

Computational modeling for addiction medicine: From cognitive models to clinical applications

Woo Young Ahn^{*,†}, Junyi Dai[‡], Jasmin Vassileva^{*}, Jerome R. Busemeyer[§]
Julie C. Stout^{¶,1}

^{*}*Department of Psychiatry, Institute for Drug and Alcohol Studies, Virginia Commonwealth University, Richmond, VA, USA*

[†]*Department of Psychology, The Ohio State University, Columbus, OH, USA*

[‡]*Centre for Adaptive Rationality, Max Planck Institute for Human Development, Berlin, Germany*

[§]*Department of Psychological and Brain Sciences, Indiana University, Bloomington, IN, USA*

[¶]*School of Psychological Sciences and Monash Institute of Cognitive and Clinical Neuroscience, Monash University, Clayton, VIC, Australia*

¹*Corresponding author: Tel.: +61(3)9905-3987; Fax: +61(3)9905-3984, e-mail address: julie.stout@monash.edu*

Abstract

Decision-making tasks that have good ecological validity, such as simulated gambling tasks, are complex, and performance on these tasks represents a synthesis of several different underlying psychological processes, such as learning from experience, and motivational processes such as sensitivity to reward and punishment. Cognitive models can be used to break down performance on these tasks into constituent processes, which can then be assessed and studied in relation to clinical characteristics and neuroimaging outcomes. Whether it will be possible to improve treatment success by targeting these constituent processes more directly remains unexplored. We review the development and testing of the Expectancy-Valence and Prospect-Valence Learning models from the past 10 years or so using simulated gambling tasks, in particular the Iowa and Soochow Gambling Tasks. We highlight the issues of model generalizability and parameter consistency, and we describe findings obtained from these models in clinical populations including substance use disorders. We then suggest future directions for this research that will help to bring its utility to broader research and clinical applications.

Keywords

Addiction, Substance abuse, Cognitive modeling, Decision making, Iowa Gambling Task, Soochow Gambling Task, Expectancy-Valence model, Prospect-Valence Learning model, Reward sensitivity

For the past 10 years, we have been developing and applying cognitive models of decision making to understand decision-making deficits in brain-damaged, drug addiction, and psychopathological populations. The basic idea is to investigate performance of clinical populations on standard laboratory decision-making tasks and then compare their performance to nonclinical or healthy control samples. The decision tasks used in these studies are designed to be somewhat complex and capture important aspects of real-life decision making. However, this task complexity implies that performance is an interaction and synthesis of several different underlying components, including motivational, learning, and choice processes. Cognitive models of these complex decision tasks are used to break performance down into these components (Busemeyer and Stout, 2002). The parameters associated with these components can then be used to understand the source of the decision-making deficits in these special clinical populations. Using these methods, we have uncovered important differences in decision processes in various populations including individuals with orbital frontal cortex damage, Huntington's disease, Parkinson's disease, heroin addiction, cocaine addiction, alcohol addiction, stimulant drug addiction, depression, schizophrenia, bipolar disorder, and also incarcerated criminal offenders.

Uncovering the sources of decision-making processes has two main purposes which may be exploited in research on clinical populations such as substance use disorders. First, cognitive models make it possible to test specific hypotheses about specific neuroanatomical substrates that underlie decision-making deficits in a given clinical population. Whereas the outcomes of decision tasks reflect the complex interplay among several cognitive components, such as reward sensitivity and the ability to learn from feedback, models allow these processes to be separately estimated using different parameters, making them available for separate consideration and investigation. Second, by decomposing these complex tasks into constituent processes that are relevant to particular clinical populations, and also characterizing individuals on these constituent processes, it may be possible to develop treatment strategies tailored to specific disorders or individuals, which may yield important improvements in outcomes. Such an eventuality may be particularly important in addiction disorders where treatment success is notably limited.

The purpose of this chapter is to review the progress that we have made using these cognitive modeling methods to study decision-making deficits in clinical populations. This chapter has three main parts. First, we describe two decision-making tasks that have been used in our past work. Then, we present a brief and intuitive description of the models and the parameters that we developed for these tasks. Third, we review our applications of these tasks, and the findings that we have discovered using our cognitive modeling methods.

