Running head: UNRELATED BEHAVIOR BUT RELATED PROCESSES

Similar Processes Despite Divergent Behavior in Two Commonly Used Measures of Risky Decision-Making

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Abstract

Performance on complex decision-making tasks may depend on a multitude of processes. Two such tasks, the Iowa Gambling Task (IGT) and Balloon Analog Risk Task (BART), are of particular interest because they are associated with real world risky behavior, including illegal drug use. We used cognitive models to disentangle underlying processes in both tasks. Whereas behavioral measures from the IGT and BART were uncorrelated, cognitive models revealed two reliable cross-task associations. Results suggest that the tasks similarly measure loss aversion and decision-consistency processes, but not necessarily the same learning process. Additionally, substance using individuals (and especially stimulant users) performed worse on the IGT than healthy controls did, and this pattern could be explained by reduced decision-consistency.

KEYWORDS: Loss Aversion, Risky Decisions, Substance Use, Iowa Gambling Task, Balloon Analog Risk Task

Similar Processes Despite Divergent Behavior in Two Commonly Used Measures of Risky Decision-Making

Performance on any single decision-making task depends on a combination of several psychological processes, processes such as “loss aversion” (Kahneman & Tversky, 1979), “impulsivity” (Ainslie, 1975; Eysenck & Eysenck, 1978), and “exploration” (March, 1991), to name a few. The theoretical usefulness of these psychological process terms depends on their ability to generalize beyond a single task. If such constructs did not generalize at all, then “exploration”, for example, would have a completely new meaning for each new task that was used to measure it. The goal of the current research is to determine whether two commonly used risky decision-making tasks measure related psychological processes. Specifically, the Iowa Gambling Task (Bechara, Damasio, Damasio, & Anderson, 1994) and the Balloon Analog Risk Task (Lejuez et al., 2002) are examined. These tasks have recently become popular due to their sensitivity to risky real-world behaviors, such as illegal drug use (Bechara et al., 2001; Lejuez et al., 2002; Verdejo-Garcia, Vilar-Lopez, Perez-Garcia, Podell, & Goldberg, 2006). What is not known, however, is the degree to which these tasks draw on the same underlying processes.

The Iowa Gambling Task (IGT) and the Balloon Analog Risk Task (BART) have several structural similarities. Both tasks require sequential and repeated decisions for real money. Furthermore, both involve an initial uncertainty about the inherent risks in the tasks. Despite these similarities, two studies have failed to find significant correlations between IGT and BART performance (*r*s ranged from -.11 to +.14; Aklin, Lejuez, Zvolensky, Kahler, & Gwadz, 2005; Lejuez et al., 2003). On the surface, these studies suggest that the tasks are quite different. However, in each task, the behavioral measure of performance depends on several interacting psychological processes. It is possible that the two tasks overlap in some processes, but that this overlap, which is difficult to observe in behavioral measures, becomes more apparent when processes underlying these behaviors are considered.

Our approach is to examine psychological processes underlying observable behaviors by using computational cognitive models. Both the IGT and the BART have been studied using cognitive models (Busemeyer & Stout, 2002; Wallsten, Pleskac, & Lejuez, 2005, respectively). These models extend behavioral results by yielding parameters that quantify the cognitive processes at play during each task. To the extent that the models address similar underlying processes, they permit more direct assessment of the degree to which these cognitive processes are similar across the IGT and the BART. Next we introduce the IGT and the BART, in turn, and briefly describe the cognitive models of each task.

Iowa Gambling Task and Expectancy Valence Learning Model

In the IGT (Bechara et al., 1994), there are four decks of cards from which participants can choose. Each card is associated with winning a certain amount of money (e.g., 50 cents), but some cards are also associated with losses, sometimes very large ones (e.g., 5 dollars). Two of the decks are advantageous with positive expected returns in the long run, and the other two decks are disadvantageous with negative expected returns. The outcomes of each deck are not known to participants beforehand, and so the outcomes must be learned though experience.

Healthy controls tend to choose more from the advantageous decks than do a number of clinical populations, including drug using populations (Bechara & Damasio, 2002; Bechara, et al. 2001; Goudriaan, Oosterlaan, de Beurs, & van den Brink, 2005; Grant, Contoreggi, & London, 2000; Mazas, Finn, & Steinmetz, 2000), patients with ventro-medial prefrontal cortex lesions (Bechara et al., 1994), amygdala damage (Bechara, Damasio, Damasio, & Lee, 1999), and Huntington's disease (Stout, Rodawalt, & Siemers, 2001). Although these clinical populations may exhibit similar behavioral patterns in the IGT, it is unlikely that they occur for similar cognitive reasons. To address this problem, Busemeyer and Stout (2002) developed the expectancy-valence learning (EVL) model. The basic properties of the EVL model share much in common with models developed for other experience-based decision making tasks (see Barron & Erev, 2003; March, 1996; Weber, Shafir, & Blais, 2004).

Table 1 provides an overview of the model parameters. According to the EVL model, wins and losses in the IGT cause an affective reaction, or valence (see Busemeyer & Stout, 2002). Participants develop expected valences for each deck based on the wins and losses that they have experienced from each deck in the past. On each trial, participants decide which deck to pick based on their current expectancies (see the Appendix for model details).

The BART and the Bayesian Sequential Risk Taking Model

In the BART, a simulated balloon is presented on a computer screen (see Lejuez et al., 2002). Every time a participant pumps the balloon by pressing a key, the balloon inflates and money is earned. However, if the balloon is pumped too much, it will explode and the money is lost.

Therefore, choosing to pump the balloon is a gamble. If the gamble is won, the balloon inflates, and a small amount of money (5¢ in this study) is placed in a temporary bank that holds the earnings for the current balloon. However, if the gamble is lost, the balloon explodes and all money in the temporary bank is lost. If instead of inflating the balloon, a participant decides to stop and collect the money, the money earned on that balloon is transferred from the temporary bank to the permanent bank. The permanent bank holds the participant's collective earnings for the entire experimental session. Participants get to pump several balloons with the goal of accumulating as much money as possible across balloons.

The most common measure of performance, the adjusted BART score, is the average number of balloon pumps a person makes on non-exploding balloons (Lejuez et al., 2002). The adjusted BART score is a good predictor of self-reported polysubstance use and other unhealthy risk taking behaviors (see for example Aklin et al., 2005; Lejuez et al., 2002). In particular cocaine users (Bornovalova, Daughters, Hernandez, Richards, & Lejuez, 2005) and MDMA (ecstasy) users (Hopko et al., 2006) show more risky behavior in the form of higher number of adjusted balloon pumps on the BART. The BART has also been used in studies of cortical involvement in risk taking behavior (Fecteau et al., 2007; Fein & Chang, 2008), social psychological manipulations of power (Maner, Gailliot, Butz, & Peruche, 2007), and to show age-related differences in risk taking (Mitchell, Schoel, & Stevens, 2008). However, like the IGT, there are a number of latent cognitive processes that could be responsible for these behavioral level correlations. To identify the latent processes and measure individual differences in the processes, Wallsten and colleagues developed a Bayesian model of sequential risk taking (see Wallsten et al., 2005, Model 3).

