Data analysis plan for Iowa Gambling Task and Two-Stage Task

For: *Determining the feasibility and efficacy of Goal Management Training for executive functions, and treatment retention and outcomes during residential treatment for methamphetamine use disorder*

Alex H. Robinson

20/12/2021

Iowa Gambling Task (IGT)

Initial screening of behavioural data

Initial screening of outliers and appropriate task engagement will be screened by observing the behavioural outcomes obtained from the VSE Toolbox (Ligneul, 2019; please see: https://github.com/romainligneul/igt-toolbox). Outliers will be defined as ± 3.29 z-scores from the mean (Tabachnick & Fidell, 2013), and any outlier on the behavioural measures will lead to the exclusion of that participant's entire data from the IGT analysis.

The behavioural data to be examined will include: net score (number of selections from decks C and D) – (number of selections from decks A and B), win/stay frequency, lose/stay frequency, choice entropy, mutual information of success choices, and sequential exploration (number of times participants select three/four different decks across three/four trials).

We will also compare behavioural outcomes between in-person and online administration of the task to see if there are any significant differences (i.e., $p < .05$, $BF_{10} > 3.0$) between administration type, prior to further computational analysis. If there are, a dichotomous variable of administration (in-person versus on-line) will be included in group comparisons.

Computational modelling

The first step will be to identify whether the VSE model is the best fitting model for our participants' IGT behaviour. This will be identified by using AIC values (Wagenmakers & Farrell, 2004) to compare the VSE model to the following: 1) a modified VSE model which includes separate parameters for sensitivity towards reward and losses; 2) the Expectancy Valence model (Stout et al., 2004); 3) the Prospect Valence Learning model (Ahn et al., 2008); 4) the Value Plus Perseverance model (Worthy et al., 2013); and, 5) the Outcome-Representation Learning model (Haines et al., 2018). Given, previous work by our lab (Robinson, Chong, Verdejo-Garcia, *under review*) we are confident the VSE model will best fit participants data. However, if it does not, we will perform exploratory analysis on the parameters of any other best fitting model in addition to the VSE model.

Following this, we will obtain model parameter estimates at pre- and post-intervention from the VSE toolbox. These model parameters will then be qualitatively compared to the behavioural data, to increase confidence in their validity and then implemented into the linear mixed model analysis described in our broader analysis plan (please see: https://www.anzctr.org.au/Trial/Registration/TrialReview.aspx?id=379190&isReview=true).

Finally, if there are any difficulties with the functioning of this linear mixed model (i.e., singularity or convergence concerns) we may simplify it by removing complex random effects and interactions until a functioning model exists.

Two-Stage Task (2ST)

Initial screening of behavioural data

We will base exclusion of any participants based on Gillan et al.'s (2016) criteria. These include any participants who missed more than 10% of the trials, responded with the same key for more than 95% of trials; and/or responded much faster than expected (>2 standard deviations from the mean). Importantly, this last criterion will be waived for online administration of the task due to technical issues in data collection. As per the IGT analysis, we will also compare outcomes (number of rewards) between in-person and online administration to see if there are any significant differences (i.e., $p < .05$, $BF_{10} > 3.0$). If there are, a dichotomous variable of administration form (in-person versus on-line) will be included in any group comparisons.

Furthermore, we will conduct two different types of analysis of the 2ST, as is common in the model-based/model-free literature. One is a more basic logistic regression, and the other a more detailed computational parameter estimation approach.

Logistic regression

For the first basic logistic regression we will primarily follow the example of Gillan et al. (2016, p. 15). This is to predict how likely a participant is to repeat their choice, using their previous choice, whether that previous choice was rewarded, and whether the previous transition between spaceship to planet was rare or common.

Our coding of the variables will be identical to Gillan et al., however, our equation will slightly differ to favour model simplicity and avoid singularity issues. We will apply the model for each group separately, to obtain specific coefficients for model based (previous_win * previous_transition) and model_free (previous_win) behaviour.

Our first attempt at modelling this behaviour will be: stay ~ previous_win * previous_transition + (previous_win * previous_transition + 1|ID).

However, if this model is too complex and fails singularity and convergence tests, we will instead apply: stay ~ previous_win * previous_transition + (1|ID).

We will then take the predicted coefficients for the relevant outcomes at both pre- and post-intervention and implement them into the linear mixed model analysis described in our broader analysis plan, with the same caveats of model simplication if required.

Computational modelling

We will apply the model-based/model-free computational model presented by Foerde et al. (2020, p. 468). This analysis will attempt to be as close to the source material, except using Python instead of the Julia language.

Such an approach will give us five outcome parameters: α (both learning rate and decay rate) β_{MF} (strength of model-free learning), β_{MB} (strength of model-based learning), β_{Stage2} (consistency of choices at stage two) and β_{rep} (preference to repeat stage 1 choice). We will present all five variables, however our analysis will particularly focus on β_{MF} and β_{MB}.

If there is qualitative evidence that the fit of a model-based/model-free fit is poor across many participants (i.e., many hitting lower bounds, little support from logistic regression outcomes, we may also devise a pure model-free model and compare AIC and parameter fits.

Again, similar to the above sections, we will then take both pre- and post-intervention parameters and implement them into the linear mixed model analysis described in our broader analysis plan, with the same caveats of model simplification if required.

References

Ahn, W.-Y., Busemeyer, J. R., Wagenmakers, E.-J., & Stout, J. C. (2008). Comparison of decision learning models using the generalization criterion method. *Cognitive Science, 32*(8), 1376–1402. doi:10.1080/03640210802352992

Foerde, K., Daw, N. D., Rufin, T., Walsh, B. T., Shohamy, D., & Steinglass, J. E. (2020). Deficient goal-directed control in a population characterized by extreme goal pursuit. *Journal of Cognitive Neuroscience, 33*(3), 463–481. doi:10.1162/jocn_a_01655

Gillan, C. M., Kosinski, M., Whelan, R., Phelps, E. A., & Daw, N. D. (2016). Characterizing a psychiatric symptom dimension related to deficits in goal-directed control. *ELife, 5*, e11305. doi:10.7554/eLife.11305

Haines, N., Vassileva, J., & Ahn, W.-Y. (2018). The Outcome-Representation Learning Model: A novel reinforcement learning model of the Iowa Gambling Task. *Cognitive Science*, *42*(8), 2534–2561. doi:10.1111/cogs.12688

Ligneul, R. (2019). Sequential exploration in the Iowa gambling task: Validation of a new computational model in a large dataset of young and old healthy participants. *PLOS Computational Biology*, *15*(6), e1006989. doi:10.1371/journal.pcbi.1006989

Stout, J. C., Busemeyer, J. R., Lin, A., Grant, S. J., & Bonson, K. R. (2004). Cognitive modeling analysis of decision-making processes in cocaine abusers. *Psychonomic Bulletin & Review*, *11*(4), 742–747. doi:10.3758/BF03196629

Tabachnick, B. G., & Fidell, L. S. (2013). *Using Multivariate Statistics: Pearson New International Edition*. Pearson Education Limited, UK.

Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review*, *11*(1), 192–196. doi:10.3758/BF03206482

Worthy, D. A., Pang, B., & Byrne, K. A. (2013). Decomposing the roles of perseveration and expected value representation in models of the Iowa gambling task. *Frontiers in Psychology, 4, Article 640*. doi:10.3389/fpsyg.2013.00640