A formal cognitive model of the Go/No-Go discrimination task: Evaluation and implications

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Abstract:

The present paper proposes and tests a formal cognitive model for the Go/No-Go discrimination task. In this task the performer chooses whether to respond to stimuli, and receives rewards upon responding to certain stimuli and punishments for responding to others. Three cognitive models were evaluated based on data from a longitudinal study involving 400 adolescents. The results show that a Cue-Dependent model presupposing that participants are able to differentiate between cues was the most accurate and parsimonious. This model has three parameters denoting the relative impact of rewards and punishments on evaluations, the rate that the contingent payoffs are learned, and the consistency between learning and responding. Commission errors were associated with increased attention to rewards, and omission errors were associated with increased attention to punishments. Both error types were associated with low choice consistency. The parameters were also shown to have external validity: Attention to rewards was associated with externalizing behavior problems on the Achenbach scale, and choice consistency was associated with low Welsh anxiety. The present model can thus potentially improve the sensitivity of the task to differences between clinical populations.

Key words: decision making, impulsivity, individual differences, cognitive models, reinforcement learning

In the last few years there has been increased interest in the use of complex choice tasks for studying individual differences. In fact, tasks such as the Iowa Gambling Task (Bechara, Damasio, Damsio, & Anderson, 1994) and the Go/No-Go discrimination task (Helmers, Young & Pihl, 1995; Newman, Widom & Nathan, 1985) have become part of the array of tasks used by clinical scientists. Clearly, the advantage of using such tasks is that they capture key aspects of impulsive and risky behavior exhibited in real-world situations. In particular, the Go/No-Go discrimination task assesses the ability of a participant to learn to respond to cues (in the form of numbers presented on the screen) that have been previously paired with rewards, and withhold a response to cues that have been paired with punishments. It has been postulated that impulsive individuals respond more frequently to negative cues, owing to an increased focus on reward and an inability to alter this dominant response set (Newman, 1987).

Yet it is quite possible that other factors lead to poor performance in this Go/No-Go task. One such factor is a tendency to completely ignore the cues (in the form of numbers) and to focus on the rewards and punishments contingent on responding. Another factor is a slow learning rate, due for instance to forgetting of the different cues. Finally, some individuals may respond more randomly, alternating between “go” and “no go” irrespective of outcomes, either due to wanting to explore the outcome further, or owing to such factors as boredom, tiredness, or frustration. Accordingly, there are multiple component processes that can lead to a behavior that may seem impulsive. The goal of the present paper is to present a formal cognitive model for measuring these component processes.

Cognitive models, often used in cognitive science and allied disciplines, provide a tool for identifying the relative contributions of distinct subcomponents of a behavior and may be particularly useful to the study of decision-making deficits in different clinical populations (see Yechiam, Veinott, Busemeyer & Stout, in press). Cognitive models explain intelligent (human or animal) behavior by simulating behavior (usually on a computer). Within the approach, cognitive mechanisms are mapped to computational algorithms, and cognitive representations are mapped to computational data structures.

A cognitive model has been successfully used to analyze performance deficits in a related choice task, the Iowa Gambling Task (Bechara et al., 1994). Both the Iowa Gambling Task and the Go/No-Go discrimination task (see e.g., Hoaken, Shaughnessy & Pihl, 2003) are often used as putative measures of prefrontal circuitry, which modulate behavioral inhibition. In the Iowa Gambling Task, high performance level is achieved by rejecting (i.e., not selecting) alternatives that produce high gains and even higher losses, and instead selecting alternatives with inferior gains but with smaller losses. Poor task performance occurs in various clinical populations, ranging from Huntington's disease (Stout, Rodewalt & Siemers, 2001) and obsessive-compulsive disorder (Cavedini et al., 2002) to individuals with antisocial personality (Mazas, Finn, Steinmetz, 2000), incarcerated criminal offenders (Yechiam, Kanz, et al., 2005), and chronic drug abusers (Bartzokis et al., 2000; Bechara et al., 2001; Grant, Contoreggi, & London, 2000; Petry, Bickel & Amett, 1998). Busemeyer and Stout (2002) posed the question of whether in addition to measuring overt impulsivity and risky behavior, the underlying component processes associated with poor task performance could be measured. They designed a learning model, called Expectancy-Valence (EV), for identifying constructs that lead to poor choices in the task. The model's latent components include the relative impact of gains and losses, the impact of recent compared to past outcomes, and choice consistency. In several studies, the EV model was found to identify distinct component processes associated with poor task performance (see review in Yechiam, Busemeyer, et al., 2005). For example, chronic cannabis abusers were found to focus on the most recent outcomes, ignoring negative outcomes that occurred in the past (Yechiam et al., 2004), whereas cocaine abusers focused more on gains and discounted potential losses (Stout, Busemeyer, et al., 2005). These findings suggest that the use of the cognitive model can increase the sensitivity of the analysis to the underlying component processes, and to differences between clinical and neuropsychological populations.

The present paper applies a similar type of model to the Go/No-Go discrimination task. As in the Iowa Gambling Task, studies have found poor performance in this task in several diverse clinical populations including, for example, incarcerated psychopaths, extraverts, and juvenile delinquents (Finn, Mazas Justus & Steinmetz, 2002; Kindlon, Mezzacappa & Earls, 1995; Newman, 1987; Newman, Patterson, Howland & Nichols, 1990; Patterson, Kosson & Newman, 1987; Scerbo et al., 1990), as well as attention-deficit hyperactivity disordered children (Hartung, Milich, Lynam & Martin, 2002; Iaboni, Douglas & Baker, 1995; Vaidya & Gabrieli, 1999), defensive copers (Shane & Peterson, 2004), and high-anxious individuals (in females: Segarra, Molto & Torrubia, 2000). The present cognitive model analyzes the source of performance deficits in the task, and can be used to discover if the performance errors in these populations are driven by the same factor.

