**Longitudinal Computational Modeling**

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. Thus, observable output behavior represents a gross measure of many competing and complementary processes. 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 tasks psychometrics and better clarity for probing associations with psychopathological processes7,14,15. The emphasis of this proposal is to critically examine the functioning of a commonly used behavioral task, the Iowa Gambling Task, using computational modeling.

**A.1 Development of the Iowa Gambling Task (IGT).**

The IGT is a task used to assess reward learning1 within the Positive Valence Systems of the Research Domain Criteria16. In the original task, participants can freely select one of four stimuli, two of which have advantageous (i.e., net monetary wins) and two of which have disadvantageous (net monetary losses) outcomes, on average, across all task trials. Based on trial-by-trial feedback, participants are expected to learn to select advantageous and diminish selection of disadvantageous stimuli. Given that participants are fully in control of their selections, participants’ performance conflates learning to approach rewards and learning to avoid punishments. Initial studies found associations between IGT performance and depression17–19 and substance use20. However, there have been inconsistent results across studies10,21–26, suggesting traditional indices of IGT performance are not consistently associated with theoretically meaningful and critical outcomes.

Later studies altered the task, such that participants were presented with a specific stimulus on each trial and they had the opportunity to ‘play’ or ‘pass’ on the particular stimulus9,27. Thus, in the revised play or pass version of the IGT, ‘approach of advantageous’ and ‘avoidance of disadvantageous’ stimuli are dissociable processes. Even with this adaptation, simple scoring of performance on this task considers probability of playing on each individual trial as independent from one another and with each equally contributing to the computation of task performance. However, as participants engage in the task, they have updated information about the probability that each stimulus source is advantageous or disadvantageous.

**A.2 Computational Modeling Advances IGT Scoring**

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| --- | --- | --- |
| ORL Model Parameter | | Higher Values Indicate |
| *A*+ | Reward/ Punishment Learning Rates | Faster learning/ more volatile trial-level updating in a gains or loss domain, respectively |
| *A -* |
| β*f* | Win Frequency Sensitivity | Greater preference for decks with a higher win frequency over objectively equivalent decks that win less often |
| β*p* | Perseveration Tendency | More choice consistency, less switching between stimuli |
| *K* | Memory Decay | Greater forgetting; remembering a shorter (rather than longer) sequence of past selections |

Whereas one approach to refining estimation of reward and punishment processes from the original IGT was to focus on task design features, a complementary approach focused on advancements in mathematical modeling. Computational models mathematically delineate the generative processes that give rise to the observed data (i.e., stimuli choice on trials in the IGT). The Outcome-Representation Learning (ORL) model is a trial-level reinforcement learning computational model built specifically for the original Iowa Gambling Task8,28. The ORL model builds on previous computational models for the IGT29–31, and has been shown to perform well in predicting participants’ earnings and trial-to-trial choices (Haines, et al., 2018). The ORL model decomposes task behavior into distinct processes, yielding five parameters: reward learning rate, punishment learning rate, win frequency sensitivity, perseveration tendency, and memory decay (adjacent table). Each parameter is mathematically operationalized and integrated within a linear model to inform value signals that are updated trial-by-trial for each stimuli set.

Despite reinforcement learning (RL) models being employed regularly to study relations between learning mechanisms and self-reported measures using general learning paradigms, there have been sparingly few studies using RL models to examine associations with individual differences in reward seeking behavior via self-report or neural response in the context of the IGT. Past work has focused on examining associations between RL parameters and depressive symptoms and suicidality21,32–34. However, this work relied on the original IGT design; the validity of the improved ‘play or pass’ IGT has not yet been examined with the ORL model. The ORL will be adapted to include possible additional RL parameters. The advantages of the ‘play or pass’ IGT permits clear separation between approaching advantageous and avoiding disadvantageous stimuli, and the five parameter ORL model is well-suited to be generalized to the ‘play or pass’ IGT given the task’s similarity to the original IGT. However, given the task alterations, parameters may have different psychometric properties than in the original IGT35 or new parameters, such as sensitivity to reward and sensitivity to punishment, could be estimated to improve construct validity. Given the historic inconsistency in the associations between IGT performance and purported correlates10,36, including history of internalizing disorders, internalizing symptoms, reward sensitivity, threat sensitivity, and personality, indices of more specific processes should yield more consistent patterns of results. Moreover, as individuals across different developmental periods have different cognitive abilities and sensitivity to rewards37–40, the specific model that is appropriate to explain behavior may differ across youth, late adolescents/early adults, and adults41,42. Though studies have shown developmental differences in models explaining reward seeking behavior43 these studies have been cross-sectional. Critical tests of development require within-person longitudinal designs44.

