A Hierarchical Bayesian Approach to the Reliability and Validity of Cognitive Control

UNIVERSITÄT HEIDELBERG
ZUKUNFT SEIT 1386

Jean-Paul Snijder[1], Julie M. Bugg[2], Rongxiang Tang[3], Andrew R.A. Conway[4], Todd S. Braver[2]

Heidelberg University; **Presenter**[1]
Washington University in St. Louis[2]
University of California, San Diego[3]
Claremont Graduate University[4]

Introduction

Experimental manifestations of Cognitive Control (CC) have been found to be very robust (i.e., everybody Stroops). However, whether CC can be considered a domain-general construct with measurable and reliable individual differences cannot be summed up so straight-forwardly. This is *possibly* due to some measurement issues that exist in CC tasks. For one, the tasks are created to minimize between-subject variance while emphasizing high within-subject variance to detect an effect; reliable individual differences require the opposite (i.e., high between, low within). Indeed, the results of many correlational studies examining CC show poor reliability and weak between-task correlations.

The Dual Mechanisms of Cognitive Control task battery (DMCC; Braver et al., 2021[1]; Tang et al., 2021[2]) was created in an attempt to address this reliability paradox. The battery is based on the DMC framework which postulates that distinct proactive and reactive modes of control (Braver et al., 2007[3]; Braver, 2012[4]) may reflect key dimensions of individual variation in control function. The DMCC task battery includes conditions that are designed to experimentally and independently bias subjects towards the use of proactive and reactive control modes.

Here we examined the psychometric properties of the DMCC battery from a frequentist and (hierarchical) Bayesian perspective, offering insight into the advantages and disadvantages of both methods in measuring individual differences in cognitive control.

