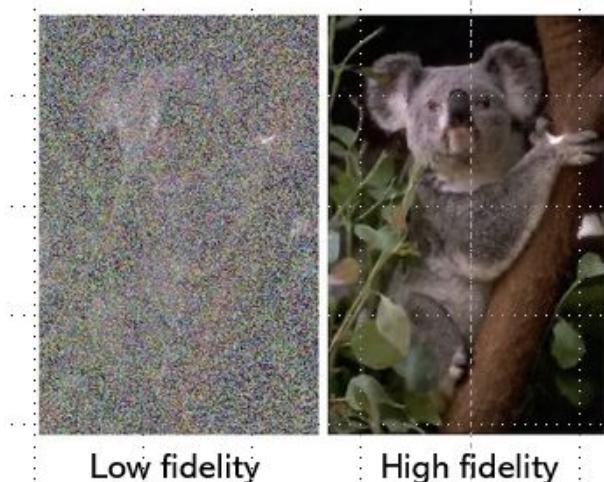
Sensory processing

- Variability in sensory processes could cause interindividual differences in encoding efficiency
- Endogenous neuronal noise (Li, von Oertzen & Lindenberger, 2006)

Neuron

Perspective

Behavior needs neural variability



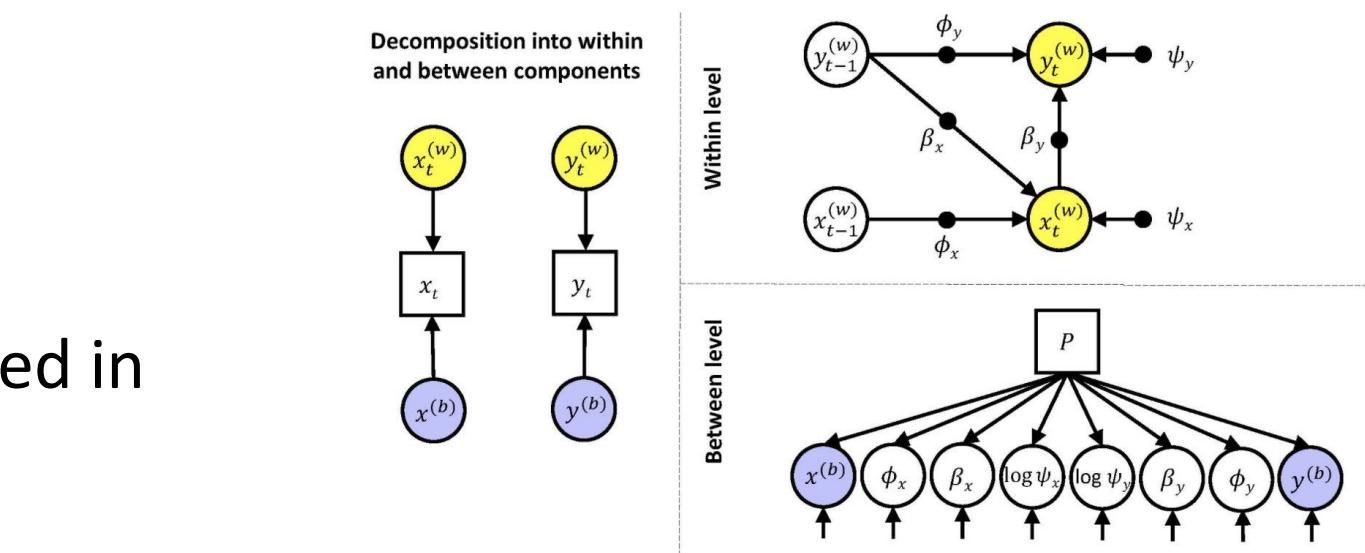
DSEM overview

Dynamic Structural Equation Modelling

- Overcomes many previous limitations
 - Conflation of parameters, convergence challenges
- Combines
 - Time-series analysis ($t > 10/20$)
 - Multilevel modeling (trials nested in days nested in people)
 - Structural equation modeling
 - Variables can be cause/consequence
 - Include latent variables

Multilevel Model 3

In the third multilevel model, we include an observed predictor for the random effects at the between level.



Asparouhov, T., Hamaker, E. L., & Muthén, B. (2018). Dynamic structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, 25(3), 359-388.

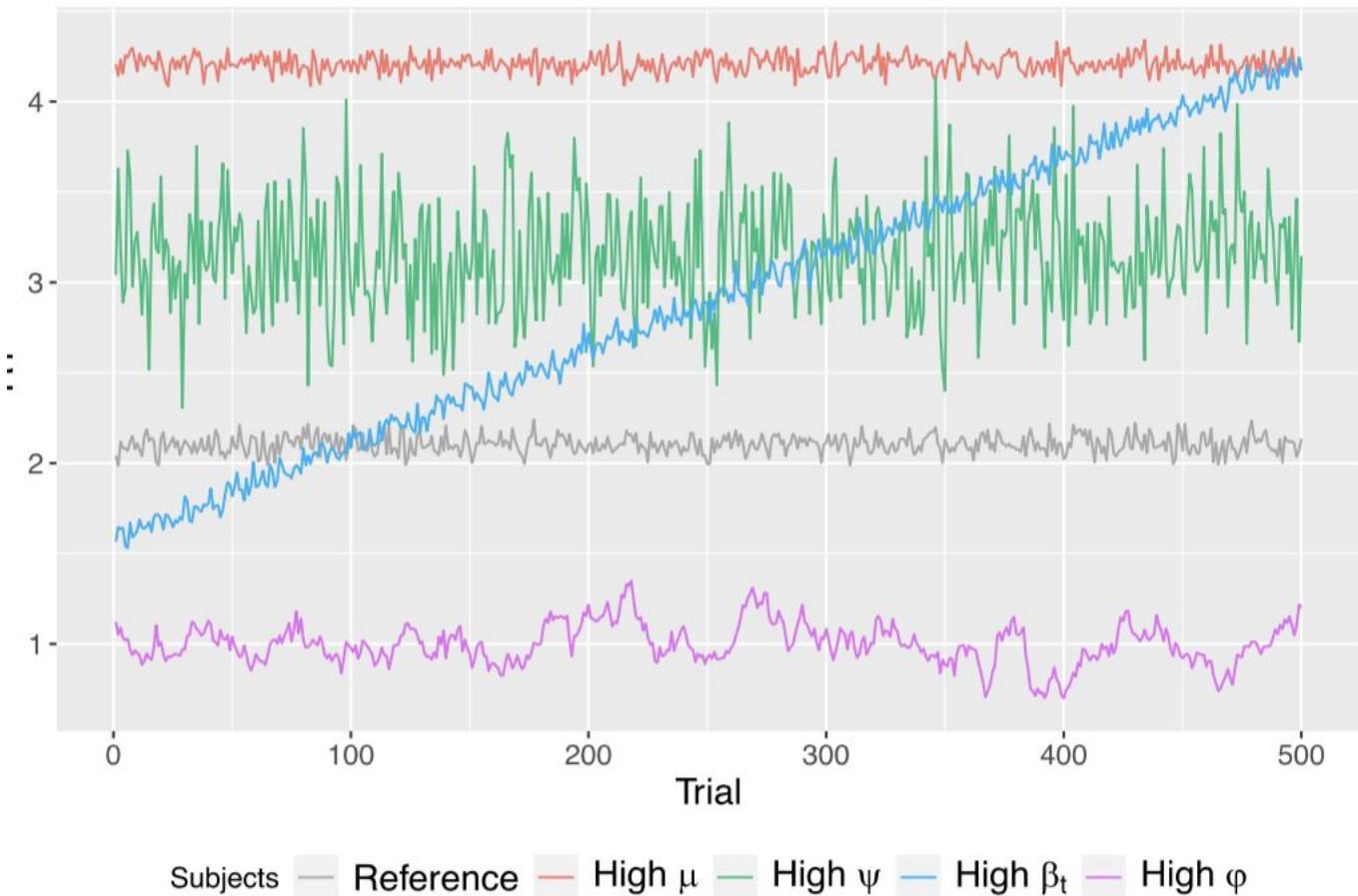
Hamaker, E. L., Asparouhov, T., Brose, A., Schmiedek, F., & Muthén, B. (2018). At the