**A.3. Further Tests of Validity for ORL Parameters**

In addition to examining associations between IGT performance, indexed by generative models, and dimensions of individual differences, there are multiple additional critical tests of the utility and validity of model parameters. There is an extensive literature on the heritability of youth personality and temperament using behavior genetic designs45,46, which includes dimensions of reward senstivity47,48. However, there are sparingly few studies reporting significant associations between parent and offspring personality49–51. Genetic contribution, but lack of parent-offspring associations are a marked contradiction. One possibility is that parent and offspring personality assessments are conducted when they are in different developmental stages. There could be different personality presentations across development that obscure associations for traits. Alternatively, personality assessments examined may be too broad (even at narrow facet levels) to find associations between parents and offspring. More specific processes, such as those indexed by parameters of behavioral performance, could reveal associations like those seen in other biological systems52–54.

A second aspect of validity to be examined is that of associations between behavioral performance and pubertal development27,55,56. Multiple theoretical models suggest that emergence of risk taking behaviors and risk for multiple forms of internalizing and externalizing problems may be, in part, due to changes in reward processing and associated behaviors observed in adolescence37–40,44,57–59. The empirical work conducted has relied on single summary metrics of task behavior or neural response. **The use of summary behavioral performance metrics may obscure how specific processes (e.g., reward vs. punishment learning) change across development and which may be particularly associated with risk of psychopathology.**

**A.4. Test-Retest Reliability and Modeling Practices**

Repeated administration of the same task affords multiple analytic options to evaluate reliability of performance. Models c be estimated for each assessment and parameters (and their posterior distributions) can be extracted and used in subsequent analyses. This preserves independent estimation of parameters. However, this approach does not account for measurement imprecision in the individual estimates, which can attenuate the strength of subsequent correlations. An alternative generative modeling approach includes data across multiple assessments and uses hierarchical Bayesian analyses (HBA) to simultaneously estimate individual-level parameters for both assessments, as well as the cross-time association (reliability) for each parameter60. Although estimated jointly, these HBA models yield parameter estimates for each of the individual administrations. As demonstrated by our group (see C.1.1), this approach greatly enhances test-retest reliability for performance indices of the original IGT compared to a summary metric.

**A.5. Beyond Two Time Points**

Few computational modeling studies have examined repeated assessments. Studies require multiple assessments to chart developmental change over time, with studies requiring at least three time points per participant to estimate linear growth61–63. Within the family of growth models, trajectories are characterized by starting points (i.e., intercepts) and rates of change (i.e., slopes) with variance estimates to model individual differences62. There are analytic options for longitudinal modeling. One option is to estimate computational models separately for each assessment and extract the parameters from each time point to be fit within a separate growth model. While this method preserves independent estimation of parameters at each time point, previous research has shown that the reliability of reinforcement learning parameters modeled separately for different administrations is not strong64–66. An alternative generative modeling approach involves including behavioral data from all time points, as well as estimates of change, within a single hierarchical model. **This hierarchical approach to generative modeling enhances the precision of individual parameter estimates, answering a challenge52, particularly for using RL in developmental research**41,60**.**

Very little is known about how reinforcement learning parameters change across development or in developmental psychopathology41,67,68. Multiple models of reward system development highlight dramatic changes in this system during adolescence37–40,44,57–59. Generative models permit examination of changes in more specific processes than summary behavioral performance metrics. Moreover, individual differences in trajectories of development are important for identifying those at greatest risk for psychopathology57,69. Multiple studies show associations between markers of risk for depression, particularly family history of depression, and reward seeking and responsivity55,69–74; however little is known about specific mechanisms conferring risk. Further, **most of these investigations have examined only cross-sectional associations, leaving critical questions about true longitudinal change of specific RL processes leading to psychopathology.**