Method

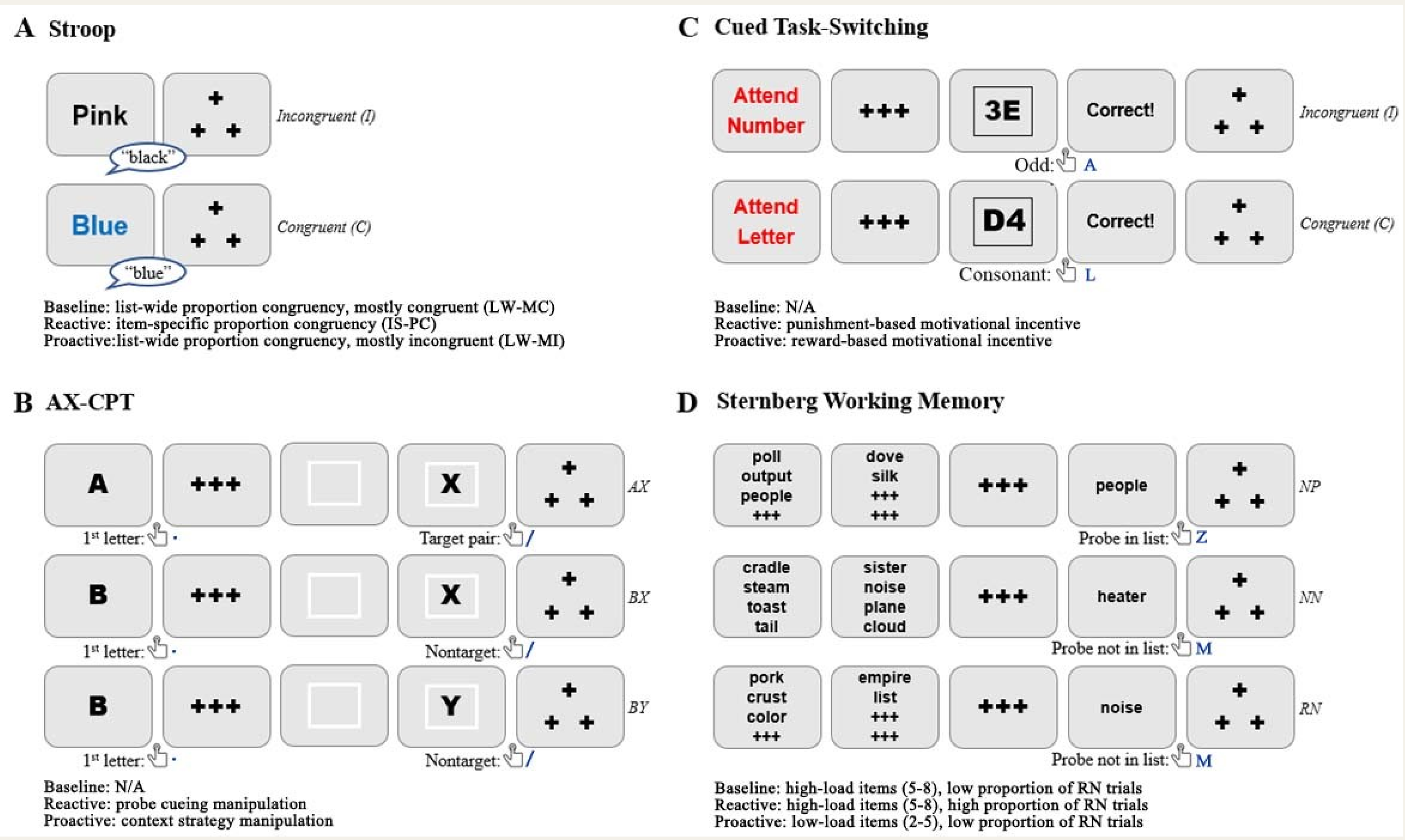

Figure 1:DMCC Task Paradigms and Overview of Session Manipulations

Hierarchical Model Parameters:

$$RT_{(i,c,p)} \sim Lognormal(\mu_{(i,c,p)}, exp_{(i,c,p)})$$
$$\mu_{(i,c,p)} \sim N(\mu_{(mean,c,p)}, \mu_{(sd,c,p)})$$
$$\sigma_{(i,c,p)} \sim N(\sigma_{(mean,c,p)}, \sigma_{(sd,c,p)})$$
$$\mu_{(mean,c,p)} \sim N(0,1)$$
$$\sigma_{(mean,c,p)} \sim N(0,1)$$
$$\Delta_{(i,test)} = \mu_{i,interference,test} - \mu_{i,control,test}$$
$$\Delta_{(i,retest)} = \mu_{i,interference,retest} - \mu_{i,control,retest}$$

Results: Test-Retest Reliabilities

Session	Task	Index	$r(\Delta_1, \Delta_2)$	r_{MPE}	n
Baseline	Stroop	Stroop Effect	.92	.54	122
Proactive			.98	.59	119
Reactive			.88	.55	122
Baseline	AX-CPT	BX Interference	.79	.50	112
Proactive			.93	.51	116
Reactive			.86	.49	113
Baseline	Cued TS	TRCE	.81	.22	116
Proactive			.94	.28	112
Reactive			.90	.39	122
Baseline	Sternberg	Recency Effect	.77	.16	120
Proactive			.89	.20	106
Reactive			.52	.20	127

Figure 2:Reaction Time Test-Retest Correlations of the Delta Parameter from the DMC Task Battery.

Results: Between-task correlations (Validity)

Session	Index 1	Index 2	r_{test}	r_{retest}	$r_{combined}$	n
Baseline	Stroop Effect	BX Interference	.05	.17	.10	90
Baseline		TRCE	.02	.02	.02	90
Baseline		Recency Effect	-.01	-.02	-.02	90
Baseline	BX Interference	TRCE	-.01	.05	.03	90
Baseline		Recency Effect	-.12	-.12	-.13	90
Baseline	TRCE	Recency Effect	.11	-.04	.00	90
Proactive	Stroop Effect	BX Interference	.01	.01	.01	76
Proactive		TRCE	.00	.02	.01	76
Proactive		Recency Effect	-.06	-.07	-.07	76
Proactive	BX Interference	TRCE	-.09	-.16	-.13	76
Proactive		Recency Effect	-.03	-.04	-.04	76
Proactive	TRCE	Recency Effect	-.12	-.13	-.13	76
Reactive	Stroop Effect	BX Interference	.12	.01	.08	107
Reactive		TRCE	-.09	-.10	-.09	107
Reactive		Recency Effect	.06	-.10	-.05	107
Reactive	BX Interference	TRCE	-.04	-.01	-.02	107
Reactive		Recency Effect	.23	.15	.22	107
Reactive	TRCE	Recency Effect	-.10	.00	-.04	107

Figure 3:Reaction Time Between-Task Correlations of the Delta Parameter from the DMC Task Battery.

Conclusion

- Using Hierarchical Bayesian Modeling provides stronger reliability estimates when compared to classic frequentist approaches (e.g., split-half, ICC)
  - *Hierarchical Bayesian Modeling is better at handling measurement error and modeling uncertainty*
- Although the difference score measures (delta parameters) were found to be highly reliable, they did not correlate across tasks of CC
  - *This indicates poor construct validity and supports recent concerns in the CC community*
- CC difference scores (e.g., Stroop effect) are currently not suitable for detecting individual differences
  - *Our theory-based task manipulations did not show any improvements in construct validity*

References

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Contact Information

- Email: jean-paul.snijder@psychologie.uni-heidelberg.de
- Web: http://www.jpsnijder.com/