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COGNITIVE HSE RESEARCH

Vladislav Khvostov

Part #1: Independent and parallel visual processing of ensemble statistics: Evidence from dual tasks

Part #2: Confidence intervals in within-subject designs

Part #1

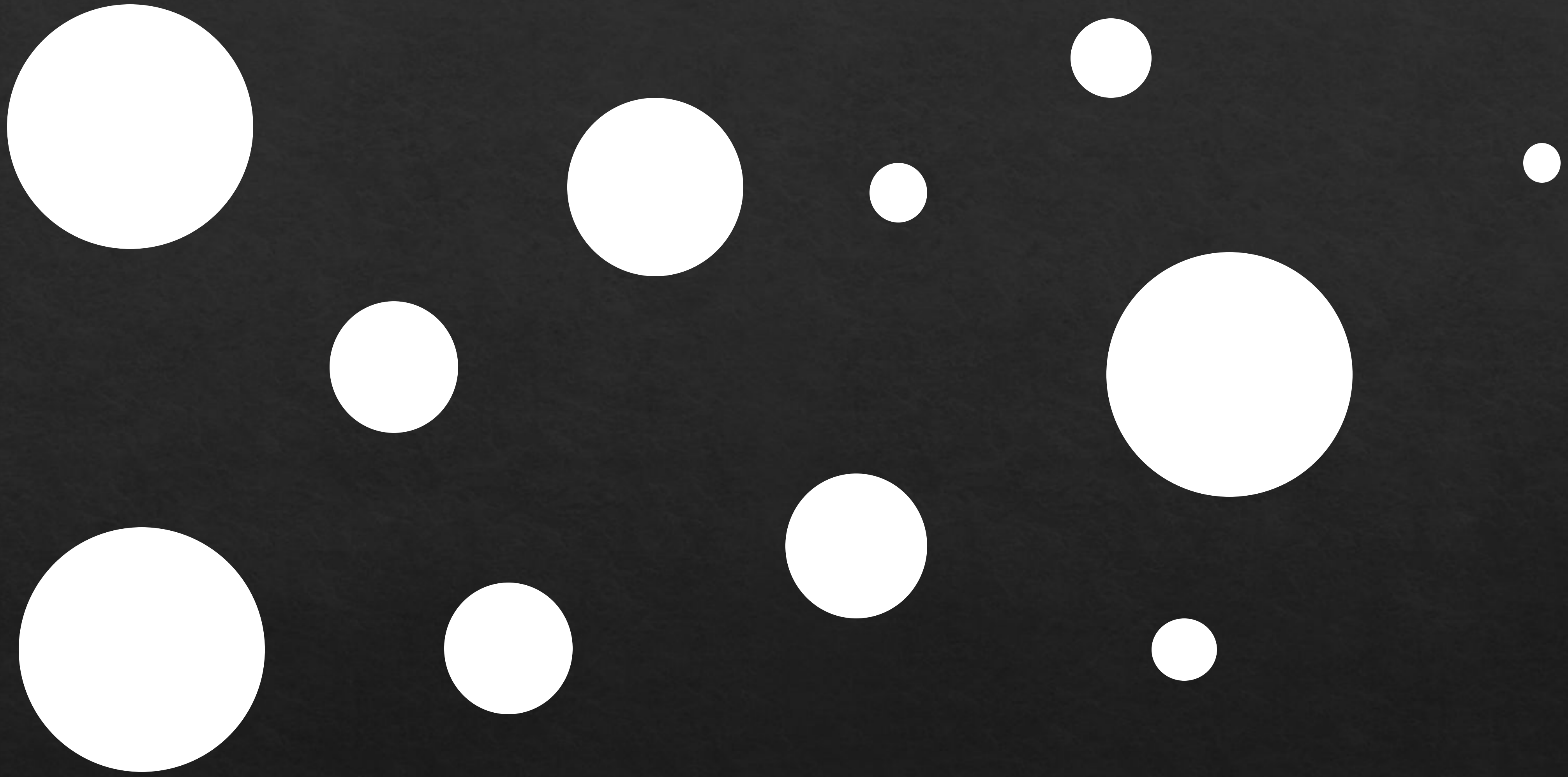
NATIONAL RESEARCH UNIVERSITY

Independent and parallel visual processing of ensemble statistics: Evidence from dual tasks

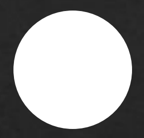
spoiler

Vladislav Khvostov and Igor Utochkin

An example



Greater or smaller than average?



Ensemble summary statistics

- The visual system can compute **mean** (Alvarez & Oliva, 2009), **numerosity** (Halberda, Sires, & Feigenson, 2006), **variance/range** (Dakin & Watt, 1997)

- Ensemble statistics can be calculated for low-level features:
  - **color** (Gardelle & Summerfield, 2011),
  - **orientation** (Parkes, Lund, Angelucci, Solomon, & Morgan, 2001),
  - **size** (Ariely, 2001),

  and for high-level features:

  - **emotions, gender, etc.** (Sweeny & Whitney, 2014, Haberman & Whitney, 2007, 2009).

Independenc e

Independent mechanisms

INPUT

MEAN

NUMEROSITY

RANGE

One mechanism

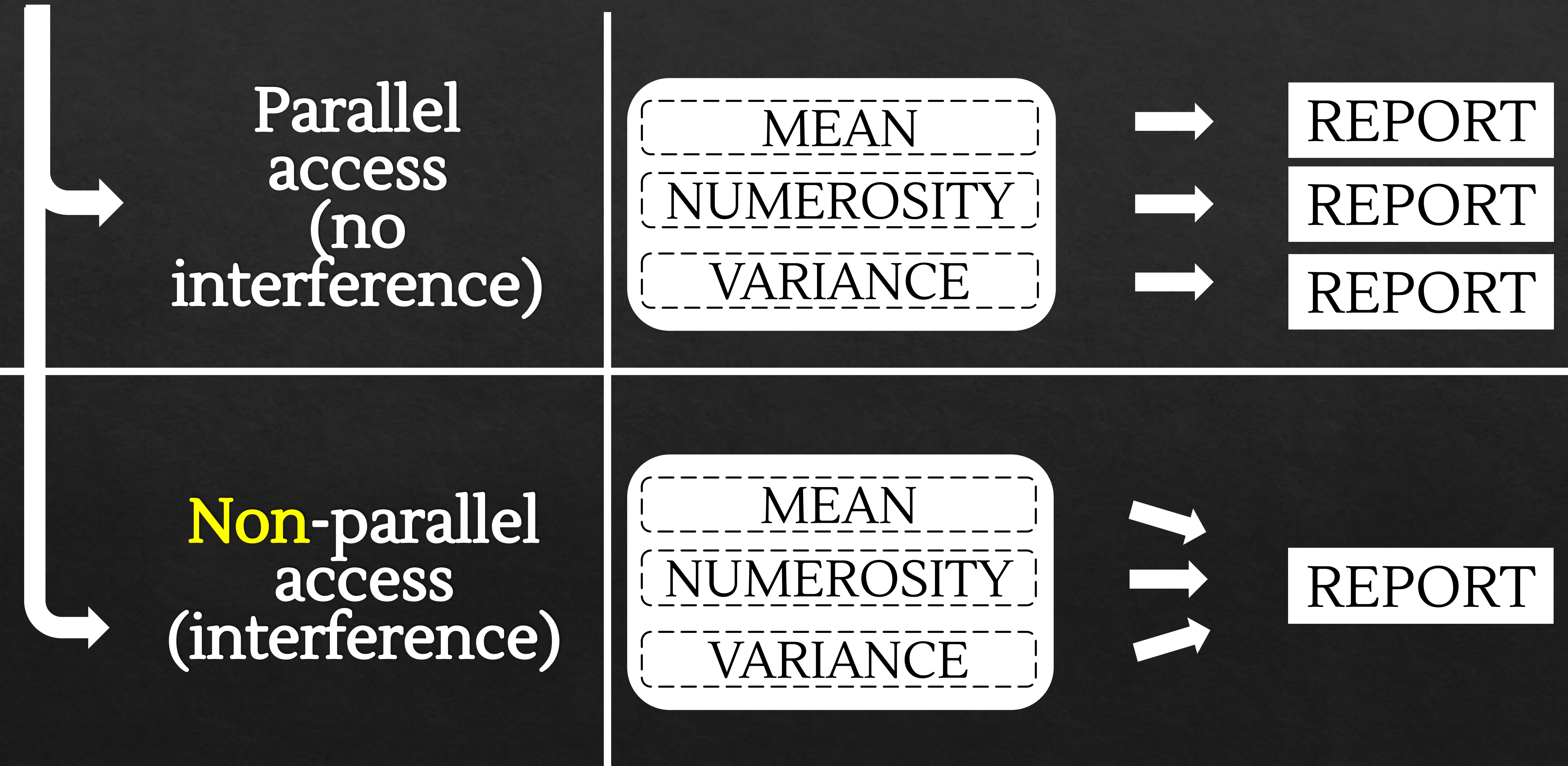
INPUT

«GENERAL ENSEMBLE PROCESSOR»
Mean, Numerosity, Range

Correlational approach

Independence	Prediction
Independent mechanisms  → MEAN → NUMEROSITY → RANGE	Different sources of noise → **No correlation** between errors in reports of different statistics
One mechanism  → «GENERAL ENSEMBLE PROCESSOR» Mean, Numerosity, Range	One source of noise → **Correlation** between errors in reports of different statistics

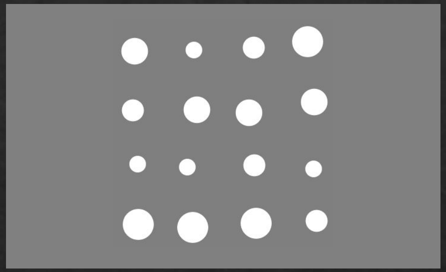
Parallelism



Parallelism test

Single task

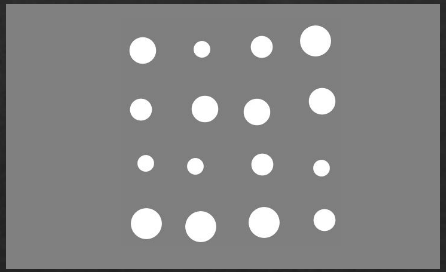
"Calculate MEAN"



MEAN report

Dual task

"Calculate MEAN and RANGE"



