Longitudinal Computational Modeling

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# Abstract

In this study, we evaluated decision-making in a sample of adults using the play-or-pass version of the Iowa Gambling Task (IGT). The IGT is used to assess decision-making deficits in clinical populations. The updated play-or-pass IGT allowed us to better distinguish approach and avoidance learning and explore differences in those learning processes across multiple forms of psychopathology: substance use, depression, and anxiety. Among a sample of adults, we examined performance on the play-or-pass Iowa Gambling Task as a function of depressive, anxiety, and substance use disorders. Here, we evaluated the test-retest reliability of the play-or-pass IGT and examined associations with self-reported measures of reward/punishment sensitivity and internalizing symptoms. Participants completed the task across two sessions, and we calculated mean-level differences and rank-order stability of behavioral measures across the two sessions using traditional scoring, involving session-wide choice proportions, and computational modeling, involving estimates of different aspects of trial-level learning. Measures using both approaches were reliable; however, computational modeling provided more insights regarding between-session changes in performance, and how performance related to reward/punishment sensitivity and internalizing symptoms. Our results show promise in using the play-or-pass IGT to assess decision-making; however, further work is still necessary to validate the play-or-pass IGT.

*Keywords:* Iowa Gambling Task, Test-Retest Reliability, Construct Validity, Computational Modeling, Hierarchical Bayesian Analysis

# Longitudinal Computational Modeling

## 1 Introduction

Research on psychopathology aims to assess the processes associated with risk for onset, course, and/or outcome of a range of mental health disorders (Goodman & Gotlib, 1999; Kendler et al., 2002). Many of the instruments used to assess these processes involve behavioral assessments, including performance-based measures (e.g., decision-making tasks). For these measures, a critical challenge is that individual behavioral outputs are produced via multiple psychological processes (Wiecki et al., 2015), and behavioral measures frequently represent gross characterizations of the many competing and complementary processes that give rise to the observable behavior. While conventional scoring procedures are unable to discriminate between these processes, more recently developed computational models of behavior are well-positioned to discriminate between individual psychological processes, yielding enhanced specificity in behavioral metrics as well as improved task psychometrics. Doing so provides a more robust approach for probing associations with psychopathological processes, importantly, the processes that relate to psychopathology (Ahn et al., 2017; Chen et al., 2015; Huys et al., 2016).

Here, we extend our previous computational work, which focused on single or two-timepoint analyses of behavior, to assess longitudinal changes in computationally-derived measures of behavior. We begin with a brief overview of longitudinal research and common modeling practices. Next, we describe how to improve upon these practices with computational modeling. Finally, we illustrate how to extend computational models in the proposed framework with two examples. In the first example, we show proof-of-concept with a simple one-parameter reinforcement learning model fit to simulated data. In the second example, we show a practical extension of this framework with a more complex computational model from our laboratory fit to data collected from adults completing the Iowa Gambling Task across five timepoints. We end with recommendations for researchers interested in extending computational models for their longitudinal work.

### Longitudinal Research

Broadly, longitudinal research is frequently described as any study that includes variables measured across time. Ployhart and MacKenzie (2014) use a more strict definition of longitudinal research in which only studies that measure the same variable across at least three timepoints should be considered longitudinal because such designs can study *change over time*. With only two timepoints, we are only able to assess increases or decreases between two timepoints; however, with three timepoints, we can assess the pattern of change beyond those represented simply by straight lines that either increase or decrease, the only patterns that can be assessed with two timepoints.

#### 1.1.1 Describe what qualifies as longitudinal

Longitudinal research is vital for assessing the etiology of socially significant health behaviors and for identifying pathways between risk factors and health outcomes (e.g., maternal history of depression & the development of depression in offspring). The methods used to analyze longitudinal data Advances in the ease of use in longitudinal modeling frameworks such as multilevel longitudinal models can be used to examine such relations well; however, the use of the hierarchical framework to assess longitudinal changes in behavioral processes has not been well-established. Thus far, researchers examining longitudinal changes in behavioral processes do so in two-stage approaches. First, a behavioral model is fit to the data at each timepoint separately, and then second, the longitudinal model is fit to the parameters from the behavioral model. Such an approach has yielded important insights so far regarding how some behavioral processes develop across time. For example, Klein et al. (2022) used a hyperbolic discounting model and a multilevel model to examine developmental changes in delay discounting across time, finding that the degree of delay discounting tends to decrease rapidly early in childhood and begins to level off in mid-to-late adolescence. We can improve upon these methods to provide further insights regarding longitudinal changes in behavioral processes by embedding the behavioral model within the longitudinal model to avoid having to use two-stage approaches. Such a method could improve estimates of how computationally-derived parameters change over time because we can use information derived from all participants and all timepoints to inform estimates of different individuals and at different timepoints.