Our evaluation was based on a dataset of 400 adolescents that was collected as part of a longitudinal study called the Child Development Project (see Pettit, Bates & Dodge, 1997). The goal of the project has been to assess the antecedents and development of externalizing behavioral problems from early childhood to early adulthood. The present study analyzed self and parent reports of internalizing and externalizing behaviors to test the validity of the model's latent constructs. In particular, based on previous studies (e.g., Stout, Busemeyer, et al., 2005; Stout, Rock, et al., 2005; Yechiam, Kanz et al., 2005; Yechiam, Stout et al., 2005) and theoretical accounts (Finn, 2002; Gorenstein & Newman, 1980; Newman & Wallace, 1993; Quay, 1993), it was assumed that the model's "attention to gains" component would be correlated with externalizing behavior problems (such as delinquency and aggressive behavior), but not with internalizing behavior problems (such as depression and somatic complaints).

The remainder of the present paper is organized as follows. First, we describe the version of the Go/No-Go task used in the present study. Second, three competing plausible cognitive models for the task are presented. Third, the models are compared in terms of their ability to predict participants' choices in the task. Fourth, the best fitting model is used to provide individual-differences assessments underlying poor performance in the Go/No-Go task. Finally, we study the relationship between model constructs and psychological variables measured by ability tests and self and parent reports of behavior problems. The discussion section summarizes the potential value and limitations of the present cognitive model.

<u>The Go/No-Go discrimination task</u>

The present study employs a version of the Go/No-Go task developed by Newman et al. (1985) and Helmers et al. (1995), called the "The Go/No-Go discrimination task" or the "passive avoidance task". The task was originally designed to explore behavioral inhibition in psychopathic individuals, following Lykken's (1957) and Fowles' (1980) theories that psychopaths have a deficient behavioral inhibition system (see review in Hiatt & Newman, 2004). The earliest study of passive avoidance in psychopaths was conducted by Lykken (1957), who used a 20-step four-choice decision task in which participants responded by pressing one of four response levers. There was one correct lever at each decision point. The passive avoidance component of the task involved latent shock contingencies: at each decision point, one of the three incorrect response levers was paired with an electric shock. Passive avoidance was measured by the increased avoidance of previously shocked levers across trials. Lykken (1957) found that psychopaths committed more passive avoidance errors than non-psychopathic controls.

More recent studies have shown that passive avoidance deficits exist even with loss of money (Siegel, 1978; Newman et al., 1985; Newman & Kosson, 1986). Newman, Patterson, Howland and Nichols (1990) argued that each of the studies demonstrating poor passive avoidance under conditions of monetary loss also involved a competing reward contingency. Namely, in a situation where the reward contingency is a salient component of the task psychopathic individuals tend to take risk in order to obtain uncertain rewards. In the Go/No-Go discrimination task employed by Newman et al. (1985; 1986; 1990) the computer flashes a series of numbers on the screen. Participants have to decide when to respond (by pressing a key) and when not to respond. Upon responding correctly, participants receive positive feedback; and upon responding incorrectly, they receive negative feedback. There are ten different stimuli: five "good" numbers (e.g., 11, 15, 24, 38, 47), which produce positive feedback, and five "bad" numbers which produce negative feedback. These stimuli are presented in a pseudo-random order for 90 experimental trials. Participants have to decide whether to take risk by responding to numbers which may be "good" or "bad" numbers[1].

The usual dependent measures in the task are the mean number of commission errors (failure to inhibit a response to a "bad" number) and the mean number of omission errors (failure to respond to a "good" number), as well as the overall number of errors (see Mezzacappa, Kindlon & Earls, 1999; Noble, Tottenham & Casey, 2005; see also Guillem, Rougier & Claverie, 1999). This analysis of error type differentiates between individuals performing poorly for two different reasons, denoting too little behavioral inhibition (i.e., passive avoidance errors) in the case of commission errors, and too much behavioral inhibition in the case of omission errors. Consistent with the theories of psychopathy, it has been found that incarcerated psychopaths, extraverts, and juvenile delinquents had more errors of commission than their respective controls but similar errors of omission (Newman, 1987; Newman et al., 1990; Patterson et al., 1987; Finn et al., 2002). The task has since been used extensively as a measure of the cognitive aspects of impulse control in diverse populations (for some examples, see Hoaken et al., 2003;

[1] This task is a variant of the typical Go/No-Go task, in which the number of digits is smaller (typically two to four) so that the participants learn the stimulus-response associations very quickly, and errors are considered to be due to faulty motor programming (see review in Bechara, 2004). The relatively larger number of cues and the small number of trials in the passive avoidance task most likely change the emphasis of the task from the motor component to the cognitive component.

Hartung et al., 2002; Segarra et al., 2000). Adequate test-retest reliability has been demonstrated for the task by Kindlon, Mezzacappa, and Earls (1995).

The present cognitive model allows the examination of the influence of cognitive processes that lead to commission errors. Performing an error of commission (i.e., pressing the key while seeing a "bad" number) could be due to increased attention to gains relative to losses, but it could also be due to the following additional factors: (1) Ignoring the numbers and paying too much attention to the gains and losses, (2) a slow learning rate, or (3) an erratic and random choice pattern. Commission errors could also reflect a combination of some or all of the factors. Cognitive modeling provides a theoretical basis for identifying cognitive components that lead to behavioral errors. Thus, a cognitive model may help to identify the factors underlying performance deficits in the Go/No-Go task.