1 IGT AND SGT DECISION-MAKING TASKS

It is important to examine decision-making deficits across different kinds of decision-making tasks in order to obtain converging evidence for the underlying cognitive sources of decision-making deficits. Two critical assumptions underlying our

past work are the assumptions of model generalization and parameter consistency. A model generalizes if one can fit the parameters of the model to one task for an individual, and then use these same parameters to predict performance on other closely related tasks for the same individual. Parameters are consistent if the parameters estimated from one task for an individual correlate with the parameters estimated from another closely related task for the same individual. These assumptions are crucial if we want to interpret these parameters as measuring a stable characteristic of the individual rather than some inessential characteristic of an arbitrary task.

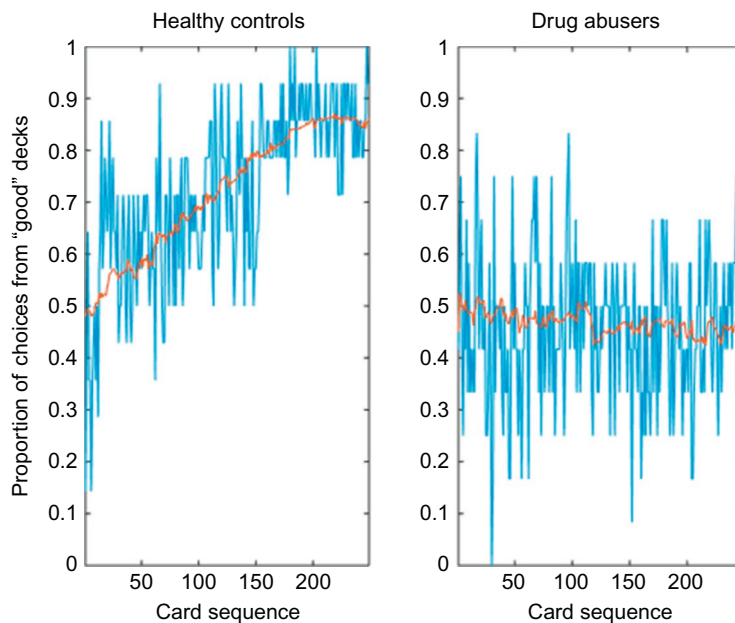
1.1 THE IOWA GAMBLING TASK

This decision task was developed by [Bechara et al. \(1994\)](#) to be a simulated gambling task in which decision makers learn from experience to choose among four decks of cards that produce both wins and losses. An important feature of the Iowa Gambling Task (IGT) is the complex interplay among motivational, cognitive, and response processes underlying the explicit choice behavior revealed in this task. The task requires participants to choose a card from one of the four decks (labeled decks A, B, C, and D, respectively) on each trial, and the total number of trials is unknown to participants. When a card is chosen, the gains and losses produced by that card are revealed. Decks C and D are better than decks A and B in terms of long-term net gain, and therefore, the former are typically called the advantageous or good decks, while the latter are disadvantageous or bad ones. The actual payoffs are shown in [Table 1](#).

A typical finding in the initial application of the IGT to clinical populations is that normal people tend to learn to choose the good decks (i.e., decks C and D) more frequently than the bad ones (i.e., decks A and B), but various clinical populations tend to persist in choosing from the bad decks throughout the task (see [Fig. 1](#)). However, the poor performance by clinical populations can arise from at least three different sources in this task. First is a motivational source—they may be insensitive to losses; second is a cognitive source—they may fail to learn the contingencies or forget the consequences; and the third is a decision-making source—they may be more inconsistent and less optimal with their choices. Cognitive models provide a method to decompose performance and determine parameters associated with each of these three sources.

Table 1 The Payoff Distribution of the IGT

| Deck | A | B | C | D |
|---|-------|--------|-------|-------|
| Gain from each trial (\$) | 1.00 | 1.00 | 0.50 | 0.50 |
| Loss amount(s) in each set of 10 trials | -1.50 | -12.50 | -0.25 | -2.50 |
| | -2.00 | | -0.50 | |
| | -2.50 | | -0.50 | |
| | -3.00 | | -0.50 | |
| | -3.50 | | -0.75 | |

**FIGURE 1**

Proportion of advantageous choices on the IGT by nonabusers (left panel) and cocaine abusers (right panel). Jagged curve shows observed choice proportions, and smoother curve shows average predictions from EVL model.

From Stout et al. (2004).

