Research Article

Using Cognitive Models to Map Relations Between Neuropsychological Disorders and Human Decision-Making Deficits

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ABSTRACT—*Findings from a complex decision-making task (the Iowa gambling task) show that individuals with neuropsychological disorders are characterized by decision-making deficits that lead to maladaptive risk-taking behavior. This article describes a cognitive model that distills performance in this task into three different underlying psychological components: the relative impact of rewards and punishments on evaluations of options, the rate that the contingent payoffs are learned, and the consistency between learning and responding. Findings from 10 studies are organized by distilling the observed decision deficits into the three basic components and locating the neuropsychological disorders in this component space. The results reveal a cluster of populations characterized by making risky choices despite high attention to losses, perhaps because of difficulties in creating emotive representations. These findings demonstrate the potential contribution of cognitive models in building bridges between neuroscience and behavior.*

The Iowa gambling task (Bechara, Damasio, Damasio, & Anderson, 1994) is a popular method for investigating basic decision-making deficits of individuals with neuropsychological disorders. Participants make a series of 100 choices from four decks of cards; their goal is to maximize their net payoff across trials (see Fig. 1). Each card selection leads to a monetary gain but may also lead to a loss. The outcomes of each of the decks are not known to the decision makers beforehand and must be learned from experience. Two of the decks are disadvantageous and risky in that they lead to relatively high gains ($100 each time) but also to occasional large losses (up to $1,250), which result in an average loss (−$25 per trial). The two other decks are advantageous, as they lead to lower gains each time ($50) but produce smaller losses, resulting in an average gain (+$25 per trial).

Initially, the task was found to be effective in differentiating individuals with bilateral damage to the ventromedial prefrontal cortices (VMPC) from control subjects (Bechara et al., 1994). VMPC lesions are associated with a syndrome in which individuals have normal IQ and reasoning ability, but demonstrate excessive risk taking in their decision-making behavior (Bechara et al., 1994; Damasio, 1994). This deficit was reflected in the Iowa gambling task by an increased number of choices from disadvantageous decks. Poor performance in the Iowa gambling task (persistence in selection from disadvantageous decks) was subsequently found in several other neuropsychological syndromes and disorders, including lesions in the right somatosensory and insular cortex (RSIC; Bechara, Tranel, & Hindes, 1999), Huntington's disease (Stout, Rodawalt, & Siemers, 2001), chronic drug abuse (Bechara et al., 2001; Stout, Busemeyer, Lin, Grant, & Bonson, 2004; Yechiam et al., 2004), obsessive-compulsive disorder (Cavedini et al., 2002), and Asperger's syndrome (Johnson, Yechiam, Murphy, Stout, & Busemeyer, 2004).

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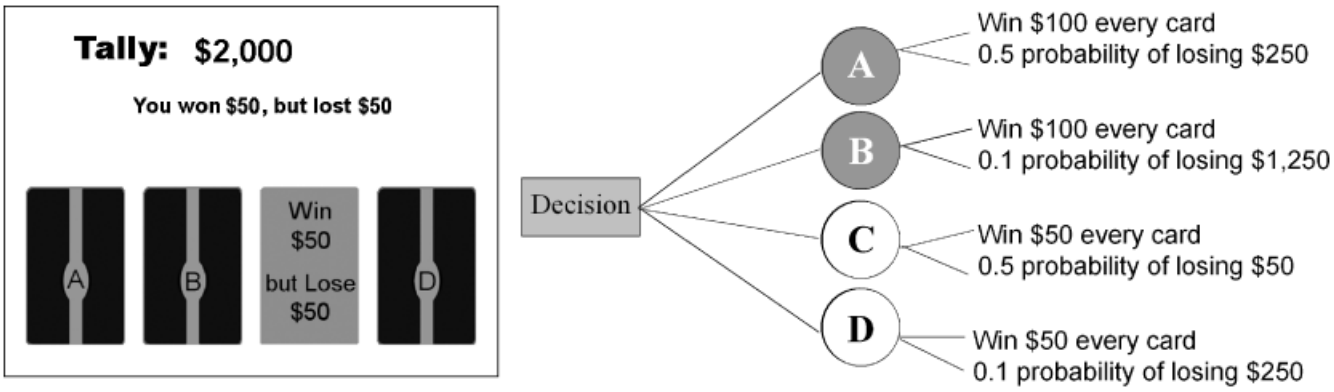

Fig. 1. A screen from the computerized version of the Iowa gambling task, with an explanation of the available alternatives and their outcomes. Decks A and B are disadvantageous, and Decks C and D are advantageous. Note that gains and losses can occur simultaneously on the same trial, as in this case (the decision maker chose Deck C and had a gain of $50 and a loss of $50).