Cognitive modeling of the task

The first step in any type of cognitive modeling application is to compare the accuracy of different models. We compare three cognitive models for the Go/No-Go task. One model is Busemeyer and Stout's (2002) Expectancy Valence model (EV) model. This model assumes that participants base their choice on the positive and negative outcomes they get in each trial, irrespective of the cue. Namely, getting a positive outcome upon pressing a key increases the likelihood of pressing the key again, and vice versa for negative outcome (following Thurstone, 1927; Luce, 1959). Of course, this model ignores the relative complexity of the Go/No-Go task, where responses should be associated with specific cues ("good" and "bad" numbers). Still, it might be postulated that some participants indeed do not pay attention to the cues, and most of their responses are determined by the gains and losses pooled across the different cues.

The second model considered here is a Cue-Dependent learning model (CD). In this model, each cue is treated as a separate task, including two alternatives (responding and not responding). Decision makers learn by associating each cue with a specific negative or positive outcome. Learning is specific to the cues that produced the outcome (see Logan, 1988; Wenger, 1999). This model assumes that participants are generally able to tell apart the various cues. Accordingly, this model reflects the assumption made by previous analyses of the task (e.g., Newman et al., 1985; for a related issue in conditioning, see Pineno & Miller, 2004).

We also consider a third model, called a Mixed Cue-Valence model (MCV). This model assumes that learning is directed by two factors. The first factor is the association of each trial with an outcome, irrespective of the cue. The second factor is the association of specific cues with outcomes. The degree that learning is dictated by these two factors is a free parameter of the model. In other words, the model assumes that some participants learn trial-based associations, some learn cue-based associations, and still others base their choices on a mixture of cue-based and trial-based associations.

All three cognitive models are comprised of three basic assumptions, which are described next.

Attention to gains vs. losses: The motivation parameter. The first parameter of all three models is a motivational parameter that represents the attention to gains compared to losses. This motivational explanation of the behavior is similar to the concept of promotion and prevention focus (Higgins, 1997). Promotion focus denotes concerns with the presence or absence of gains, and prevention focus denotes concerns about the presence or absence of losses. On each trial, a response is made, and payoffs are delivered or not delivered. The decision maker is assumed to evaluate the gains and losses experienced after making a response by a prospect theory type utility function (Kahneman & Tversky, 1979). The valence of the payoffs experienced on trial t is denoted $v(t)$, and it is calculated as a weighted average of gains and losses in trial t:

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

where $win(t)$ denotes the amount of money won on trial t; $loss(t)$ is the amount of money lost on trial t; and W is a motivational parameter that controls the weights to gains versus losses. The parameter values are limited from 0 and 1. Small values of the parameter (less than .5) indicate that losses impact the decision more than gains. This can lead to omission errors since gains do not motivate participants to respond as frequently as they should. Higher values of the parameter (greater than .5) indicate that gains impact the decision more than losses. This tendency can lead to commission errors since losses do not motivate the participant to respond less frequently. Finally, a parameter value of .5 indicates that gains and losses impact the decision equally.

Attention to recent outcomes: The learning rate parameter. The second parameter of the model represents the attention to the most recent outcomes compared to past outcomes. The three models above have different assumptions pertaining to how this parameter is calculated.

I) The Expectancy-Valence (EV) model. According to the EV model, performers are assumed to form anticipated consequences for the alternatives of responding and for not responding (independent of the cue). These anticipated consequences are called expectancies. When a response is made, the expectancy E_j for responding (j=1) is updated as a function of its previous value (which reflects the past experience), as well as on the basis of newly experienced outcomes on the current trial. For not responding (j =2) there is no outcome, and so the expectancy does not get updated. Formally:

$$E_j(t) = E_j(t\text{-}1) + \phi\cdot[v(t) - E_j(t\text{-}1)] \qquad (2)$$

In other words, the new expectancy equals the previous expectancy plus an adjustment resulting from the prediction error $[v(t) - E_j(t\text{-}1)]$ (Rumelhart & McClelland, 1986; Busemeyer & Myung, 1992). The amount of adjustment is controlled by the learning rate parameter, ϕ. The parameter is limited from 0 to 1. Very small parameter values produce slower learning, which can result in commission and omission errors (depending on whether the attention to gains is high or low). Large values of ϕ produce rapid learning and rapid discounting of past outcomes. Very rapid discounting is similar to forgetting and can also produce commission and omission errors.

II) The Cue-Dependent (CD) model. According to the CD model, performers are assumed to form separate expectancies for each of the cues of the task. Thus, there are ten expectancies denoting the anticipated consequences of responding to each separate cue, and ten expectancies denoting the anticipated consequences of not responding to each cue (but only the former get updated). The model has the following updating process:

$$E_j(t) = E_j(t\text{-}1) + \phi \cdot \delta_j(t) \cdot [v(t) - E_j(t\text{-}1)] \qquad (3)$$

Note that the term *j* is used in a different meaning then in formula 2. It denotes the current cue, and runs from 1 to 10. The formula updates the expectancy of responding to cues 1 to 10 based on new outcomes. It includes a dummy variable $\delta_j(t)$ which is a weight associated with the current cue *j*. δ equals 1 if a cue appears on trial *t,* and 0 otherwise. This simply means that for all the cues that are not seen on the trial, the expectancy does not get updated.

A second major difference between the CD and EV models is in the operationalization of the recency parameter. Under both models low recency leads to a slow learning rate. However, under the CD model (as well as the MCV model) a fast learning rate is adaptive, and does not lead to discounting of past payoffs, because payoffs are invariable for responding (and not responding) to each cue. Accordingly, under the CD (and MCV) model only a slow learning rate (low recency) can produce omission and commission errors, whereas a fast learning rate results in fewer errors.