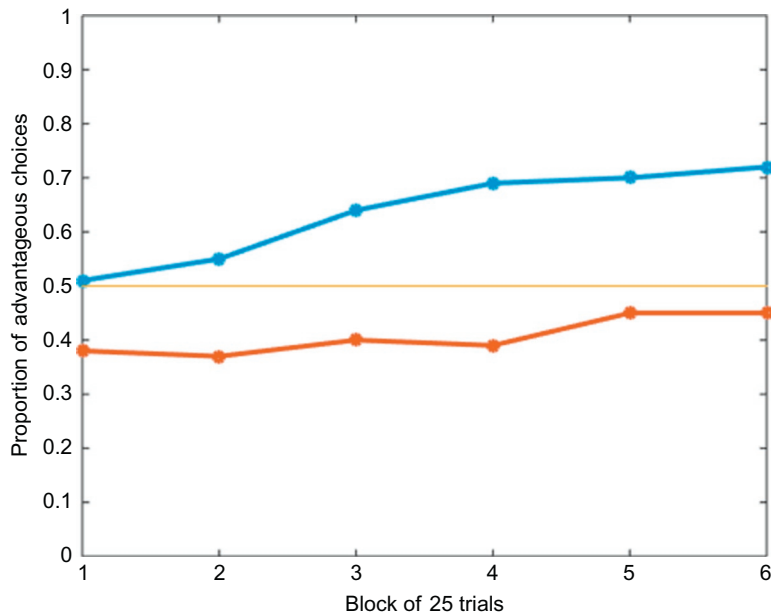
Table 2 The Payoff Distribution of the SGT

| Deck | A | B | C | D |
|---|-------|-------|-------|-------|
| Payoffs in each set of five trials (\$) | 1.00 | 0.50 | -1.00 | -0.50 |
| | 1.00 | 0.50 | -1.00 | -0.50 |
| | 1.00 | 0.50 | -1.00 | -0.50 |
| | 1.00 | 0.50 | -1.00 | -0.50 |
| | -5.25 | -3.25 | 5.25 | 3.25 |

1.2 SOOCHOW GAMBLING TASK

Chiu et al. (2008) developed another simulated gambling task that is closely related to the IGT. However, unlike the IGT, which presents both a win as well as a loss on each trial, the Soochow Gambling Task (SGT) only presents the single net payoff on each trial. The payoffs used in the SGT are shown in Table 2.

Although the IGT and SGT share many similarities, the choice behaviors produced by these two tasks are quite different (see Fig. 2). Theoretically, however, the same learning and decision-making processes should underlie each task, and

**FIGURE 2**

Proportion of advantageous choices from normal participants on IGT (curve above 0.50) and SGT (curve below 0.50).

From Ahn et al. (2008).

the differences in behavior should result from the change in payoff structure. Therefore, if the same individual performed both tasks, then we expect to obtain similar parameters for an individual to be used across both tasks.

2 THE EVL AND PVL MODELS

Our purpose here is to provide a general overview. Additional information and mathematical equations can be found in the original articles. The Expectancy-Valence Learning (EVL) model was originally developed for the IGT by [Busemeyer and Stout \(2002\)](#), and subsequently, it has gone through several revisions to improve its performance, which has resulted in a newer version called the Prospect-Valence Learning (PVL) model ([Ahn et al., 2008](#); [Dai et al., 2015](#)).

2.1 MODEL

All of the variations of the EVL model are built upon three general assumptions. First, participants use a *utility function* to evaluate the positive and/or negative pay-offs that they experience after their choice on each trial. Second, the participants use

a *reinforcement learning rule* to update their expectations for each deck based on the utility of the payoff produced by the choice on each trial. Third, the participants use a *choice probability function* to choose a deck on each trial on the basis of the expectations for each deck. The newer PVL model has revised the details for the utility, learning, and choice probability functions as compared to the original EVL model. See [Table 3](#) for the classification of the cognitive models based on their utility functions and learning rules.

2.2 PARAMETERS

The utility function entails a “loss” parameter that measures a person’s sensitivity to losses. For example, one reason for poor choices on the IGT is that a participant is insensitive to the large losses experienced with disadvantageous decks. The learning rule involves a “recency” parameter that determines the rate of decay of past experience. For example, another reason for poor choices on the IGT is that although a person may be sensitive to losses, the person may discount or forget those losses too rapidly. The choice probability function includes a “sensitivity” parameter that determines the tendency to exploit (optimize) versus explore (random) choices. For example, a third reason for poor choices on the IGT is that although a person may learn that some decks are generally better than others, this person may still wish to explore decks more randomly rather than sticking systematically to the optimal choice.