According to the Bayesian model of sequential risk taking, participants have a prior belief about the chances of the balloon popping or not. That belief is updated in a Bayesian fashion based on participants' experience with balloons popping and not popping. Participants use their beliefs and the payoffs associated with each pump to decide how far to pump the balloon (see Table 1 and Appendix for further details).

Comparing Underlying Processes in the IGT and BART

Because the cognitive models are fit at the participant level, separate parameter estimates are available for each individual participant. These individual parameters provide a useful means of comparing underlying process associations across the IGT and the BART. Three processes associations are particularly relevant to consider across tasks: sensitivity to losses, decision consistency, and learning rate.

Sensitivity to Losses. The idea that losses are treated differently than gains is an idea that figures prominently in several theories of decision-making (e.g., Kahneman & Tversky, 1979; Loomes & Sugden, 1982). Sensitivity to losses can have two components: the weighting of the magnitude of losses, and the perceived probability of losses. The weighting of the magnitude of losses is assessed by the Attention to Losses parameter in the IGT. The perceived probability of losses is assessed by the Prior Belief parameter in the BART, as that parameter governs the belief that money will be lost from the temporary bank by pumping too much. If the weighting of the magnitude of losses and the perceived probability of losses are related, then the Attention to Losses and Prior

Belief parameters may be correlated. More specifically, $\hat{q}_1$ may be correlated with ω, and negatively so because $\hat{q}_1$ is the belief that the balloon will *not* pop.

Decision-Consistency. Both models have a free parameter that controls the random error in participants' choices. These parameters have a common psychological interpretation: some participants' decisions may be highly consistent with what they have learned, whereas others may be more random or haphazard. For example, participants who are bored or fatigued might choose more randomly. If these two tasks tap a meaningful consistency construct that generalizes across domains, then the consistency parameters of the two tasks should be correlated. Specifically, c and β should be positively correlated across tasks.

Learning Process. A variety of decision-making tasks involve experience based learning (e.g., Barron & Erev, 2003; Hertwig, Barron, Weber, & Erev, 2004; Hau, Pleskac, Kiefer, & Hertwig, in press), though it is unclear if the same learning process applies to all tasks. There are some differences between the IGT and the BART that may lead to qualitatively distinct learning processes. In the IGT, respondents learn the payoff structure, whereas in the BART, they know the payoffs, but have to learn about the stochastic structure of the simulated balloon. Furthermore, the BART model's learning is Bayesian, and therefore assumes trial-order invariance (i.e., the posterior probability does not depend on the order in which trials occur). The IGT model uses reinforcement learning, and so it does not make this assumption. Not surprisingly, the models use different learning rate parameters. Despite these differences, it is possible there may be some relationship between the two learning processes. In the IGT, the recency parameter ϕ governs the rate of learning, with smaller values indicating a more cumulative learning process (less forgetting). In the BART, the uncertainty parameter δ affects the learning rate through a Bayesian process. If uncertainty is high, there is more room for learning through Bayesian updating. Therefore, if a common learning process underlies both tasks, recency in the IGT (ϕ) should be negatively correlated with uncertainty in the BART (δ).

Of course, whether there is any association in sensitivity to losses, decision-consistency, and learning across tasks and models is an empirical question. To investigate cross-task associations, we examined individuals who would be likely to provide a wide range of parameter values, and thereby make it easier to detect correlations among parameters. Specifically, we examined healthy controls and different kinds of illegal drug users.

Comparing Decision-Making across Drug Users

Illegal drug use is a real-world behavior that is obviously risky. Therefore, comparing IGT and BART performance across drug users can help identify the processes that are relevant to real-world risk taking. To this end, three groups of adult participants were compared: healthy controls, marijuana users, and stimulant/polysubstance users. In the IGT, poor decision-making has been observed in marijuana (Bolla, Eldreth, Matochik, & Cadet, 2005; Whitlow et al., 2004) and stimulant users (Stout, Busemeyer, Lin, Grant, & Bonson, 2004). In the BART, increased balloon pumping has also been observed in drug users (Aklin et al., 2005; Lejuez et al., 2002), and cocaine users (a stimulant) in particular (Bornovalova et al., 2005). Therefore, it was anticipated that substance users, when compared to healthy controls, would show more disadvantageous deck selection in the IGT and more balloon pumping in the BART. Marijuana use is perceived to be less risky than stimulant use (Colbry & Duitsman, 1995), and so marijuana users may exhibit less risky behavior in the IGT and the BART compared to the stimulant group. We also examined whether the relationship between drug use and IGT/BART performance could be accounted for not by drug use per se, but by variables associated with drug use, such as alcohol use, demographic, or personality variables.

Examining model parameters across different kinds of drug groups, the decision consistency parameters (c and β) were of particular interest. Lower decision consistency in drug users may indicate more haphazard or exploratory decision-making, a style of decision-making that could be a risk factor for drug use. Studies using cognitive modeling with the IGT have previously found use of cocaine to be associated with significantly lower decision-consistency and lower attention to losses (Stout et al., 2004). Marijuana use has been associated with lower attention to losses and a higher recency parameter (Yechiam, Busemeyer, Stout, & Bechara, 2005), but the EVL model fit poorly in that study, and so it is unclear how meaningful the estimated parameter values were. BART model parameters have only been examined with college samples (rather than samples recruited for drug use habits). In college students, drug experimentation has been associated with lower consistency and higher payoff sensitivity (Wallsten et al., 2005; Pleskac, 2008).

Previous studies have suggested that the BART might be more sensitive than the IGT to drug and alcohol use. However, these studies have tended to focus on adolescents and have often involved lighter, less risky drug use. For example, in some studies, relative to IGT performance, BART performance has tended to be more strongly associated with smoking in undergraduate students and drug use in adolescents (Lejuez et al., 2003; Aklin et al., 2005). We were interested in the degree to which these findings generalized to more severe substance using adult populations. Studies that have examined the IGT but not the BART have found the IGT to be sensitive to heavy drug use among adults (e.g., Bechara & Damasio, 2002), but it is not clear how the IGT's sensitivity would compare to the BART's sensitivity for this population.

Method

Participants and Design

The three groups were: Healthy Controls (n=32, 15 female), Marijuana Users (n=21, 10 female), and Stimulant Polysubstance Users (n=19, 11 female). Table 2 shows demographic, drug use, drug problem, and personality information for each group.

Participants were recruited via newspaper advertisements and flyers posted in the Bloomington and Indianapolis, Indiana communities. Potential participants were excluded if they showed evidence of psychosis or were taking medication for attention-deficit hyperactivity disorder (e.g., methylphenidate), narcotic pain medication, tranquilizers, epilepsy drugs, AIDS treatment drugs, antipsychotics, or any medications that might significantly affect behavior or have significant side effects.

