Exploring the post-reinforcement pause using drift-diffusion models

University of Cologne

Deutsche Forschungsgemeinschaft

S. Geysen[1], L. Mohr[2], A. Brands[1], R. Hanßen[3], J. Koenig[4], M. Tittgemeyer[3], & J. Peters[1]

[1] Biological Psychology, Department of Psychology, University of Cologne, Germany

[2] Department of Medical Psychology and Medical Sociology, Faculty of Medicine, Ruhr University Bochum

[3] Max Planck Institute for Metabolism Research, Germany

[4] Department of Child and Adolescent Psychiatry, Psychosomatics and Psychotherapy, University Hospital Cologne, Germany

Correspondence: sgeysen@uni-koeln.de

BIOLOGICAL PSYCHOLOGY COLOGNE

BACKGROUND

- While playing on electronic gambling machines (EGMs) participants show increased reaction times (RTs) after positive outcomes[1, 2]
  - **Post-reinforcement pause** (PRP)
- Volatility is an important characteristic of popular EGMs[3] (e.g., slot machines)
- The **Volatile Kalman Filter** (VKF) describes choice behaviour in volatile environments[4]

→ Here we present preliminary results of reanalysed RT data of an EGM study[5] where we compared VKF modulated drift-diffusion models (DDMs) to covariate models in their ability to describe PRPs.

METHODS

Design

Electronic Gambling Machine[5]

- "Play slot machine with €20"
- $N = 46$ with 200 trials
- Possible actions (among others)
  - Place bet
    - Small (€0.20)
    - Big (€0.60)
  - Playing out the gamble
- Fixed task structure
  - All trial outcomes fixed
  - Difference in monetary outcome due to different betting behaviours

Computational Modelling

Only trials with no other actions before betting or spinning the wheels used

RT cutoff: 150 ms < RT

Hierarchical Bayesian modelling in RStan[6]

Drift-diffusion model

- Non-decision time (τ)
- Boundary separation (α)
- Response bias (β)
- Drift rate (δ)

Volatile Kalman Filter

- Volatility learning rate (λ)
- Initial volatility (v_0)
- Outcome noise (σ^2)