1. **Innovation**

This work has important implications for and advances the field in several key ways. First, although there are a number of studies examining generative modeling in youth samples41,68,75–77, **few studies examine development longitudinally**. Thus, developmental inferences are drawn from weak study designs comparing children, adolescents, and adults, rather than **examining true within-person change**. Second, this work can have profound implications for the future use of the IGT. By **improving the task design *and* analytic methods**, there is a high likelihood that **the parameters estimated will have greater reliability and validity**. Third, given the extensive amount of additional data from the parent studies, **there are a wide array of theoretically meaningful, novel, critical covariates to examine**, including dimensions of individual differences in reward and threat sensitivity in both youth and adults, reward-related brain function, and associations between parents and offspring on performance-based parameters.

1. **Approach**

**C.1 Preliminary Data.** Preliminary data demonstrate proof-of-concept and feasibility of the study, as well as shortcomings of the typically used IGT scoring.

**C.1.1 Initial Application of Generative Models to the Original IGT**

We have conducted an initial analysis on a study of undergraduate students (*n* = 50) who completed the original IGT on two occasions separated by one month. In addition to standard scoring, two modeling approaches were employed. First, the five parameter ORL model was estimated for each administration and parameter estimates were extracted (with their posterior distributions) and test-retest correlations were estimated on the posterior means (two-step approach). Second, the five parameter ORL model was estimated using a full generative model that included both assessments simultaneously, as well as estimations of group-level effects, within a single hierarchical model. Test-retest correlation for the standard IGT scoring was moderate (r = .37, p < .05). The test-retest correlations for the two-step approach showed moderate reliability (reward learning rate *r* = .40; punishment learning rate *r* = .46; memory decay *r* = .42; win frequency sensitivity *r* = .40; perseveration *r* = .64). In the full generative model, test-retest associations were markedly stronger (reward learning rate *r* = .76; punishment learning rate *r* = .70; memory decay *r* = .81; win frequency sensitivity *r* = .67; perseveration r = .85). Thus, the more sophisticated hierarchical modeling approach provides more reliable parameter estimates. However, we found inconsistent associations between ORL parameters and self-report measures of reward seeking (e.g., behavioral activation system functioning) across assessments. **This suggests that the ORL computational model enhances internal validity; however, there may be limitations of the original task design that diminish the associations with external criteria.**

**C.1.2 Standard Scoring of Play or Pass IGT and Family History of Depression**

Within the proposed sample, we examined associations between maternal history of depression and IGT standard scoring using the play or pass version of the IGT. We found no significant differences between offspring of parents with and without a history of depression on standard IGT scoring (i.e., proportion of plays on good/bad decks; change in proportion of plays on good/bad decks from the first to third blocks of the task) in either cross-sectional or longitudinal models. **The null associations are suggestive that a more nuanced understanding of task functionality is needed. Adapting the ORL model for the improved play or pass IGT will permit further critical tests of associations between family history and ORL parameters.**

**C.2 Research Design & Methods**

***Overview.***

Data for this project come from completed/ongoing work. Sample 1 includes undergraduate students who completed a study of test-retest stability (n = 50 at baseline; n = 46 with both assessments) of reward seeking behaviors. Sample 2 includes youth participants (*n =* 248; aged 9-13 at the initial assessment) and their primary caregivers who participated in a longitudinal study of developmental change in reward function and risk for depression (final assessments will be completed in January 2022). Youth participants and their caregivers were assessed on up to five occasions separated by approximately 9-month intervals. In both studies, all participants completed the play or pass version of the IGT, additional behavioral assessments, and self-report measures. In Sample 2, youth participants completed MRIs at baseline and 18-month assessments.

**C.2.1 Procedure.**

**C.2.1.1 Sample 1.** Undergraduate students (mean age = 20.34 [SD = 1.43] years, 78.7% female; 55% White; 21% Black/African American; 15% Asian/Asian American; 9% Other; 89% non-Hispanic) completed the play or pass IGT on two occasions separated by approximately four weeks. Participants were recruited from the undergraduate subject pool at Temple University.