Controls were defined as individuals who had no more than one binge drinking session (5+ drinks) per month. For the past 6 months, they had no more than 4 uses of any drug, 2 uses per month, and 2 total uses of nitrous oxide. Before 6 months previously, they had no more than 2 marijuana uses per month, 6 total, and 3 total nitrous oxide uses. In addition, control participants were screened to exclude individuals that reported any drug-related problems or DSM-IV symptoms of abuse or dependence as indicated by the Semi-Structured Assessment for the Genetics of Alcoholism (SSAGA-II; see *Materials* below).

Marijuana participants were defined here as individuals with at least 21 marijuana uses in the past year. Stimulant polysubstance participants were defined as individuals with at least 11 lifetime stimulant uses. These criteria were used to create 3 groups with relatively different drug use patterns. Table 2 gives additional information about drug usage and lifetime DSM-IV defined problems associated with drug usage (e.g., withdrawal symptoms, unsuccessful attempts to quit, problems with social/occupational/recreational functioning). [1]

Participants were excluded if during testing they showed a blood-alcohol level of at least .01 as revealed by a breathalyzer test. Participants were also excluded if they were suspected of being under the acute influence of a drug.

Materials

IGT. Participants were presented with 4 decks of cards. Participants were instructed to draw from any of the four decks and to try to maximize their profits. Each card was associated with a win of .50 or 1 dollar, but some cards were also associated with losses ranging from .75 to 5 dollars. Two of the decks were advantageous; selections from those decks resulted in an average return of +.25 dollars per card. The other two decks were disadvantageous; selections from those decks resulted in an average return of -.25 dollars per card. In most previous versions of the task, both advantageous decks have had smaller sure wins than the disadvantageous decks. So as to deconfound deck advantage with size of sure wins, we used sure wins of 1 dollar for one advantageous *and* one disadvantageous deck, and did the same for sure wins of .50

dollars (Cantrell, Finn, & Rickert, 2007). There were 120 trials in the IGT. The primary measure of interest in the IGT was proportion of advantageous deck selections across 6 blocks of 20 trials each.

BART. For this task, a simulated balloon was presented on a computer screen and participants could press the spacebar to pump up the balloon. Holding down the spacebar would result in several rapid balloon pumps. With each successful pump, the balloon would inflate and 5 cents would be deposited in a temporary bank. This temporary bank was not shown on the screen. If the balloon was pumped too many times, it would explode and all money in the temporary bank would be lost. Participants decided when to stop pumping by pressing "s." Pressing that key would transfer all money from the temporary bank to the permanent bank shown on the screen labeled "Total Earned." The screen also displayed the amount of money won on the previous trial, or 0 if the last balloon popped. After each money collection or explosion, that balloon disappeared, and the next trial began with a new balloon. There were 3 blocks of 30 trials each.

Participants were not informed about what determined when the balloon would explode. In fact, the computer allowed a maximum of 1 to 128 pumps before explosion, with the number drawn from a random uniform distribution with replacement across trials, and drawn randomly for each participant. Because there were a certain number of pumps allowable for each balloon, the probability of a balloon exploding increased with each successful pump until the balloon actually exploded. To measure a participant's risk propensity, the average number of pumps taken on balloons that did not explode (i.e., the adjusted BART score) was used in all analyses (Lejuez et al., 2002).

Personality Measures. The Eysenck I_7 Impulsiveness Questionnaire (Eysenck, Pearson, Easting, & Allsopp, 1985) is a 54-item questionnaire that is designed to assess individuals on three factors of personality: Impulsiveness, Venturesomeness, and Empathy. The factors of Impulsiveness and Venturesomeness have been shown to be separate components of a broader construct of "impulsivity" that correlate with the personality factors of Psychoticism and Extraversion, respectively (Eysenck et al., 1985; Eysenck & Eysenck, 1978).

The Sensation-Seeking Scale, version 5 (SSS; Zuckerman, 1979) was designed to measure individual differences in preferred or optimal levels of stimulation and arousal. The SSS contains four 10-item subscales that represent the factors of Thrill and Adventure Seeking (TAS), Experience Seeking (ES), Disinhibition (DIS), and Boredom Susceptibility (BS). The TAS subscale measures the desire to engage in activities that involve physical danger, such as mountain climbing. The ES subscale measures the desire to seek new experiences through the mind or senses. The DIS subscale measures willingness to engage in disinhibited social behavior by such activities as substance use or partying. Lastly, the BS subscale examines the ability to tolerate dull, repetitive work or uninteresting people.

Three subscales from the Multidimensional Personality Questionnaire (MPQ; Tellegen & Waller, 1994) were used: the Control (CON) subscale, the Harm Avoidance (HA) subscale, and the Aggression (AGG) subscale. The CON subscale consists of 24 items that represent the "opposite" of impulsivity; individuals that rate highly on this scale are cautious, rational, and display a tendency to plan activities in detail. The HA subscale assesses avoidance of dangerous activities in favor of safer experiences, even if those experiences may be dull or tedious. High scorers on the AGG subscale may be described as physically aggressive and vindictive, with a tendency to become involved in antagonistic interpersonal exchanges.

Reliability was generally good for the Eysenck I_7 and MPQ subscales, but less so for some SSS subscales. Cronbach's alpha was as follows: Eysenck I_7 Impulsiveness=.82, Venturesomeness=.68, and Empathy=.65; SSS TAS=.81, ES=.47, DIS=.58, and BS=.54; and MPQ CON=.89, HA=.85, and AGG=.88.

Semi-Structured Assessment for the Genetics of Alcoholism. The SSAGA-II (Bucholz et al., 1994) was used to ascertain lifetime symptoms of marijuana and other drug abuse or dependence. The SSAGA-II assesses problems using DSM-IV criteria (Diagnostic and Statistical Manual of Mental Disorders – 4th Edition, American Psychiatric Association, 1994).

Procedure

Participants were instructed to abstain from all drugs for 12 hours prior to the study. After signing consent, participants took a breathalyzer test. An experimenter then administered the SSAGA-II and short questionnaires about recent drug and alcohol use. Participants then completed the SSS, Shipley Institute of Living Scale (to provide an estimate of IQ; Zachary, 1986), Eysenck I_7, and MPQ. The IGT was then administered manually, and finally, the BART was administered via computer. All participants were tested individually. Participants were paid $7 per hour in addition to all earnings on the IGT and BART.

Modeling Analyses

The IGT and the BART were each modeled using previously published methods specific for each task (for equations and other details, see Busemeyer & Stout, 2002; Wallsten et al., 2005, Model 3). In both cases, individual participants' data were fit to models, yielding parameter estimates for each individual. For the IGT, the Expectancy-Valence Learning Model was compared to a baseline model where the predicted probably of choosing any particular deck was the marginal probability of choosing that deck. For the BART, the Bayesian learning model was compared to a baseline model where the predicted probability of pumping the balloon was the total number of pumps taken by that participant divided by the total number of pumping opportunities.

