IGT Computational Model

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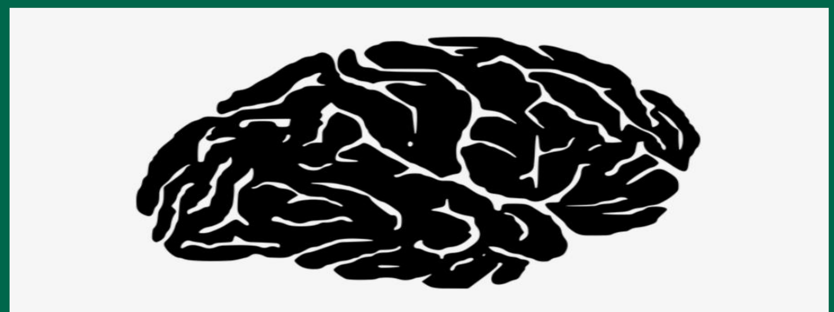
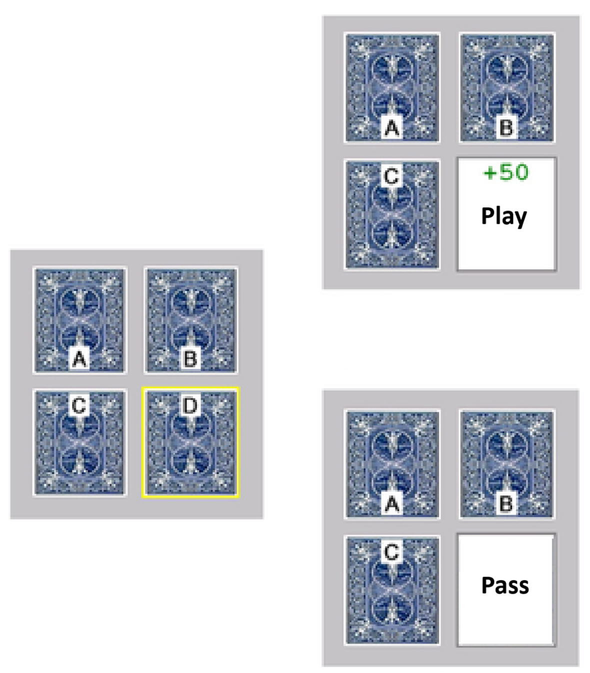


Introduction

- The Iowa Gambling Task (IGT) is a useful tool for studying experience-based decision-making under uncertainty.
- The IGT simulates real-world decision-making where outcomes can be hard to predict.
- In the IGT, participants are shown four decks (A, B, C, D).
- This IGT version does not allow for participants to choose decks freely, instead the deck they can play or pass is highlighted for them.
- Decks A and B are **disadvantageous** and decks C and D are **advantageous**. Disadvantageous decks offer higher per trial gains but lead to net losses over time.
- The goal is to win the most points possible for 400 trials



Deck Payouts

Deck A	Deck B	Deck C	Deck D
130	130	70	70
100	120	60	60
100	100	50	50
90	100	50	50
80	100	40	50
-50	100	-5	50
-100	90	-10	40
-150	80	-15	40
-200	80	-15	40
-250	-1,150	-25	-200

Background

- The Win-Stay/ Lose-Shift (WSLS) model by Worthy et al., (2012) is made for the free-choice IGT
- WSLS uses the previous choice's outcome to help predict the current trial's choice, this model was consistently a better fit than base or null models.
- Win-play/lose-pass (WPLP) is an adapted version of WSLS
- The WPLP model suggests that participants will choose "play" or "pass" by taking into account the result (win/loss) of the last time they played that same deck.
- The WPLP model has two free parameters
  - The probability of playing the highlighted deck given the last time it was highlighted; it was played and resulted in a win
  - The probability of passing given the last time it was highlighted; it was played and resulted in a loss.
- We compare the WPLP to the base model, which doesn't use previous choices and has a free parameter for each deck.
- The Akiak Information Criterion AIC is used to compare model fit. Lower values indicate better model fit.