DSEM in action: Level 1

- (log) reaction time at time t for person i
- A function of
 - Mean (μ_i)
 - Trend (β) (training, growth)
 - Autoregression (φ) (mean reversion)
 - Residual variability (ε_{ti})

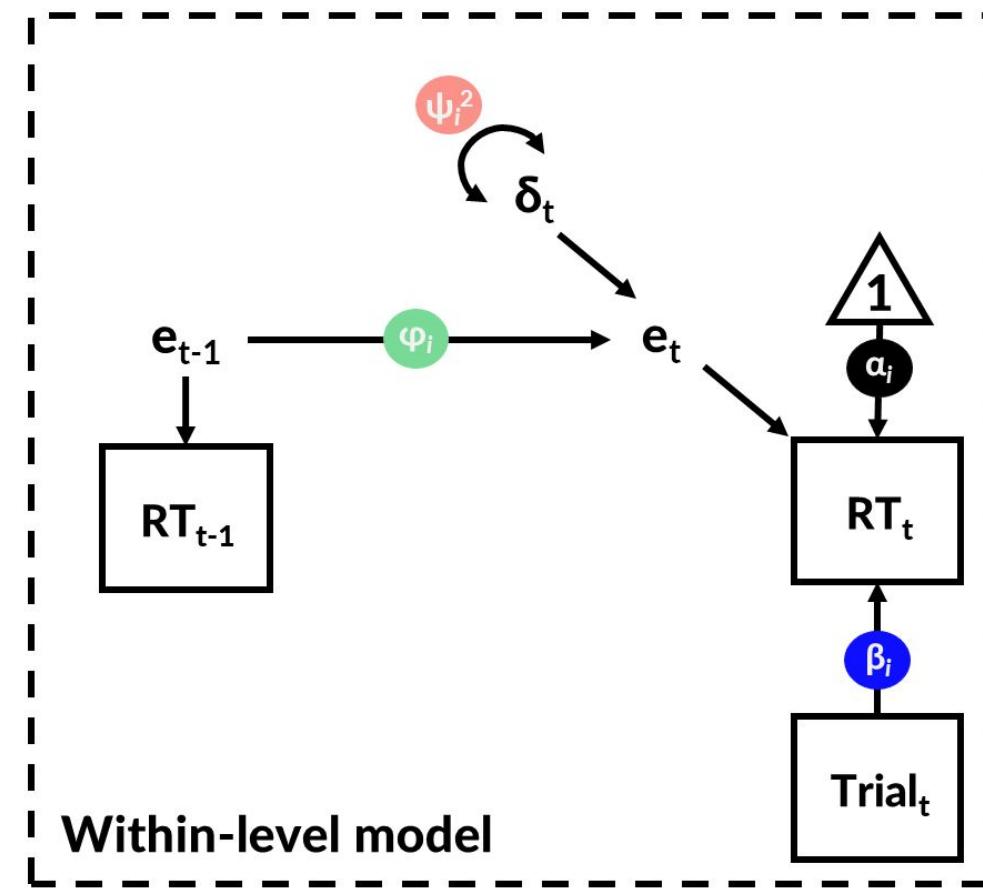
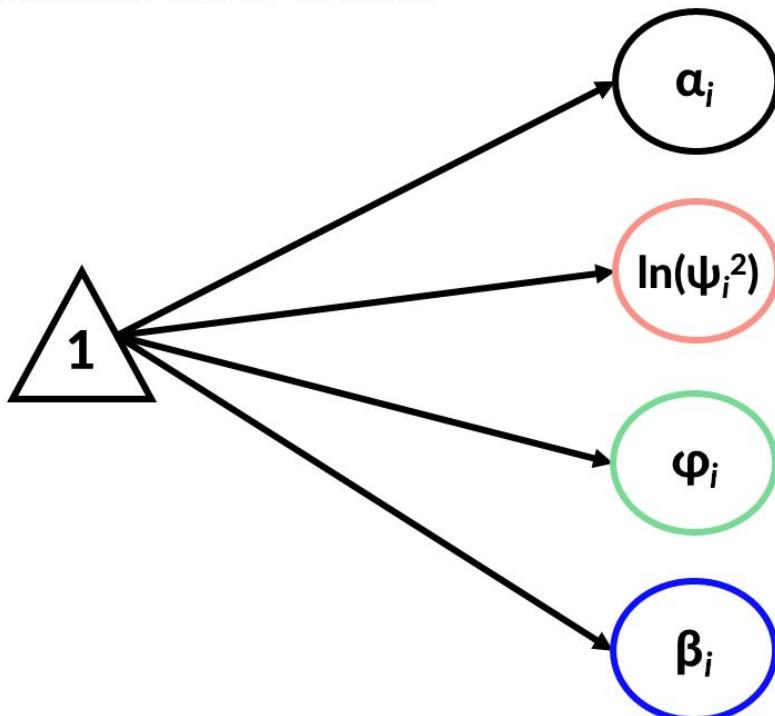
$$\log(RT_{t,i}) = \mu_i + \varphi_i RT_{t-1,i} + \beta_{ti} Trial_{t,i} + \varepsilon_{t,i}$$

$$\varepsilon_{t,i} \sim N(0, \psi_i)$$

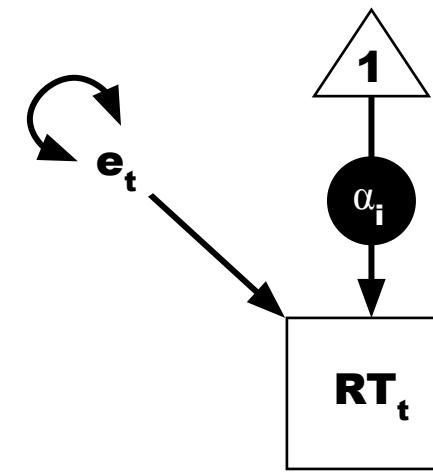
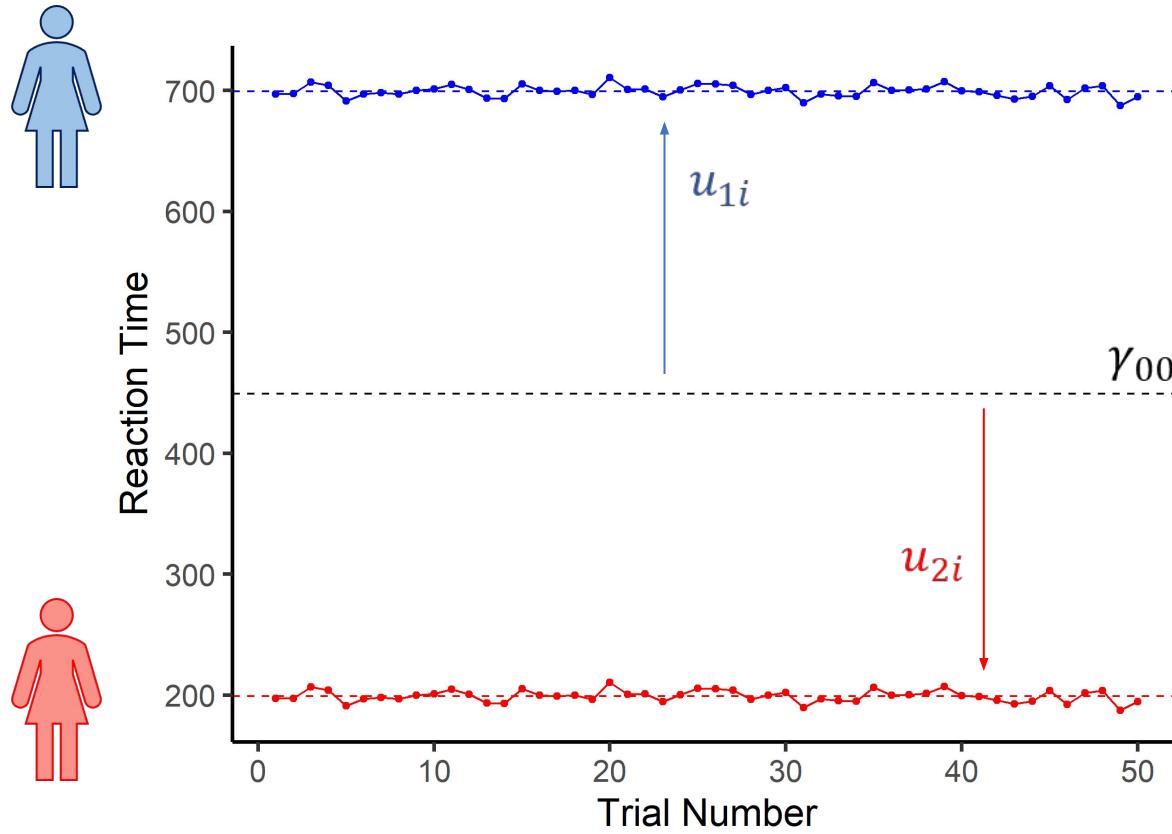