Covariate model

- Covariate for each different trial type

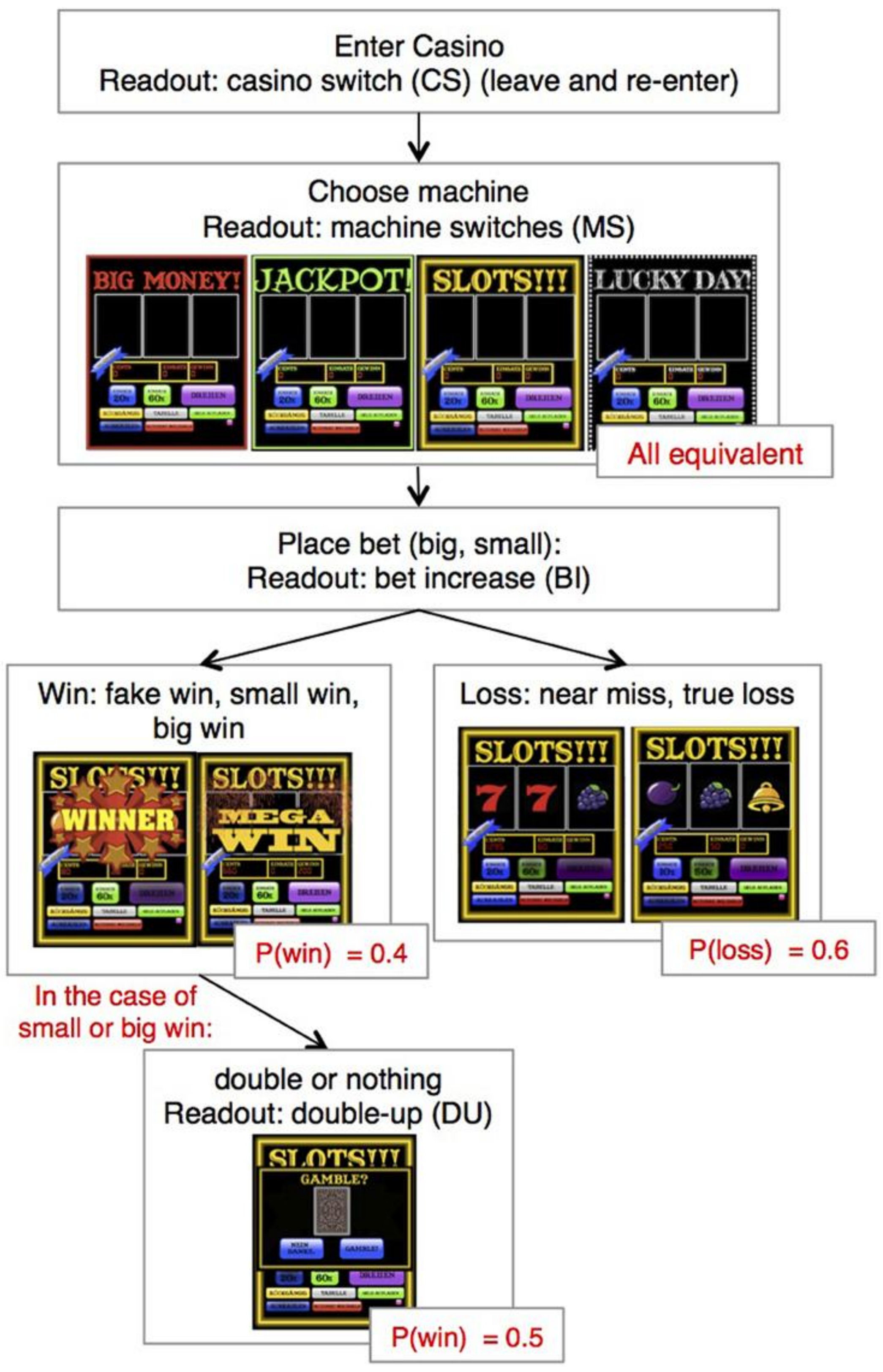

Figure 1. *Structure of the Electronic Gambling Machine.* From "A model-based analysis of impulsivity using a slot-machine gambling paradigm" by Paliwal and colleagues, 2014, *Front. Hum. Neurosci. 8*, p. 5.

RESULTS

Model-agnostic

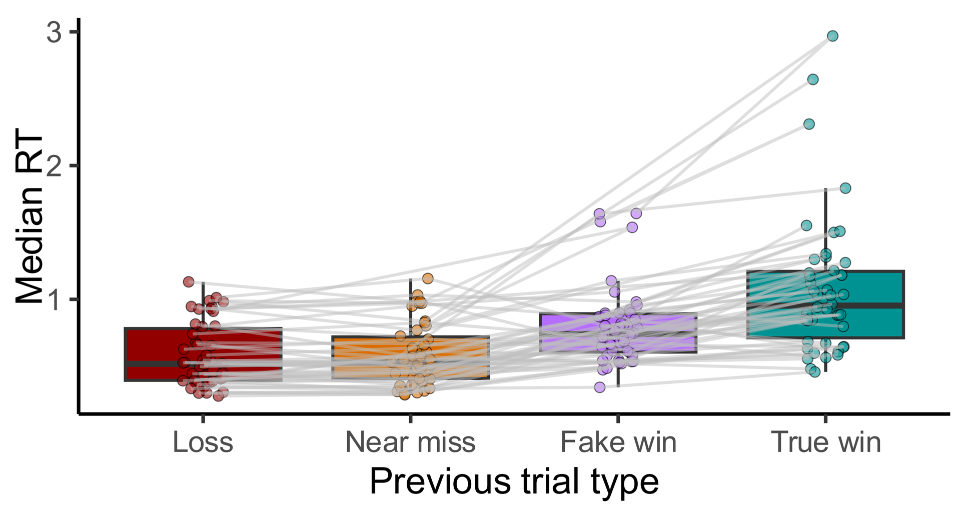

Figure 2. *Observed RTs.* The data provided extreme evidence for a difference in RT after true wins compared to any other outcome. The same was true for the difference between fake wins (losses disguised as wins) and loss outcomes (losses and near misses).

