Rapid, Reliable, and Precise Behavioral Assessment Using Adaptive Design Optimization

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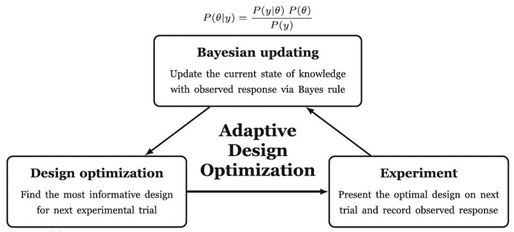
Introduction

- **Substance use disorders (SUDs) are heterogeneous**, highlighting the need for reliable and efficient tools to capture individual differences in neurocognitive mechanisms.
- **The Addictions Neuroclinical Assessment (ANA)** is a neuroscience-based, multidimensional framework designed to better characterize this heterogeneity; however, **full administration can take up to 10 hours** (Kwako et al., 2016).
- **Adaptive Design Optimization** (ADO; Myung et al, 2013), a Bayesian model-based algorithm, provides an effective approach by maximizing information gain and **enabling precise parameter estimation with fewer trials.**
- In this study, we validate **ADO-based tasks** as the first step toward developing a **rapid, reliable, and scalable task battery** for assessing SUD.

Methods

Adaptive Design Optimization (ADO; Myung et al, 2013)

$$P(\theta|y) = \frac{P(y|\theta)\ P(\theta)}{P(y)}$$



$$d^* = \underset{d}{\operatorname{argmax}} \iint u(d,\theta,y)\ P(\theta)\ P(y|\theta,d)\ d\theta\ dy$$

(Yang et al., 2021)

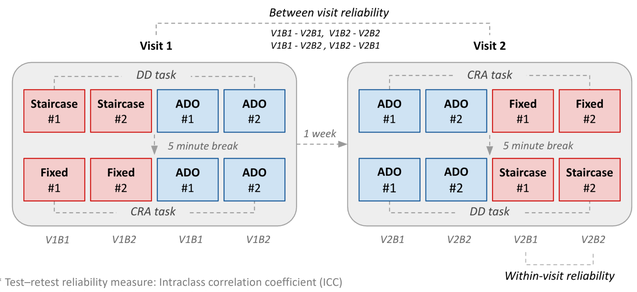
- Bayesian model-based optimization
- Individual-level parameter estimation
- Implemented using ADOpy (Yang et al., 2021)

Participants

Country	Recruitment site	N	Age, M (SD)	Female, n
South Korea	Seoul National Univ. (SNU)	50	22.54 (2.47)	34
USA	Ohio State Univ. (OSU)	101	19.14 (1.83)	52
	Virginia Commonwealth Univ. (VCU)	50	20.90 (1.50)	31
Bulgaria	New Bulgarian Univ. (NBU)	50	22.48 (4.20)	45
	Total	251	21.06 (3.00)	162

Note. Age missing: n = 30; gender missing: n = 30.

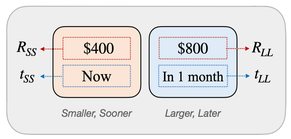
Methods: Experimental Design



* Test–retest reliability measure: Intraclass correlation coefficient (ICC)
* The order of tasks and designs is counterbalanced.

Methods: Tasks

Delay Discounting (DD) task (Green & Myerson, 2004)



Computational model

$$\text{discounting factor } D(t) = \frac{1}{1+kt}$$

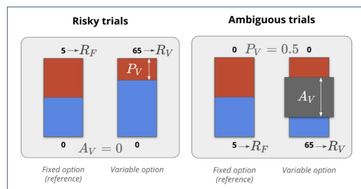
$$V_{SS} = R_{SS} \cdot D(t_{SS})$$
$$V_{LL} = R_{LL} \cdot D(t_{LL})$$
$$P(LL\ over\ SS) = \frac{1}{1+\exp[-\tau \cdot (V_{LL} - V_{SS})]}$$

Design variables
- R_{SS}: Reward for SS option
- t_{LL} : Delay for LL option

Parameters
- k: Discounting rate parameter (0~1)
- τ : Inverse temperature (0~1)

* Staircase (SC): 42 trials = 7 (t_{LL}) X 6 (R_{SS})

Choice under the Risk and Ambiguity (CRA) task (Levy et al., 2010)



Computational model

$$U_F = 0.5 \cdot (R_F)^{\alpha}$$
$$U_V = \left[p_V - \beta \cdot \frac{A_V}{2}\right] \cdot (R_V)^{\alpha}$$
$$P(V\ over\ F) = \frac{1}{1+\exp[\gamma(U_F - U_V)]}$$