Isolate cognitive fluctuations via DSEM

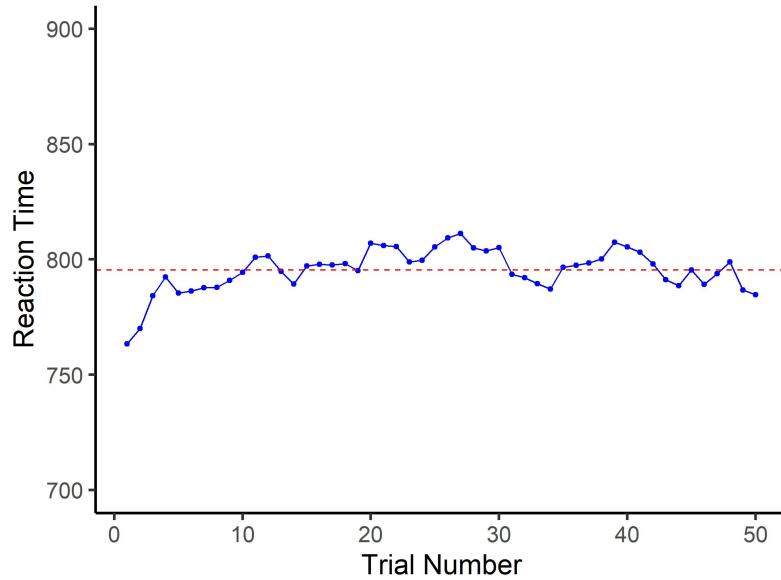
Between-level model



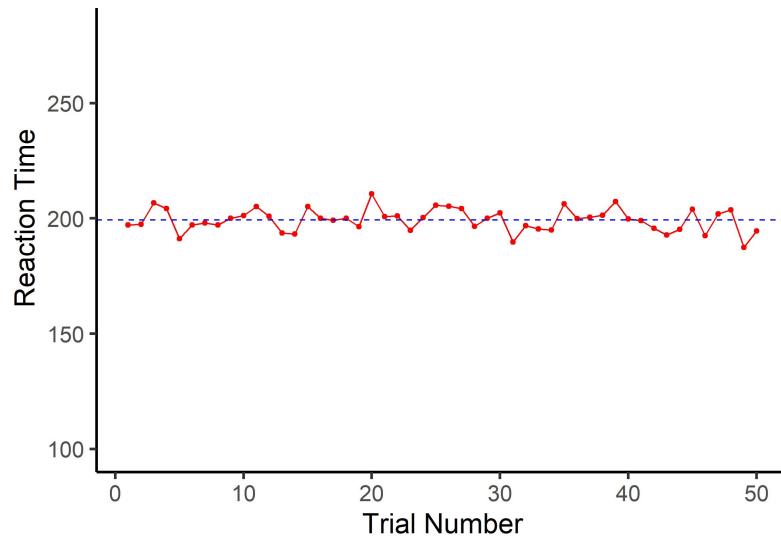
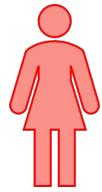
MEAN RESPONSE SPEED



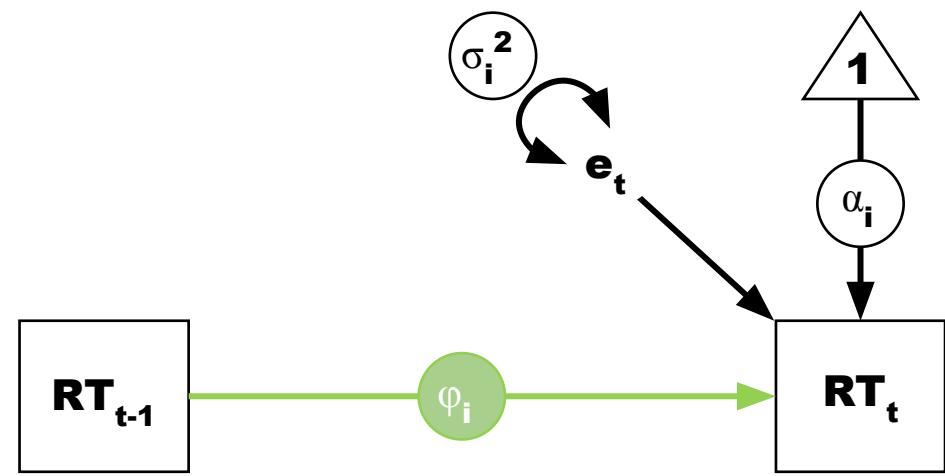
INERTIA (SPILLOVER)



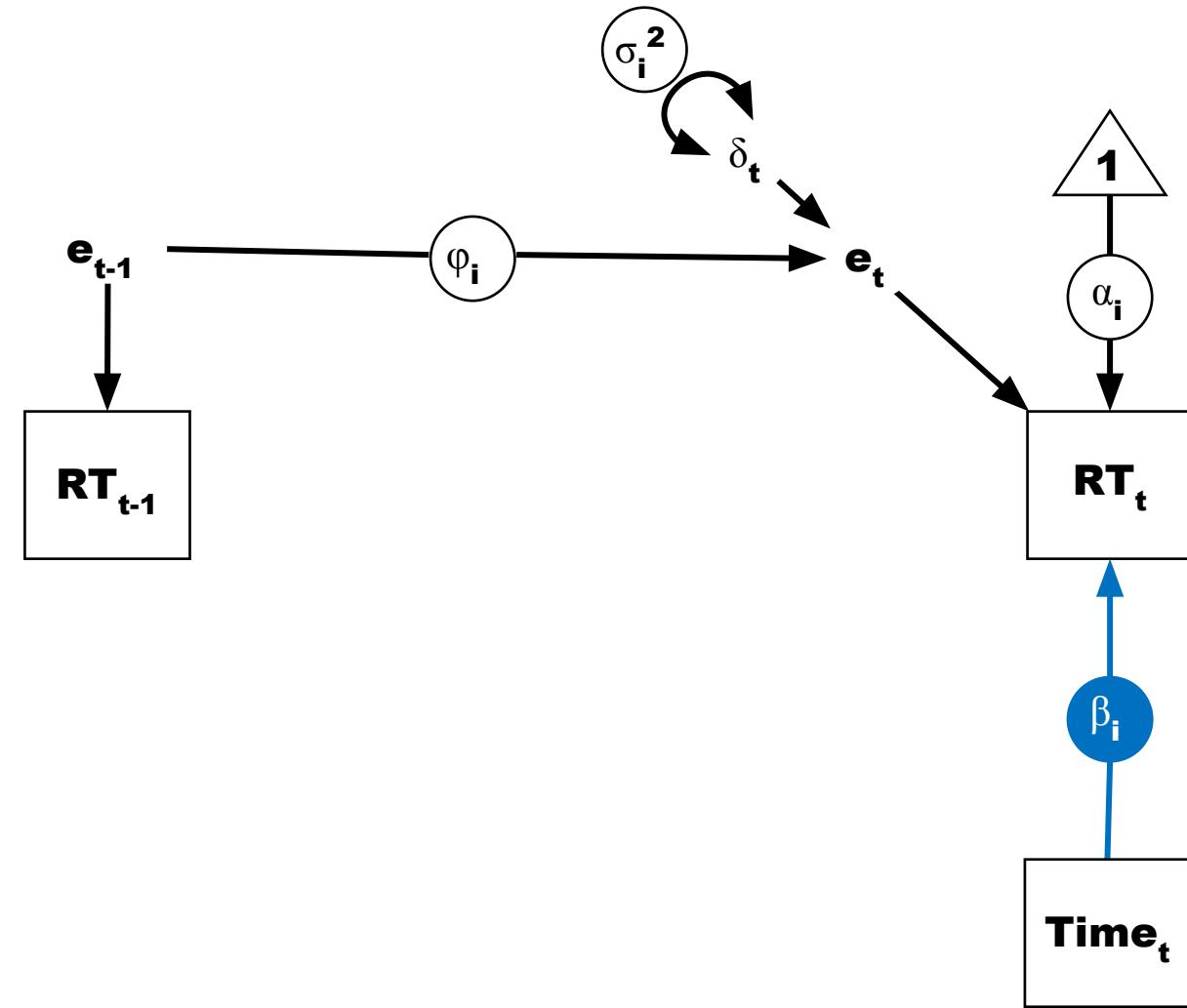
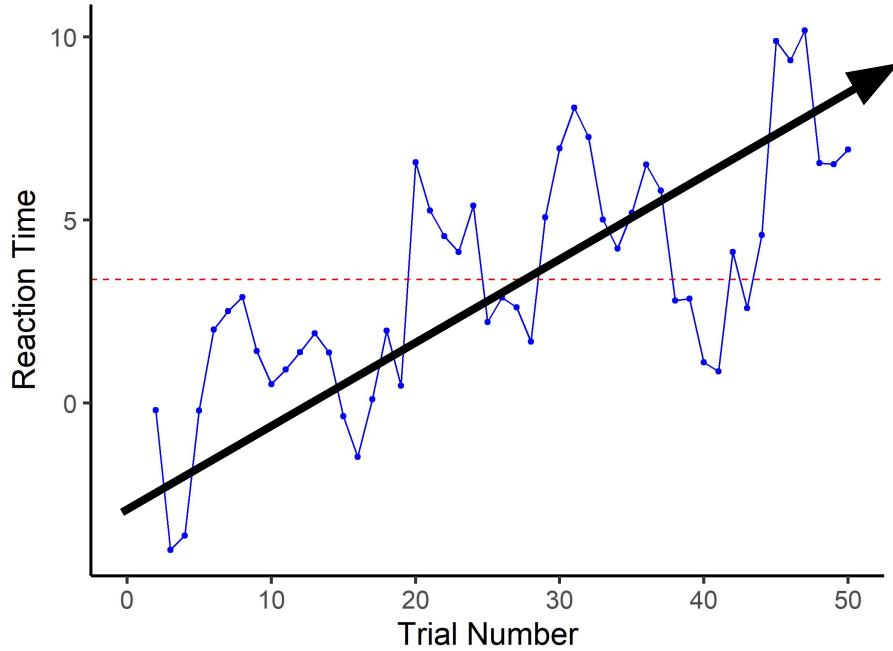
**High
AR(1)**