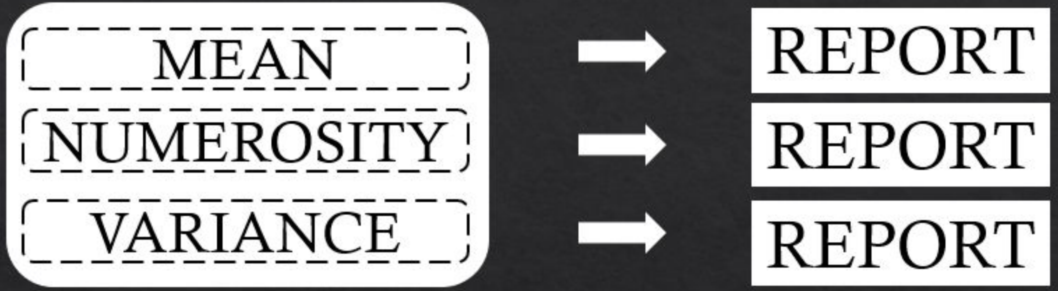
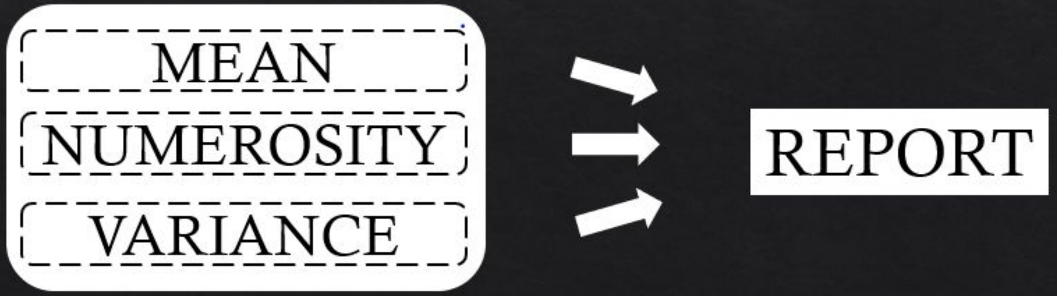
MEAN report

RANGE report

Observers should compute only one statistics

Observers should compute both statistics

Parallelism test

Access	Prediction
Parallel access 	No interference Error in single task = Error in dual task
Non-parallel access 	Interference Error in single task < Error in dual task

Experiment 1

Whether mean and numerosity can be calculated independently and in parallel?

N=23

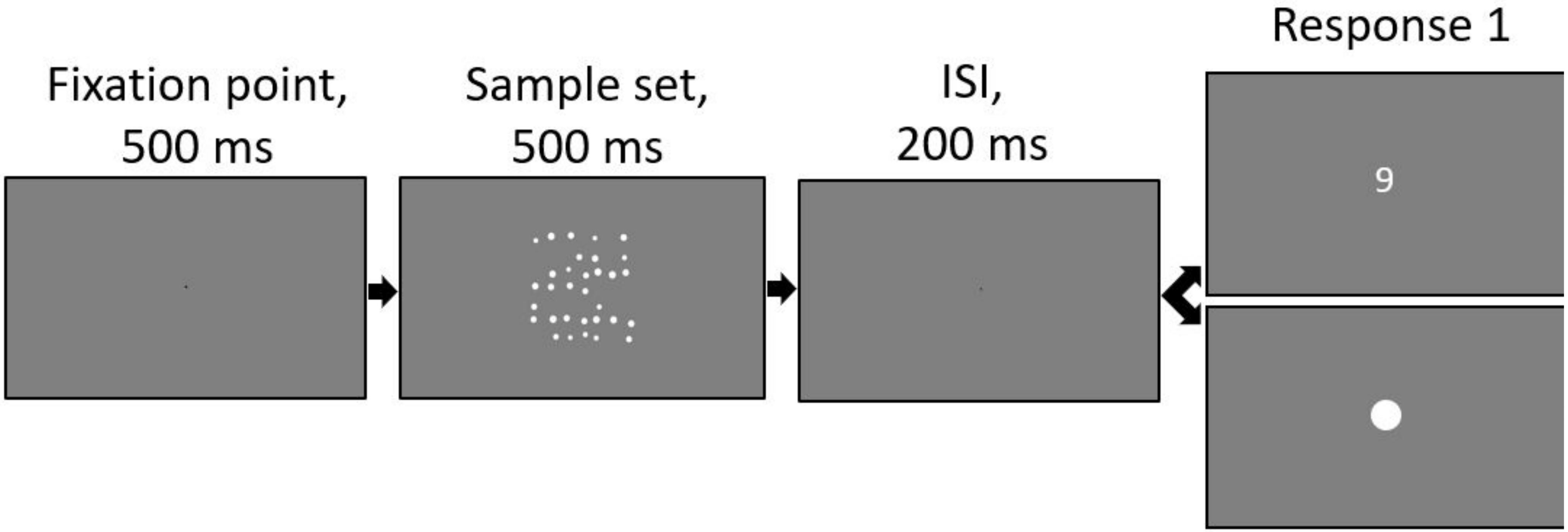
Procedure

Baseline condition

1 block (MEAN or NUMEROSITY)

Both condition

2 blocks (MEAN + NUMEROSITY)



Design

3 blocks	6 “variables”	
MEAN	MEAN baseline	
NIMEROSITY	NIMEROSITY baseline	
BOTH	MEAN reported first NIMEROSITY reported first	MEAN reported second NIMEROSITY reported

Data analysis

$$\textbf{Error} = \left|\frac{oobserver's\ response - correct\ response}{correct\ response}\right|$$

(1) Correlation between mean errors of 6 variables (across observers)

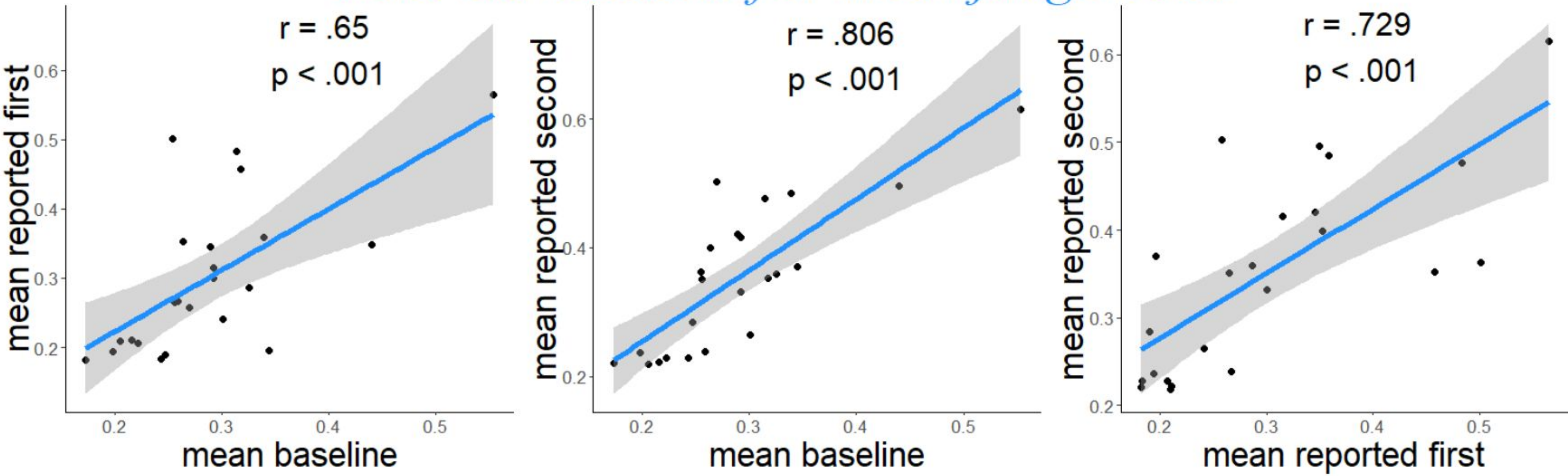
(2) Trial-by-trial correlation between an error in the mean judgment and an error in the numerosity judgment (separately for each participants)

Independenc
e

(3) Comparison of mean errors in baseline and both conditions

Parallelism

Auto-correlations for Mean judgements

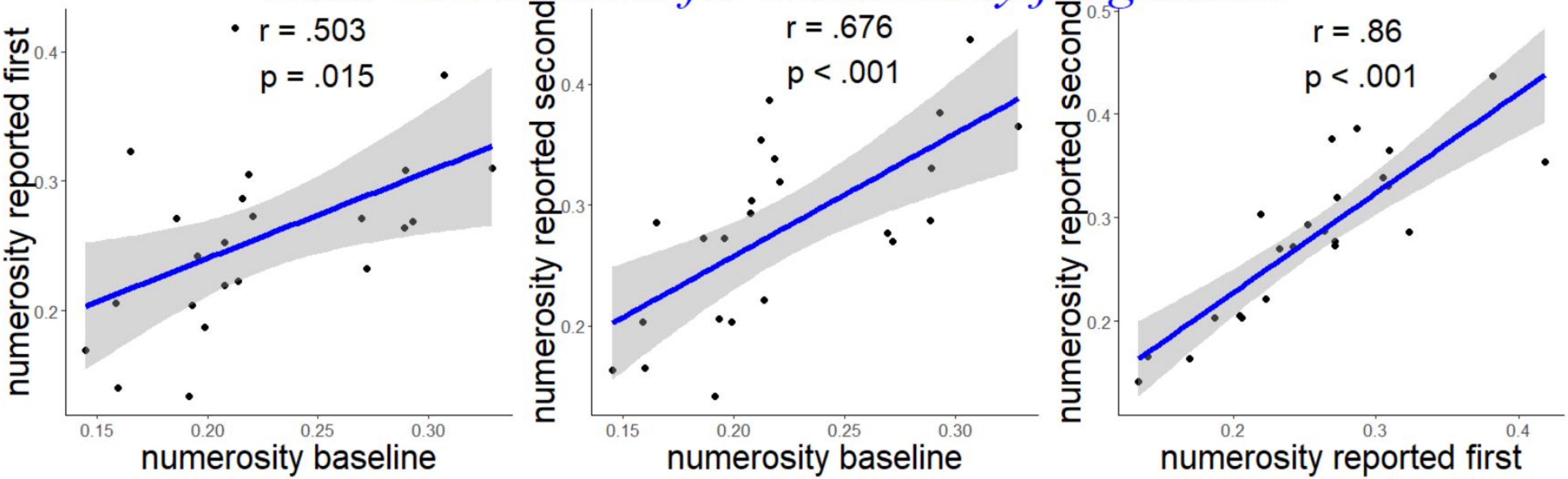


Positive correlation between errors in reporting MEAN in different conditions

⬇

Reliable measure of MEAN calculation across

Auto-correlations for Numerosity judgements



Positive correlation between errors in reporting NUMEROSITY in different conditions