Both model comparisons used the Bayesian Information Criterion (BIC) to adjust for complexity differences. Positive BIC values represent better fits to the data for the Expectancy-Valence Learning or the Bayesian Learning model relative to their respective baseline models:

$$\mathrm{BIC} = 2(\mathrm{L}_{\mathrm{cognitive}} - \mathrm{L}_{\mathrm{baseline}}) - \Delta k(\log(t)) \qquad (1)$$

L is the log-likelihood of the model. The Δk term refers to how many more free parameters the cognitive model has compared to the baseline model. $\Delta k=0$ for the Expectancy-Valence Learning Model, and $\Delta k = 3$ for the BART model. The t refers to the number of trials being predicted. In the IGT, the model was not fit to any trials after a deck of cards was depleted for a participant. This was done so that the model could not predict choices that the participant was unable to make. Because of deck depletion, t was sometimes less than the total number of trials in the IGT (M = 114.2, SD = 11.4). In the

BART, each pump opportunity for each balloon was a predicted trial. Consequently, each individual had a different number of predicted trials (M = 3,626.8, SD = 875.5).

Distributions of model parameters often showed large violations of normality. Because of this, model parameters were routinely analyzed with nonparametric tests.

Results

First, results are described separately for the IGT and the BART. Within each task, controls, marijuana, and stimulant users are initially compared via the primary behavioral measure (e.g., advantageous deck selection), and then via model fits and model parameters. Next, relationships between the IGT and the BART are examined through correlation and multiple regression. In all sections, results are reported as “significant” where $p < .05$. Because of power limitations due to the samples sizes of relatively unusual populations, results are reported as “marginally” significant or related where $.05 < p < .10$.

IGT Advantageous Deck Selection

Drug Groups. As shown in Figure 1, control group made better deck choices than the marijuana group, who in turn made better deck choices than the stimulant group. Proportion of advantageous deck selection was examined with a 3(Groups) x 6(Blocks) mixed ANOVA (with separate proportions for each subject). There was a significant main effect of Group, $F(2,69)=8.48$, $p < .001$, $\eta_p^{2} = .20$. T-tests revealed that the control group had significantly higher proportion advantageous than the stimulant group, $p < .05$, and all other differences between groups were marginally significant, ps < .06. There was evidence of learning, as indicated by a significant main effect of Block with the

Greenhouse-Geisser correction for violated sphericity, $F(3.3,228.5) = 3.32$, $p < .05$, $\eta_p^2 = .05$. The Block X Group interaction was not significant, $F(6.6,228.5) = 1.25$, $p = .28$.

Next, we considered whether group differences in IGT deck selection were the result of demographic, alcohol use, or personality differences rather than drug use per se. We addressed personality with a separate set of analyses as there was inadequate power to assess all of these variables simultaneously.

Demographics and Alcohol Use. Gender neither had a main effect nor did it interact with group, as shown by a 2(Gender) X 3(Groups) ANOVA, ps > .18. Age, Shipley IQ, and alcoholic drinks per week significantly differed across drug group (see Table 2). Because these three variables differed across groups, it could be that these variables explained differences in IGT performance rather than drug group per se. When these three variables were entered as covariates in ANCOVA, none of them exerted a significant effect, all Fs < 1. Group continued to have a significant effect, $F(2,65) = 3.40$, $p < .05$, $\eta_p^2 = .09$. In other words, drug group differences in demographic variables and alcohol use could not account for drug group differences in IGT deck selection.

Personality. As shown in Table 2, drug use groups had higher SSS Disinhibition, higher Eysenck Impulsivity, lower MPQ Control, and higher MPQ Aggression than controls. Of these variables, only Impulsivity and Control were significantly associated with IGT deck selection, $r = -.34$ & .28, respectively, ps < .05. This suggests that group differences in IGT deck selection could potentially be accounted for by drug users being more impulsive and less cautious compared to non-users. Impulsivity and Control were themselves highly interrelated, $r = -.80$, and so they were collapsed into a single Impulsivity/Control factor via factor analysis prior to use in ANCOVA. ANCOVA revealed a main effect of Group, $F(2,67)=4.95$, $p < .01$, $\eta_p^2 = .13$, but the effect of Impulsivity/Control was not significant, $F(1,68)=2.73$, $p > .10$.

These results show that IGT behavioral performance was sensitive to drug use, and this pattern could not simply be explained by differences in personality, demographics, or alcohol use in the drug groups. The difference between the drug groups may be better explained through process estimates from the Expectancy-Valence Learning model.

IGT Model

IGT Model Fits. The Expectancy Valence Model generally fit the data well, and especially well for the control group. Overall, this model fit better than the baseline model for a majority of participants, as indicated by 81.9% of participants having a positive BIC. This was significantly higher than 50% by a binomial test, $p < .001$. The mean BIC improvement of the expectancy valence model over the baseline model was 32.87, 10.52, and 17.64 for the control, marijuana, and stimulant groups, respectively. A one-way ANOVA showed a significant effect of group, $F(2,71)=3.29$, $p < .05$, $\eta^2 = .09$.

IGT Model Parameters. As shown in Table 3, stimulant users had lower consistency than controls, but no other group differences were significant. The Recency and Attention to Losses parameters were not related to group, *p*s > .22. The Consistency parameter was higher in the Control group than the two drug using groups, as revealed by a significant overall Kruskal-Wallis H test for Consistency, $\chi^2(2)=6.39$, $p <.05$. In simple comparisons of the consistency parameter using Mann-Whitney U tests, controls had higher consistency than stimulant users, U = 174, $p < .05$, but the remaining comparisons were not significant, *p*s > .11.[2]

Balloon Pumping in the BART

Drug Groups. Figure 2 shows the average number of pumps per balloon (excluding trials where the balloon exploded) as a function of drug group. A one-way ANOVA showed no significant effect of group, $F < 1$.

Abstinence, Demographic, Alcohol, and Personality Variables. Further analyses on balloon pumping revealed no significant effects or interactions of gender, *p*s > .11. All group and covariate effects were nonsignificant in an ANCOVA controlling for age, Shipley IQ, or alcoholic drinks per week, all *p*s > .22. No personality variables were significantly related to both group and BART balloon pumping.

Overall, balloon pumping behavior in the BART showed no meaningful relationships with drug use. As described below, model parameters in the BART were also insensitive to drug use.

BART Model

BART Model Fits. The Bayesian Learning Model generally fit the data well. This model fit better than the baseline model for a majority of participants, as indicated by 94.4% of participants having a positive BIC. This was significantly higher than 50% by a binomial test, $p < .001$. The mean BIC improvement of the Bayesian Learning Model over the baseline model was 67.42, 77.16, and 81.42 for the control, marijuana, and stimulant groups, respectively. These values were not significantly different, $F < 1$. Note that model fits for the BART and IGT are not comparable, both because the tasks are qualitatively different and also because their respective baseline models are different.