These results are usually interpreted as indicating that all of these syndromes and disorders share a common decision-making deficit. Yet it is possible that markedly different psychological processes lead to the same qualitative finding of poor performance in the gambling task. Theoretically, the decision-making deficits observed in the Iowa gambling task can be broken down into three basic components: The first is a motivational factor, a tendency to be attracted by gains and to ignore losses; the second is a learning-rate factor, a tendency to focus on recent events and to forget or rapidly discount past losses; the third is a response factor, a tendency for choices to be made erratically owing to factors such as loss of interest, boredom, or tiredness. Thus, to improve discriminability between different populations, it is necessary to distill the overt behavior in the Iowa gambling task so as to reveal potential differences in more basic components.

Busemeyer and Stout's (2002) expectancy-valence model can be used to sort out these three components. This mathematical model yields quantitative parameter estimates that provide a continuous mapping of populations along the three different psychological dimensions. Note that other models could lead to different implications and conclusions, but the expectancy-valence model captures the essential properties of most plausible attention and memory-processing interpretations of the Iowa gambling task, as well as similar repeated-choice tasks (see, e.g., Camerer & Ho, 1999; Erev & Roth, 1998; Weber, Shafir, & Blais, 2004).

This article reviews a set of 10 applications of the cognitive model to a wide variety of populations, normal older individuals (seniors) and 9 populations with neuropsychological syndromes and disorders. The results show that poor performance in the Iowa gambling task is associated with distinct psychological components in different neuropsychological disorders.

THE EXPECTANCY-VALENCE MODEL

The expectancy-valence cognitive model comprises three basic parameters.

Attention to Losses Versus Wins: The Motivation Parameter

The first parameter of the model is a motivational parameter that represents attention to gains and losses. On each trial, a deck is selected, and payoffs contingent on the selected deck are delivered. It is assumed that after the decision maker makes a choice and experiences gains and losses, he or she differentially weighs the gains and losses, as in prospect theory (Kahneman & Tversky, 1979). The valence of the payoffs experienced on trial t is denoted $v(t)$ and is calculated as a weighted average of gains and losses in trial t:

$$v(t) = W \cdot win(t) - (1 - W) \cdot loss(t),$$

where $win(t)$ is the amount of money won on trial t, $loss(t)$ is the amount of money lost on trial t, and W is a parameter that indicates the weight given gains versus losses. The motivation parameter (i.e., W) ranges from 0 to 1. Small values of the parameter denote attention to losses. Higher values denote increasing attention to gains, a tendency that can increase the preference for the high-gain, disadvantageous decks.

Updating Expectations: The Learning-Rate Parameter

The second parameter of the model represents attention to the most recent outcomes versus attention to past outcomes. Decision makers are assumed to form expectancies that represent the anticipated consequences of choosing a card from each deck. When deck j is chosen, the expectancy for that deck, E_j, is updated as a function of its previous value (which reflects past experience), as well as the newly experienced payoffs on the current trial:

$$E_j(t) = E_j(t-1) + \phi \cdot [v(t) - E_j(t-1)]$$

In other words, the new expectancy equals the previous expectancy plus an adjustment resulting from the prediction error, $[v(t) - E_j(t)]$ (Busemeyer & Myung, 1992; Rumelhart & McClelland, 1986). The amount of adjustment is controlled by the learning-rate parameter, ϕ. This parameter ranges from 0 to

1. Small parameter values produce more persistent influences across longer lags, and less discounting of past outcomes. Large values of ϕ produce rapid adjustments, strong recency effects, and rapid discounting of past outcomes. A tendency to select from the disadvantageous decks could be due to such rapid discounting, because these decks produce infrequent losses.

Choice Consistency: The Response-Sensitivity Parameter

The decision maker's choice on each trial is based not only on the expectancies produced by the decks, but also on the consistency with which the decision maker applies those expectancies when making choices. According to the model, the probability of choosing a deck is determined by the strength of that deck relative to the sum of the strengths of all decks:

$$Pr[G_j(t+1)] = \frac{e^{\theta(t)\cdot E_j(t)}}{\sum_k e^{\theta(t)\cdot E_k(t)}},$$

where $Pr[Gj(t)]$ is the probability that the model will select deck j on trial t.