III) The Mixed Cue-Valence (MCV) model. In the MCV model a fourth parameter is added, denoting the specificity of the responses to the cues. According to the MCV model, performers are assumed to form expectancies for each of the cues of the task. However, these expectancies are not updated strictly as a function of cue-specific consequences but also as a function of the more general consequences of responding and not responding, as follows:

$$E_j(t) = E_j(t\text{-}1) + \phi \cdot \{\gamma \cdot [\,1 - \delta_j(t)] + (1 - \gamma) \cdot \delta_j(t)\,\} \cdot [v(t) - E_j(t\text{-}1)] \qquad (4)$$

The term 1 - $\delta_j(t)$ refers to all of the cues not present in trial *t*. The formula thus divides the updating into cue-specific $\delta_j(t)$ and non-specific [1 - $\delta_j(t)$] components. The parameter γ is the generalization parameter, denoting how much updating is given to the cues that are not presented on trial *t*. The parameter is limited from 0 to 1. When $\gamma = 0$, the MCV model reduces to the CD model. The CD model is therefore a special case of the MCV model. Small values of γ produce more influences of cue specific outcomes. Larger values produce more generalization to other cues. Commission errors can result from over-generalization of positive outcomes to negative cues[2].

Choice consistency: The response sensitivity parameter. The decision maker's choice on each trial is based not only on the expectancies produced by each alternative, but also on the consistency with which the decision maker applies those expectancies when making choices. According to all three models, the probability of making a response is determined by the strength of responding (or not responding) relative to the sum of strengths of responding and not responding (Luce, 1959). Formally, for the EV model:

$$\Pr[G(t+1)=k] = \frac{e^{\theta(t)\cdot E_k(t)}}{\sum_{k=1}^{2} e^{\theta(t)\cdot E_k(t)}} \tag{5}$$

where Pr[G(t+1) = k] is the probability that a response k will be made by the model on trial t+1. The term k denotes responding (k=1) and not responding (k=2). In the CD and

[2] We also considered a model where the degree of generality decreases with time. In this model the constant parameter γ is replaced by γ', calculated as: $\gamma' = 1 / (1 + t^{\gamma})$. However, since this did not improve the fit of the model, the results are not detailed here.

MCV model the expectancies for responding and not responding depend on the cue j in trial t+1, thus formally:

$$\Pr[G(j,t+1)=k]=\frac{e^{\theta(t)\cdot E_{j,k}(t)}}{\sum_{k=1}^{2} e^{\theta(t)\cdot E_{j,k}(t)}} \tag{5a}$$

where Pr[G(j, t+1) = k] is defined as the probability that a response k will be made by the model to cue j that appears on trial t+1, and $E_{j,k}$ is the expectancy of either responding (k=1) or not responding (k=2) to cue j on trial t.

In equations 5 and 5a the variable $\theta(t)$ controls the consistency between choices and the expectancies, and it is assumed to change with experience. Consistency is assumed to increase with experience, reflecting greater reliance of choice on one's expectancies. This is formalized by a power function for the sensitivity change over trials:

$$\theta(t)=(t/10)^{c} \tag{6}$$

where c is the response sensitivity parameter. When the value of the response sensitivity parameter is high, choices converge towards one's expectancies. This reflects diminishing exploration and the emergence of preference. When the value of c is low, the exploration process is longer. Extremely low values of c produce responses that are inconsistent, random, and independent of the expectancies over time. This can emerge due to boredom, tiredness, lack of motivation, or frustration with a lack of success. Such an erratic choice pattern is an additional reason for performers to make commission (or omission) errors.

<u>Model evaluation and comparison</u>

The evaluation of the three models was based on the accuracy of 'one step ahead' predictions generated by each model for each individual performer compared to a baseline model. The baseline model is a statistical model that generates choices with constant probabilities across trials. Namely, according to this model the probability (of a certain decision maker) to respond in each trial is equal to the average probability of responding for that person. The baseline model thus has only one free parameter: The average choice proportion of responding.

Unlike the cognitive models, this baseline model does not assume any learning or other fluctuations in selections as a result of the outcomes. Rather, it assumes that choices are identically distributed across trials. Accordingly, a cognitive model is advantageous over the baseline model only if it succeeds in explaining how choices change as a function of learning or some other trial-to-trial dependencies.

The complete model evaluation method appears in Appendix 1. The final output of the evaluation is a Bayesian Information Criterion (BIC) index (Schwartz, 1978). Relatively high values of the BIC index show that a model predicts the next step with greater accuracy, and is thus a better candidate for representing participants' behavior in the task. Positive BIC values denote an improvement over the baseline model. Because the distribution properties of the BIC index are uncharted we rely on ordering of model accuracy.

Method

Participants. The models were evaluated based on data collected in the Child Development Project (see Pettit et al., 1997), which surveyed adolescents and mothers from Bloomington, Indiana and Nashville and Knoxville, Tennessee. Parents were approached at random during kindergarten preregistration or were contacted by phone or letter on the first day of school and asked if they would participate in a longitudinal study of child development. Of those asked, approximately 75% agreed to participate. Originally, the study followed 585 participants annually since preschool (age 5) with low attrition. There were no exclusion criteria. The Go/No-Go task was performed by 400 participants at the age of sixteen. Nine participants were excluded because of missing trial by trial information, so that the final number of participants was 391. Two hundred and three (52%) of the participants were male and 188 (48%) were female. Eighty one percent of the participants were eleventh grade pupils. The rest were ninth grade (5%), tenth grade (13%), or twelfth grade pupils (1%). Eighty three percent of the participants were European American, 15% were African American, and 2% belonged to other ethnic groups.

