Longitudinal Computational Modeling

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Author Note:

This research was supported by National Institute of Mental Health grants (R01 MH107495 & R21 MH130792) awarded to TMO. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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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 disorders11,12. 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 processes13, 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 psychopathology7,14,15.

Here, we provide an extension of previous work to assess longitudinal changes in computationally-derived measures of behavior. Longitudinal research is vital for assessing the etiology of health-related problems and identifying pathways between risk factors and health-related outcomes (e.g., maternal history of depression & the development of depression in offspring). 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.

The purpose of this tutorial is to illustrate how to build a longitudinal computational model. We begin by first describing what constitutes a longitudinal model, the benefits and drawbacks of longitudinal models, some of the most commonly-used longitudinal models leading up to hierarchical longitudinal models which are considered gold-standard for longitudinal modeling at this point in time. Next, we introduce a simple reinforcement learning model that could be used to assess longitudinal changes in behavior and simulate data to examine how well longitudinal model performs. After illustrating the benefits of longitudinal computational modeling with simulated data, we generalize a model developed from our lab and how that model can be used to examine longitudinal changes in an adult sample of participants who completed the Iowa Gambling Task. We describe a simple behavioral model to illustrate how

### 1.1 Characteristics of longitudinal data and longitudinal models

#### 1.1.1 Describe what qualifies as longitudinal

3+ waves of data on the same measures for the same people (Ployhart & MacKenzie)

#### 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

## 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

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**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.

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* **Writing – Original Draft Preparation**
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## Conflicts of Interest

# Tables

# Figures