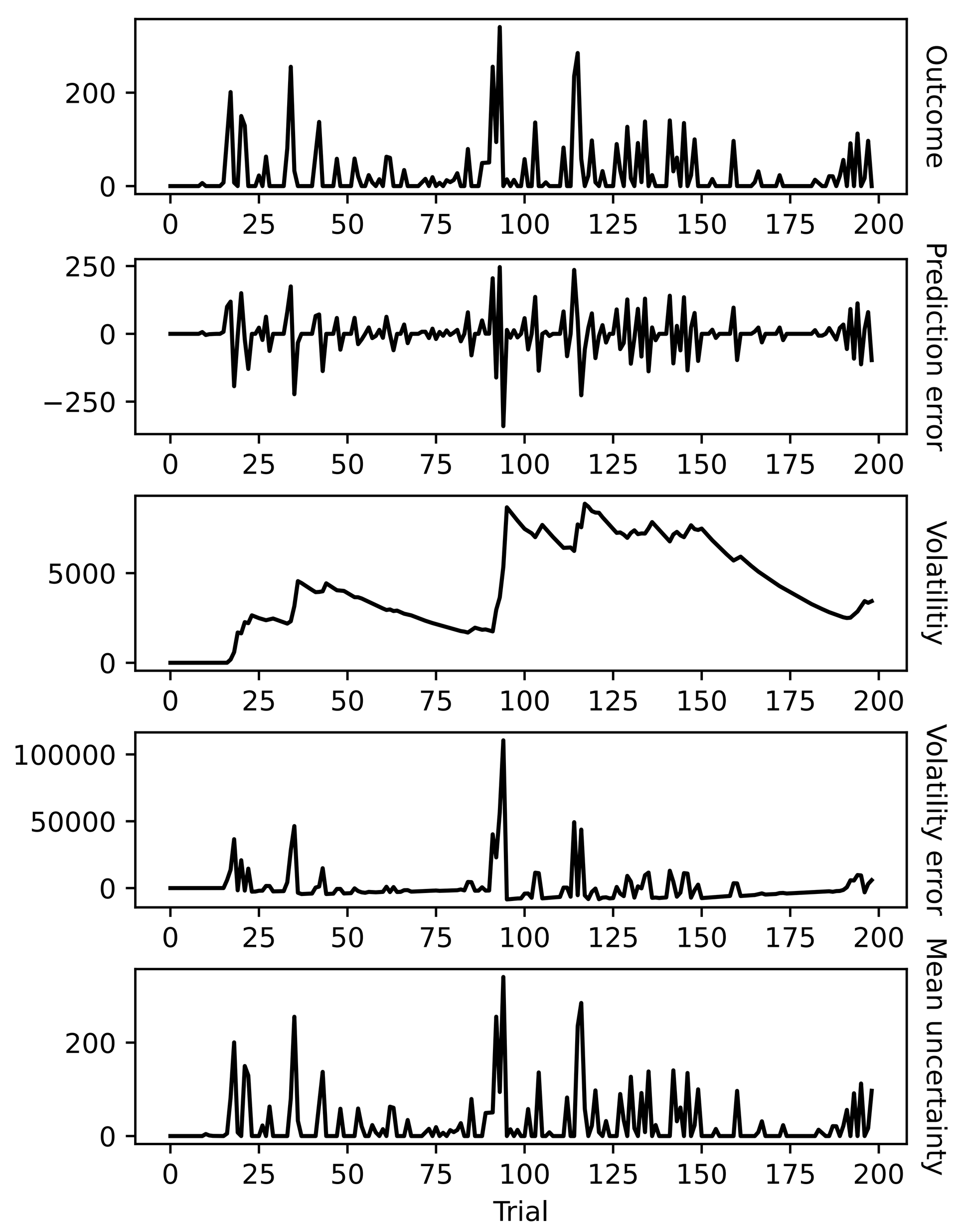

Figure 3. *Simulated Volatile Kalman Filter.* Several variables of the VKF compared to the average outcome of the EGM paradigm. $\lambda = 0.03,\ V_0 = 1.63, \sigma^2 = 1.16$

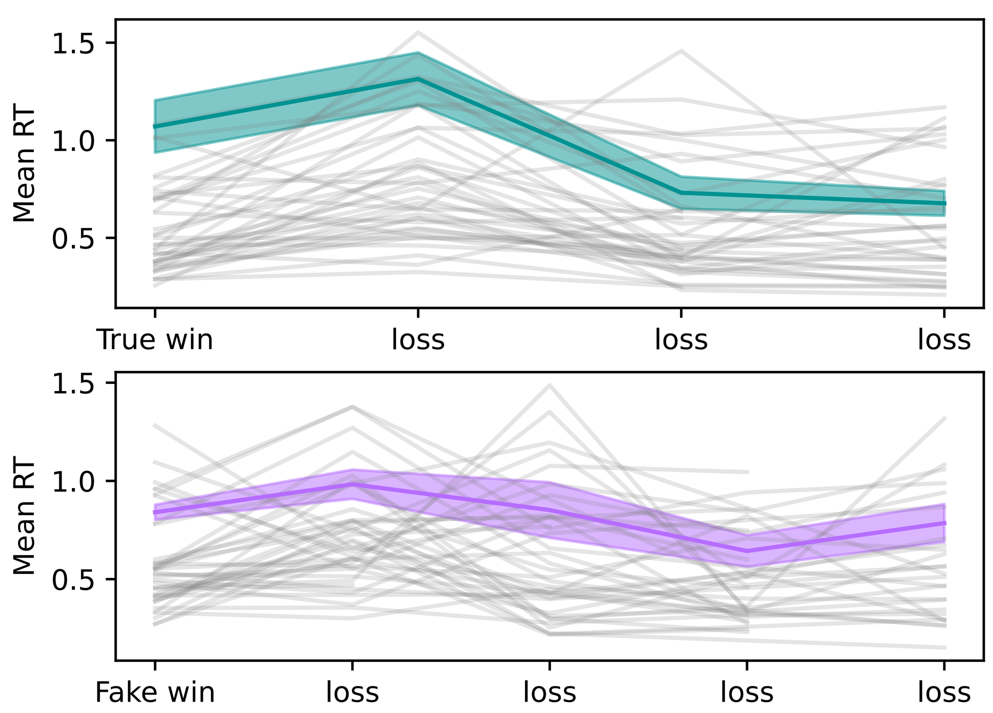

Figure 4. *Sequenced Outcomes.* Bold lines show the mean across participants (±SEM), grey lines represent the mean within participants.