Apparatus. In the Go-No/Go discrimination task stimuli consist of “good” and “bad” two-digit numbers (e.g., 11, 15, 24, 38, 47) presented in a pseudo-random order for 90 experimental trials. These trials are preceded by five trials in which all of the “good” numbers are presented. Participants learn by trial-and-error which numbers are “good” and which are “bad”. The stimuli are displayed on the screen until participants respond, or for up to 2.5 seconds. After each response, the participants are given visual, auditory, and monetary feedback. Lack of response leads to neither punishment nor reward. A correct response (responding to a "good" number") is followed by a high-pitched tone (400 Hz), the appearance of the message "You WIN 25 cents!" and the addition of money to the participant's tally of earnings. An incorrect response (responding to a "bad" number) is followed by a low-pitched tone (100 Hz), the appearance of the message "You LOSE 25 cents", and the subtraction of money from the participant's tally. Based on their performances, participants can earn between $0 and $15.00.

Modeling Comparison Results

Table 1 summarizes the BIC scores of the three models. The Expectancy Valence model was less accurate than the baseline model, generating a higher BIC index for only 3% of the participants. This implies that participants' behavior cannot be approximated by the assumption that they do not differentiate between cues. In contrast, the Cue Dependent and Mixed Cue-Valence models, in which participants are assumed to differentiate between cues, had positive BICs, indicating better accuracy compared to the baseline model. The improvement was highest for the CD model, with the learning model leading to superior accuracy for 70% of the participants.

The CD model was more parsimonious than the MCV model. Despite the fact that the MCV model improved the model's accuracy (by an average 6.5 in the log likelihood difference score, G^2), its BIC was worse than the CD model for 81% of the participants. This suggests that only few participants were not able to discriminate between the different cues. Indeed, a summary of the model parameters (see Table 2) shows that the average value of the parameter γ of the MCV model, reflecting the degree of generalization (or non-specify), was close to zero (0.08 on average). Only 5.1% of the participants had γ values that were above 0.5, indicating that they made their choices mainly on the basis of trial-based associations. Accordingly, for most participants performance reflects the specific building of associations by the number and its outcome.

In the subsequent analyses we focus on the most accurate and parsimonious model, the Cue Dependent learning model. Figure 1 shows the actual responses to positive and negative cues, and the simulated average responses of the CD model. Note that this simulation analysis is different from the previous and subsequent analysis of prediction errors (see review in Yechiam & Busemeyer, 2005). In the prediction-based analysis the model is given the previous trial of the individual and has to predict the next step ahead based on that information. In contrast, in the simulation, the model's choices are not based on the actual previous trials of participants (but on the previous choices of the model). In addition, the simulation is based on the estimated parameters averaged across the different subjects. It can therefore only be considered a general descriptive model of the population behavior in the task (see Haruvy & Erev, 2001).

The simulation results presented in Figure 1 capture the increased responses to positive cues and decreased responses to negative cues. The Mean Square Deviation (MSD) of the simulation was 0.012 for positive cues and 0.014 for negative cues. It is worth noting that for positive cues, the simulation predicts a lower rate of responses than the actual rate (a conservative bias) and for negative cues the simulation predicts a higher rate of responses than the actual rate (a risky bias). The former bias is considered to be partially because experimental trials are preceded by five trials in which all of the “good” numbers are presented. These trials were not part of the model input because they are usually not recorded. Indeed, when we focus on a sub-population ($N= 172$) for which the responses in the five training trials were recorded, the MSD in the first block of 20 trials improves substantially (from 0.045 to 0.015). In the absence of these five trials, the model has a longer latency in learning to respond to positive cues. Still, in subsequent analysis we preferred to examine the full participant population.

The source of performance deficits in the task

In addition to predicting the next step ahead, the parameters of a cognitive model can be used as estimates of cognitive components. We examined the association between the estimated parameters of the CD model and omission and commission errors made in the task. This can bring to light whether the cognitive components measured by the model are associated with the performance deficits observed in the task.

The average rate of errors was calculated as the number of errors of a certain type divided by the number of relevant cues (45). The average rate of omission errors was 0.23 and the average rate of commission errors was significantly higher, 0.38 ($t\ (391) = 9.48$, $p < .01$). The Pearson correlation between the rate of omission and commission errors was –0.42 ($p < .01$). That is, across all trials, there was a tendency of decision makers to commit one type of error more frequently (*either* errors of omission or of commission).

To examine the association between the model parameters and the observed error rates, the behavioral results and the parameters were submitted to two linear regressions, with omission and commission errors as dependent variables, and the three parameters of the model as predictors. Both regression models were significant (Omission: $F\ (3,387) =$

56.38, $p < .01$, $r^2 = 0.30$, Commission: $F(3,387) = 74.68$, $p < .01$, $r^2 = 0.37$). The results appear in Table 3. The most prominent factor associated with both omission and commission errors was the motivational parameter, denoting the relative impact of gains and losses. As predicted, attention to gains was positively associated with the rate of commission errors ($r = 0.57$) but negatively associated with the rate of omission errors ($r = -0.52$). This result is interesting since it helps explain the negative association between the rate of omission and commission errors. Commission errors are made, on average, by performers for which gains loom larger, while omission errors are made by performers for which losses loom larger. The results show that a single factor, namely the relative impact of gains and losses, is associated with a significant part of the variability in both of those types of errors.

In addition, poor choice consistency was associated with a high rate of both omission and commission errors. As predicted, poor choice consistency, producing more erratic choices, can increase the rate of both types of errors. Finally, low recency was associated with making more commission errors. This represents the tendency to learn slowly that certain cues produce negative outcomes. Yet, while all three parameters were associated with the rate of commission errors, the effect size for choice consistency and recency was small (combined r^2 of less than 0.05) compared with the effect size for the attention to gains and losses.