2.3 ESTIMATION METHODS

The model parameters are estimated for each individual based on the decks that they chose on each trial, where each person typically provides over 100 choices. Two different estimation methods have been used: one uses maximum likelihood methods to estimate the parameters for each person separately (e.g., [Busemeyer and Stout, 2002](#)); the second uses hierarchical Bayesian methods that include a model of the distribution of individual differences ([Ahn et al., 2011, 2014](#)). We have investigated

Table 3 Cognitive Models for the Iowa Gambling and Similar Tasks Classified Based on Their Utility Functions and Learning Rules

| Learning | Utility Function | | |
|---|--------------------|--------------------------|--------------------|
| | Expectancy Valence | Prospect Valence | Prospect Valence 2 |
| Delta Learning Decay Reinforcement (DecayRI) | EVL | PVL-Delta PVL-DecayRI | PVL2 |

Note: The EVL and PVL models also use a different choice probability function. EVL, Expectancy-Valence Learning; PVL-Delta, Prospect-Valence Learning model with the delta rule; PVL-DecayRI, Prospect-Valence Learning model with the Decay Reinforcement rule; PVL2, Prospect-Valence Learning model with an alternative form of prospect utility function.

the properties of each method of parameter estimation using computer simulation methods. Although both methods are effective at recovering the mean values of the parameters for each simulated group, the hierarchical Bayesian method provides better recovery of the distribution of parameters (Ahn et al., 2011, 2014). Programs are available for estimating model parameters on the authors' web sites.

2.4 MODEL TESTING AND COMPARISON

Before one can place trust in the model parameters, it is necessary to first test and compare various competing models and evaluate the capability of a model to account for the trial-by-trial choices of an individual. We have conducted several such model comparisons using a variety of methods (see, e.g., Ahn et al., 2008; Yechiam and Busemeyer, 2005, 2008). One method (see, e.g., Busemeyer and Stout, 2002) is based on comparing model fits using model comparison indices, such as the Bayesian information criterion, which evaluates the accuracy as well as the complexity of each model (measured by number of parameters). A stronger test is based on a method called the generalization criterion (Busemeyer and Wang, 2000). In the latter case, the basic idea is to estimate the model parameters for an individual from one task (e.g., the IGT) during the calibration stage, and then use these same parameters for the same person to predict performance on the other task (e.g., the SGT) during the generalization test phase. Yechiam and Busemeyer (2008) and later Ahn et al. (2008) used the generalization criterion to identify the model that best predicts behavior during the generalization test phase in these simulated gambling tasks. These model tests are the basis for revising the EVL model to the new PVL model. It is likely that further modifications and improvements will continue in the future.

2.5 PARAMETER CONSISTENCY

We would like to interpret the parameters of a model as measuring something about an individual, rather than simply reflecting something about the task. Therefore, if we estimate the same parameters from two different tasks that are designed to measure the same learning and decision processes, such as the IGT and SGT, then the parameters obtained from the two tasks should be correlated. For example, a person with an above-average "loss" sensitivity parameter from one task should have an above-average "loss" sensitivity from the other task. This question was initially investigated by Yechiam and Busemeyer (2008) using maximum likelihood methods to fit individuals, and they found moderate support for parameter consistency using a version of the EVL model. However, the correlations were modest, and this is partly a result of sampling error produced by fitting each person separately using maximum likelihood methods. A small number of learning trials can produce estimates that have a large variance. More recently, we have used hierarchical Bayesian methods to increase the stability of parameter estimates and improve parameter consistency, which resulted in some tentative but promising outcomes.

3 APPLICATIONS OF THE EVL AND PVL MODELS TO CLINICAL POPULATIONS INCLUDING ADDICTION

3.1 EARLY APPLICATIONS

In one of our initial studies (Yechiam et al., 2005), we collected 10 different data sets from various clinical populations that examined performance on the IGT, and analyzed these data sets using EVL model. The clinical populations included brain-damaged populations (ventral medial prefrontal cortex damage, lesions of the right somatosensory and insular cortex, basal ganglia damage from Parkinson's disease and Huntington's disease), drug abusers (young alcohol abusers, young polydrug abusers, long-term cannabis users, cocaine users), a special clinical sample (Asperger), and an older-aged sample. The performance of each of these groups on the IGT was compared to an appropriate control group. Most interesting was the finding that although many of the special (e.g., clinical, neurological) populations produced the same behavioral pattern of poor performance relative to the control group, the populations produced strikingly different patterns with respect to the EVL model parameters. For example, both the ventral medial prefrontal cortex and the cocaine abusers performed poorly compared to controls on the IGT; however, the former population differed from controls mainly with respect to the learning rate parameter, and the latter differed from controls mainly with respect to the gain/loss utility parameter. This suggests different cognitive and motivational sources for the decision-making deficits in these two groups.