RESULTS

Model-based

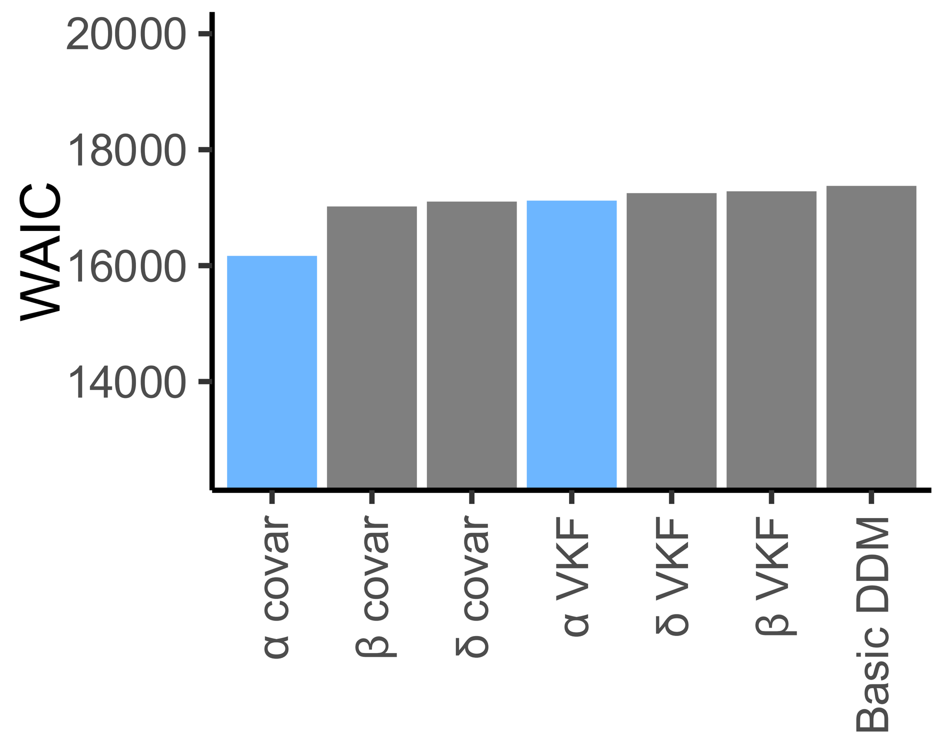

Figure 5. *WAIC Scores of Model Space.* The total WAIC score of each model. The best scoring models of each group are highlighted.