**C.2.1.2 Sample 2.** The sample included 248 community-based adolescents (57.03% female) recruited from the community78. English-speaking families from the Philadelphia community with a child between 9-10 or 12-13 years at baseline (Mage= 11.10, SD = 5.25) who resided with at least one biological parent were eligible for participation. Exclusion criteria included child or parental history of bipolar disorder or psychotic spectrum disorder. Youth were also excluded if they were currently taking any psychotropic medications (with the exception of ADHD medication), met criteria for diagnosis of a serious neurological illness, or had learning or developmental disabilities. Overall intellectual ability for children was also examined at the baseline assessment using the Kaufman Brief Intelligence Test (KBIT-279), and participants with estimates of overall intelligence levels falling two or more SDs below the mean were excluded (KBIT-2 FSIQ < 70). The sample of youth was racial diversity (46.12% white; 38.79% Black/African American; 12.07% Multiracial; 3.02% Other), but limited variability in ethnic diversity (11.21% Hispanic).

**C.2.2 Assessments.**

Both samples completed the play or pass version of the IGT on all study occasions. The IGT was composed of three blocks, with each block consisting of 40 trials. Participants were presented with a card from one of four decks on the screen and were asked whether they wanted to “Play” or “Pass” on that card. If they selected to pass, they proceeded to another trial; if they selected to play, participants won money, lost money, or had no monetary gain or loss for that trial. Each deck varied on the frequency and rate of reward and punishment. Participants were not aware of the contingencies during the task and needed to learn from feedback which decks were most profitable to draw.

**C.2.2.1 Sample 1.** Participants completed a battery of self-report measures focusing on reward sensitivity, anhedonia, and approach motivation. Focal instruments administered include Chapman Physical Anhedonia Scale80; Chapman Social Anhedonia Scale; Fawcett-Clark Pleasure Scale81; Snaith-Hamilton Pleasure Scale82; Anticipatory and Consummatory Interpersonal Pleasure Scale83; Temporal Experience of Pleasure Scale 84; and the Behavioral Activation Scales85. The constructs assessed by each of these measures are represented in the RDoC PVS. Within Sample 1, internal consistency estimates for these scales were satisfactory (α > .80).

**C.2.2.2 Sample 2.** Youth participants from Sample 2 completed a battery of self-report measures focusing on reward sensitivity, anhedonia, and approach motivation, as well as the KSADS86 to assess lifetime history of psychopathology. Youth participants also completed an MRI assessment that included structural, diffusion, and functional imaging protocols. Parent participants completed a battery of self-report measures focusing on reward sensitivity, anhedonia, and approach motivation, as well as the SCID to assess lifetime history of psychopathology. All assessments were conducted at each assessment, except for MRIs, as noted above.

Youth provided self-reports of PVS functioning using the Behavioral Activation Scales85; Pleasure Scale for Children87; and Anticipatory and Consummatory Interpersonal Pleasure Scale83. Parents also provided reports of offspring PVS using the Behavioral Activation Scales (adapted as an informant report measure); affiliation using the scale from the Early Adolescent Temperament Questionnaire88.

Parent self-reports of PVS functioning were from the Chapman Physical Anhedonia Scale; Chapman Social Anhedonia Scale80; Fawcett-Clark Pleasure Scale81; Behavioral Activation Scales85; and Temporal Experience of Pleasure Scale84. These constructs will be used in correlational analyses with ORL parameters for within person associations.

Parents were interviewed using the Structured Clinical Interview for DSM-589 at the baseline, 18-month, and 3-month assessments. We have diagnoses of lifetime history of depression. We will use these diagnoses to compare ORL parameters between parents with and without a lifetime history of depression, as well as differences in ORL parameters between offspring of parents with and without a lifetime history of depression.

**Youth Measures of Reward Related Brain Functioning.** We will implement two fMRI tasks to assess neural reward responsivity using monetary and social stimuli.

***Monetary Reward Task.***The study used a monetary incentive task frequently used in studies of adolescent development90 and depression71,91,92. Each trial included both anticipation and outcome trials, and participants received win, loss, or no-change feedback for each trial. Task pre-processing and first-level analyses estimated reward anticipation vs. anticipation control and reward outcome vs. outcome control contrasts.

***Social Reward Task.***In the Chatroom Interact Task70,93 (an updated version of the chatroom task94–96), adolescents chose and were chosen vs. not chosen for online interactions by same-sex virtual peers. Task pre-processing and first-level analyses estimated a peer acceptance > motor control task contrast.