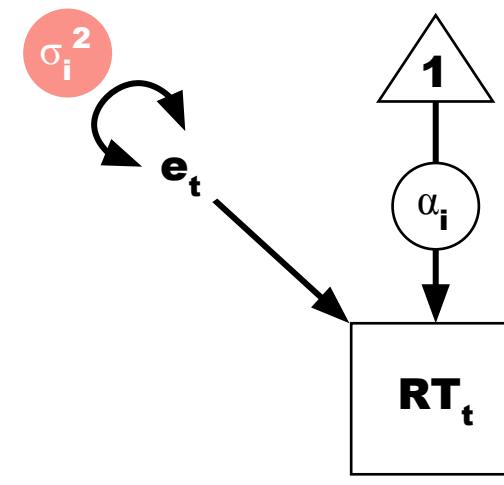
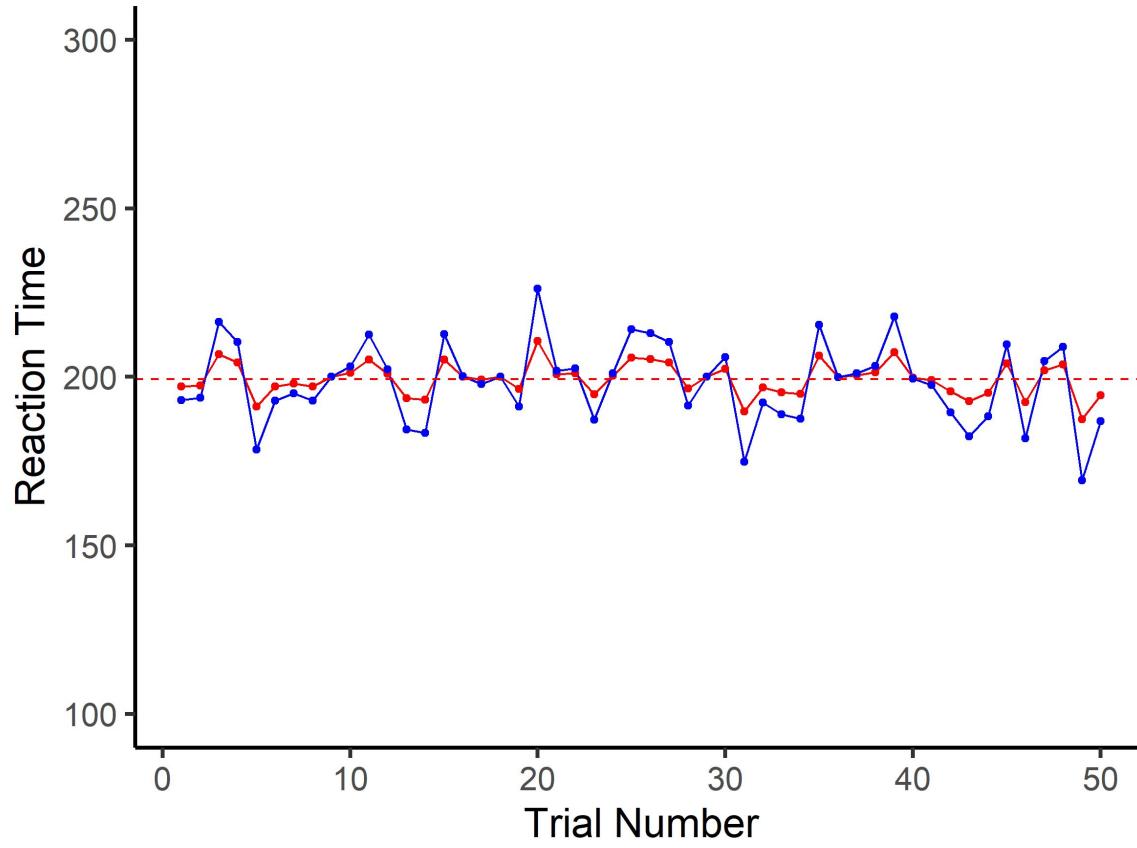
**Low
AR(1)**