What we expect

- We hypothesize that the WPLP model will be a better fit to our data than the base model.
- Based on previous research, we also hypothesize that the WPLP model should perform better in high performance (engaged) participants compared to low performance participants.

Results

- 77 participants were used for our analyses
- The models were fit using maximum likelihood estimation, showing a mean AIC difference of 4.6 with the WPLP performing better
- Only 30% of our participants are best described by the WPLP, leaving 70% best described by the base model
- Analyzing our data in blocks of 40 trials for a total of 10 blocks reveals a strong downward trend in AIC for both models as the game progresses. The trend indicates players' choices are becoming more predictable
- Interestingly, The WPLP model is much better at fitting choices in the first block than the base model

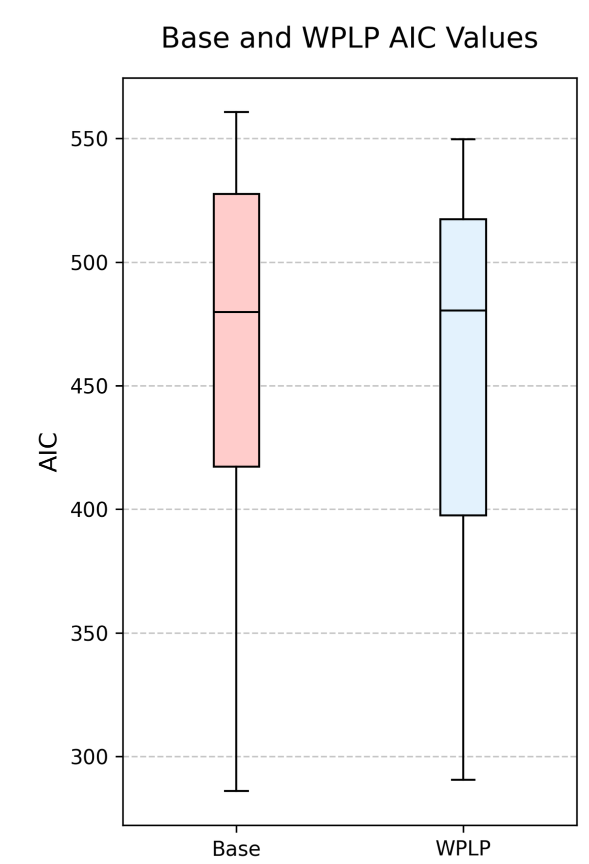


Figure 1

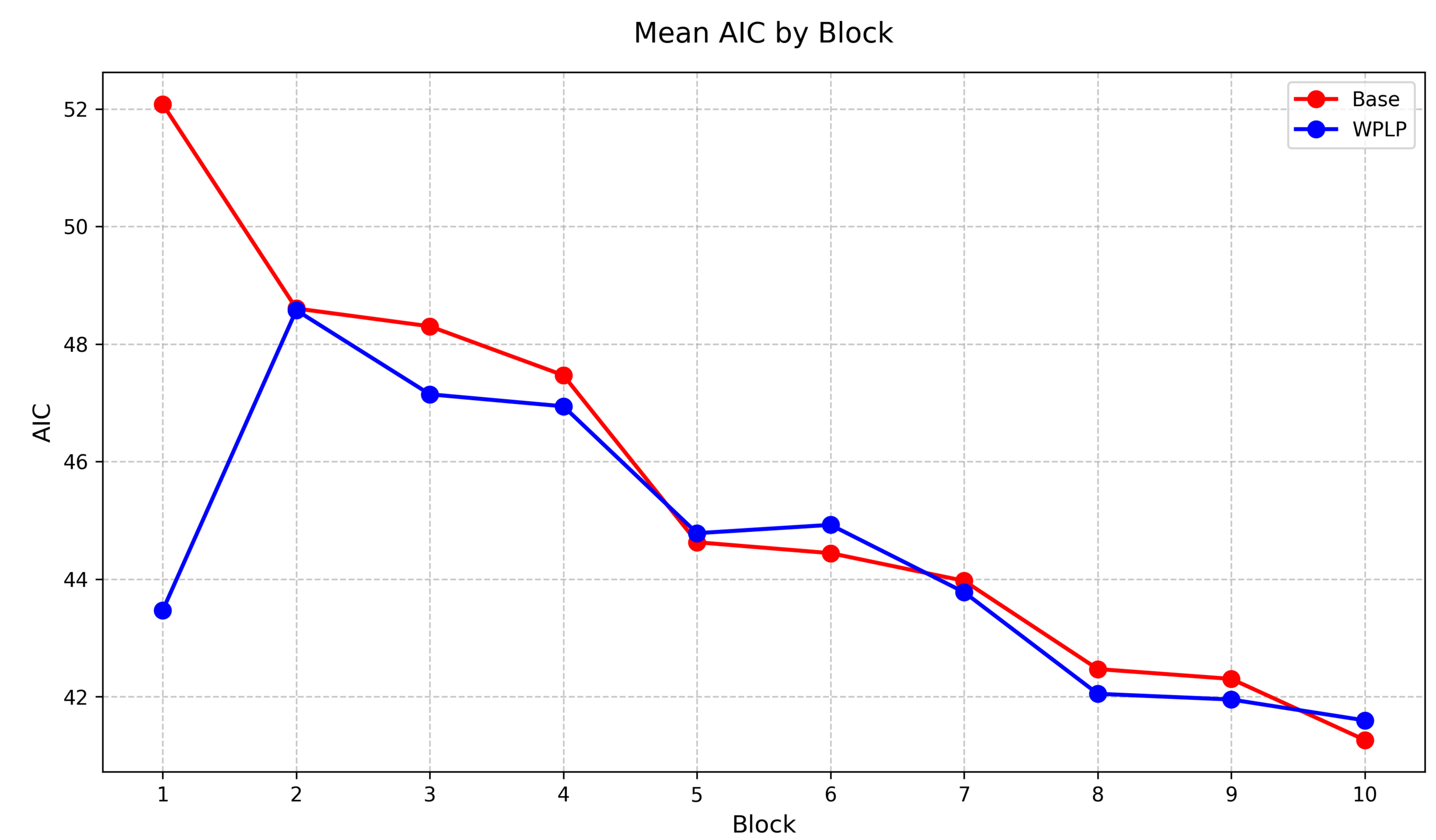


Figure 2

- A median split on participants' final score shows two distinct trends. High scoring participants continue to increase their consistency throughout the game, while low scoring participants plateau at around block 5.
- When we look at high scorers' and low scorers' deck choices by block, we see high scorers more consistently playing advantageous decks C and D, while low scorers play all 4 decks more randomly, matching the trend in AIC