The variable $\theta(t)$ controls the consistency between choices and the expectancies, and it is assumed to change with experience. Specifically, consistency is assumed to increase (i.e., choice is assumed to rely more on expectancies) with increasing experience. This assumption is formalized by a power function for the sensitivity change over trials:

$$\theta(t) = (t/10)^c,$$

where c is the response-sensitivity parameter. When the value of the response-sensitivity parameter is high, choices converge toward the deck with the maximum expectancy. When the value of c is low, choices become inconsistent, random, and independent of the expectancies over time. Such an erratic choice pattern is a third reason for participants not to learn to choose from advantageous decks.

MODELING ANALYSES

In the analyses of the 10 populations, the parameters of the expectancy-valence model were optimized separately for each individual decision maker by maximizing the likelihood of the observed sequence of 100 choices produced by that individual. In optimization, the fit of the cognitive model (in log likelihood) is compared with the fit of a baseline model. The baseline model's prediction is based on the optimized proportion of choices from each deck. That is, the baseline model's three parameters are the average choice proportions of Decks A, B, and C (Deck D's parameters are calculated accordingly).

The improvement in the fit of the cognitive model over the fit of the baseline mode is G^2, which is a model-fit statistic analogous to the chi-square. Positive values of the G^2 statistic indicate that the cognitive model performs better than the baseline model, whereas negative values indicate the reverse.

In addition to calculating the fit index, we estimated the parameters for each individual. This analysis resulted in three parameter estimates: W, which measures importance of gains versus losses; ϕ, which measures rate of adjustment and recency effects; and c, which measures consistency between expectancies and choices. We summarized the distribution of parameter estimates from each population by computing the average and standard deviation for each parameter. For each group, we obtained data from a control group, matched on extraneous variables such as age, gender, and education, and followed the same modeling procedures. The differences between each population studied and its corresponding control group were then computed.

MODELING RESULTS

Figure 2 maps the 10 populations studied with the Iowa gambling task according to their differences (from their corresponding control groups) in the parameters of the expectancy-valence model. Each mean difference score is located at the center of a circle, which is positioned along two dimensions. The horizontal dimension represents differences in the weight for gains relative to losses, and the vertical dimension represents differences in the learning-rate parameter. The standard errors of these differences are denoted by a cross aligned at the center of each circle. The radius of each gray circle represents difference in the response-sensitivity parameter. Table 1 shows the results of the comparisons between the learning and baseline models for the entire experiment (control groups and subject populations). The G^2 column in the table indicates the percentage of subjects in the two groups combined whose difference from the baseline model was greater than 0. These results indicate that for most individuals, the cognitive model improved the predictions relative to the baseline model. The table also shows the results of the significance tests for parameter differences between the subject populations and their control groups.

Of the 10 populations, 2 showed parameter values very similar to those of their respective control groups: young polydrug abusers, who were mostly students (Yechiam, Stout, Busemeyer, Rock, & Finn, 2005), and young alcohol abusers (Mazas, Finn, & Steinmetz, 2000). The other 8 populations showed a variety of differences from their control groups.

The top right portion of the map in Figure 2 shows a cluster of populations with high attention to gains and greater recency effects compared with control subjects. The populations in this cluster were characterized by both a focus on gains and a discounting of past outcomes relative to control subjects. These differences reached significance for the chronic (5+ years) cocaine abusers (in the attention-to-gains parameter; Stout et al., 2004) and for the chronic cannabis abusers (in both the attention-to-gains and the recency parameters; Yechiam et al., 2004). Note that both populations abstained from drugs prior to the experiment. The results for Huntington's patients with an