BART Model Parameters. Kruskal-Wallis H tests revealed no significant differences in model parameters as a function of group, all *p*s > .13. To summarize, the

BART was not sensitive to substance use either in terms of behavioral performance or model parameters.

Relationship Between the IGT and BART

There was little apparent relationship between the IGT and the BART as measured by standard behavioral measures, but there were relationships as measured by model parameters. Table 4 shows the Kendall's Tau B correlations among IGT and BART behavioral measures and parameters. Of most interest are the cross-task correlations, which are in the lower left quadrant of Table 4. The behavioral measures from the two tasks, Proportion Advantageous from the IGT and Pumps without explosion from the BART, were not significantly correlated with one another. However, in terms of the model parameters, 6 out of 12 cross-task correlations were significant, suggesting a complicated relationship between processes involved in the tasks.

To determine which cross-task correlations were most relevant, further analyses were conducted using simultaneous multiple regression. For these analyses, parameter distributions were made more normal through logit and logistic transformations. To determine the association of the IGT parameters to BART parameters, the set of all 3 IGT parameters were simultaneously entered to examine their association with one BART parameter at a time.[3] Results are reported wherever R^2 was at least marginally significant, $p < .10$, along with any standardized regression coefficients (β) that were at least marginally significant. Note that β does not represent a model parameter here.

Overall, regression analyses revealed two relationships: a relationship supporting a sensitivity to losses process and a relationship supporting a decision-consistency process. Supporting the notion of a common sensitivity to losses process, a higher attention to losses parameter in the IGT was associated with less optimism about the balloons (lower values of $\hat{q}_1$) in the BART, $F(3,68) = 2.70$, $R^2 = .11$, $p = .053$; $\beta = -.28$, $p < .05$. Supporting the notion of a common decision-consistency process, higher IGT consistency marginally related to higher BART consistency, $F(3,68) = 2.95$, $R^2 = .12$, $p < .05$; $\beta = .26$, $p < .09$. Note that this relationship is in the predicted positive direction, and for a directional, one-tailed test on the regression weight, $p < .05$. Both of these relationships were also supported by significant bivariate relationships, *p*s < .05, as shown in Table 4. In the regression analyses, no other relationships reached or approached significance, including the relationship between recency and uncertainty parameters that would implicate a common learning process.

Discussion

The IGT and the BART may measure overlapping aspects of risk-taking, and that overlap might only be detectable through a modeling approach. Whereas there was no significant relationship between the IGT and BART in their standard behavioral measures, there were theoretically meaningful relationships at the model parameter level. Attention to losses on the IGT was related to belief that the balloon would pop, and hence money would be lost, on the BART. This relationship suggests that both tasks may assess loss sensitivity in decision-making. The consistency parameters were also related across tasks, suggesting that both tasks may assess the haphazardness of choices in decision-making.

These results have two important implications. First, these results support the theoretical utility of using cognitive models to estimate underlying processes in risky decision-making tasks. The EVL model has been previously used to interpret different decision-making behaviors observed in various clinical populations, including not only substance using individuals (e.g., Stout et al., 2004), but also patients with Parksinson's disease, Huntington's disease (Busemeyer & Stout, 2002), and a variety of other special populations (see Yechiam et al., 2005). Our findings suggest that model parameters are not simply ad-hoc labels. Rather, parameters behave in predictable ways such that, as a parameter increases in one task, a theoretically related parameter increases in another task.

Second, and perhaps more importantly, these results support the theoretical usefulness of the constructs of loss sensitivity and decision-consistency for decision-making research more generally. Loss sensitivity has been previously shown to vary systematically across different individuals and contexts (e.g., Lerner, Small, & Loewenstein, 2005; Tom, Fox, Trepel, & Poldrack, 2007). Our results add support to the concept of loss sensitivity by showing systematic variance across people. The associations occurred despite the use of different tasks and different models, models that were developed by two independent research groups (Busemeyer & Stout, 2002; Wallsten et al., 2005). Furthermore, the current results likewise show a systematic variation across individuals for a decision-consistency process. Lower decision consistency may represent a general preference for exploratory over exploitative search strategies.

Although sensitivity to losses and decision-consistency both were related across tasks, it is important to note that the different models define these constructs in slightly different ways. In the IGT model, sensitivity to losses is defined by the weight given to loss magnitude. In the BART model, it is defined by the perceived probability of losing.

Given our results, it is possible that the magnitude and probability of losses influence decisions via similar processes, such as the emotional reaction associated with losses in general.

Although consistency parameters were related across tasks, definitions of consistency are also subtly different across models. Whereas the BART consistency parameter is stable, the IGT consistency parameter represents a change in decision-consistency over time. The latter parameter allows for the possibility of decisions becoming more deterministic with task experience (see Wallsten, Bender, & Li, 1999). Aside from this difference, the two consistency parameters are mathematically similar. Importantly, both parameters measure some aspect of randomness or exploration in decision-making.

Whereas the two tasks showed common sensitivity to losses and decision-consistency processes, there was no reliable evidence for a common learning process across the tasks. In previous research, modifying the IGT and BART procedures so as to minimize learning demands has produced different results across the two tasks. When learning demands were minimized in a modified version of the IGT, the task became *less* sensitive to drug use (Stout, Rock, Campbell, Busemeyer, & Finn, 2005). When learning demands were minimized in a modified version of the BART, the task became *more* sensitive to drug use (Pleskac, 2008). Such contrasting results suggest that the IGT and the BART may involve qualitatively different learning processes.

One possible reason for a qualitative difference in learning processes is that the outcomes are defined explicitly in the BART but are ambiguous in the IGT. In the BART, each balloon pump has 2 well defined outcomes that are explicitly stated in the instructions: a gain of 5 cents or a balloon pop. Each choice in the IGT, though, has several possible win and loss outcomes, outcomes that must be learned gradually. Outcome ambiguity is known to affect decision-making (Ho, Keller, & Keltyka, 2001), and it is plausible that such ambiguity would affect the learning process in decision-making tasks.

Cognitive modeling of the IGT suggested that substance use was related to lower decision consistency, and this effect was driven mainly by the stimulant group. Lower consistency has been found previously in abusers of the stimulant cocaine (Stout et al., 2004). Stout and colleagues also found lower attention to losses in that group, perhaps due to the higher levels of stimulant use in their participants.[4] In addition, modifications made to the IGT for the current study might have had a substantive impact on the processes involved. Modifying the IGT to balance the size of sure wins with advantageous vs. disadvantageous decks might have resulted in a less prominent win/loss distinction. This could account for the absence of a group difference in attention to losses, leaving only a difference in decision-consistency.