SYSTEMATIC CHANGE



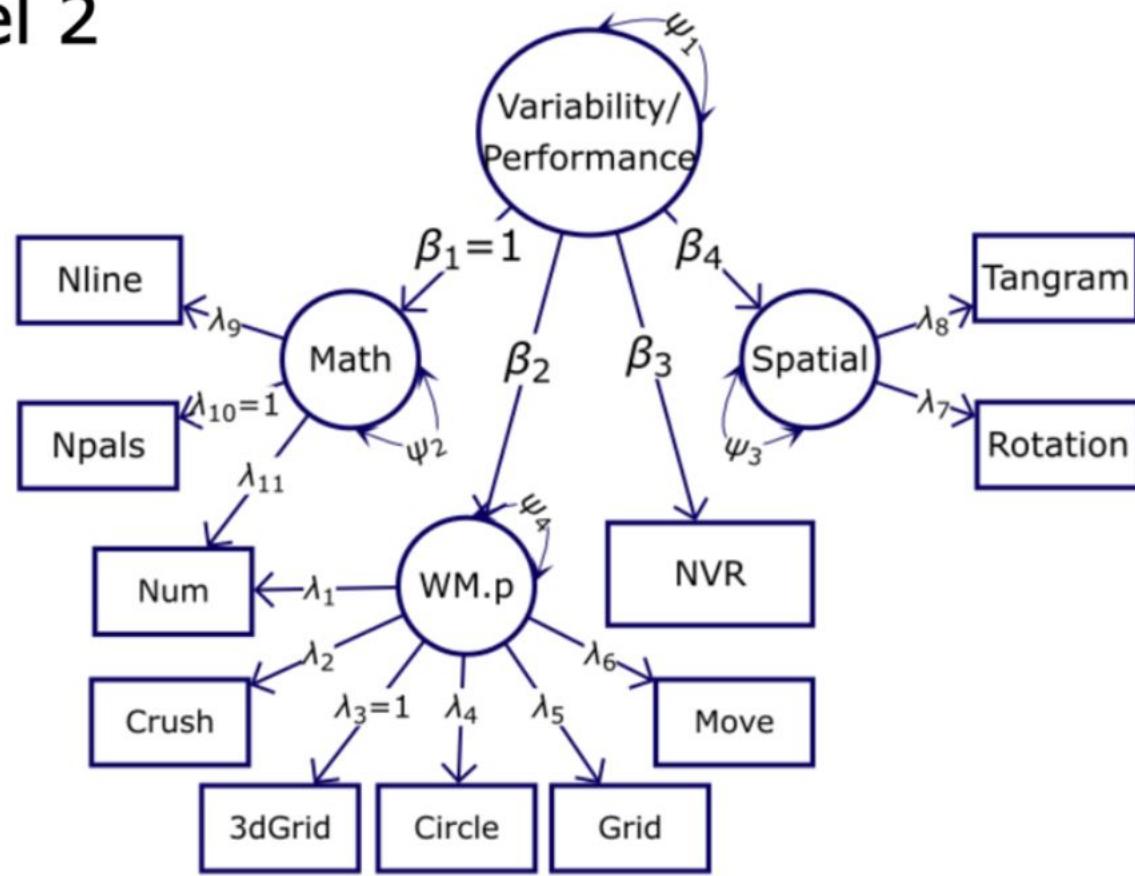
TRIAL-TO-TRIAL VARIABILITY



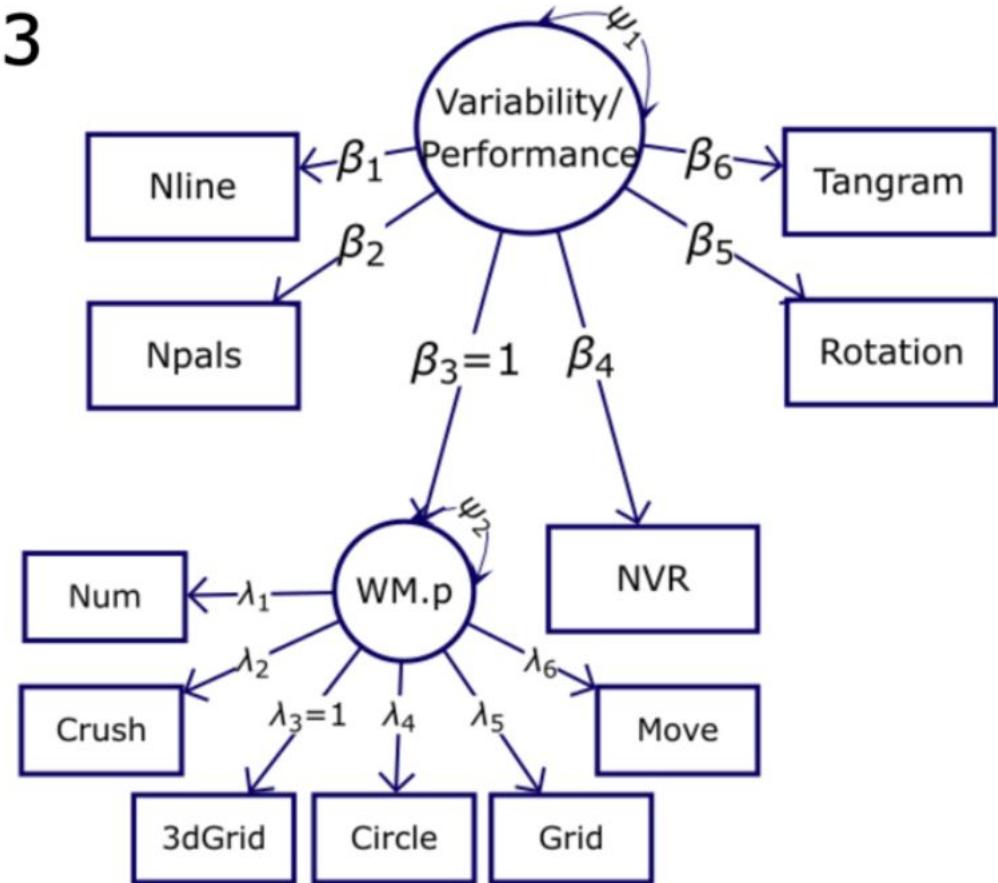
CFA results

CFA slide

b) Model 2

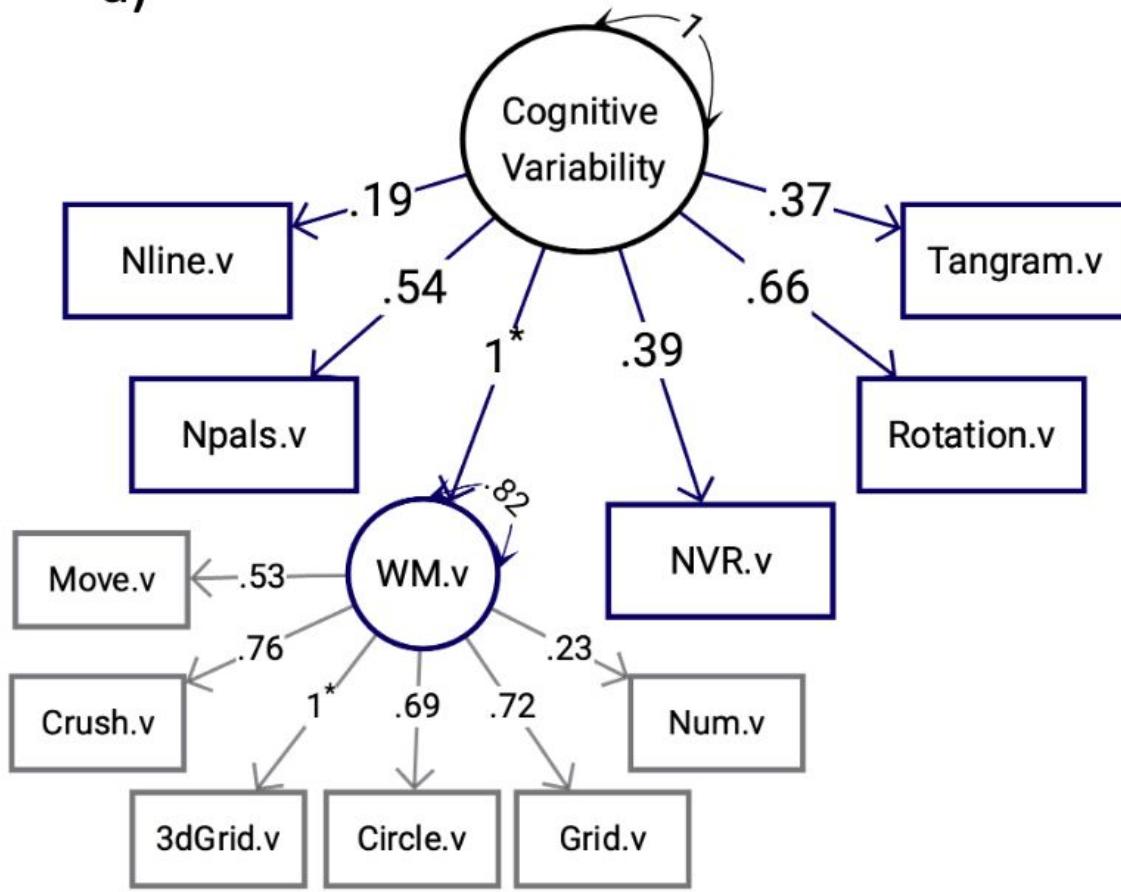


c) Model 3

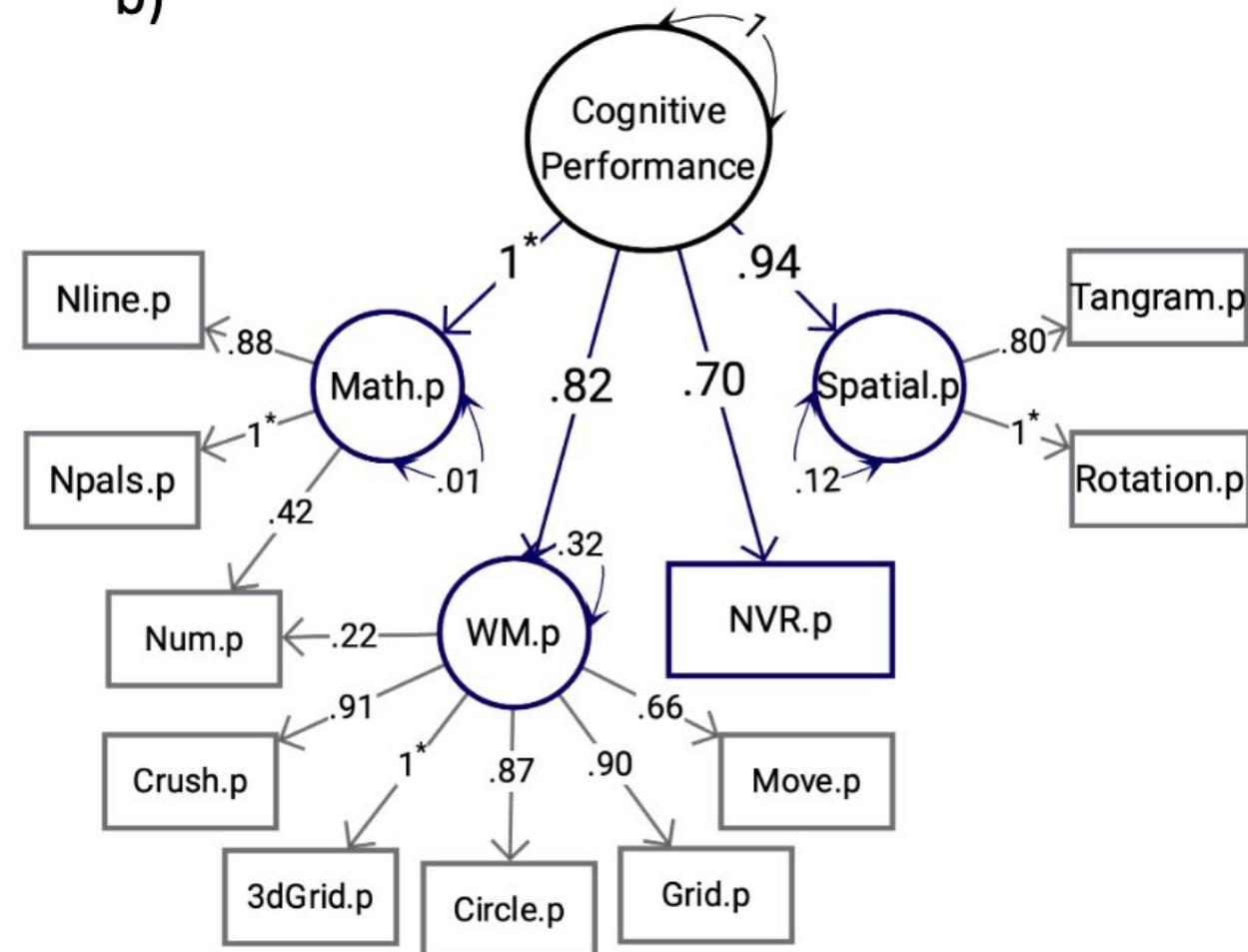


CFA slide