**fMRI Acquisition and Preprocessing.** Neuroimaging data were acquired using a using wide bore (70cms) 3T Philips Ingenia scanner located at the Thomas Jefferson University. Structural 3D axial MPRAGE images will be acquired (1mm thick; TR=2200ms; TE=3.29ms; FOV=256x256; Matrix= 256x256; Flip Angle=9°; 192 slices). BOLD functional images were acquired with a gradient echo planar imaging sequence and cover 34 axial slices (3 mm thick) beginning at the cerebral vertex and encompassing the entire cerebrum and the majority of the cerebellum (TR/TE=2000/25 msec, field of view=20 cm, matrix=64×64). Scanning parameters were selected to optimize BOLD signal quality while maintaining a sufficient number of slices to acquire whole-brain data. Scanning was synchronized to stimulus presentation, and multiple images were obtained during the course of a trial. Data preprocessing and analysis was conducted with Statistical Parametric Mapping software, Version 12 (SPM 12; http://www.fil.ion.ucl.ac.uk/spm) using standard procedures. For each scan, images for each participant were realigned to the first volume in the time series to correct for head motion. Realigned images were spatially normalized into Montreal Neurological Institute stereotactic space using a 12-parameter affine model, then smoothed to minimize noise and residual difference in gyral anatomy with a Gaussian filter set at 6 mm full width at half-maximum. Voxel-wise signal intensities were ratio normalized to the whole-brain global mean. The analyses focused on contrasts of monetary reward anticipation > baseline and reward win > baseline and peer acceptance > motor control task. For each contrast, neural responses were extracted from an *a priori* bilateral VS ROI defined as two 8mm spheres based on MNI coordinates (right: x = 9, y = 9, z = -8; left: x = -9, y = 9, z = -8) from previous meta-analyses[234](#_ENREF_234), [235](#_ENREF_235). These indices will be used in correlational analyses with youth ORL parameters.

**C.2.3 Data Analysis.**

A table with equations and formulas

Description automatically generated**C.2.3.1 Computational model estimation.** In the updated play or pass IGT, the structure of the task was modified such that individual stimuli are presented to the participants giving them a binary play or pass decision, rather than participants having free choice among four stimuli sets throughout the task. Thus, the existing ORL computational model for the IGT requires adaptation. Adaptations will test possible additional RL parameters to the model such as reward and punishment sensitivity. A competing computational model, the Prospect Valence Learning (PVL) model with delta rule29 will be fit to the IGT data in Sample 1 at the initial and follow-up administrations. We will evaluate models quantitatively based on the Watanabe-Akaike Information Criteria (WAIC) and Leave-One-Out Cross-Validation (LOOIC)97 and qualitatively using predictive posterior checks in which fitted model parameters will be used to simulate data and simulated data will be plotted against observed data. The best fitting model will then be used in subsequent analyses. As the ORL model performs well compared to the PVL model8, we expect the ORL model will show the best fit. Equations for ORL parameters are shown in the adjacent Table8.

In Sample 2, we will estimate the best-fitting model from Sample 1 for the youth and adult samples. For examination of test-retest reliability, HBAs will be estimated to examine the correlations between adjacent assessments (H2.1). As we have multiple measures of reward, anhedonia, and approach constructs, principal component analysis will be performed on measures of like constructs to reduce the number of statistical tests conducted and increase reliability of measures. After deriving this parsimonious set of constructs, we will examine associations between self- and parent-report measures of reward sensitivity and ORL parameters (H2.2) using complementary methods. First, we will examine these associations at each time point separately in generative models. Second, we will also examine associations between self- and parent-report measures of reward sensitivity treating those repeated assessments as time-varying covariates and examining all assessments simultaneously in a single full generative model.

For examinations of associations between parent and offspring ORL parameters (H2.3), we will examine the models in at least three different ways. First, we will estimate parameters for parents and offspring, separately, and extract parameters for use in analyses outside of generative models. Second, we will estimate models for parents and offspring within-time point within a full generative model. Third, we will estimate a model including all time points for parents and offspring within the same model.