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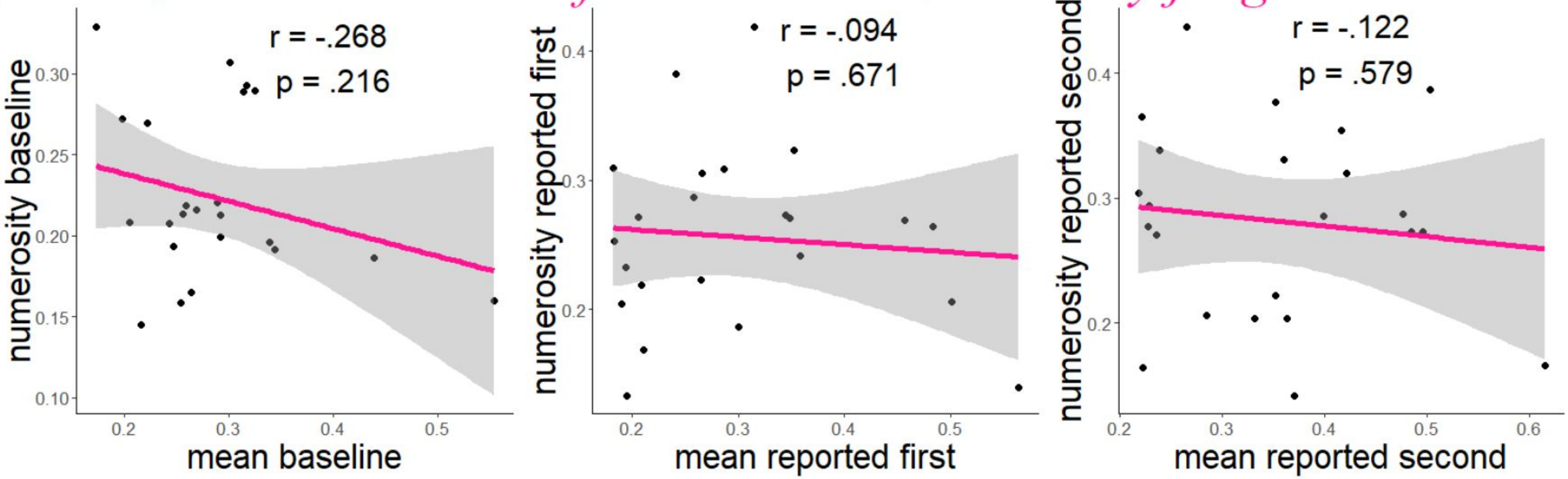
Reliable measure of NUMEROSITY calculation across

Cross-correlations for Mean and Numerosity judgements

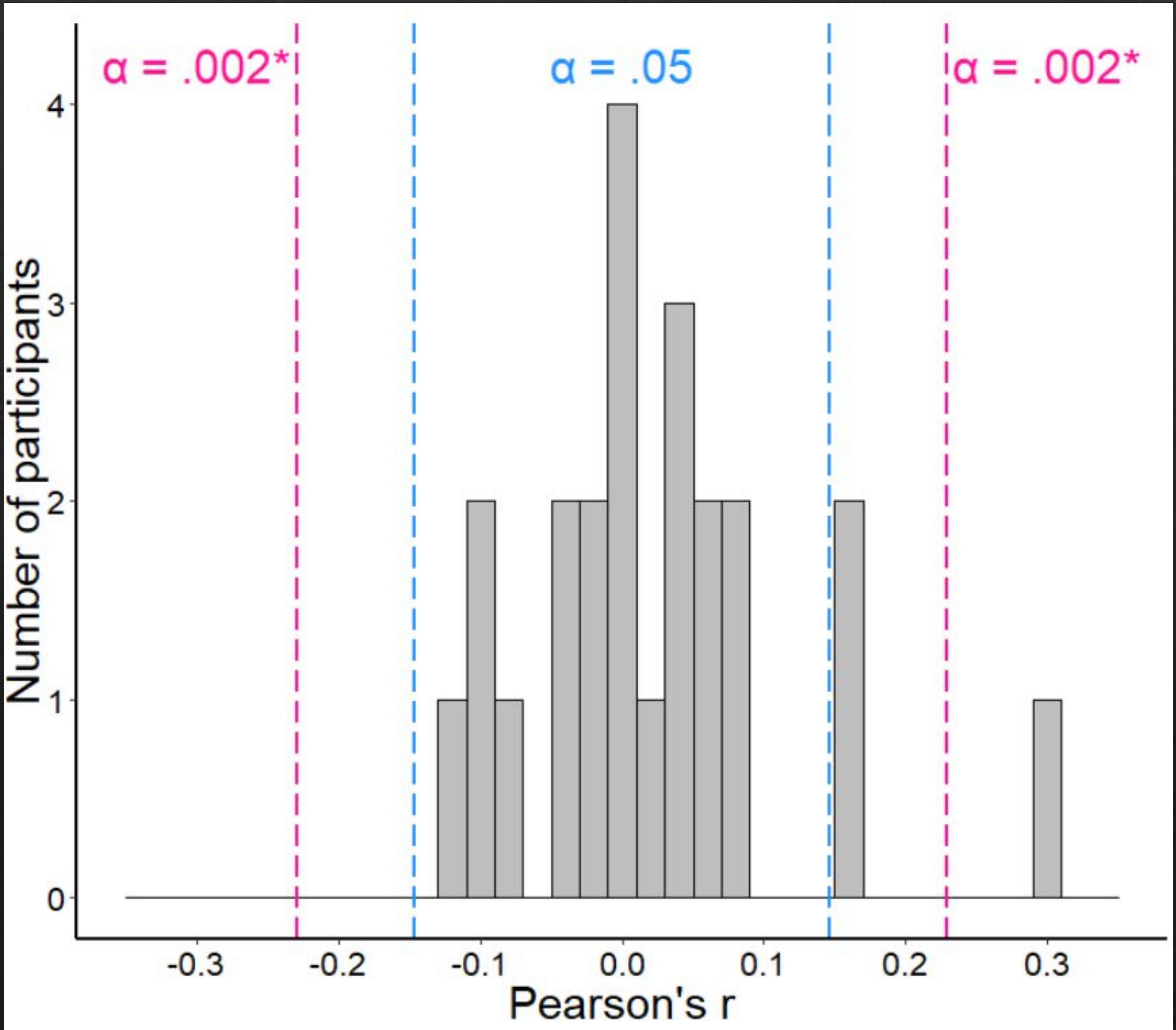


No correlation between errors in reporting different statistics

⬇

Independence between MEAN and NUMEROSITY calculations

Individual correlations

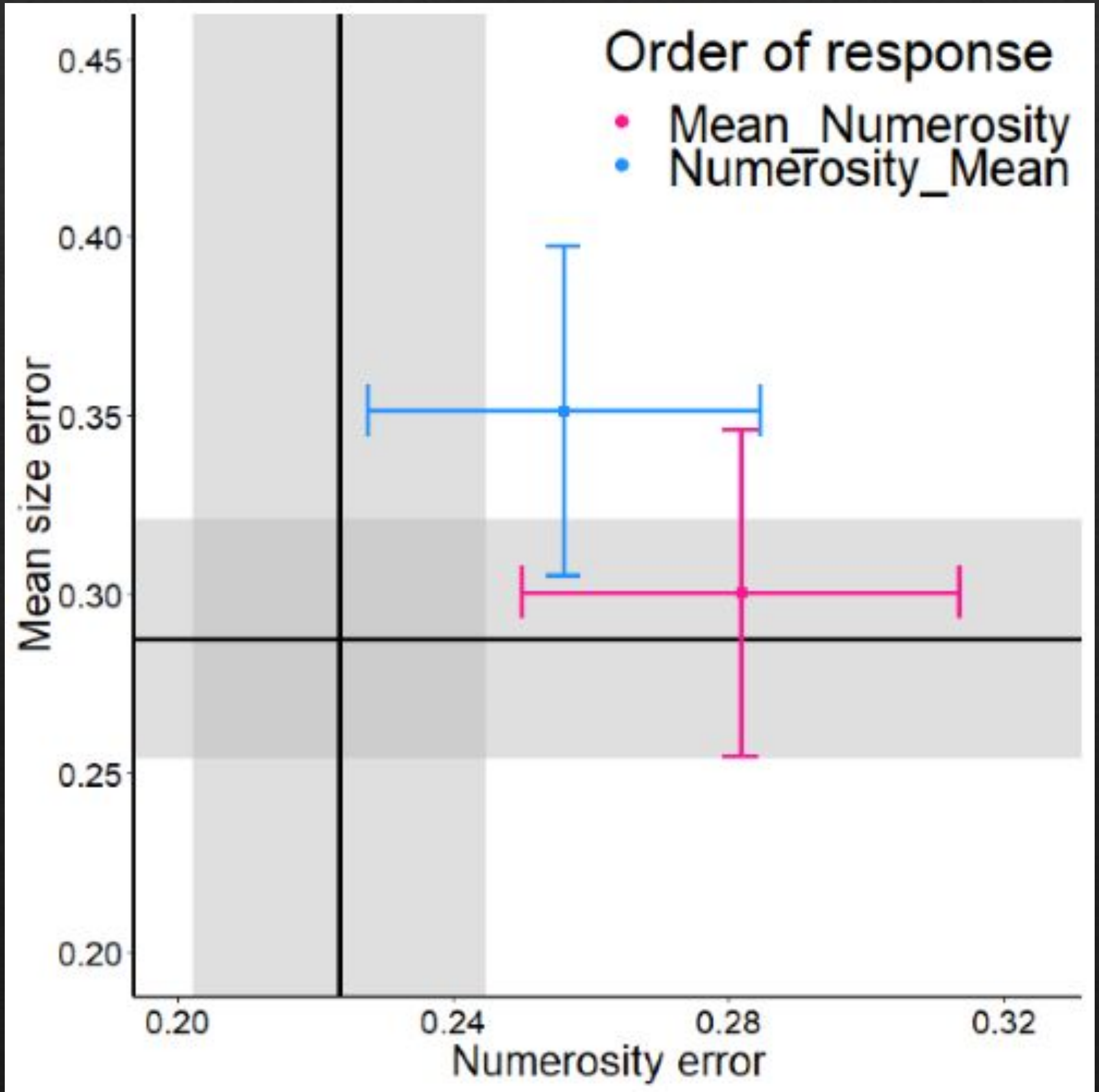


Only one participant showed significant correlation between raw errors in *both condition*

⬇

Independence between MEAN and NUMEROSITY calculations

Average errors



No difference between mean errors in *baseline condition* and the first response in *both condition*
(both for NIMEROSITY and MEAN).

Conclusion

Mean and numerosity are calculated **independently and in parallel**

Experiment 2

Whether mean and range can be calculated independently and in parallel?