Interestingly, decision-consistency might be a process that is not limited to typical risky decision-making tasks such as the BART and the IGT. A task used to measure executive function, the Wisconsin Card Sort Task (Berg, 1948; Grant & Berg, 1948), can also be decomposed via cognitive modeling. Cognitive modeling of that task uses a decision-consistency parameter mathematically related to the consistency parameters of the BART and IGT models. Notably, decision-consistency in the Wisconsin Card Sort Task is lower among substance dependent individuals than healthy controls (Bishara et al., in press). This suggests that a variety of tasks, even those that might appear unrelated to one another, may assess haphazard or exploratory choice in drug users. Substance users' exploratory choice across a variety of tasks may be related to the exploratory behavior that originally lead to drug experimentation in this population.

Though substance users made riskier decisions on the IGT, they did not do so on the BART. This finding demands some explanation, as it contrasts with previous findings that the BART was more strongly related to drug use than the IGT was (Aklin et al., 2005; Lejuez et al., 2003). There are at least two possible explanations. First, even though there were no significant group differences in the BART, there was a trend in the means for drug users to pump more than controls, which would be consistent with previous literature. The lack of significance may simply reflect inadequate power. This study and the previous studies comparing the IGT and the BART have not had large sample sizes, with *n* ranging from 51-72. An inconsistent pattern of significant and nonsignificant results in the literature would be expected when studies tend to be underpowered (Maxwell, 2004). Second, and perhaps most importantly, IGT and BART results might not converge across studies simply because the two tasks measure only slightly overlapping constructs. At the behavioral level, IGT deck selections and BART pumps did not correlate here or in previous research (Aklin et al., 2005; Lejuez et al., 2003). At the process level, there was a complicated relationship between the two tasks. Even the significant correlations were small to medium in size.

This pattern highlights the idea that risky decision-making is not a unitary construct (see Reynolds, Ortengren, Richards, & de Wit, 2006; Weber, Blais, & Betz, 2002). Different task structures may lead to measurement of different combinations of processes. The IGT and BART in particular may both involve sensitivity to losses and decision consistency, processes that may be fundamental to risky decision-making more generally. Rather than treating tasks as process pure, a cognitive modeling approach allows for the separation of such processes within tasks. Because of this, modeling can help identify the diverse processes involved in complex decision-making tasks.

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Appendix: Model Equations

The Expectancy Valence Learning Model (Busemeyer & Stout, 2002)

In the IGT, participants experience an affective reaction, or valence, toward each deck based on the combination of wins and losses. The valence on each trial (*v*) is a weighted average of gains (*R*) and losses (*L*):

$$v_t = (1-\omega) \cdot R_{d,t} + \omega \cdot L_{d,t} \tag{1}$$

where *t* is the trial, *d* is the chosen deck, and ω is a free parameter that allows for different amounts of attention for wins and losses.

Across trials, participants learn to expect the valences for each of the decks based on their previously experienced valences. The expected valences (EV) are updated by an adaptive learning mechanism:

$$Ev_{d,t} = (1-\phi) \cdot Ev_{d,t-1} + \phi \cdot v_t \tag{2}$$

where ϕ is a free parameter that determines the weight given to the previous expected valence versus the weight given to the most recently experienced valence. The expected valence of unchosen decks does not change.

The predicted deck choice is probabilistic, where decks with higher expected valences are more likely chosen. The predicted probability (Pr) of choosing deck *d* is:

$$\mathrm{Pr}_{d,t+1} = \frac{\exp(Ev_{d,t} \cdot \theta_t)}{\sum_{j=1}^{4} \exp(Ev_{j,t} \cdot \theta_t)} \tag{3}$$

where *j* represents all decks, 1 through 4. θ is the sensitivity of the choice probabilities to expected valences. As θ approaches 0, choices become more random and independent of expected valences. As θ becomes larger, choices become more deterministic and dependent on expected valences. Sensitivity may change with experience in the task, potentially increasing (e.g., through familiarity with the task) or decreasing (e.g., through boredom or fatigue). Specifically,

$$\theta_t = (t/10)^c \tag{4}$$

where c is a free consistency parameter, representing the change in sensitivity over trials.

Bayesian Sequential Risk-Taking Model (Wallsten et al., 2005)

For the BART, we used the Bayesian sequential risk-taking model developed and validated in Wallsten et al. (2005; see Model 3). At the start of each trial (each new balloon), participants evaluate their potential options of pumping and stopping. The expected gain on trial *h* for each pump opportunity *i* is

$$v_{h,i} = \hat{q}_h^i (ix)^{\gamma^+}, \tag{5}$$

Where $\hat{q}_h^i$ is the probability that balloon *h* will not explode on pump opportunity *i,* and *x* is the reward for a successful pump. Lower values of γ^+ indicate less sensitivity to changes in payoffs and higher values indicate greater sensitivity. Participants are assumed to target a pump G_h that maximizes expected payoffs. The maximizing option G_h is found by optimizing

$$G_h = \frac{-\gamma^+}{\ln(\hat{q}_h)}. \tag{6}$$

This equation illustrates how participants with different values of γ^+ will behave differently during the BART. Participants with larger values of γ^+ will have larger values of G_h, and so they will typically choose to pump more on a given balloon.

Decision makers probabilistically choose between pumping and stopping based on their distance from G_h. The response rule assumes that the probability of choosing to pump, $r_{h,i}$, on balloon *h* at pump opportunity *i* strictly decreases with each pump.

Participants are indifferent between pumping and stopping at G_h. Formally, the response rule:

$$r_{h,i} = \frac{1}{1 + \exp(\beta d_{h,i})} \tag{7}$$

captures these properties where $d_{h,i} = i - G_h$, and β is a free parameter representing how consistently participants follow their targeted evaluation. Participants with lower values of β will be more variable in their pumping behavior.

Participants update their beliefs about the probability of the balloon not exploding, $\hat{q}_h$, using Bayes' rule. Their prior opinion of the balloon not exploding on the first balloon, $\hat{q}_1$, is modeled with a beta distribution described by parameters a_1 and m_1, where $a_1 \geq 0$ and $m_1 > 0$. The model can be reparameterized into the mean of the beta distribution, $\hat{q}_1 = a_1/m_1$, and the variance,

$$\mathrm{var}(\hat{q}_1) = \frac{a_1 m_1 - a_1^2}{m_1^3 + m_1^2} \tag{8}$$

Because $\mathrm{var}(\hat{q}_1)$ tends to be close to 0 and prone to rounding error in analyses, we analyzed δ where:

$$\delta = \log(\mathrm{var}(\hat{q}_1)) \tag{9}$$

Participants learn about and refine their opinion of $\hat{q}_h$ after each trial in accord with Bayes' Rule. The beta distribution is a conjugate distribution of the binomial, so the Bayesian updating process is straightforward. After each balloon, m is increased by the total number of pumps on the previous balloon, c, such that $m_{h+1} = m_h + c_h$. If the balloon ended with an explosion, then a is only increased by the number of pumps that were successful, $a_{h+1} = a_h + c_h - 1$.If the balloon did not end with an explosion, a is increased by the total number of pumps, $a_{h+1} = a_h + c_h$. The estimate for the probability of no explosion for each balloon is $\hat{q}_h = a_h / m_h$.