It could be argued that the correlation of omission and commission errors to the attention to gains parameter is simply a by-product of the negative association between commission and omission errors. To refute this possibility, we conducted two additional regression tests, in which the rate of omission (commission) errors was the dependent variable, and the model parameters along with the rate of commission (omission) errors were used as predictors. The model for omission errors ($F(4,386) = 48.75$, $p < .01$, $r^2 = 0.34$) showed that the most prominent factor remained the low attention to gains ($r^2 = 0.27$, $p < .01$). The increment r^2 of the rate of commission error was only 0.03 ($p < .01$), and the increment of the choice consistency parameter remained at 0.03 ($p < .01$). The model for commission errors ($F(4,386) = 63.32$, $p < .01$, $r^2 = 0.40$) showed that the most prominent predictor was high attention to gains ($r^2 = 0.33$, $p < .01$), followed by the choice consistency parameter ($r^2 = 0.03$, $p < .01$). The increment r^2 of the rate of omission errors was only 0.026 ($p < .01$). This indicates that the motivational parameter modulates the negative association between the two types of errors.

Note that the present study is preliminary in the sense that a regression analysis is not sufficient to conclude that causal relationships exist between the parameters and the overt error rates (since both constructs are measured at the same time). Yet the results are evocative in showing that a strong association exists between the cognitive constructs and the rate of errors. Moreover, these results are easily interpretable. They suggest that performance deficits can be classified onto two axes. The main axis is attention to gains, in which high values lead to commission errors and low values lead to omission errors. A second major axis is choice consistency, in which low values lead to both commission and omission errors. Further studies are required to determine the causal characteristics of the present model.

External validity of the model

To assess the external validity of the constructs elicited by the cognitive model, we examined the association between model parameters and the ability tests and self and parent reports collected in the longitudinal study. After performing the Go/No-Go task, participants completed the Youth Self-Report form (YSR; Achenbach, 1991) and their parents completed the Child Behavior Checklist (CBCL; Achenbach, 1991). Participants also completed the Welsh anxiety scale (Welsh, 1956). We also examined associations with gender and parent income as well as with WISC-R IQ scores (Wechsler, 1974), which were measured three years prior to the current study (at age 13).

It was predicted that externalizing behavior problems would be associated with high attention to gains. This prediction is based on the findings that externalizing behavior problems are markers for future drug abuse and delinquent behavior (see review in Helstrom et al., 2004). Theories of the behavior of drug abusers in choice tasks (see reviews in Finn, 2002; Gorenstein & Newman, 1980) indicate that for those at risk for drug abuse, signals of positive reward may carry larger weight over signals of potential punishments due to stronger appetitive processes and weaker inhibitory mechanisms. Additionally, findings using the Expectancy Valence model with the Iowa Gambling Task indicate that students who are moderate abusers have high attention to gains (e.g., Stout, Rock, et al., 2005; see also Yechiam, Stout, et al., 2005), Accordingly, the model has a clear prediction for externalizing behavior problems, and it predicts no difference in the motivational parameter for internalizing behavior problems. In addition, based on findings in the Iowa Gambling Task with healthy adolescents, it was predicted that high-anxious individuals (on the Welsh test) would have a more erratic choice pattern, denoted by lower choice consistency (see Johnson et al., 2005). This pattern is assumed to reflect the fact that high-anxiety individuals are more likely to find the task stressful, and to detach themselves from it (and choose randomly) after a short experience (see Harriott, Ferrari & Dovidio, 1996).

Because of the skewed distribution of some of the tests, we used rank ordered Spearman correlations. The results are described in Table 4. As predicted, there was a small but significant positive correlation between attention to gains and externalizing behavior problems in both the CBCL and the YSR. There was also a positive correlation between attention to gains and attention problems (on both scales). These positive correlations shed light on the curious fact that adolescents with externalizing behavior and attention problems (on the CBCL) had more commission errors but less omission errors than other adolescents. High impact to gains is naturally associated with a greater number of commission errors but also with fewer omission errors.

As predicted, there was no significant correlation between attention to gains and internalizing behavior problems. Moreover, there was a negative correlation between choice consistency and Welsh anxiety. This indicates that low choice consistency is a specific factor associated with high anxiety[3]. Thus, while both high anxiety group and individuals with externalizing behavior display more commission errors ($r = 0.13$; 0.18, accordingly) the latent factors associated with these errors are different.

[3] A post-hoc stepwise regression analysis with Welsh anxiety as a dependent variable and the three model parameters as predictors shows that low choice consistency is in fact the only factor associated with Welsh anxiety (F (1,387) = 4.55; $p < .05$; $r = -0.14$). The marginal association of attention to gains and Welsh anxiety is not significant.

In addition, high IQ was associated with greater attention to losses and better choice consistency. Males tended to have slightly more attention to losses than females (which replicates results on the gambling task; see Stout, Rock, et al., 2005). Females tended to have higher recency than males, denoting a faster learning rate, consistent with performance in other episodic memory tasks with verbal components (see Lewin, Wolgers & Herlitz, 2001).

In summary, the model parameters differentiate between clinical populations that display a similar tendency to make commission errors. Specifically, both externalizing behavior problems and anxiety were associated with the rate of commission errors. However, adolescents that were high on externalizing behavior problems (but not on internalizing problems) displayed greater attention to gains. In contrast, high-anxiety individuals on the Welsh test displayed lower choice consistency. These findings are consistent with previous findings using the Iowa Gambling Task.