a)



b)



Day to day fluctuations

Day to Day fluctuations

- For WM grid there is no day to day fluctuations, yet this changes for other tasks (i.e., NVR)

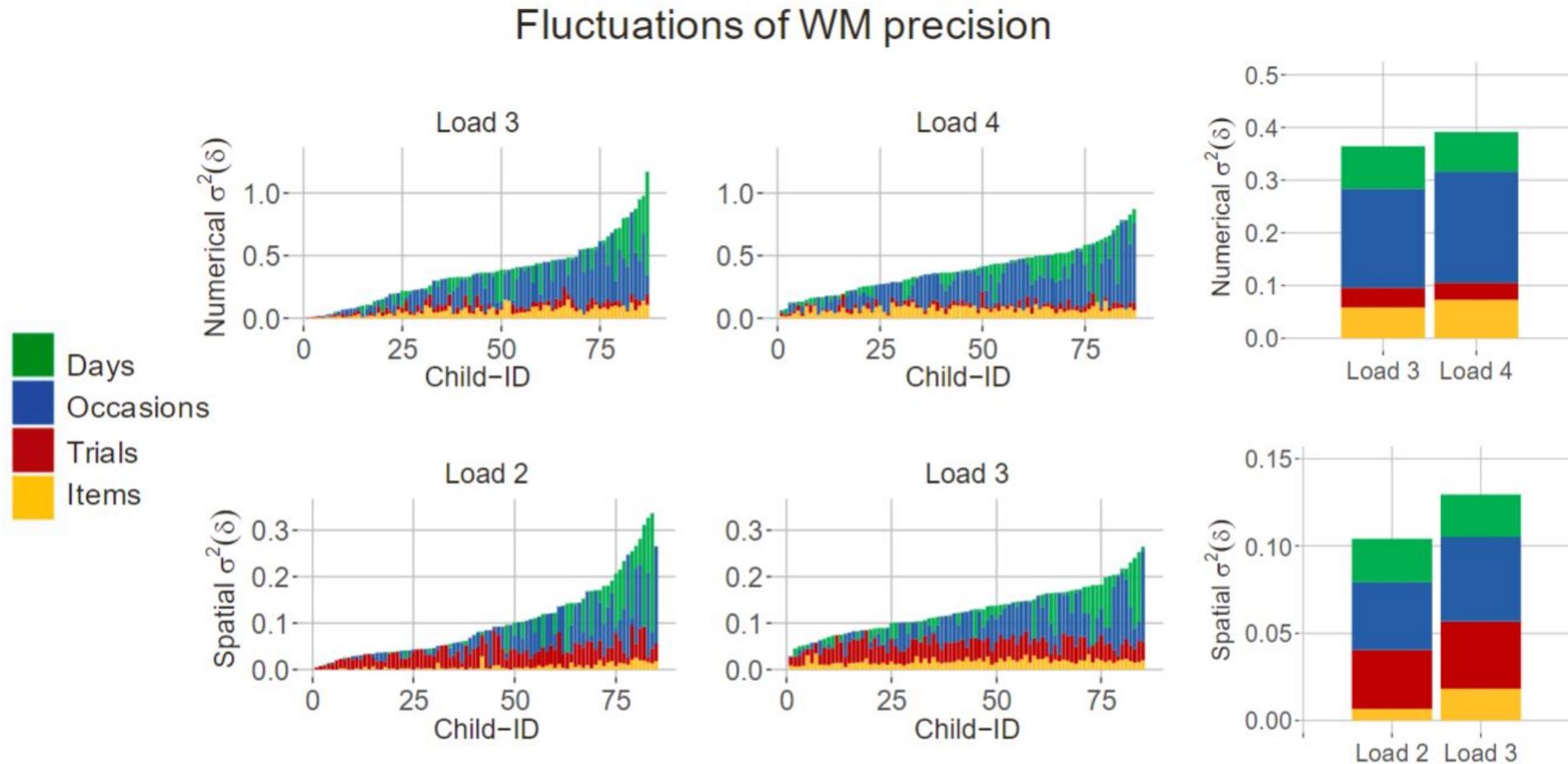
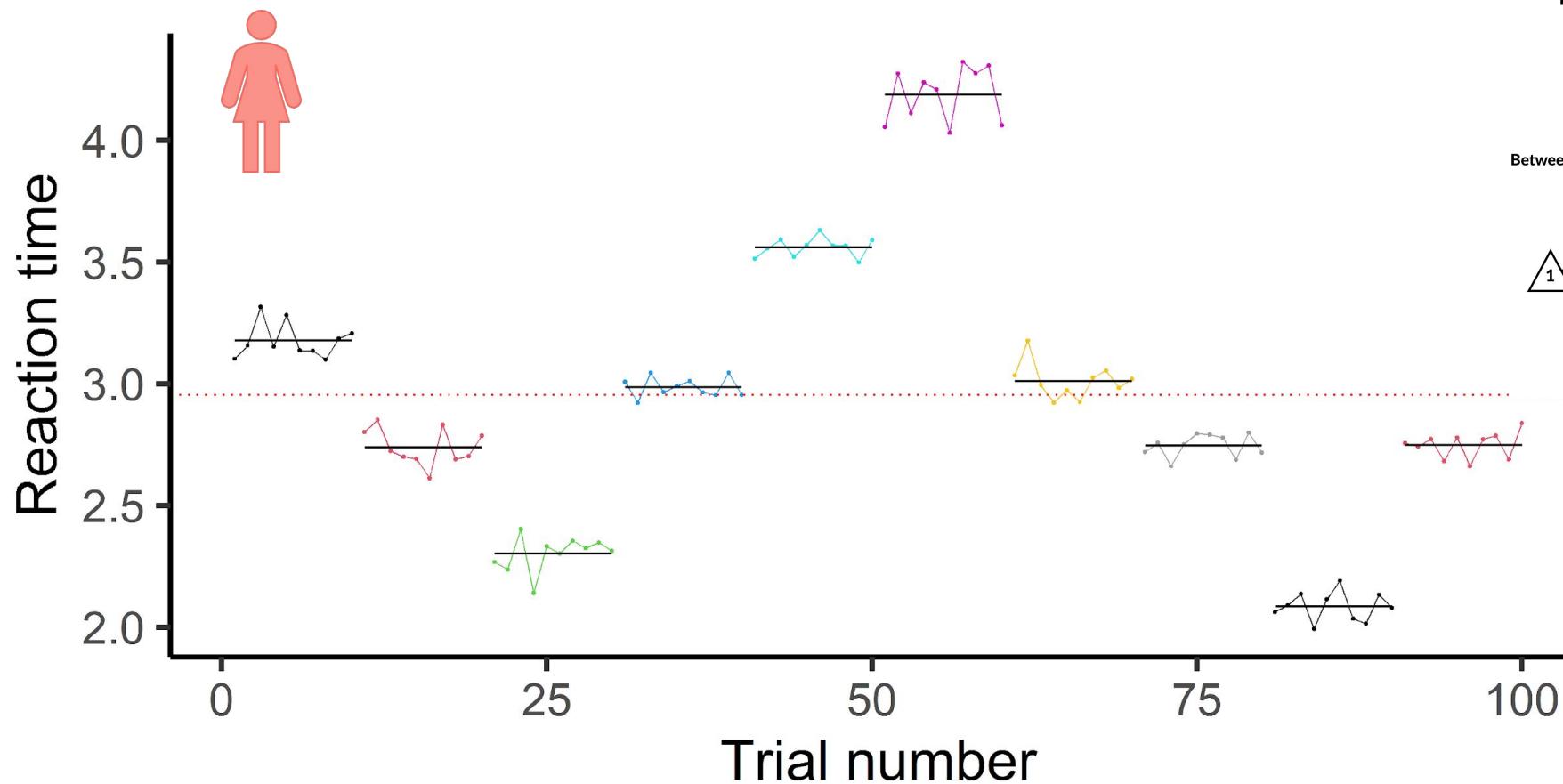
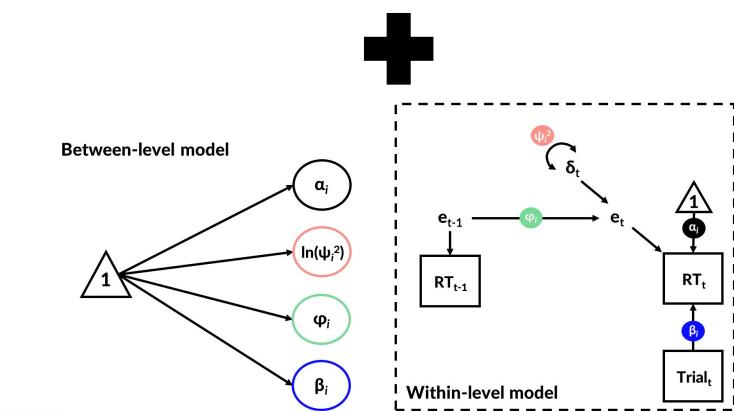