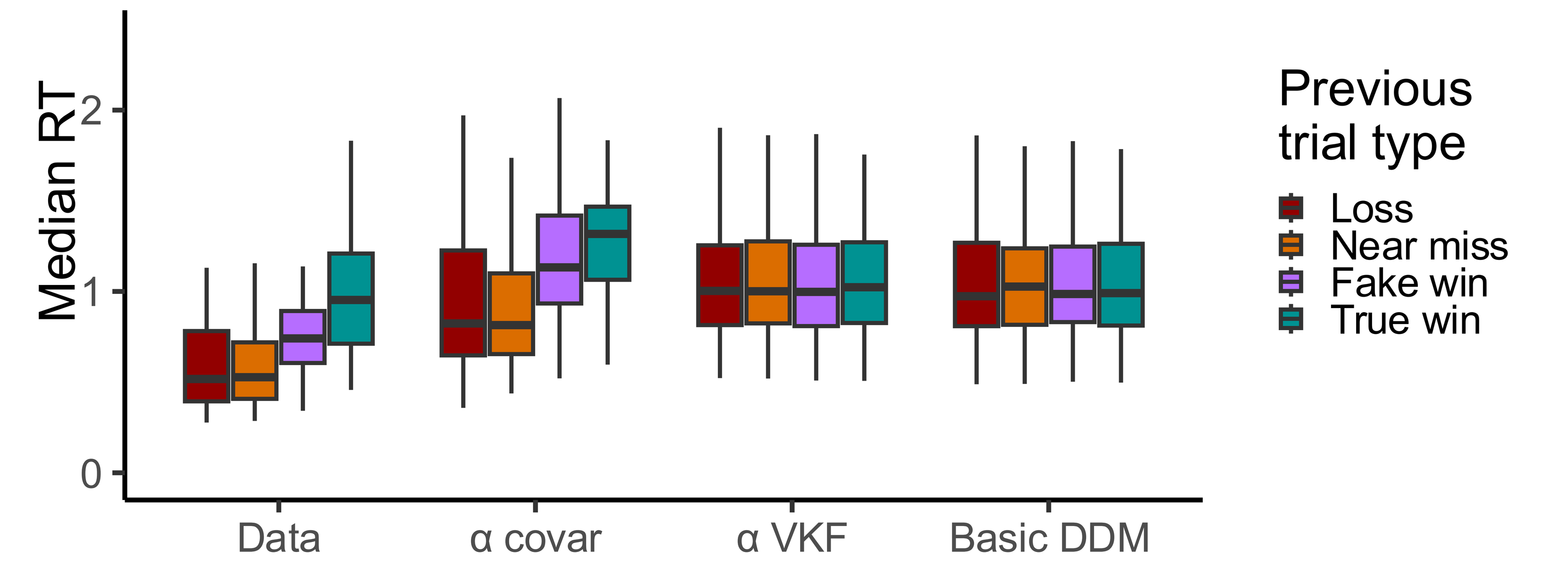

Figure 6. *Posterior Checks of PRP Effect.* Data simulated ($N_{sim} = 50$) with the basic DDM showed no effect of the previous trial type on the RT. The same was true for the VKF modulated DDM. The covariate model was able to replicate the PRP effect. Note that all models are all slower than the observed data ("Data"; see Figure 2).