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Footnotes

[1] As can be seen in Table 2, stimulant polysubstance participants used marijuana in addition to stimulants. In both drug groups, all participants had used marijuana at least once within the past year. Marijuana abuse is generally common among individuals who abuse other types of drugs (Tsuang et al., 1998), and so it is difficult to recruit pure stimulant users.

[2] To determine whether group differences in consistency (*c*) could be accounted for by variables other than marijuana or stimulant use, additional analyses were performed to examine demographics, alcohol use, and personality variables. Only one covariate was significant: alcoholic drinks per week, $F(1,65) = 5.79$, $p < .05$. However, this pattern of results was not robust and should be interpreted with caution. Consistency was non-normally distributed, and there was no significant ordinal association between consistency and alcoholic drinks per week, Kendall's Tau = -.02, $p = .84$.

[3] We also conducted regression analyses in the opposite manner, with the set of all 4 BART parameters simultaneously entered to examine their association with one IGT parameter at a time. None of the individual regression coefficients were significant in these analyses, *p*s >.20, perhaps as a result of the high degree of multicollinearity among some of the BART parameters (see Table 4, lower-right quadrant).

[4] In a review (Yechiam et al., 2005) that included the Stout et al. (2004) cocaine abuse study, it was reported that cocaine abuse was significantly related to attention to losses but not consistency. Modeling analyses differed across the original study and the review. In the original study, the recency parameter was not constrained, but in the review, it was constrained to be between 0 and 1. Additionally, all 250 trials were analyzed in the

original study, whereas only the first 100 trials were analyzed in the review. Thus, low consistency in cocaine abusers may have developed on later trials.

Table 1

Model parameter descriptions

Model	Parameter	Description
Expectancy-Valence Learning Model of the IGT	Recency (ϕ)	Indexes the amount of weight given to the most recent outcomes when learning what to expect from each deck. Respondents with higher values of ϕ tend to choose decks based only on the last few choices, quickly forgetting what was learned from early choices.
	Attention To Losses (ω)	Indexes how much attention is devoted to losses relative to gains when experiencing an outcome from each deck choice. Participants with higher values of ω will tend to choose the advantageous decks more often.
	Consistency (c)	Indexes how consistent deck choices are with expectancies over time. Positive values of c indicate increasing consistency across trials and negative values indicate decreasing consistency.
Bayesian Model of the BART	Prior Belief ($\hat{q}_1$)	Indexes the subjective prior belief on the first balloon that the balloon will not explode. Respondents with higher values of $\hat{q}_1$ are more optimistic about the balloon not exploding and will pump the balloon a greater number of times on average.
	Uncertainty (δ)	Indexes the different levels of uncertainty respondents have in their prior beliefs. Respondents with higher δ values will have less confidence in their prior belief, and as a result, learn faster from experience.
	Payoff sensitivity (γ)	Indexes the level of sensitivity to changes in payoffs as a utility function. Higher values of γ indicate higher levels of sensitivity to changes in payoffs, which result in tending to pump the balloon further.
	Consistency (β)	Indexes how consistent pump choices are with participants' evaluations of balloons. Higher values of β tend to result in a higher adjusted BART score.

Table 2

Demographics, drug/alcohol use, and personality information for the Control, Marijuana, and Stimulant groups.

Variables and Measures	Control (N = 32)	Marijuana (N = 21)	Stimulant (N = 19)	
	Group			
Demographics				
Age	21.38_{ab} (2.99)	24.00_{ac} (6.35)	30.16_{bc} (8.20)	***
Years of education	13.77 (1.59)	13.85 (2.08)	13.72 (1.96)	
Shipley IQ	112.3_{ab} (7.3)	105.8_{ac} (11.1)	98.2_{bc} (10.0)	***
Drug/Alcohol Use				
Marijuana: Uses/day during period of heaviest use		5.27 (6.51)	4.95 (3.36)	
Marijuana: duration of heaviest use in months		16.84 (19.44)	44.64 (65.80)	
Marijuana: grams per week		10.65 (10.24)	13.41 (13.77)	
Stimulants: duration of heaviest use in months		0.59_{c} (2.62)	10.42_{c} (11.81)	***
Stimulants: Uses/day during period of heaviest use		3.00_{c} (1.22)	10.15_{c} (12.55)	*
Stimulants: Years since last use		1.73 (2.55)	2.42 (5.51)	
Alcohol: drinks per week	2.07_{ab} (3.04)	13.70_{a} (14.68)	19.37_{b} (35.44)	**
Lifetime DSM Defined Problems Associated With the Use of:				
Marijuana		4.52 (2.38)	5.26 (2.49)	
Stimulants		$.14_{c}$ (.65)	7.21_{c} (2.51)	***

Personality				
SSS Thrill & Adventure Seeking	6.47 (2.81)	7.14 (2.74)	5.53 (3.15)	
SSS Experience Seeking	4.84 (1.72)	5.38 (1.40)	5.11 (1.88)	
SSS Disinhibition	3.03_a (1.69)	4.43_a (1.94)	3.95 (1.35)	*
SSS Boredom Susceptibility	2.50 (1.50)	3.05 (1.88)	3.47 (2.48)	
Eysenck I_7 Venturesomeness	9.03 (3.37)	10.95_c (3.69)	8.17_c (4.42)	
Eysenck I_7 Impulsiveness	6.44_{ab} (3.58)	9.00_a (4.23)	10.28_b (5.22)	**
Eysenck I_7 Empathy	14.14 (2.36)	14.29 (3.47)	13.00 (3.20)	
MPQ Harm Avoidance	16.09 (5.34)	15.86 (5.65)	16.00 (7.15)	
MPQ Control	16.47_b (5.37)	13.52 (5.65)	11.58_b (6.45)	*
MPQ Aggression	4.41_b (3.05)	6.19 (4.99)	8.11_b (6.15)	*

Note. Values shown as Mean (*SD*). SSS = Sensation-Seeking Scale, MPQ = Multidimensional Personality Questionnaire. Asterisks indicate a significant between-groups difference on the same row as revealed by a one-way ANOVA: * $p < .05$; ** $p < .01$; *** $p < .001$. Means with the same subscript on the same row are significantly different as revealed by an independent samples *t*-test, $p < .05$.

Table 3

Model parameter medians, with interquartile ranges in parentheses.