General discussion

The present research employs a novel analysis method to study the behavior of adolescents in the Go/No-Go task. The main advantage of the present method is that it allows for the examination of the sources of errors in the task. In this way, it has been shown that the main factor that leads to both omission and commission errors is the motivational parameter, controlling the impact of gains relative to losses on response decisions. People who have very high attention to gains relative to losses tend to ignore negative cues, and as a result have more commission errors, as predicted by Newman (1987). In contrast, those who are high on attention to losses relative to gains develop negative expectancies more quickly, but stay away from positive cues as well, leading to omission errors. The present findings therefore indicate that any attempt to combine both omission and commission errors into a single "performance" measure may lead to severe distortions since these two types of errors are, in reality, associated with opposite tendencies: Commission errors with high attention to gains, and omission errors with high attention to losses.

Yet while the attention to gains and losses accounted for most of the variance in performance errors, it was by no means the only factor that was associated with error rates. As hypothesized, other subcomponents of task performance were found to contribute to errors on the task. Low choice consistency was a second factor that led to both errors of omission and commission. Slow learning rate (low recency) was also implicated in errors of commission to some extent.

It was established that the tendency to "confuse" trial-based and cue-based associations was not a significant factor for predicting participants' choices. Only about 5% of the participants behaved as if they believed outcomes were delivered just for responding (or not responding) rather than for responding to specific cues. This indicates that most errors do not stem from misunderstandings concerning the general nature of the task. Note though that the tendency to generalize across numbers was negatively associated with IQ measured 3 years previously (Spearman's $r = -0.15$, $p < .01$). Thus, in populations with large individual differences in IQ it might be important to include the generalization parameter.

In the present study of sixteen-year-old adolescents, it has been shown that, consistent with previous results, participants with externalizing behavior problems, (as well as attention problems) had higher attention to gains. On the other hand, participants with internalizing behavior problems (such as avoidance and depression) did not show elevated attention to gains, on average. In addition, adolescents with high trait anxiety displayed lower choice consistency, indicating that their choices became more erratic over time. These findings suggest that the cognitive model can improve the sensitivity of the task to different clinical populations with distinct cognitive characteristics.

It should be noted that that the present model led to two systematic deviances in its population prediction (see figure 1) which were only partially explained. Other cognitive models could in theory lead to different results. However, the present model captures the essential properties of most plausible attention and memory processing interpretations for this and similar "experience-based" choice tasks (see e.g., Camerer & Ho, 1999; Erev & Roth, 1998; Weber, Shafir & Blais, 2004). Moreover, it has been shown that the present Cue-Dependent learning model was better than a baseline model that assumes no learning and also more accurate than alternative learning models. Finally, the results of the model are consistent with theoretical predictions concerning the source of performance errors.

The present model thus increases the ability to use the information "supplied" by task performers beyond the prevailing analysis methods. Moreover, it broadens our understanding about sources of performance errors. Specifically, it suggests that the two sources of errors commonly studied (commission and omission) are not independent but rather, are strongly associated (in negative directions) with a single motivational factor. On the other hand, other factors, such as choice consistency and recency, also affect performance. This increases our understanding of the cognitive processes that lead to behavioral errors.

Appendix 1: Evaluation procedure

We define $Y_i(t)$ as a $t \times 1$ vector, representing the sequence of *choices* made by individual i in t trials. Define $X_i(t)$ as the corresponding sequence of *payoffs* produced by these choices. Further define $\delta_i(t)$ as the sequence of *cues* seen before each choice. Each model is given $X_i(t)$ and $\delta_i(t)$ and uses this information to generate the probability of responding (pressing the key; k=1) or not responding (k=2) in trial t+1, $\Pr[G(t+1) = k \mid X_i(t), \delta_i(t)]$. The accuracy of these predictions is measured using the log-likelihood criterion:

$$ln(L|\text{model}) = \sum_t \sum_k ln(\Pr[G\,(t+1) = k \mid X_i(t), \delta_i(t)]) \cdot \chi(k, t+1) \tag{7}$$

where L|model is the multinomial likelihood of the button press response set given its modeled probabilities (see Mood and Graybill, 1963). The term $\chi\,(k, t+1)$ equals 1 if a response was made on trial t+1, and zero otherwise (this is done for the sake of computational economy).

In this process a grid search of the parameter space is used to find the parameter values that produce the best prediction for the next step ahead, using the robust combination of grid-search and simplex search methods (Nelder & Mead, 1965). The starting values of the grid were chosen to be 0.15, 0.5, and 0.85 (for parameters ϕ, W, and γ) and -1, 0, and 1 for parameter c.

The outcome is a set of solutions, one for each starting point on the grid. The best solution is the one that maximizes the log-likelihood criterion. Once this set of solutions is calculated for each model, model fits can be compared. The difference between the fit of the cognitive model and the baseline model is evaluated by comparing their log-likelihood scores, as follows:

$$G^2 = 2 \cdot [ln(L|\text{Model}) - ln(L|\text{Baseline})] \tag{8}$$

Positive values of the G^2 statistic indicate that a cognitive model performs better than the baseline model, while negative values indicate the reverse. Note, however, that two of the models (EV and CD) have three parameters, and one model (MCV) has four parameters, while the baseline model has only one parameter. Accordingly, an adjustment in the fit calculation is required. This is accomplished by using the Bayesian Information Criterion (BIC) statistic (Schwartz, 1978) to compare models:

$$\text{BIC} = G^2 - k \cdot \ln(N) \tag{9}$$

In this equation, k denotes the difference in the number of parameters and N equals the number of data points. Thus, for example, when comparing the CD model and the baseline model, we have a two parameter difference, so that $k = 2$; and since task has 90 trials, $N = 90$. Accordingly, $2 \cdot \ln(90) \approx 9$. This implies that for the CD model, we subtract nine from the G^2 value to get the improvement in prediction compared to the baseline model *over and above* the increase in the number of parameters.