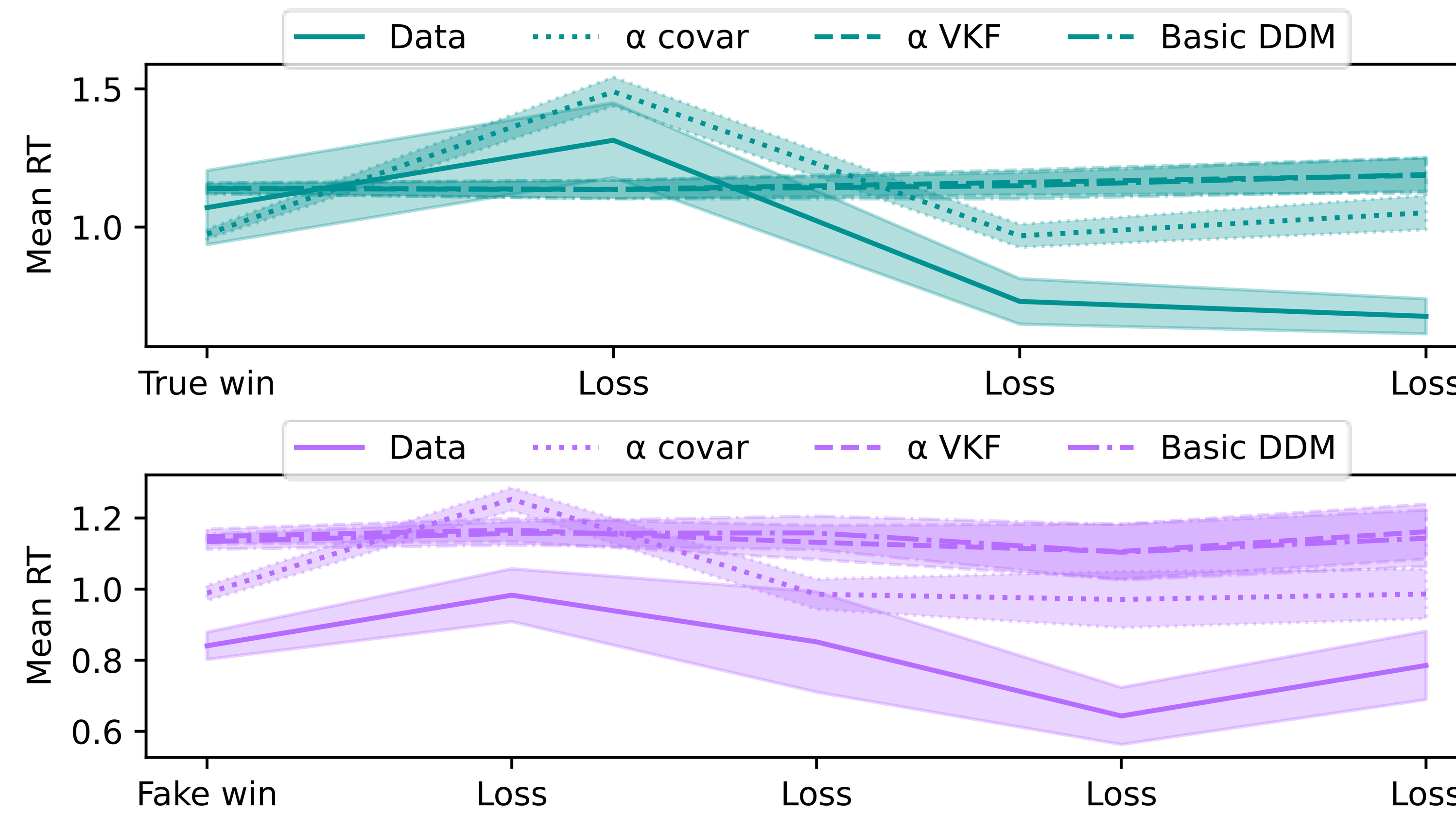

Figure 7. *Posterior Checks of Sequenced Outcomes.* The covariate model was able to replicate the pattern of the observed data ("Data"; see Figure 4). RTs simulated by the VKF modulated DDM and the basic DDM did not change over time.

CONCLUSION

Post-reinforcement pause

- Observed in the EGM study of Paliwal and colleagues[5]
- Appeared to be best captured by modulating the boundary separation
  - Increased caution after win
  - Might be related to loss chasing[7, 8]
- Not explained by only volatility prediction error

Next steps

→ Full models

- Modulators for all DDM parameters in one model

→ Further explore VKF calculations in DDM

- Volatility
- Mean uncertainty (i.e., the expected outcome)

REFERENCES

1. Delabbro, P. H., & Winefield, A. H. (1999). Poker-machine gambling: An analysis of within session characteristics. *British Journal of Psychology*, *90*(3), 425–439. https://doi.org/10.1348/000712699161503
2. Murch, W. S., Ferrari, M. A., & Clark, L. (2024). Post-reinforcement pauses during slot machine gambling are moderated by immersion. *Quarterly Journal of Experimental Psychology*, *77*(12), 2488–2496. https://doi.org/10.1177/17470218241239054