Figure from *Galaeno-Keiner et al., 2022*

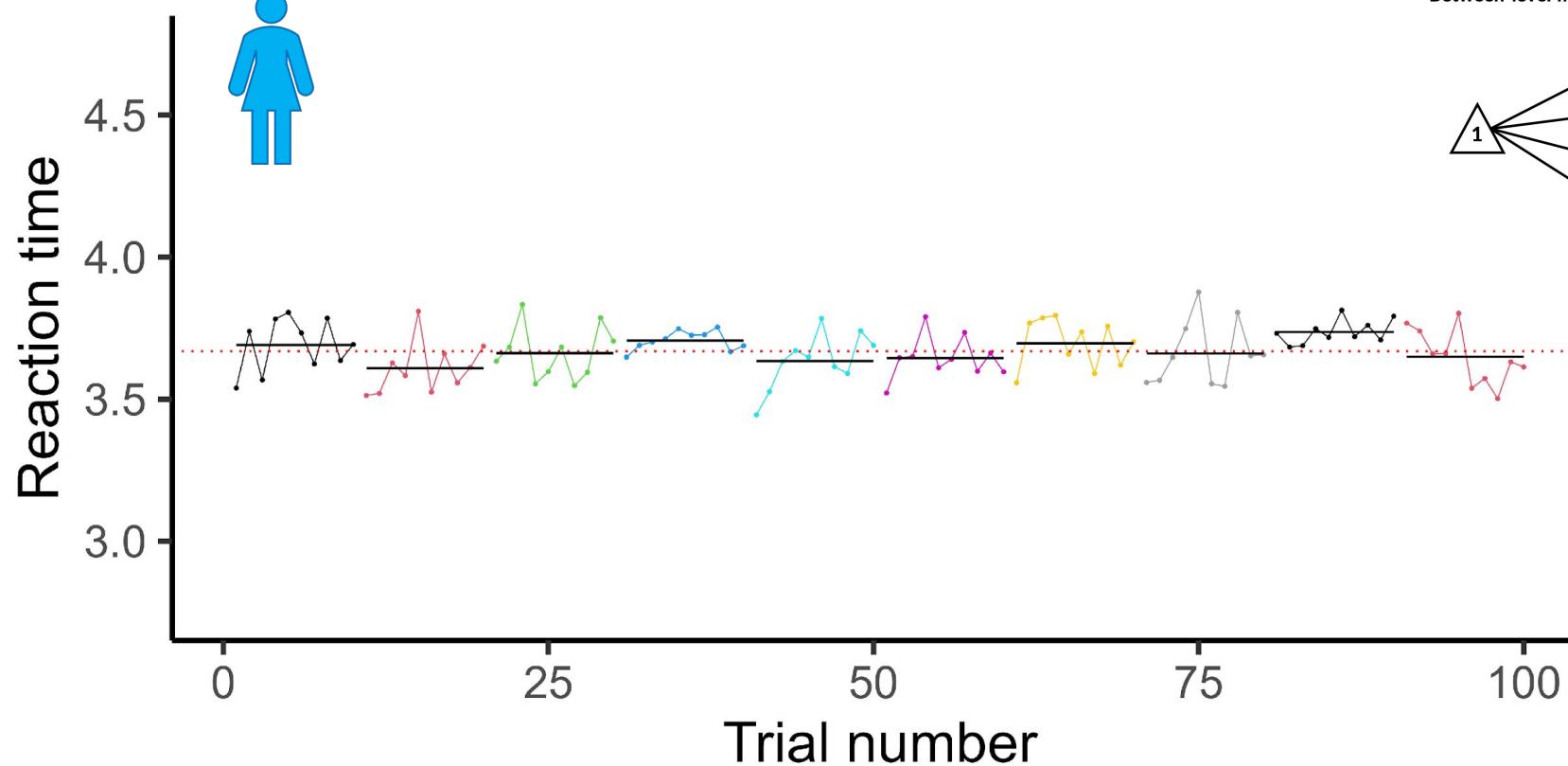
If we *fluctuate* from day to day...