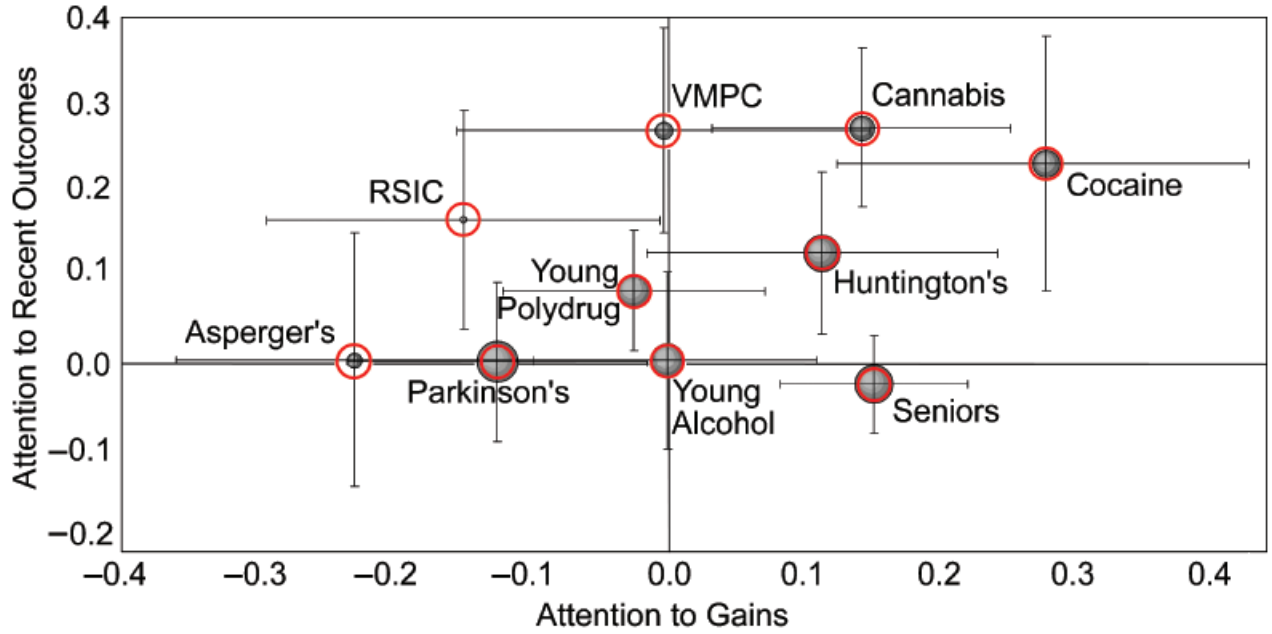

Fig. 2. Mapping of the 10 studied populations according to their performance on the Iowa gambling task. The location of each circle represents the degree to which the indicated group differed from its control group in attention to loss versus gain and in attention to recent outcomes. The standard errors of the differences are denoted by a cross aligned at the center of each circle. The diameter of each circle is proportional to the difference from the control group in the choice-consistency parameter; the red ring denotes the zero-difference boundary (circles smaller than the ring indicate low sensitivity). RSIC = individuals with lesions of the right somatosensory and insular cortex; VMPC = individuals with bilateral damage to the ventromedial prefrontal cortices.

average of 4 years since diagnosis (Busemeyer & Stout, 2002) also reflect a greater weighting of gains and more attention to the most recent trials compared with the control group (although not significantly so).

The results for normal seniors ages of 65 to 88 (average age = 77) showed significantly higher attention to gains than control participants 18 to 34 years old (Wood, Busemeyer, Koling, Cox, & Davis, in press).[1] However, they also showed higher sensitivity than control subjects.

Patients with bilateral damage to the VMPC (Bechara et al., 1994) showed a significant increase in the degree of recency compared with control subjects and also displayed an erratic choice pattern. The finding that a major difference between VMPC patients and control subjects is in the learning-rate parameter fits well with recent results showing that that the differences between these two groups disappear in decision tasks that involve no learning (i.e., description based tasks; Leland & Grafman, in press).

In stark contrast to the first cluster in the upper right portion of the map, there are three populations in the left-hand region whose decision-making style was characterized by high attention to losses. The finding of high attention to losses among Parkinson's patients (average age = 66, average of 8 years following diagnosis; Busemeyer & Stout, 2002) is consistent with previous results showing that Parkinson's patients score high on harm-avoidance tests (Kaasinen et al., 2001). The other two populations in this second cluster, individuals with RSIC lesions (Bechara et al., 1999) and adolescents with Asperger's syndrome (Johnson et al., 2004), displayed sensitivity to losses coupled with erratic choices (i.e., low choice consistency). Extremely low choice consistency has the potential to lead to disadvantageous choices despite high attention to losses because erratic choice leads to continuous shifts from the advantageous alternatives. The trial-to-trial pattern of behavior in both these populations is characterized by an extreme tendency to shift and change prior choices (Johnson et al., 2004).

Potential Mechanisms

The finding that chronic drug abusers demonstrate a motivational bias for immediate gains is consistent with theories of the behavior of drug abusers in choice tasks (see reviews in Finn, 2002, and Gorenstein & Newman, 1980), which postulate that signals of positive reward may carry more weight than signals of potential risk in drug abusers because of their stronger appetitive processes and weaker disinhibitory mechanisms compared with nonabusers.

The finding that both VMPC patients and chronic drug abusers demonstrate a degree of "myopia" for distant consequences is consistent with prior observations (Bechara et al.,

[1]Note that these results differ somewhat from those of Wood et al. The present study used a three-parameter model, which was found to be more robust than the four-parameter model they used (see Yechiam, Veinott, Busemeyer, & Stout, in press).