Beyond examining rank-order similarity of test-retest reliability, we will also examine how changes in youth ORL parameters may be influenced by development (H3.1). We will estimate the influence of offspring age as a predictor of person-level growth in each of the ORL parameters in the model. This model will be further generalized to include parental history of depression (H3.2) as a predictor of the longitudinal change in ORL parameters. These extensions of the models implement unconditional growth models in the context of HBA (H3.1) and conditional growth models in the context of HBA (H3.2). **The optimal play or pass IGT model will be added to the hBayesDM package in R.**

As a means of evaluating the incremental value of the results of the analyses with the ORL models, we will also estimate parallel analyses using standard scoring of the IGT. This would include overall proportion of plays on good and bad stimuli and changes in proportion of plays on good and bad stimuli (between the first 40 vs. last 40 trials). Comparisons of associations using the ORL parameters and standard IGT scoring (H2.4) will be made by testing generative model estimates against statistical results from the standard IGT scoring.

**C.2.3.2 Full Generative Models Incorporating Group-Level Effects**

Full generative models will jointly estimate, within a single hierarchical model, individual-level ORL parameters as well as group-level effects of interest (H1, H2.2, H2.3, H3.1, H3.2). In the most ambitious model, age will be modeled as a within-person predictor of other parameters in the full generative model67. This regression model will serve as a prior for the group-level mean for person-level parameters, and regression coefficients for the intercept and linear (or quadratic) effects of age will be sampled by the HBA model along with the person-level learning (ORL) parameters. For all parameters of interest (including age-related parameters), we will use weakly informative priors. These models are well equipped to accommodate missing observations and unequal observations, while estimating parameters without bias98.

**HBA Model Implementation**

Hierarchical Bayesian analysis (HBA) will be conducted using the Stan package99, a probabilistic programming language, which uses Hamiltonian Monte Carlo, a variant of Markov chain Monte Carlo (MCMC) method, to sample from high-dimensional probabilistic models. The RStan package100 will be used to interface with Stan. For all HBA analyses, convergence to target distributions will be checked visually by observing trace-plots and numerically by computing Rhat values 101.

**C.2.3.2 Power Analysis.**

For examining power, we used two approaches. First, we used parameter recovery simulations, in which data was simulated using parameters set to known values and a model was subsequently fit to the simulated data to “recover” parameter values. Correlations between known and recovered parameters, or “recovery statistics” represent model performance and reliability of parameters, with values closer to r =1 indicating more precise person-level measures. Using the ORL model fit to data from the original IGT (single administration) for 200 simulated subjects, recovery statistics were acceptable across all parameters (*A+ r* =.81; *A-* *r* =.77; *K r* =.52; β*f r* = .84; β*p r* = .95). As shown in previous work60, person-level parameter precision is increased when data from multiple administrations is modeled jointly in a hierarchical model, and thus our more elaborate models should show enhanced recovery statistics.

Additionally, we used a Bayesian power analysis to examine the sample size needed to detect differences in parameters between groups (e.g., adolescents with and without a maternal risk of depression), one of the most conservative statistical tests we will conduct. Previous research has reported a medium effect size for comparing decision making metrics for adolescents with/without a familial risk for depression102. Using a conservative between group comparison, we would need groups of 65 each for 82% of estimates to detect a medium effect size (d = .5) within the 95% credible interval (analogous to 80% power at an alpha of .05).

**C.2.4 Potential Pitfalls**

Our focus is on adapting the five parameter ORL model that was developed for use with the original IGT. As we administered the play or pass version of the IGT, the optimal model may be different. We have noted throughout that we would consider including additional parameters to the model. We also expect that the same form of the model will fit for our youth and adult samples. If we find that different models best describe youth and adult IGT performance, when examining associations between offspring and parent IGT performance, we will use extracted reward learning parameters (and their distributions) in a two-step approach.

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* 1. Characteristics of longitudinal data and longitudinal models
     1. Describe what qualifies as longitudinal
        1. 3+ waves of data on the same measures for the same people (Ployhart & MacKenzie)
     2. Benefits of longitudinal designs
        1. Examine change at both group and individual level
        2. Establish sequence of events (i.e., what predicts what)
     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
  2. A brief overview of longitudinal modeling methods
     1. RM ANOVAs
     2. Multilevel modeling
     3. Latent growth curve modeling
  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

i.e., better aligns statistical model with theoretical model

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

1. Discussion
   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
   2. Drawbacks of this approach
      1. Note any issues we found
      2. Computationally intensive