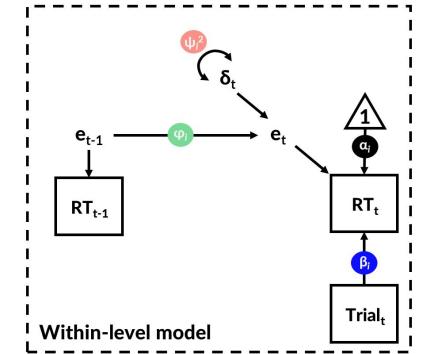
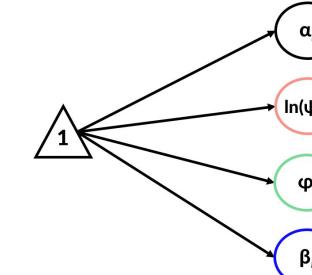
Day-to-day variance



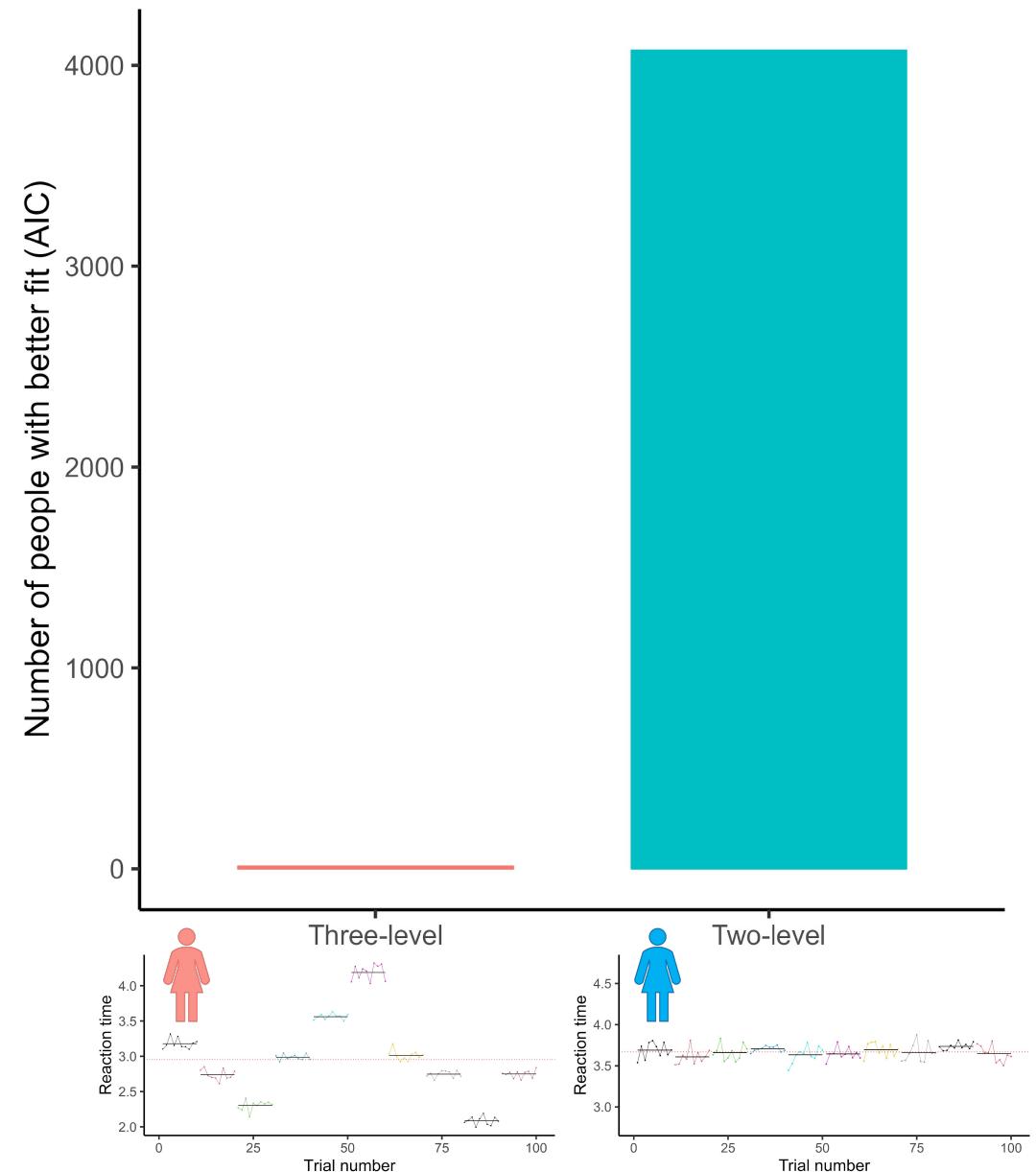
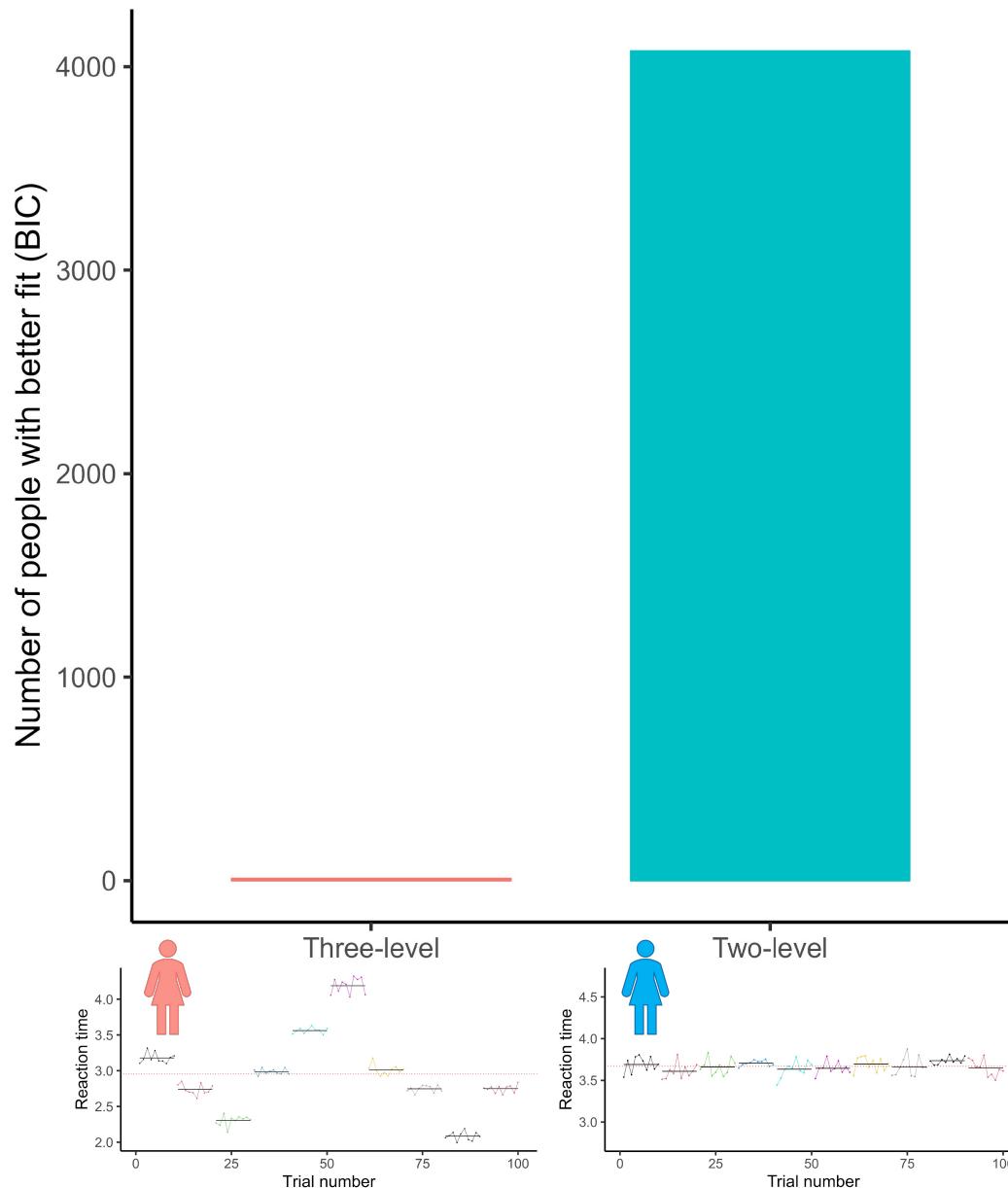
If we are *consistent* from day to day...



Between-level model



For 4090 people are **CONSISTENT** from day-to-day



For 4051 people are **CONSISTENT** from day-to-day

SPAN