3. Coates, E., & Blaszczynski, A. (2013). An analysis of switching and non-switching slot machine player behaviour. *Journal of Gambling Studies*, *29*(4), 631–645. https://doi.org/10.1007/s10899-012-9329-6
4. Piray, P., & Daw, N. D. (2020). A simple model for learning in volatile environments. *PLoS Computational Biology*, *16*(7), e1007963. https://doi.org/10.1371/journal.pcbi.1007963
5. Paliwal, S., Petzschner, F. H., Schmitz, A. K., Tittgemeyer, M., & Stephan, K. E. (2014). A model-based analysis of impulsivity using a slot-machine gambling paradigm. *Frontiers in Human Neuroscience*, *8*, Article 428. https://doi.org/10.3389/fnhum.2014.00428
6. Stan Development Team. (2023). RStan: The R interface to Stan (Version 2.36.0.9000) [Computer software]. https://mc-stan.org/
7. Zhang, K., & Clark, L. (2020). Loss-chasing in gambling behaviour: Neurocognitive and behavioural economic perspectives. *Current Opinion in Behavioral Sciences, Gambling*, *31*, 1–7. https://doi.org/10.1016/j.cobeha.2019.10.006
8. Chowdhury, N. S., Livesey, E. J., Blaszczynski, A., & Harris, J. A. (2017). Pathological gambling and motor impulsivity: A systematic review with meta-analysis. *Journal of Gambling Studies*, *33*(4), 1213–1239. https://doi.org/10.1007/s10899-017-9683-5