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Review

Clinical models of decision making in addiction

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A R T I C L E I N F O

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A B S T R A C T

As research on decision making in addiction accumulates, it is increasingly clear that decision-making processes are dysfunctional in addiction and that this dysfunction may be fundamental to the initiation and maintenance of addictive behavior. How drug-dependent individuals value and choose among drug and nondrug rewards is consistently different from non-dependent individuals. The present review focuses on the assessment of decision-making in addiction. We cover the common behavioral tasks that have shown to be fruitful in decision-making research and highlight analytical and graphical considerations, when available, to facilitate comparisons within and among studies. Delay discounting tasks, drug demand tasks, drug choice tasks, the Iowa Gambling Task, and the Balloon Analogue Risk Task are included.

1. Introduction

As research on decision making in addiction accumulates, it is increasingly clear that decision-making processes are dysfunctional in addiction and that this dysfunction may be fundamental to the initiation and maintenance of addictive behavior. How drug-dependent individuals value and choose among drug and nondrug rewards is consistently different from non-dependent individuals. A number of recent reviews from our laboratory and others have catalogued these differences (Bickel et al., 2014a, 2014b, 2012; MacKillop et al., 2011, 2010a), and we suggest that readers interested in how these measures relate to various aspects of addiction consult these papers. The present review focuses on the assessment of decision-making in addiction. We will cover the common behavioral tasks that have shown to be fruitful in decision-making research and highlight analytical and graphical considerations when available, to facilitate comparisons within and among studies.

2. Delay discounting

2.1. Role of delay discounting in addiction

It is normal to prefer a reward available now to the same reward available after some delay, but excessively discounting the value of delayed rewards can represent an overemphasis on near-term rewards (e.g., drug high) instead of more long-term rewards (e.g., career, good health, interpersonal relationships; Ainslie, 1975). Excessive delay discounting seems to be a reliable marker of short-sighted unhealthy behavior (Bickel and Marsch, 2001) with substance use and addiction being prototypical examples (Bickel et al., 2012; MacKillop et al., 2011; Madden and Bickel, 2010). The evidence supporting a link between excessive delay discounting and addiction now spans most common classes of addictive drugs including alcohol (MacKillop et al., 2010a), tobacco (Bickel et al., 1999; Johnson et al., 2007), stimulants (Coffey et al., 2003; Heil et al., 2006; Hoffman et al., 2006; Washio et al., 2011), opiates (Kirby et al., 1999; Petry et al., 1998), and possibly marijuana (Johnson et al., 2010). This body of research has firmly established a robust relationship across studies and contexts, as was confirmed by a recent meta-analysis (Amlung et al., 2017).

Research also supports an etiological role of excessive discounting in addiction. Excessive discounting predates the initiation of smoking (Audrain-McGovern et al., 2009), and the similar construct of delay of gratification predicts later drug use (Ayduk et al., 2000). Among substance users entering treatment, relatively self-controlled responding on delay discounting tasks predicts treatment success (Dallery and Raiff, 2007; MacKillop and Kahler, 2009; Mueller et al., 2009; Sheffer et al., 2012; Stanger et al., 2012; Yoon et al., 2007), indicating that excessive delay discounting may be behavioral marker of both the onset of drug use and difficulty abstaining after use is established (Bickel et al., 2014b).

2.2. Delay discounting tasks

Delay discounting tasks measure how delaying a reward reduces the value of that reward, typically by arranging a series of discrete choices between some amount of a commodity available at a short delay (or no

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delay) and a larger amount of that commodity available at a longer delay. A series of questions of this type can be used to infer *indifference points*, or a series of values that represent the amount of an immediately available commodity that is subjectively equivalent to a greater amount of that commodity available after a delay. For example, if someone were to indicate a preference for $870 right now over $1000 in one month while also indicating a preference for $1000 in one month over $850 right now, we could conclude that $1000 in one month is worth somewhere between $850 and $870 right now. In other words, this individual is indifferent between ~$860 now and $1000 in one month. By assessing a series of indifference points across a range of delays, a discount rate can be calculated.

The first addiction delay discounting studies used a task where indifference points were obtained by asking two series of questions at each of seven delays (Madden et al., 1999, 1997; Rachlin et al., 1991). The first of these series started with a question between a set amount of a commodity available after a delay and the same amount available immediately (e.g., $1000 now versus $1000 in one month), with the expectation that everyone would choose the immediate option. The amount available immediately was then progressively decreased until the participant switched to the delayed amount. An analogous series of questions started with the same delayed amount and none of the commodity available immediately (e.g., $0 now versus $1000 in one month) with the expectation that everyone would then choose the delayed option. The immediate amount was then progressively increased until the participant switched to that option. These two switchover points were then averaged for each delay. This procedure seemed to work well, but was time consuming. Adaptive algorithms were developed by a number of labs, most of which shortened the number of choice trials necessary to obtain an indifference point. Probably the most commonly used today of these is a simple adjusting amount algorithm that was developed by Du et al. (2002). This procedure starts at each delay by asking participants to choose between a set delayed amount and half that amount available immediately. The immediate amount then adjusts up or down depending on the participant's choice in a series of five choice trials to narrow in on the indifference point. These five trials take little participant time while still allowing for 2^5 or 32 discrete indifference points at each delay.