Task and Parameter	Control		Marijuana		Stimulant	
	Group					
IGT						
Recency (ϕ)	.30	(.05–.83)	.08	(.02–.89)	.72	(.11–1.00)
Attention to Loss (ω)	.37	(.21–.77)	.25	(.11–.48)	.30	(.13–.58)
Consistency (c)	1.02_a	(.40–1.71)	.85	(.22–2.39)	$.49_a$	(-.05–.66)
BART						
Prior Belief ($\hat{q}_1$)	.991	(.989–.993)	.993	(.990–.994)	.991	(.989–.993)
Uncertainty (δ)	-10.9	(-11.5 – -10.4)	-11.4	(-11.9 – -10.9)	-11.2	(-11.7 – -10.8)
Sensitivity (γ^+)	.86	(.70–1.26)	1.06	(.73–1.28)	.96	(.72–1.32)
Consistency (β)	.08	(.06–.12)	.07	(.06–.15)	.09	(.07–.13)

Note. IGT=Iowa Gambling Task. Medians with the same subscript are significantly different as revealed by a Mann Whitney U test, $p < .05$.

Table 4

Kendall's Tau B correlations amongst IGT and BART performance and model parameters.

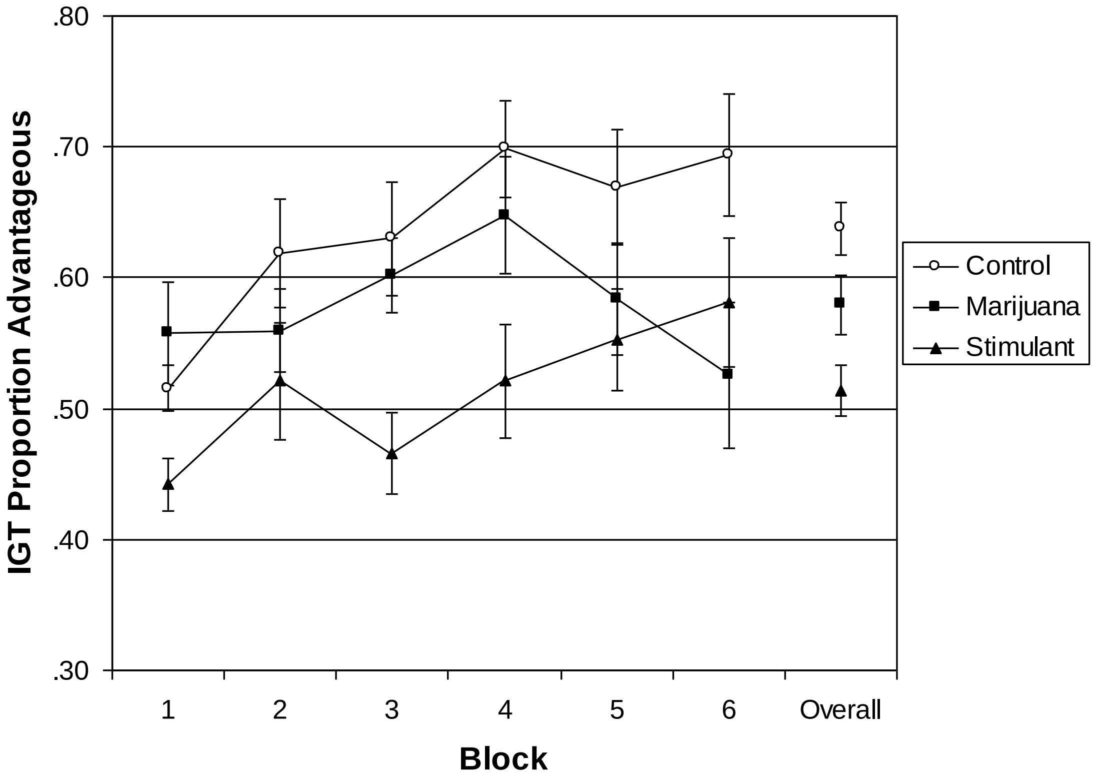
	IGT				BART			
	1	2	3	4	5	6	7	8
IGT								
1. Prop. Adv.	-							
2. Recency (ϕ)	-.10	-						
3. Att. Losses (ω)	.10	-.12	-					
4. Consistency (c)	.28***	-.45***	-.09	-				
BART								
5. Pumps	-.11	.04	-.07	-.08	-			
6. Prior Belief ($\hat{q}_1$)	-.17*	.17*	-.19*	-.12	.11	-		
7. Uncertainty (δ)	.18*	-.09	.00	.15	-.15	-.58***	-	
8. Sensitivity (γ^+)	-.02	.19*	.03	-.22**	.30***	-.14	-.02	-
9. Consistency (β)	.01	-.18*	.03	.19*	-.23**	-.08	.11	-.54***

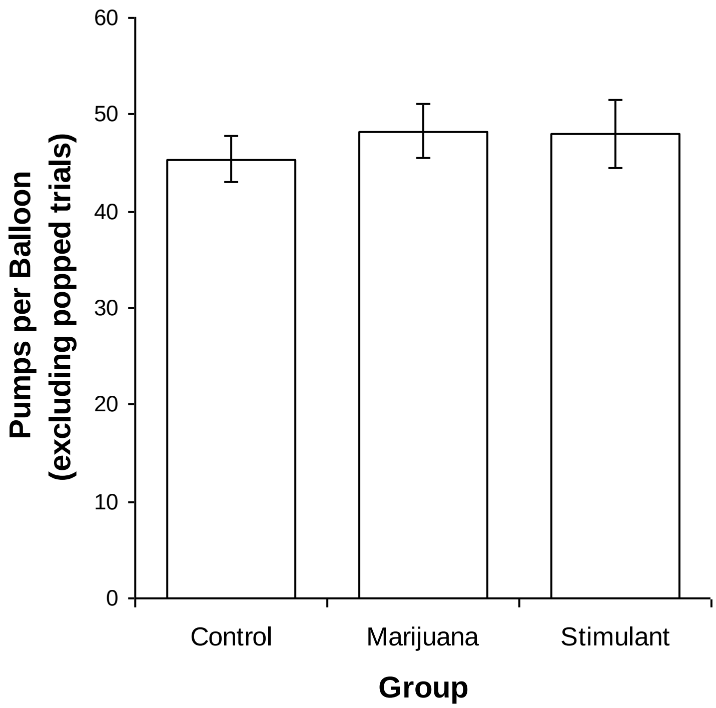
Note. IGT=Iowa Gambling Task, BART=Balloon Analog Risk Task, Prop. Adv. = Proportion Advantageous, Att. Losses=Attention to Losses parameter, Pumps=pumps per non-exploding balloon. *p<.05, **p<.01, ***p<.001.

Figure Captions

Figure 1. In the Iowa Gambling Task (IGT), mean proportion of deck selections that were advantageous within each block of 20 cards and combined across all blocks. Error bars show +/- 1 standard error of the mean.

Figure 2. In the Balloon Analog Risk Task (BART), mean number of pumps per balloons excluding trials where the balloon popped. Error bars show +/- 1 standard error of the mean.


.80
.70
.60
.50
.40
.30
IGT Proportion Advantageous
1
2
3
4
5
6
Overall
Block
Control
Marijuana
Stimulant


60
50
40
30
20
10
0
Pumps per Balloon
(excluding popped trials)
Control
Marijuana
Stimulant
Group