In a subsequent study, we (Yechiam et al., 2008) investigated the cognitive processes of criminal offenders incarcerated for various crimes. This study included violent offenders, drug and sex offenders, drivers operating a vehicle while impaired, and matched controls. The results were also contrasted to those obtained from neurological patients with focal brain lesions in the orbitofrontal cortex, and from drug abusers. The findings indicated that whereas all criminal groups tended to select disadvantageously, the analysis of the EVL model parameters indicated major differences among groups. Certain subpopulations, most significantly drug and sex offenders, overweighted potential gains compared to losses, similar to chronic cocaine abusers. In contrast, assault/murder criminals tended to make less consistent choices and to have a higher recency learning parameter similar to patients with orbitofrontal damage.

3.2 RECENT APPLICATIONS

A newer version of the model for the IGT, called the PVL model, which uses a more sophisticated utility function, has been applied to several clinical populations, including chronic cannabis users (Fridberg et al., 2010), polydrug users (Vassileva et al., 2013), HIV-seropositive individuals (Vassileva et al., 2013), individuals with eating disorders (Chan et al., 2014), and individuals with past dependence purely on amphetamine or heroin (Ahn et al., 2014).

Fridberg et al. (2010) found that chronic cannabis users, with an average of approximately 13 years of cannabis abuse, showed dramatically reduced loss aversion, higher reward sensitivity, reduced response consistency, and greater reliance on recent outcomes (i.e., greater recency) compared to healthy controls. They also found that including PVL model parameters in the logistic regression model for classifying group membership significantly improved the discrimination between groups (i.e., classification accuracy from 84.4% to 96.9%). Notably, when using just behavioral data, for example, percent accuracy, the raw behavior did not reveal any significant differences between the clinical populations and the healthy controls.

Vassileva et al. (2013) showed that HIV and drug use have distinct impacts on different decision-making processes in women. Current polydrug use, including cocaine, heroin, tobacco, or alcohol, was associated with both compromised learning/memory and reduced loss aversion, whereas HIV-seropositive status was associated only with reduced loss aversion.

In Chan et al. (2014), both anorexia nervosa and bulimia nervosa groups showed impaired behavioral performance compared to healthy controls. However, the application of the PVL model revealed differential decision-making impairments underlying anorexia and bulimia; compared to healthy controls, the anorexia group showed compromised learning/memory, whereas the bulimia group showed altered outcome evaluation, including both reward and punishment.

Ahn et al. (2014) applied the PVL and other competing models, including the Value-Plus-Perseverance model (VPP) (Worthy et al., 2013) to a sample of individuals with past dependence on amphetamine or heroin. Despite their protracted abstinence, both clinical groups showed impaired behavioral performance on the IGT compared to healthy individuals. The VPP model had the best *post hoc* model fit, but the PVL model with the decay-reinforcement learning rule outperformed the VPP model in other model comparison indices, including simulation performance and parameter recovery. With the PVL model, compared to healthy controls, past heroin users displayed reduced loss aversion, and past amphetamine users showed increased reward sensitivity, which suggests that differential decision-making mechanisms may underlie opiate and stimulant drug use.

3.3 PARAMETER CONSISTENCY

Recently, Dai et al. (2015) further advanced our modeling of the IGT and SGT from a reinforcement learning perspective by proposing an alternative prospect utility function and a mixture updating rule for the relevant models. The alternative prospect utility function combines features of both the expectancy utility function in the EVL model and the prospect utility function in the PVL model. On the one hand, like the expectancy utility function, the new prospect utility function assumes that people evaluate simultaneous gain and loss on a single trial separately before combining the results into an overall evaluation. On the other hand, the new prospect utility function retains the assumptions of nonlinear utility and loss aversion according to the prospect theory (Kahneman and Tversky, 1979). Similarly, the new

updating rule, which assumes both delta learning and memory decay, is a mixture of the learning rules in the EVL and PVL models. With the previous and new utility functions and updating rules, as well as the previous two choice rules, 18 reinforcement learning models for the IGT and SGT were generated factorially. These models were then fit to individual data from both the IGT and the SGT in a normal control sample and a group of opiate users.