N=20

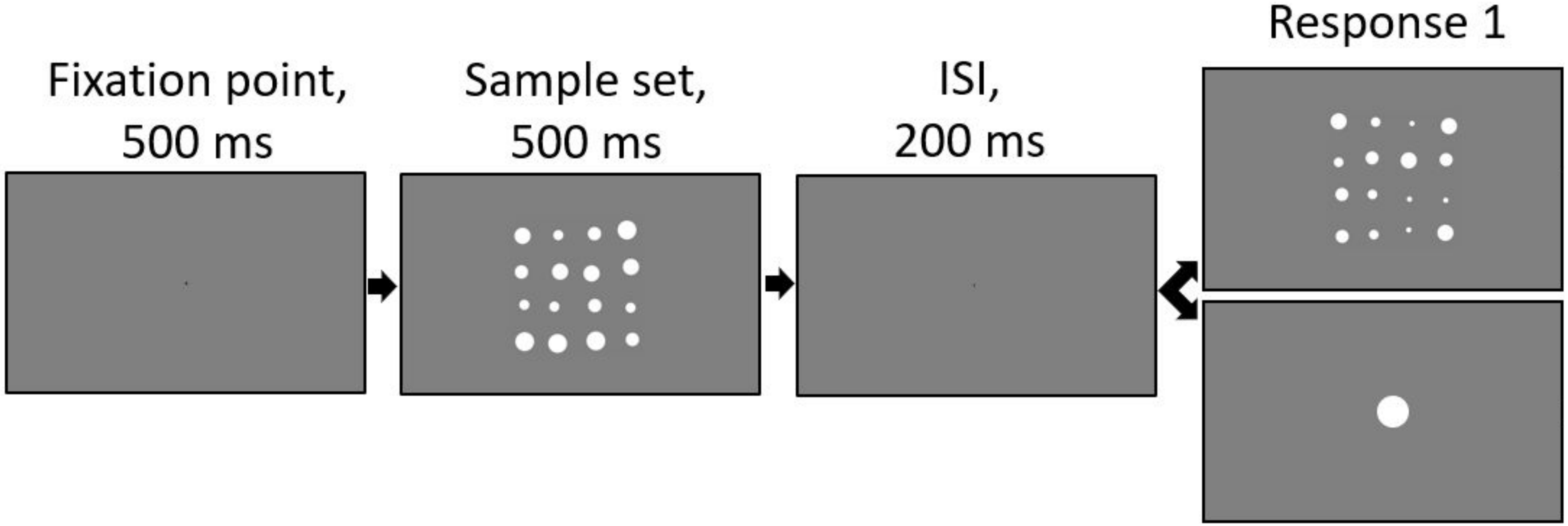
Procedure

Baseline condition

Both condition

2 blocks (MEAN+RANGE)

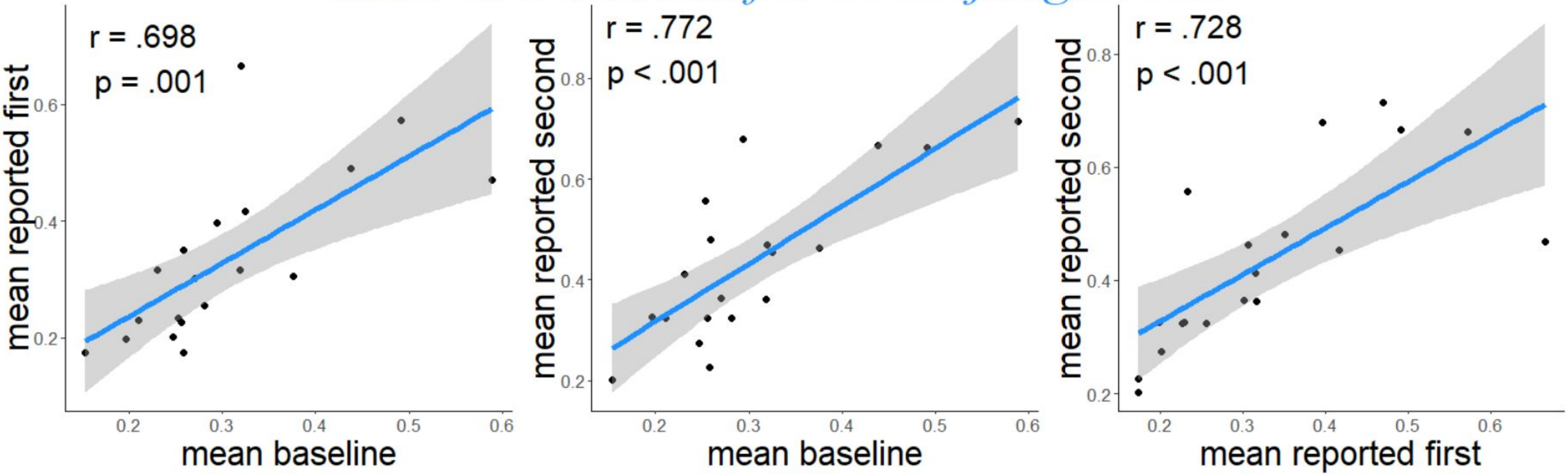
1 block (MEAN or RANGE)



Design

3 blocks	6 "variables"	
MEAN	MEAN baseline	
RANGE	RANGE baseline	
BOTH	MEAN reported first	MEAN reported second
	RANGE reported first	RANGE reported