2.3. Measuring rate of discounting

Indifference points generated from a discounting task are typically fit with a curve to obtain an overall rate of discounting. Although different methods for obtaining discount rates have been proposed (Laibson, 1997; Mazur, 1987; Myerson and Green, 1995; Rachlin, 2006; Samuelson, 1937), the most common method in the psychology literature consists of fitting the indifference points with nonlinear regression to a hyperbolic curve first validated by Mazur (1987):

$$V = \frac{A}{1 + kD} \tag{1}$$

where V is the discounted value (i.e., indifference point) of the delayed amount A at a given delay, D. The single free parameter, k, represents the rate of discounting. This model has a number of attractive features. First, it requires only a single free parameter to quantify discount rate, making comparisons among individuals or groups relatively straightforward. Second, this model has been shown to provide a good description of delay discounting data, particularly compared to an exponential decay model that was assumed to describe intertemporal choice for many years (Green and Myerson, 2004; Madden et al., 1999). The discounting rate k has a unit of 1/time or time^{-1}, which is not straightforward to interpret. A more intuitive alternative to reporting k has been proposed in the form of an effective delay 50 (ED50; Yoon and Higgins, 2008), or the delay at which the delayed commodity loses half of its subjective value. This measure can be shown to be the simple reciprocal of k (i.e., is equal to 1/k), and because of this, the transformation does not affect statistical comparisons. An ED50 of 90 days, indicating that a commodity loses half of its value when delayed 90 days, is arguably more intuitive than the equivalent k value of 0.011 days^{-1}. Both k values and ED50 values are typically not normally distributed and must be logarithmically transformed prior to parametric statistical analysis (Mitchell et al., 2015).

While the model above typically describes discounting data well, systematic deviations from the hyperbolic shape described by this function have been noted (Green and Myerson, 1996; Rachlin, 2006). Often, these deviations consist of more pronounced discounting (i.e., steep slope) over relatively brief delays and less pronounced discounting (i.e., shallow slope) at longer delays than what is predicted by Mazur's hyperbola. As a result, multi-parameter, hyperbola-like models have been proposed to better account for these deviations. The most prevalent of these are extensions of Mazur's equation with an additional free parameter. Rachlin (2006) proposed that a free parameter should be inserted as an exponent on D (delay), while Myerson and Green (1995) proposed that the entire denominator of the right side of Eq. (1) be raised to a freely varying exponent. Each of these modifications allow the shape of the discounting curve to better approximate the shape of much discounting data, albeit in slightly different ways and at the cost of an additional free parameter in the model (McKerchar et al., 2009). These additional free parameters typically improve fit, but complicate interpretation of the data. In both cases, we have shown (Franck et al., 2015) that the added exponents are not independent of the k parameter, and therefore k cannot be compared directly across conditions or individuals if the exponents also vary. This is a problem for most experiments where discount rate is the variable of interest. Furthermore, several interpretations of the exponent exist (McKerchar et al., 2010; Myerson et al., 2011), and in the context of delay discounting may be related to nonlinear scaling of time (Green and Myerson, 1996), a psychophysical phenomenon known for some time (Stevens, 1957). We have proposed ED50 as a solution to this problem of collinear parameters (Franck et al., 2015). This measure can be straightforwardly calculated from both single- and multi-parameter discounting models, and importantly, its scale and interpretation is unaffected by the underlying model. If different models are used in different experiments or even different subjects within a single experiment, the ED50 can still be compared across all the data.

The nonlinear scaling of time that forms the basis of these multi-parameter models may actually be the basis for the human tendency to discount value hyperbolically instead of exponentially (Takahashi et al., 2008). Since from a psychophysical perspective time is perceived nonlinearly, we propose that discount curves ought to be best depicted graphically in log-linear space (see Fig. 1). We propose this for several reasons. First, with a logarithmic x-axis, Mazur's (1987) hyperbolic curve forms an ‘S’ shape (compare A and B of Fig. 1). The ‘S’ curve transitions from asymptotic valuations near a proportion of 1.0 to asymptotic valuations near 0.0 with the midpoint of this transition being the participant's ED50 value. This makes differences in discount rate or ED50 more easily observed and visually discern. Second, using the same equation (the simple hyperbolic in this case), differences in discounting can be seen as a location shift of the curve. The curve itself maintains the same shape; it is its location along the x-axis that shifts. This may suggest that in psychophysical space, the shape of discounting curves do not differ by rate, only the delay range over which the valuation transition takes place differs among people. Third, depicting curves in this way provides rationale for using longer delays, especially in the case of discounting among typical controls or the general population. Panel C of Fig. 1 displays individual-subject data from a dataset we reported previously (Koffarnus and Bickel, 2014) of college participants who completed an adjusting amount discounting task (Du et al., 2002). As can be seen, the transition point of many of the curves and the corresponding ED50 values fall on the right side of graph, centered around the longer delays. In some cases, especially with control or participants unaffected by addiction, excluding longer delays