The results of model comparison showed that the model with the alternative prospect utility function, the decay-reinforcement learning rule, and the trial-independent choice rule in general performed the best among the 18 competing models, in either controls or opiate users. This model is referred to as the PVL2 model since it is identical to the PVL model except for an alternative prospect utility function.

More importantly, the PVL2 model was one of the only two models that produced significant correlations between individual estimates from the two tasks for all the involved parameters. The only other model that also produced significant correlations on all parameters was the model with expectancy utility function, decay-reinforcement learning rule, and the trial-independent choice rule. However, the strength of associations produced by this model was lower than that of the PVL2 model.

The PVL2 model has four parameters, which include the outcome sensitivity parameter (α), the loss aversion parameter (γ), the recency or memory decay parameter (A), and the choice consistency parameter (c). Specifically, the outcome sensitivity parameter indicates how sensitive an individual is to the difference in monetary outcomes; the loss aversion parameter suggests how much an individual is averse to losses relative to his/her degree of preference toward gains of the same magnitude; the recency or memory decay parameter indicates how quickly one's expectancies on the four decks decay between adjacent trials; and the choice consistency parameter suggests how much an individual's explicit choice is consistent with the underlying expectancies of the four decks. The result of the parameter consistency test on the PVL2 model suggests that choice responses in these two tasks are at least partly governed by the same mechanisms reflected by the new model.

4 CONCLUSION AND FUTURE DIRECTIONS

The past 10 years has seen the development of cognitive models for the IGT and SGT, with adequate model fits, and parameters that appear to have good utility for distinguishing between various clinical samples, and that relate to significant individual characteristics such as personality measures and severity of clinical symptoms. These have deepened the understanding of the variety and nature of differences between various substance abuse and other clinical groups, opening a potential window into the way basic psychological processes such as learning from experience or feedback, and sensitivity to reward and punishment, may be affected by substance abuse or may create vulnerability factors for developing substance use disorders. Furthermore, these models have provided a possible way in which individual characteristics can be assessed and targeted in individually tailored treatments.

What are the next steps? First, with respect to modeling studies, although cognitive models have been described for other decision-making tasks, studies that incorporate not only the IGT and SGT but also other relevant decision tasks could help to more robustly establish model generalizability and parameter consistency, thereby strengthening the claim that results from cognitive models tell us about stable characteristics of individuals rather than idiosyncratic responses to specific task conditions. We also acknowledge that our simple cognitive models only incorporate three major processes and cannot directly account for other potentially important factors such as the effect of mood state. We are currently investigating how we can improve models for the IGT and other decision-making tasks based on recent advancements in neuroscience and reinforcement learning.

Second, for the results of modeling analyses to become useful for broader neuroscience research, and particularly for clinical assessment, it will be essential to make model fitting and parameter estimation possible for individual datasets using methods that are usable for neuroscience researchers and clinicians who will not have had training in either mathematical modeling or necessarily an in-depth understanding of complex cognition. This will require careful consideration of how to create programs that can be easily adopted and reliably used by a broader set of professionals, as well as a way of communicating the utility of this method and clinical relevant language for interpreting the outcomes that can be generated by modeling analyses. For example, the IGT has been available commercially now for several years and is sold by Psychological Assessment Resources, Inc. Creating a modeling utility that could be provided when this task is sold, along with guidelines for interpreting the results from model analysis, would have the potential to transition cognitive modeling of this common decision-making task into clinical and broader research use. Further, as the IGT has been used in numerous studies, it may be possible to obtain a variety of datasets, model these data, and then assemble sets of normative data that could aid in clinical interpretation.

Specifically in the case of people with substance use disorders, for whom growing evidence points to deficits in decision making as key elements for treatment failure and relapse, the broader adoption of cognitive modeling in clinical assessment could have significant payoff. Our group is committed to disseminating these methods and assisting in their further development for use in research and clinical treatment of addictions. We aim to map relationships between cognitive processes (i.e., model parameters) and general risk/protective factors, as well as factors related to specific substance use disorders (e.g., alcohol, opioid, stimulant) (Badiani et al., 2011).