Auto-correlations for Mean judgements

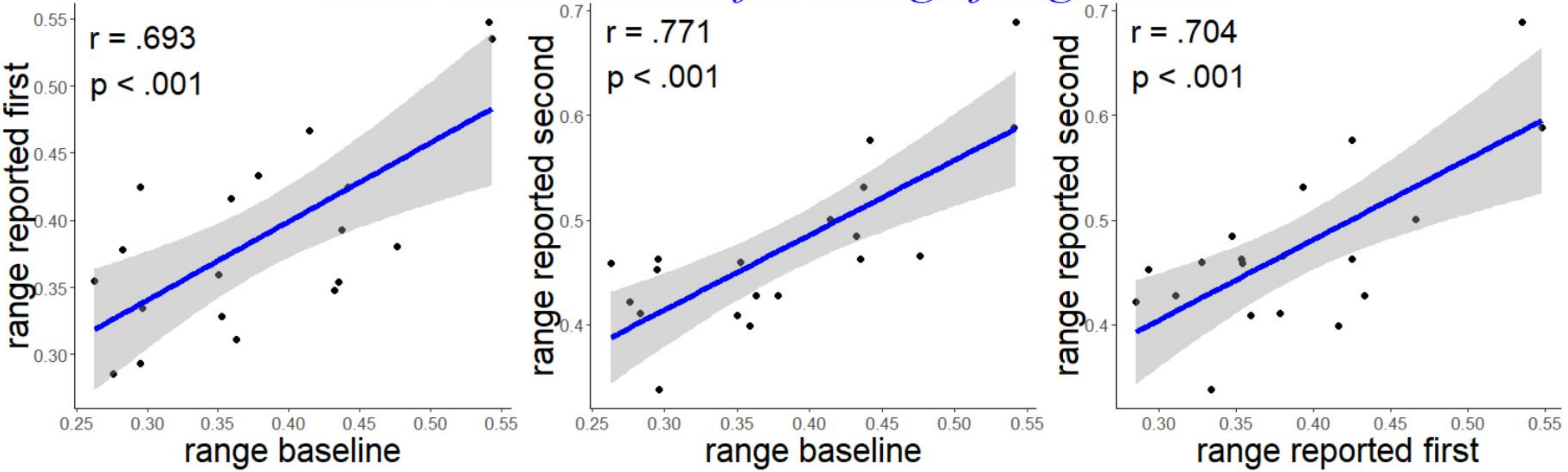


Positive correlation between errors in reporting MEAN in different conditions

⬇

Reliable measure of MEAN calculation across

Auto-correlations for Range judgements

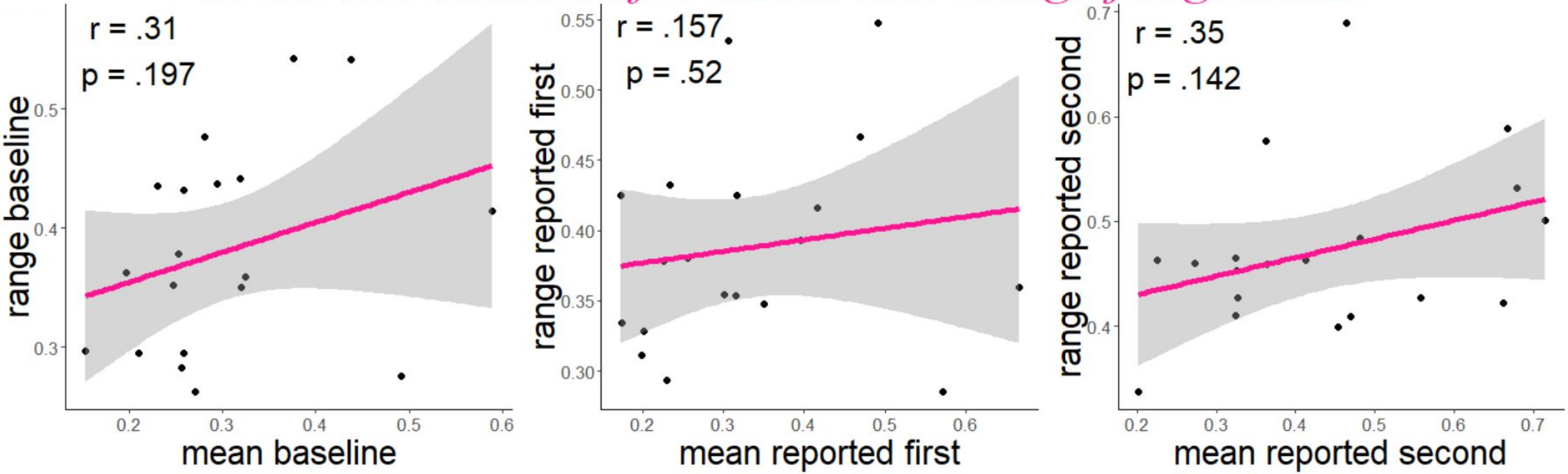


Positive correlation between errors in reporting RANGE in different conditions

↓

Reliable measure of RANGE calculation across conditions

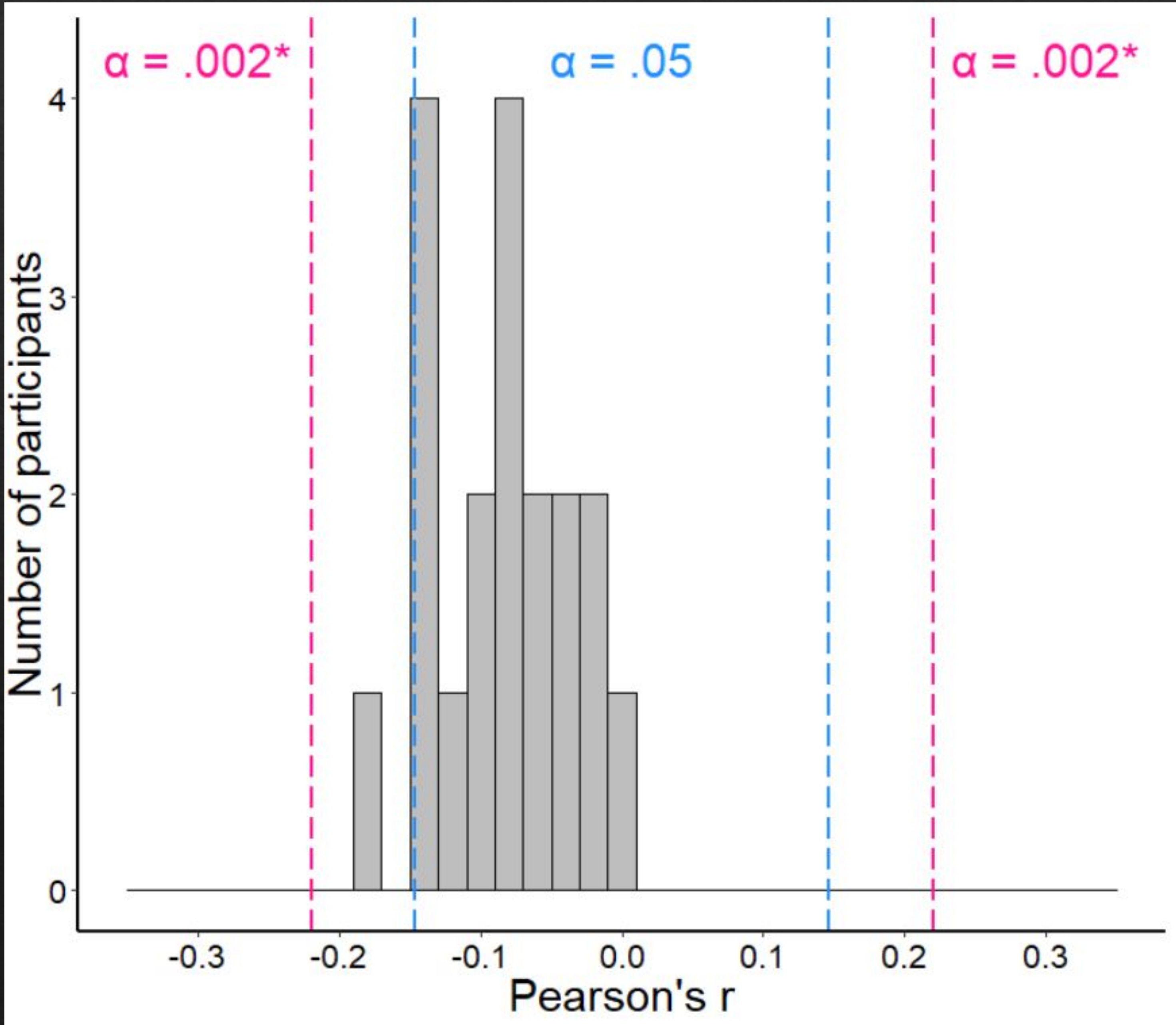
Cross-correlations for Mean and Range judgements



<u>No correlation</u> between errors in reporting different statistics

<u>Independence between MEAN and RANGE calculations</u>

Individual correlations

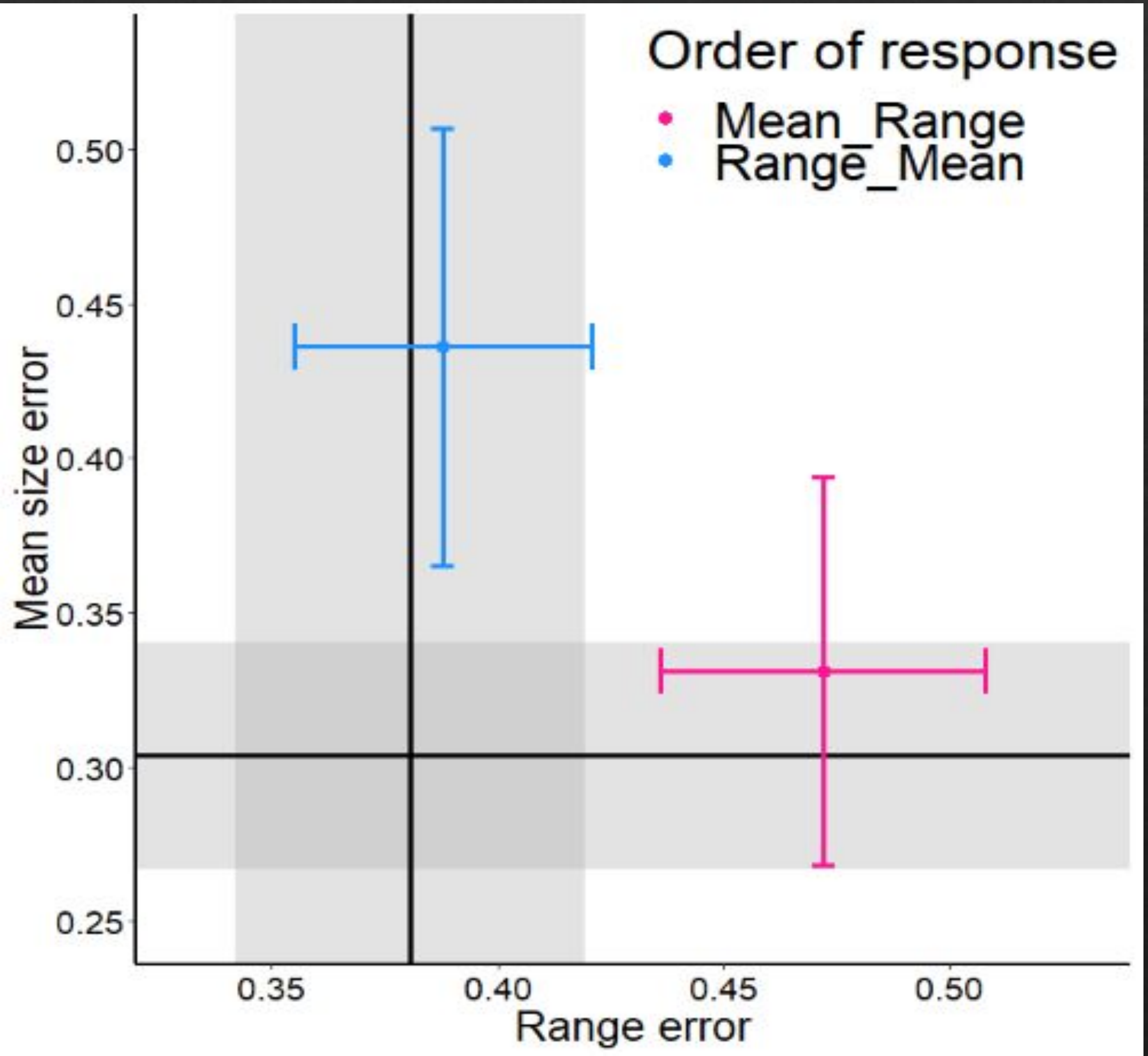


No one showed significant correlation between raw errors in *both condition*

⬇

Independence between MEAN and RANGE calculations

Average errors

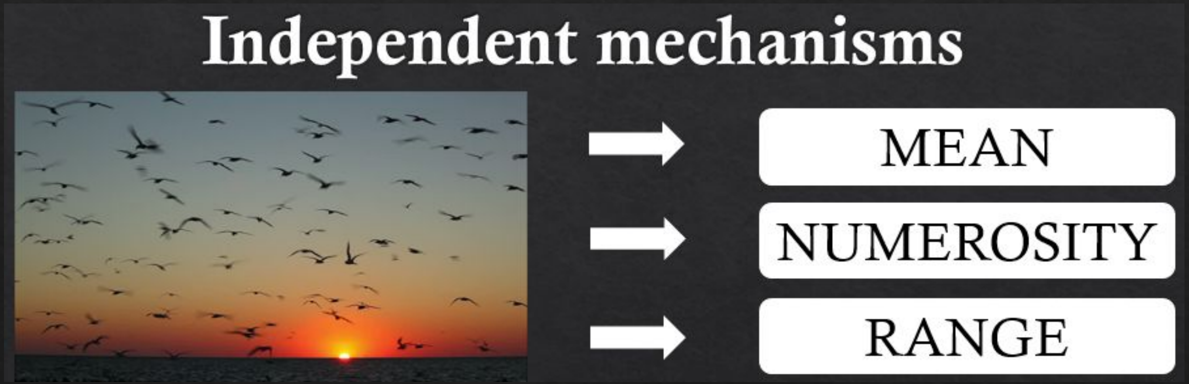


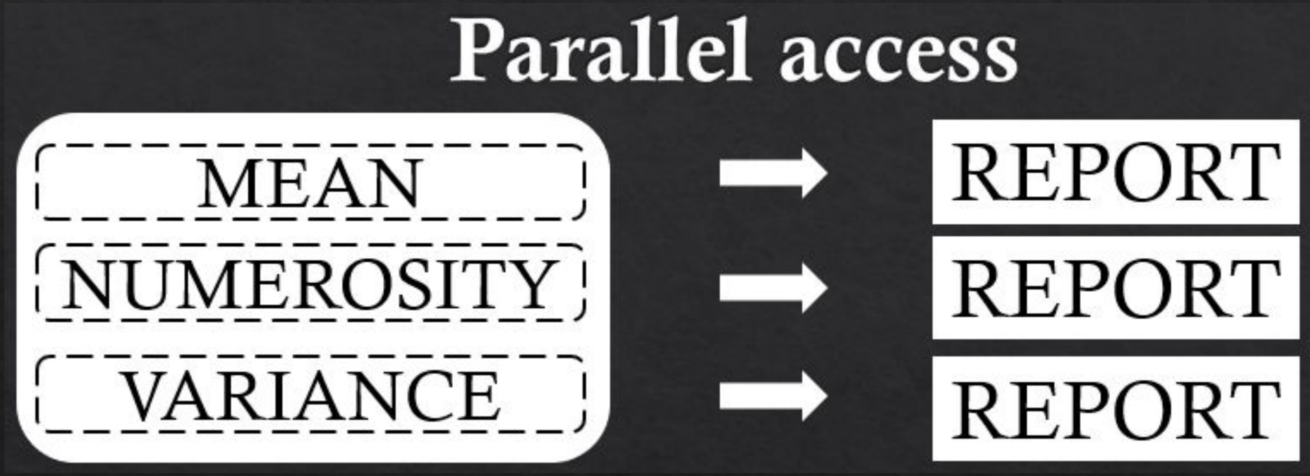
No difference between mean errors in *baseline condition* and the first response in *both condition* (both for RANGE and MEAN).