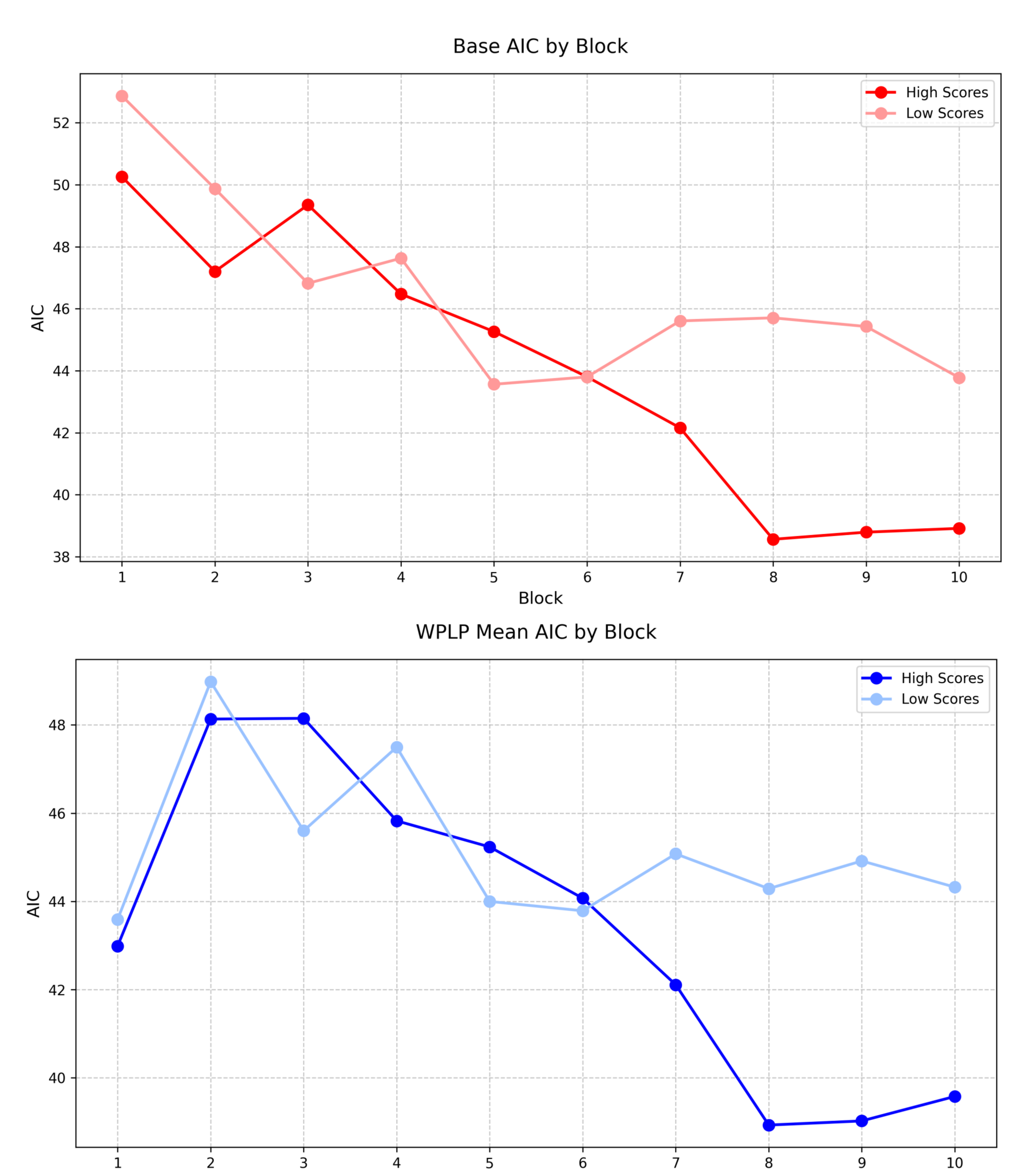


Figure 3

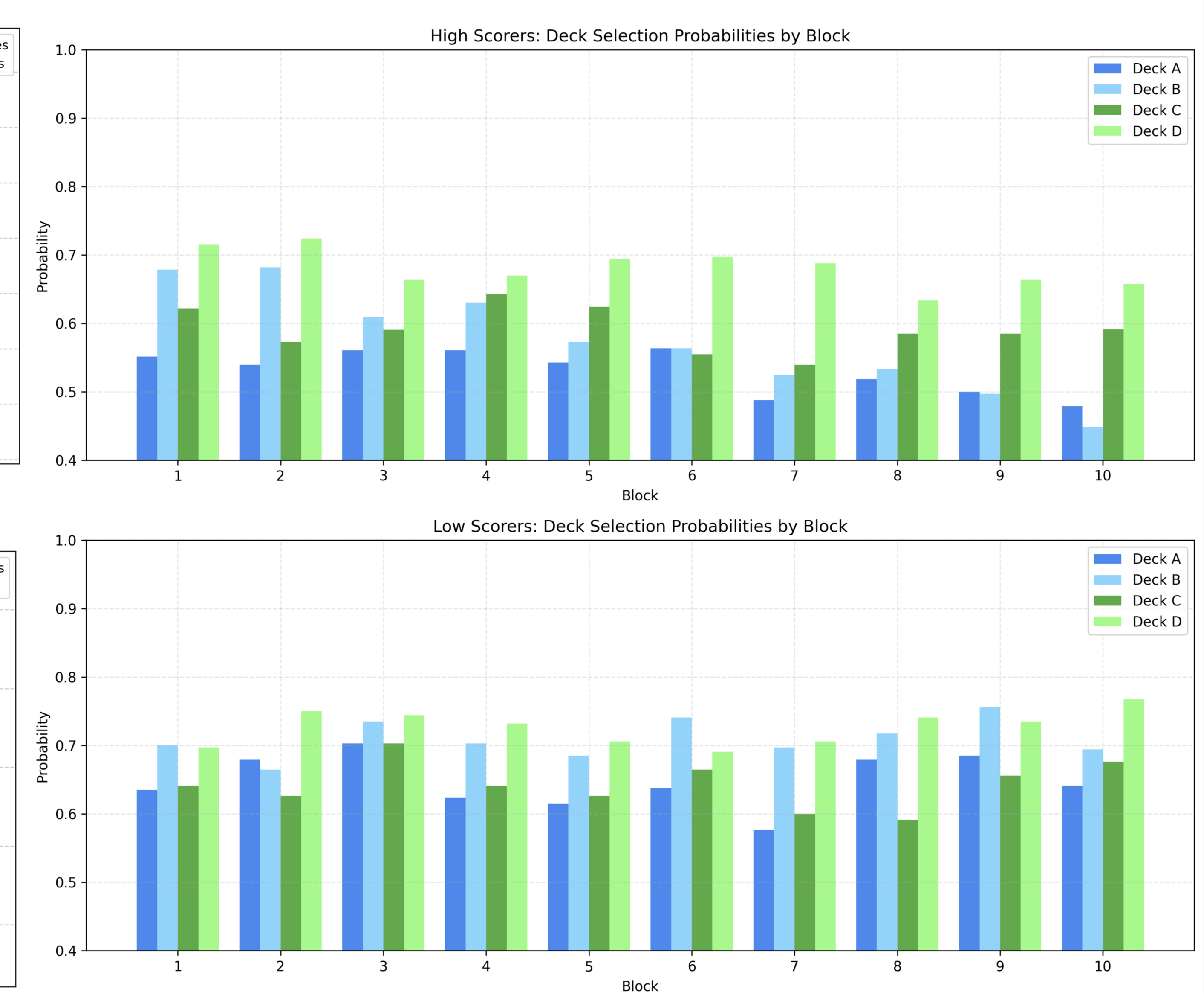


Figure 4

Discussions and Conclusions

- The results seen in WPLP compared to the WSLS model are different from what we expected. The WSLS outperformed the base model for 90% of their participants compared to the WPLP which only outperformed for 30% of our participants.
- Choice freedom may be a factor behind the low proportion of best fit data in the WPLP. Since a **random** deck is highlighted each trial, the participant must hold in working memory the previous result until the same deck is highlighted again.
- The WPLP model also shows there are higher probabilities for playing a deck if they won last time than passing if they lost, this may be due to participants' level of risk-aversion, where participants are losing and more susceptible to taking risks.
- Our hypothesis on how the WPLP model would better fit high performance participants compared to low performance participants was not fully supported. Although the WPLP performs better for high performance participants later in the game, overall it averages a similar AIC for low performance participants.
- All participants tended to be more consistent with strategy by the end of the task, despite their score.
- Our next step is to adapt the prospect-valence learning 2 model to our play/pass version of the IGT. The PVL2 model uses reinforcement learning that mimics working memory by assigning a value to each deck based on previous results, and using a variable decay parameter to slowly "forget"

References

Hu, X., Shen, Y., & Dai, J. (2023). Strategy switching in a sequence of decisions: Evidence from the Iowa Gambling Task. Acta Psychologica Sinica, 55(11).

Worthy, D. A., Hawthorne, M. J., & Otto, A. R. (2013). Heterogeneity of strategy use in the Iowa gambling task: a comparison of win-stay/lose-shift and reinforcement learning models. *Psychonomic bulletin & review*, *20*(2), 364–371. https://doi.org/10.3758/s13423-012-0324-9