#### 1.1.2 Benefits of longitudinal designs

* 1. Examine change at both group and individual level
  2. Establish sequence of events (i.e., what predicts what)

#### 1.1.3 Drawbacks to longitudinal designs

* 1. Expensive & difficult
  2. Random assignment of variables is uncommon; thus, cannot establish causation
  3. Sequence effects may bias results

### 1.2 Longitudinal Modeling Methods

#### 1.2.1 RM ANOVAs

#### 1.2.2 Multilevel modeling

#### 1.2.3 Latent growth curve modeling

### 1.3 Current study

1. Prior longitudinal methods rely only on general linear model (i.e., cannot structure theoretical model to capture growth within the model)
   1. Good place to put in McElreath quote about GLM – something like “definitely wrong but hard to beat”
   2. To incorporate theoretical model, typically have to use two-stage approach
2. Here, we show how to incorporate growth-related parameters in computational models so that our theoretical model can capture growth
   1. Benefits
      1. Propagate uncertainty across multiple levels of analysis which improves inferences
      2. Allows us to use theoretical models to examine growth instead of summary statistics
         1. i.e., better aligns statistical model with theoretical model

## 2 Simple Longitudinal RL Model

To illustrate the longitudinal computational modeling framework, we begin with a simulated example of how to construct such a model. We first constructed a hypothetical task modeled after the Iowa Gambling Task, a task for which computational models are frequently employed to understand. For the hypothetical task, participants are presented with two options with the same expected values but with different outcomes and different outcome probabilities across 60 total trials. Choices on one option yield either $75 or $25 with equal probability (i.e., *P*($75) = *P*($25) = .5), resulting in $50 on average across trials. Choices on the other option yield either $80 or $40 with a .75 and .25 probability, respectively, also resulting in $50 on average across trials. Next, we built a one-parameter longitudinal reinforcement learning model to simulate data for the task across four conditions. Choices within the task are assumed to be drawn from a Bernoulli distribution, such that

|  |  |  |
| --- | --- | --- |
|  |  | Equation 1 |

where *Yi,s*(*t*) is the choice for either option 1 (*Y* = 0) and option 2 (*Y* = 1) on trial *t* by participant *i* on session *s*, and *V0,i,s*(*t*) and *V1,i,s*(*t*) are the expected values associated with choosing option 1 or 2, updated from trial to trial according to the following function:

|  |  |  |
| --- | --- | --- |
|  |  | Equation 2 |

where *A* is a free parameter describing learning rate for both options, and *x*(*t*) is the amount of the outcome on trial *t*. Equations 1 and 2 represent a simple reinforcement learning model describing how gains on both options affect choices for those options.

The four conditions represent parametric combinations of two levels of test-retest reliability, unreliable (i.e., *r* = 0) and moderate reliability (i.e., *r* = .3) and two levels of longitudinal change, no change (i.e., *d* = 0) and moderate change (i.e., *d* = .5; Cohen, 2016). Finally, after simulating data, we examined how well parameters could be recovered using more conventional (e.g., two-stage) approaches for analyzing longitudinal data using computational modeling.

and 2) fit different versions of the base reinforcement learning model to examine parameter-recovery and assess how well the longitudinal framework could model the data.

We chose a one-parameter reinforcement learning model to simulate data for the data-generating model for this task

Simulated choices on the task were generated according to the following data-generating model.

|  |  |  |
| --- | --- | --- |
|  |  | Equation 3 |

where

|  |  |  |
| --- | --- | --- |
|  |  | Equation 4 |

## 3 Longitudinal Model of Iowa Gambling Task

1. Method/Results (a & b might be presented like separate experiments, each with their own method and results)
   1. Build simple 1-parameter reinforcement learning model of some simple yes/no decision-making task?
      1. Model-building process
         1. How it would be fit to a single person
         2. How it would be fit to multiple people (single timepoint hierarchical model)
         3. How it would be fit to multiple people across time (growth model)
      2. Simulations:
         1. Simulate data based on growth model across multiple conditions

|  |  |  |
| --- | --- | --- |
|  | No cor | Moderate cor |
| No effect | *rtime* = 0, *d* = 0 | *rtime* = .3, *d* = 0 |
| Moderate effect | *rtime* = 0, *d* = .5 | *rtime* = .3, *d* = .5 |

* + - 1. Fit single timepoint and growth RL model to each timepoint
    1. Results
  1. Present PP-ORL model
     1. Show single timepoint model
     2. Show growth model
     3. Introduce TADS data
        1. T1-5 PP-IGT data from parents only
     4. Fit both models to data
     5. Results

## 4 Discussion

### 4.1 Benefits of this approach

1. Propagate uncertainty across levels of data
2. (Hopefully) note how data were better characterized with growth model
3. Could include other covariates

### 4.2 Drawbacks of this approach

1. Note any issues we found
2. Computationally intensive

# References

## Contributions

**Conceptualization**: Ideas; formulation or evolution of overarching research goals and aims

HST, TMO

**Methodology;** Development or design of methodology; creation of models

**Data Curation:** Management activities to annotate (produce metadata), scrub data and maintain research data (including software code, where it is necessary for interpreting the data itself) for initial use and later reuse

**Writing – Original Draft**: Preparation, creation and/or presentation of the published work, specifically writing the initial draft (including substantive translation)

**Writing – Review & Editing:** Preparation, creation and/or presentation of the published work by those from the original research group, specifically critical review, commentary or revision–including pre- or postpublication stages

**Visualization**: Preparation, creation and/or presentation of the published work, specifically visualization/ data presentation

**Supervision**: Oversight and leadership responsibility for the research activity planning and execution, including mentorship external to the core team

**Project Administration:** Management and coordination responsibility for the research activity planning and execution

TMO

**Funding Acquisition**: Acquisition of the financial support for the project leading to this publication.

TMO  
  
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## Conflicts of Interest

# Tables

# Figures