Conclusions

Ensemble summary statistics (mean and numerosity, mean and range) are calculated

independently and in parallel



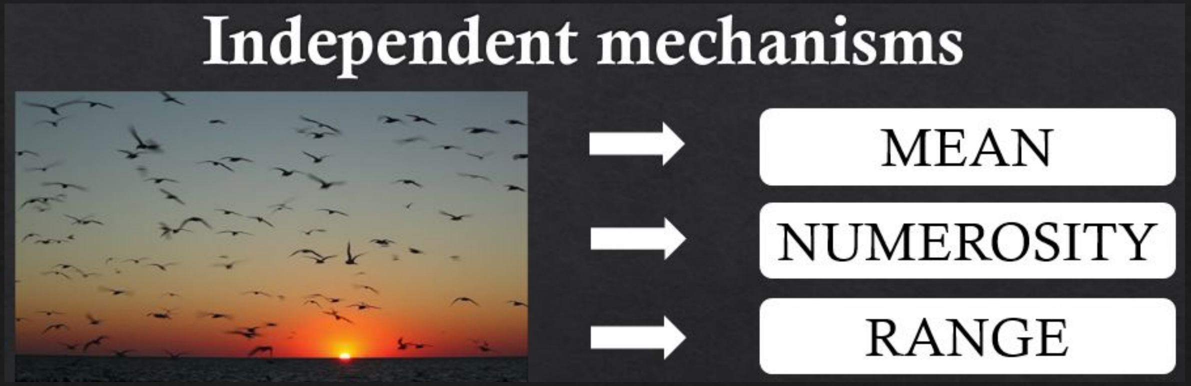


Conclusions (2)

Independent calculation of ensemble summary statistics means:

(1) Different summaries are calculated by different (partly non-overlapping) brain regions.

(2) The result of one calculation does not influence the result of the other calculation (unlike in mathematical statistics)



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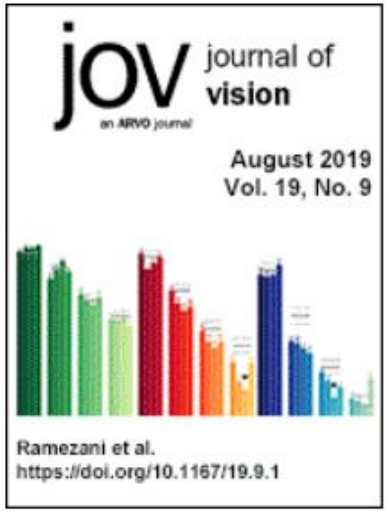

August 2019
Volume 19, Issue 9
‹ ISSUE ›

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Article | August 2019

Independent and parallel visual processing of ensemble statistics: Evidence from dual tasks

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Journal of Vision August 2019, Vol.19, 3. doi:10.1167/19.9.3

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Abstract

The visual system can represent multiple objects in a compressed form of ensemble summary statistics (such as object numerosity, mean, and feature variance/range). Yet the relationships between the different types of visual statistics remain relatively unclear. Here, we tested whether two summaries (mean and numerosity, or mean and range) are calculated independently from each other and in parallel. Our participants performed dual tasks requiring a report about two summaries in each trial, and single tasks requiring a report about one of the summaries. We estimated trial-by-trial correlations between

Thank you for being with me till the end of the first part

Part #2

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Confidence intervals in within-subject designs

*Based on Cousineau, 2005

It is all from this 4-pages paper

Tutorials in Quantitative Methods for Psychology
2005, Vol. 1(1), p. 42-45.
DOI: 10.20982/tqmp.01.1.p042

Confidence intervals in within-subject designs: A simpler solution to Loftus and Masson's method

Denis Cousineau
Université de Montréal

Within-subject ANOVAs are a powerful tool to analyze data because the variance associated to differences between the participants is removed from the analysis. Hence, small differences, when present for most of the participants, can be significant even when the participants are very different from one another. Yet, graphs showing standard error or confidence interval bars are misleading since these bars include the between-subject variability. Loftus and Masson (1994) noticed this fact and proposed an alternate method to compute the error bars. However, i) their

The problem

Different subjects can perform very differently which increases a size of error bars

⬇

Inconsistency between the results of ANOVA and the graph: ANOVA shows the effect, but the graph do not

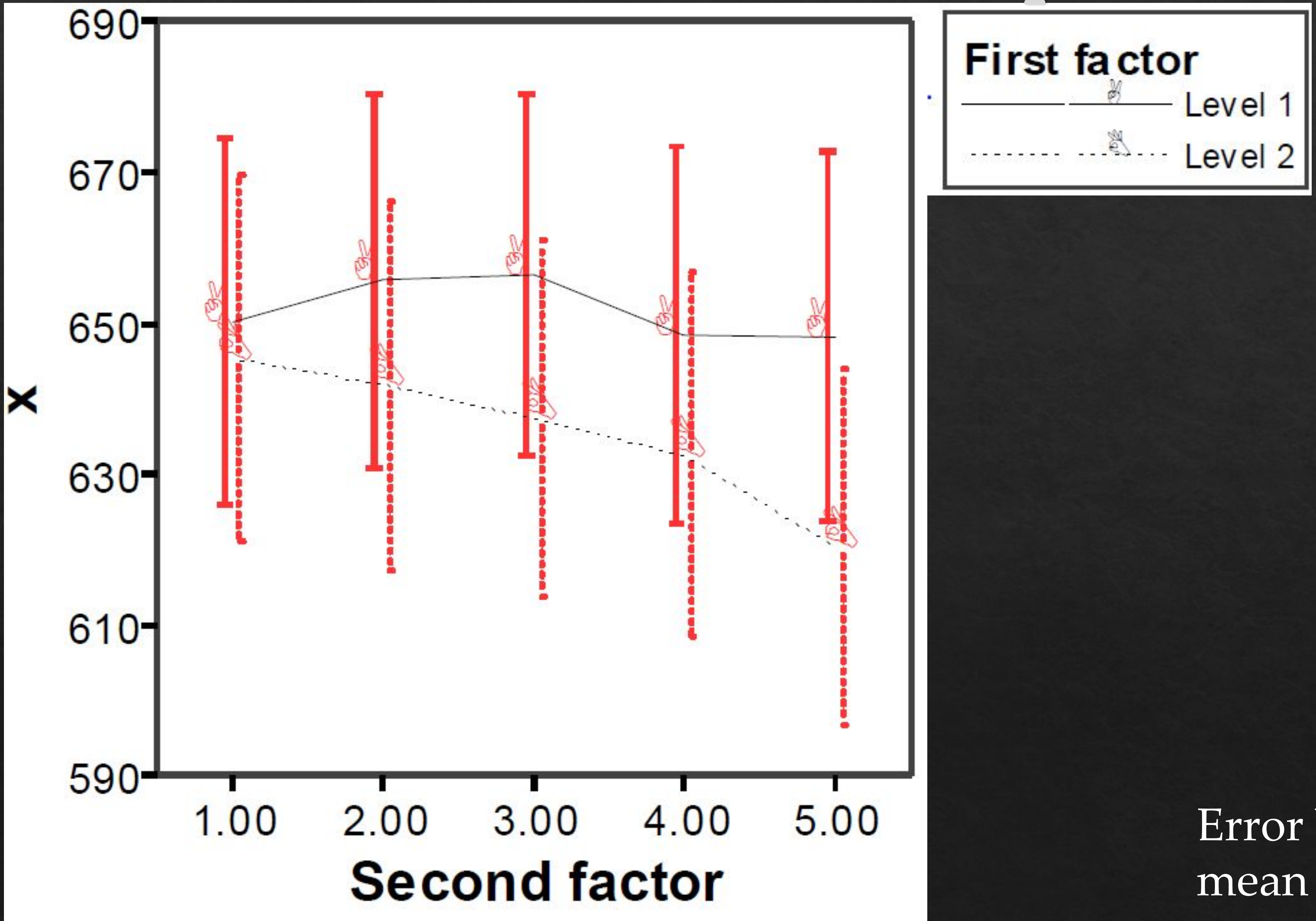
ANOVA results

an experiment with two factors, the first with two levels and the second with 5 levels

Effect name	SS	dl	MS	F	
Factor 1	10621	1	10621	76.8	***
Error	2073	15	135		
Factor 2	11784	4	8196	16.4	***
Error	4378	60	72.9		
Interaction	2250	4	562	6.52	***
Error	5171	60	86.2		

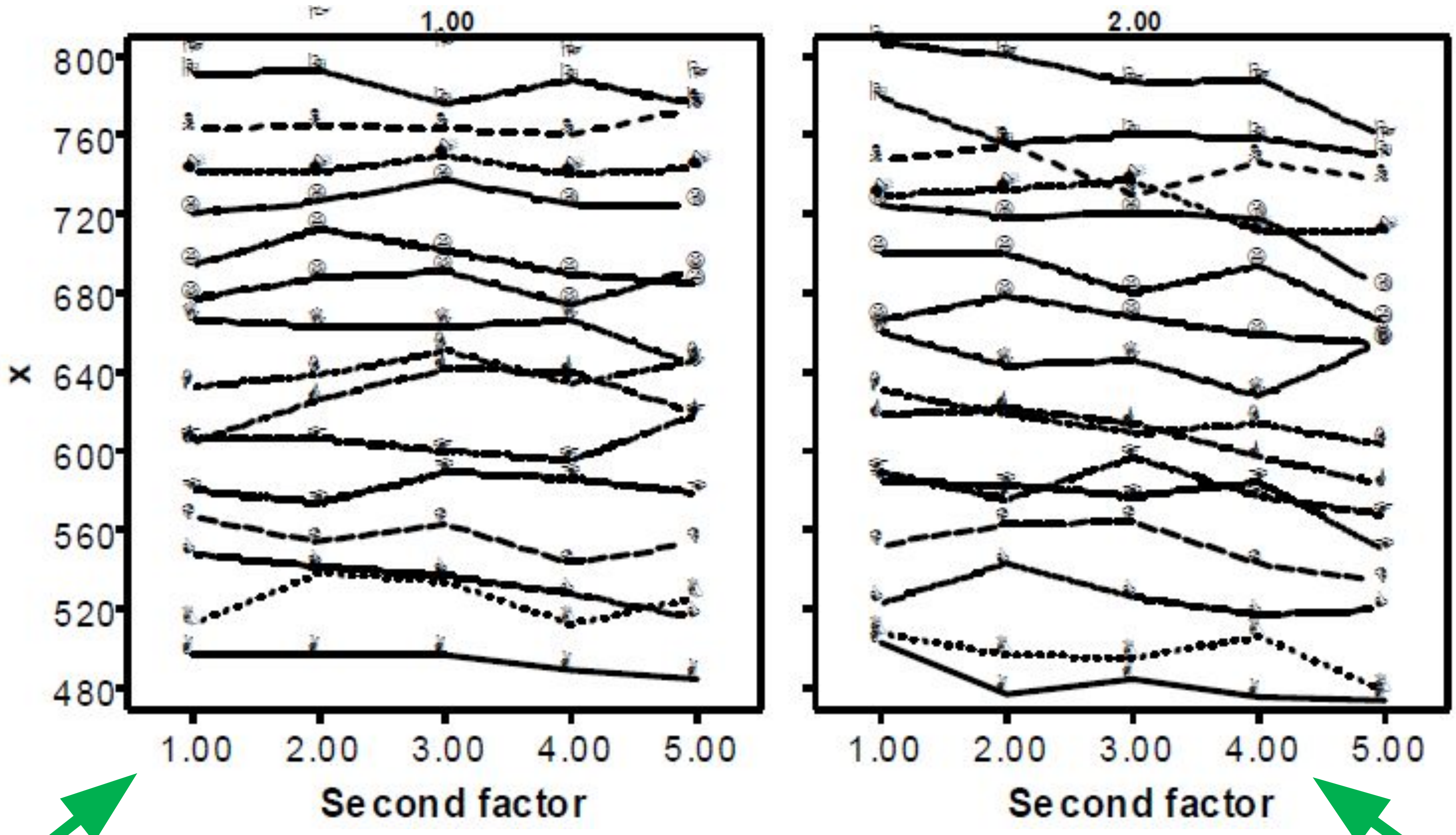
***: $p < .001$

Results of the experiment



Error bars show the mean ± 1 standard error.