ACKNOWLEDGMENTS

We wish to acknowledge support from the National Institute on Drug Abuse Grant R01 DA030551 to J.R.B. and J.C.S. and partial support from the Australian Research Council Discovery Project DP110100696 for this project.

REFERENCES

- Ahn, W.Y., Busemeyer, J.R., Wagenmakers, E.J., Stout, J.C., 2008. Comparison of decision learning models using the generalization criterion method. *Cogn. Sci.* 32, 1376–1402.
- Ahn, W.Y., Krawitz, A., Kim, W., Busmeyer, J.R., Brown, J.W., 2011. A model-based fMRI analysis with hierarchical Bayesian parameter estimation. *J. Neurosci. Psychol. Econ.* 4, 95–110.
- Ahn, W.Y., Vasilev, G., Lee, S.H., Busemeyer, J.R., Kruschke, J.K., Bechara, A., Vassileva, J., 2014. Decision-making in stimulant and opiate addicts in protracted abstinence: evidence from computational modeling with pure users. *Front. Psychol.* 5, 849.
- Badiani, A., Belin, D., Epstein, D., Calu, D., Shaham, Y., 2011. Opiate versus psychostimulant addiction: the differences do matter. *Nat. Rev. Neurosci.* 12, 685–700.
- Bechara, A., Damasio, A.R., Damasio, H., Anderson, S.W., 1994. Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition* 50, 7–15.
- Busemeyer, J.R., Stout, J.C., 2002. A contribution of cognitive decision models to clinical assessment: decomposing performance on the Bechara gambling task. *Psychol. Assess.* 14, 253–262.
- Busemeyer, J.R., Wang, Y.M., 2000. Model comparisons and model selections based on generalization criterion methodology. *J. Math. Psychol.* 44, 171–189.
- Chan, T.W., Ahn, W.Y., Bates, J.E., Busemeyer, J.R., Guillaume, S., Redgrave, G.W., Danner, U.N., Courtet, P., 2014. Differential impairments underlying decision making in anorexia nervosa and bulimia nervosa: a cognitive modeling analysis. *Int. J. Eat. Disord.* 47, 157–167.
- Chiu, Y.-C., Lin, C.-H., Huang, J.-T., Lin, S., Lee, P.-L., Hsieh, J.-C., 2008. Immediate gain is long-term loss: are there foresighted decision makers in the Iowa Gambling Task? *Behav. Brain Funct.* 4, 13.
- Dai, J., Kerestes, R., Upton, D.J., Busemeyer, J.R., Stout, J.C., 2015. An improved cognitive model of the Iowa and Soochow Gambling Tasks with regard to model fitting performance and tests of parameter consistency. *Front. Psychol.* 6, 229.
- Fridberg, D.J., Queller, S., Ahn, W.Y., Kim, W., Bishara, A.J., Busemeyer, J.R., Porrino, L., Stout, J.C., 2010. Cognitive mechanisms underlying risky decision-making in chronic cannabis users. *J. Math. Psychol.* 54, 28–38.
- Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.
- 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. *Psychon. Bull. Rev.* 11, 742–747.
- Vassileva, J., Ahn, W.Y., Weber, K.M., Busemeyer, J.R., Stout, J.C., Gonzalez, R., Cohen, M.H., 2013. Computational modeling reveals distinct effects of HIV and history of drug use on decision-making processes in women. *PLoS One* 8, e68962.
- 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. *Front. Psychol.* 4, 640.
- Yeicham, E., Busemeyer, J.R., 2005. Comparison of basic assumptions embedded in learning models for experience-based decision making. *Psychon. Bull. Rev.* 12, 387–402.
- Yeicham, E., Busemeyer, J.R., 2008. Evaluating generalizability and parameter consistency in learning models. *Games Econ. Behav.* 63, 370–394.

- Yechiam, E., Busemeyer, J.R., Stout, J.C., Bechara, A., 2005. Using cognitive models to map relations between neuropsychological disorders and human decision-making deficits. *Psychol. Sci.* 16, 973–978.
- Yechiam, E., Kanz, J.E., Bechara, A., Stout, J.C., Busemeyer, J.R., Altmaier, E.M., Paulsen, J.S., 2008. Neurocognitive deficits related to poor decision making in people behind bars. *Psychon. Bull. Rev.* 15, 44–51.