TABLE 1

Percentage of Positive G^2 Values, Indicating an Improvement of the Adaptive Learning Model Over the Baseline Model, and Results of Significance Tests for the Parameters

Sample	Sample *n*	Control *n*	$G^2 > 0$ (sample + control)	Parameters significantly different between groups[a]
Asperger's syndrome	15	14	66%	W^b, c
RSIC lesion	22	12	62%	c
Parkinson's disease	20	33	75%*	—
Young polydrug abusers	39	37	49%	—
Young alcohol abusers	27	32	67%*	—
VMPC lesion	21	12	76%*	ϕ, c
Normal seniors	63	87	61%*	W, c
Huntington's disease	14	33	75%*	—
Chronic cannabis abusers	25	16	24%	ϕ, W
Chronic cocaine abusers	12	14	69%*	W

Note. RSIC = right somatosensory and insular cortex; VMPC = ventromedial prefrontal cortex.
[a]A significance level of $p < .05$ was adopted. [b]This parameter became significant after 150 trials.
*$p < .05$ in a binomial test.

1994, 1999; Damasio, 1994). Huntington's patients also show this pattern. Given the close anatomical and functional links between the striatum and prefrontal cortex, and the fact that Huntington's disease is characterized by atrophy of the striatum (see, e.g., Kassubek et al., 2004), finding similar decision-making profiles in Huntington's and VMPC patients is not surprising. In addition, the strong recency effect in drug abusers and Huntington's patients could be due to a memory deficit. The greater influence of recency in chronic cannabis abusers as compared with chronic cocaine abusers is consistent with the known effect of cannabis abuse on cannabinoid receptors, which have regional binding specificity within the caudate nucleus, putamen, and hippocampus, brain areas important in memory (Bolla, Brown, Eldreth, Tate, & Cadet, 2002). Huntington's patients are likewise known to have memory impairments (see, e.g., Huber & Paulson, 1987; Stout et al., 2001).

Patients with RSIC lesions and individuals with Asperger's syndrome show low attention to gains (or pay relatively more attention to losses), but most important, they have a pronounced erratic choice pattern (i.e., low sensitivity parameter). The fact that these two populations tend to make erratic choices is consistent with the notion that a deficit in the neural systems subserving emotions and feelings is the source of this choice pattern (Bechara et al., 1999; Damasio, 1994). "Feeling" the pleasure of gain, or the pain of loss, may be dependent on neural processes within the right insular and somatosensory cortices (Damasio, 1994). Patients with RSIC lesions can generate physiological responses to gains and losses, but their subjective ratings of how good or bad they felt when they won or lost in the past are severely reduced, as indicated by the finding that they could not imagine and reexperience a previous emotional experience (Bechara et al., 1999). Asperger's patients are also often detached when the target of attention is outside their restricted set of interests (Gillberg, 2002). These two groups of patients may therefore have difficulties in establishing an emotive representation of the different decks in the Iowa gambling task. Perhaps this feeling deficit translates into a cognitive deficit, in that the subjects may never learn how to win because they never "care" about winning. They may adopt a simple "win-stay/lose-shift" strategy, which would produce a tendency to oscillate between alternatives.

Conclusions

In summary, the analysis using the expectancy-valence cognitive model shows that poor choices, rather than reflecting a single common decision-making deficit, tend to be associated with different component processes that reflect the continuous influence of attention to gains and losses, recency effects, and response sensitivity. Cognitive neuroscience is just beginning to unravel the brain mystery of human decision making. In the past, the predominant approach to studying this complex function focused on simple tasks that measured specific component processes of decision making, such as learning reversal, working memory, and other executive functions. Unfortunately, this approach did not lead to a satisfactory understanding, for example, of the decision-making impairments observed in patients with VMPC lesions (Bechara et al., 1994). However, researchers had success in capturing key aspects of human decision making and its disorder when they used complex laboratory tasks, such as the Iowa gambling task, which mimics real-life choices in requiring participants to integrate rewards and punishments, and the uncertainties of their occurrence. The research on the Iowa gambling task and similar complex tasks has led to the revival of old interest in the relationship between emotion and cognition. Yet although the Iowa gambling task succeeded in capturing many of the critical elements of decision making that were missed by using simple tasks, the relative complexity of this task

still prohibited a finer resolution of its underlying neural processes. However, the cognitive model described in this study provides a novel way for circumventing this problem by distilling the component processes from the behavior in this more complex task. Thus, the present approach is helpful in building a new bridge between cognitive neuroscience and complex human behaviors.

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