The individual results of the 16 participants



The first level of the first factor.

The second level of the first

The solution of the problem

$$Y = X_{ij} - \overline{X}_1 + \overline{X}$$

Y = results of the participant in a particular condition − the participant mean + the group mean

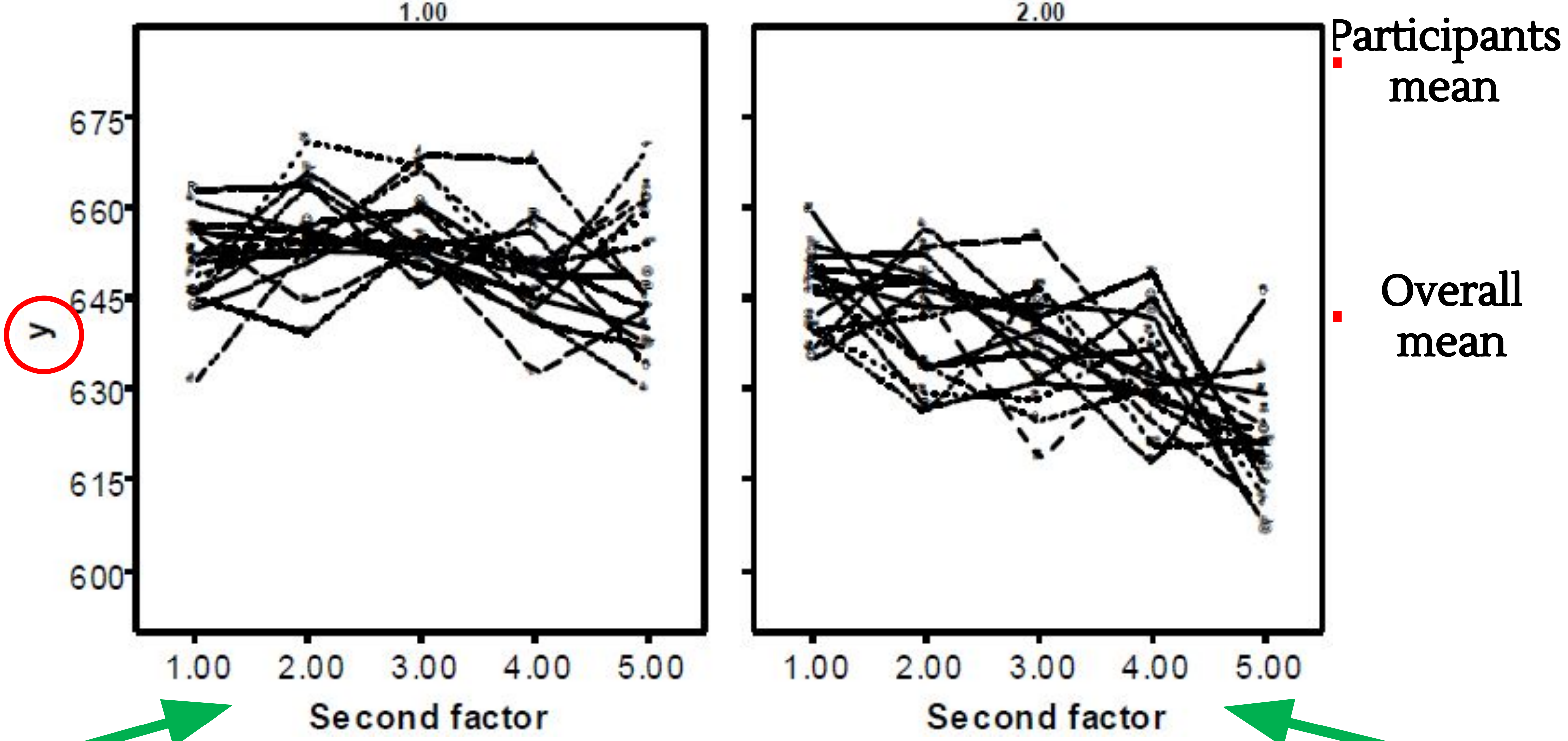
Example of calculations

Participant	Condition 1	Condition 2	Condition 3	*Mean*
1	550	580	610	*580*
2	605	635	655	*635*
3	660	690	710	*690*
Mean	*605*	*635*	*655*	*635*

⬇

Participant	Condition 1	Condition 2	Condition 3	*Mean*
1	550−580+635=605	580−580+635=635	610−580+635=665	*580*
2	605 − 635 +635	635 − 635 +635	655 − 635 +635	*635*
3	660 − 690 +635	690 − 690 +635	710 − 690 +635	*690*
Mean	*605*	*635*	*655*	*635*

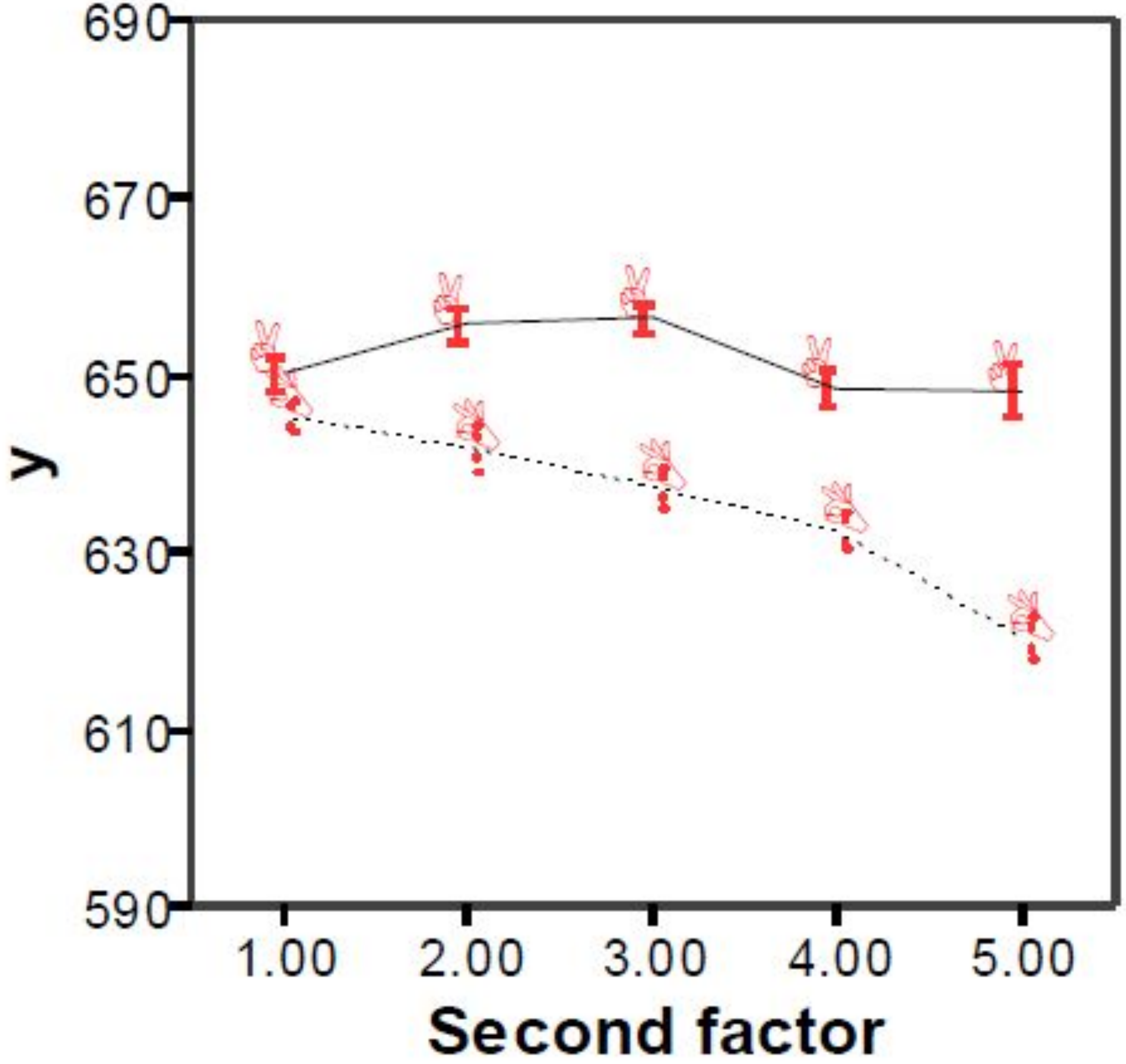
The individual results of the 16 participants after the individual differences were removed



The first level of the first factor.