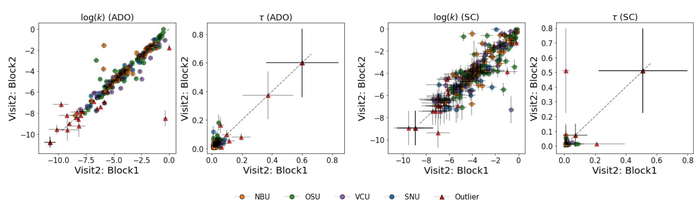
Design variables
- R_V : reward of variable option
- R_F: reward of fixed option
- P_V : probability of variable option
- A_V : ambiguity level of variable option

Parameters
- α: risk attitude parameter (0~2) ($\alpha > 1$ — risk-taking; $\alpha = 1$ — risk-neutral; $\alpha < 1$ — risk-aversion)
- β: ambiguity attitude parameter (-3~3)
- γ: inverse temperature (0~5) ($\beta > 0$ — ambiguity-averse; $\beta = 0$ — ambiguity- neutral; $\beta < 0$ — ambiguity-taking)

* Random design: 60 trials = 5 (R_V) x 6 [3 (P_V)+3 (A_V)] x 2 (color counterbalance)

Results: parameter estimation

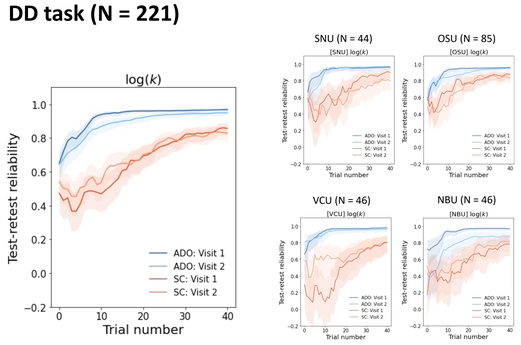
DD Visit 2 parameter estimation



* Outlier detection: $SD_i > \mu_{SD} + 3\sigma_{SD}$
* Error bar: $\pm SD_i$

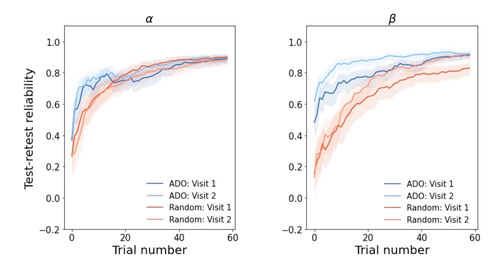
Results: within-visit reliability

DD task (N = 221)



Parameter	Measures		ADO	SC
log(k)	Reliability (max ICC)	Visit 1	0.968	0.861
		Visit 2	0.950	0.836
	Precision (mean SD)	Visit 1	0.118	0.374
		Visit 2	0.123	0.395
	Efficiency (trials to 0.9 ICC)	Visit 1	10	>N_TRIAL (42)
		Visit 2	17	>N_TRIAL (42)

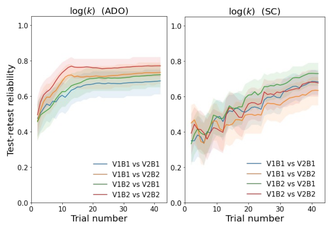
CRA task (N = 226)



Parameter	Measures		ADO	Random
α	Reliability (max ICC)	Visit 1	0.891	0.901
		Visit 2	0.903	0.885
	Precision (mean SD)	Visit 1	0.070	0.099
		Visit 2	0.068	0.101
	Efficiency (trials to 0.9 ICC)	Visit 1	>N_TRIAL (60)	60
		Visit 2	>N_TRIAL (60)	>N_TRIAL (60)
β	Reliability (max ICC)	Visit 1	0.917	0.831
		Visit 2	0.933	0.914
	Precision (mean SD)	Visit 1	0.135	0.245
		Visit 2	0.144	0.252
	Efficiency (trials to 0.9 ICC)	Visit 1	25	49
		Visit 2	8	30

Results: between-visit reliability

DD task (N = 221)



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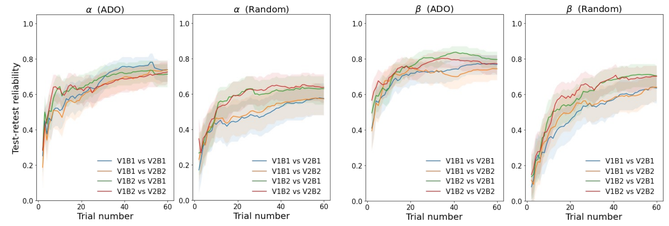

Conclusion

- **ADO-based tasks** improved **efficiency and precision** while preserving high or comparable reliability relative to conventional designs.
- These findings provide a foundation for developing a **rapid, reliable, and precise task battery for future clinical applications across countries**.

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Website

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