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Figure 1. Average proportion of responses to positive cues (top) and negative cues (bottom). The dotted lines denote the simulated average choices of the learning model.

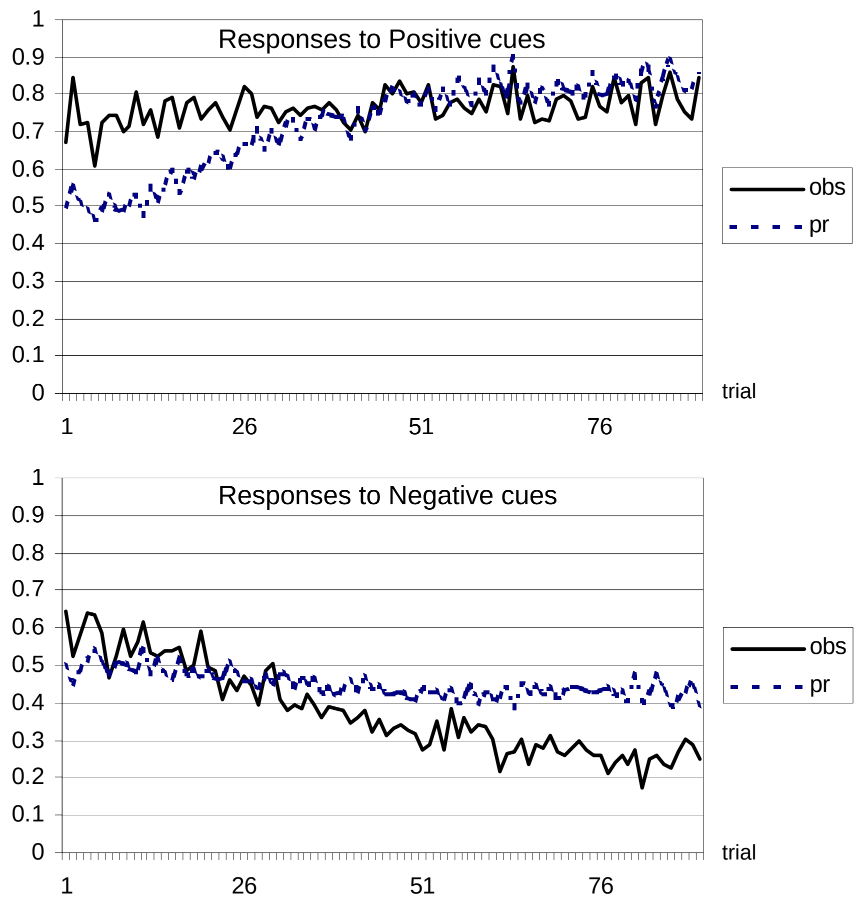

Table 1. Averages, medians, and standard deviations of the BICs of the three cognitive models, and the percent of individuals for which the BICs where better compared to the baseline models (BIC > 0).

	Average BIC	Median BIC	SD	% (BIC > 0)
Expectancy Valence (EV)	-11.93	-9.72	9.4	3%
Cue Dependent (CD)	8.85	9.07	21.0	70%
Mixed Cue-Valence (MCV)	7.47	6.91	19.8	63%

Table 2. Averages and standard deviations (in parenthesis) of the parameters of the three cognitive models.

	Att. Gains W	Recency ϕ	Consistency c	Specificity γ
Expectancy Valence (EV)	0.74 (0.47)	0.26 (0.33)	-0.42 (3.16)	-
Cue Dependent (CD)	0.75 (0.35)	0.60 (0.35)	2.28 (1.23)	-
Mixed Cue-Valence (MCV)	0.71 (0.37)	0.57 (0.38)	2.51 (1.52)	0.08 (0.22)

Table 3. Results of the regression analysis examining the association between the model parameters (Attention to gains, Recency, Consistency) and omission and commission errors.

Omission	Model			Increment	
Errors	*Cum* R^2	F	β	R^2	F_I
Attention to gains	0.27	92.67**	-0.27	0.27	145.27**
Recency	0.28	3.40	-0.05	0.01	3.40
Consistency	0.30	17.36**	-0.03	0.03	14.58**
Commission	Model			Increment	
Errors	*Cum* R^2	F	β	R^2	F_I
Attention to gains	0.33	190.09**	0.29	0.33	146.57**
Recency	0.36	4.05*	-0.04	0.03	4.05*
Consistency	0.37	19.26**	-0.03	0.01	22.72**

Regression equation:

Omission = 0.25 - (0.27× Attention to gains) – (0.03 × Consistency)

Commission = 0.26 + (0.29× Attention to gains) – (0.03 × Consistency) - (0.04 × Recency)

** = p < .01, *= p < .05

Table 4: Spearman correlations between the model parameters and error rates and the measures collected in the Child Development Project.

	Att. gains	Recency	Consistency	Omission	Commission
YSR					
Internalizing	0.02	0.06	0.01	-0.03	0.06
Externalizing	0.13**	0.08	-0.02	0.02	0.11*
Attention problems	0.11*	0.07	0.00	-0.03	0.06
CBCL					
Internalizing	0.04	0.02	0.00	-0.05	0.07
Externalizing	0.14*	0.01	-0.03	-0.09	0.18**
Attention problems	0.13*	0.08	0.01	-0.15*	0.16**
Other Measures					
Gender (F =1; M= 0)	0.13*	0.13*	-0.07	-0.01	0.08
IQ	-0.15**	-0.01	0.11*	-0.04	-0.24*
Parent’s income	-0.11*	0.01	0.07	0.05	-0.22
Welsh Anxiety	0.10*	0.07	-0.10*	-0.02	0.13*

** = $p < .01$, *= $p < .05$