The second level of the first

The graph after the individual differences were removed



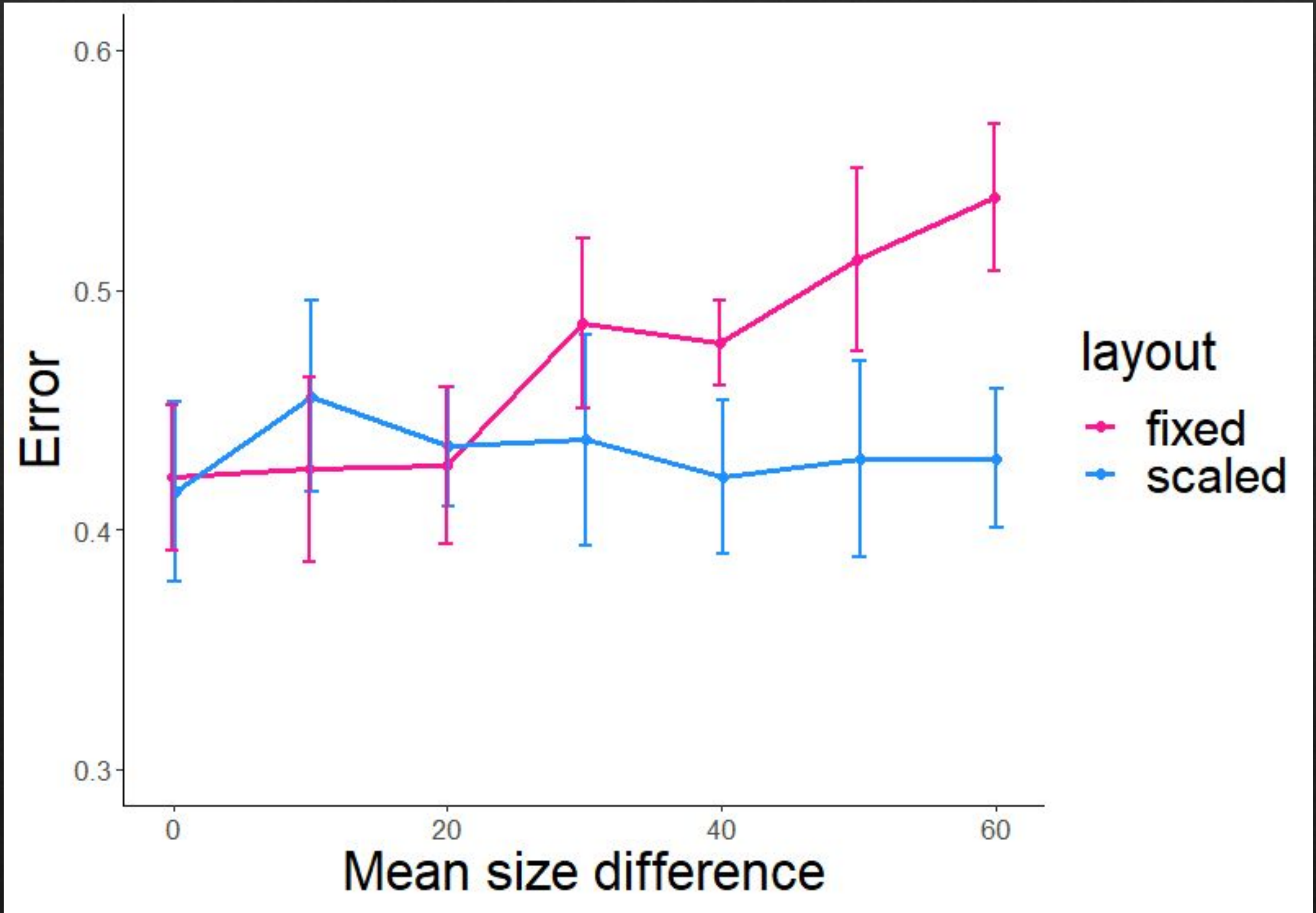
Error bars show the mean ± 1 standard error.

$$Y = X_{ij} - \overline{X}_1 + \overline{X}$$

Y = results of the participant in particular condition − the participant mean + the group mean

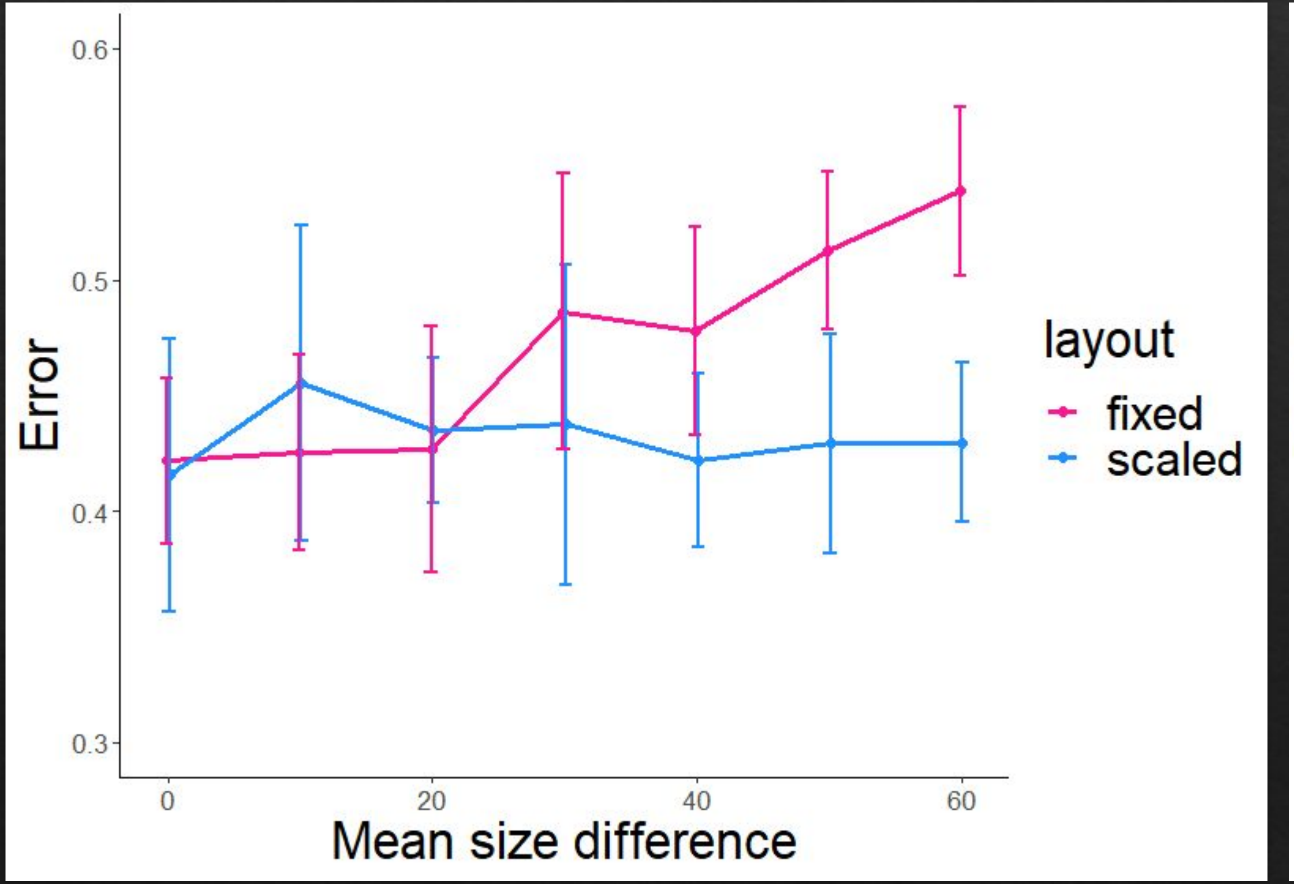
NOTE: Y is only useful for graphing purposes; for the analyses, continue to use the original data.

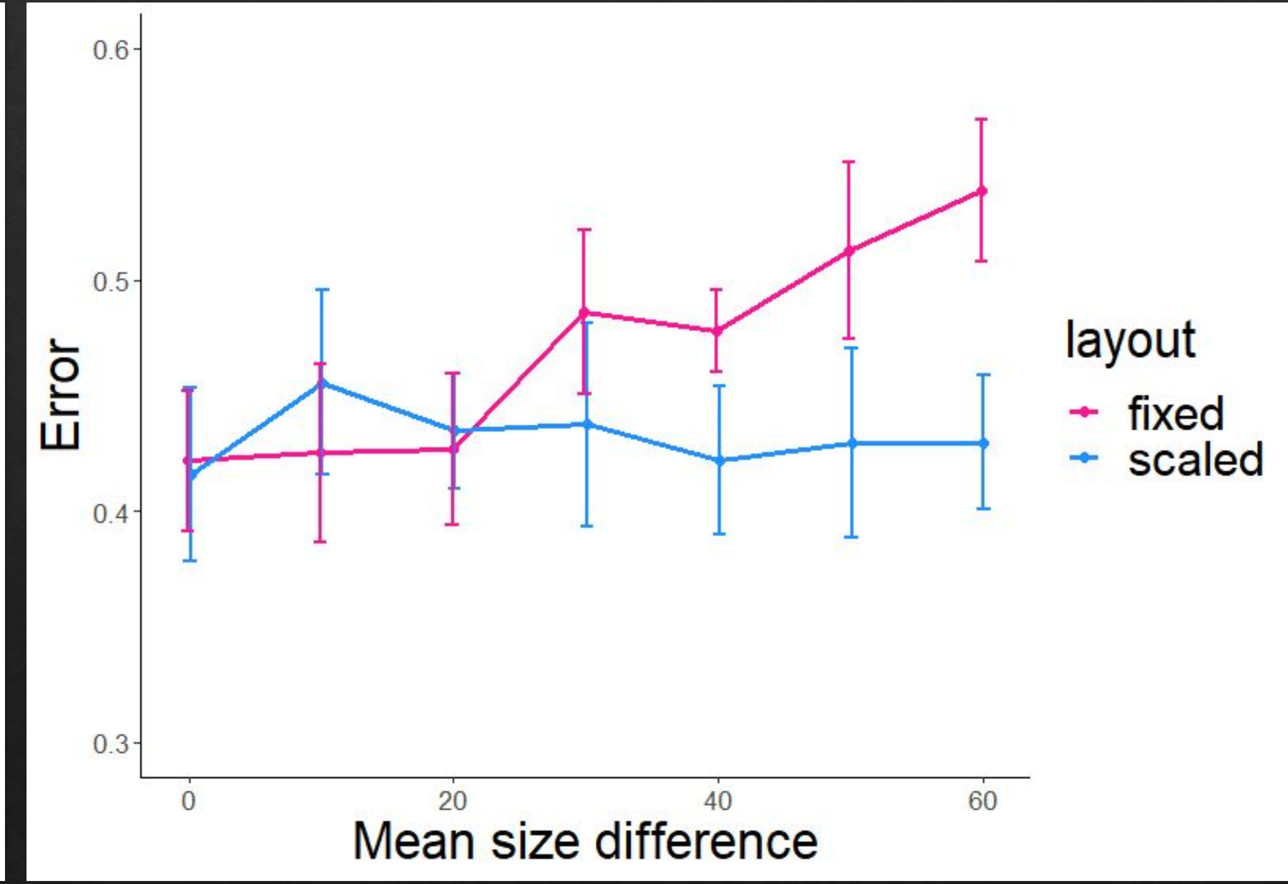
Example from real life



Error bars show SEM.

Example from real life





Error bars show SEM.

Hope you will use it

Thank you
For your attention