Published in final edited form as:

Addiction. 2017 January ; 112(1): 51–62. doi:10.1111/add.13535.

Steep Delay Discounting and Addictive Behavior: A Meta-Analysis of Continuous Associations

Michael Amlung^a, Lana Vedelago^a, John Acker^b, Iris Balodis^a, and James MacKillop^{a,c}

^aPeter Boris Centre for Addictions Research, McMaster University/St. Joseph's Healthcare Hamilton; 100 West 5th St, Hamilton, Ontario, Canada L8N 3K7

^bCenter for Integrated Healthcare, Syracuse VA Medical Center; Syracuse, NY 13210 USA

^cHomewood Research Institute, Homewood Health Centre; 150 Delhi St, Guelph, Ontario, Canada N1E 6K9

Abstract

Aims—To synthesize continuous associations between delayed reward discounting (DRD) and both addiction severity and quantity-frequency (QF); to examine moderators of these relationships; and to investigate publication bias.

Methods—Meta-analysis of published studies examining continuous associations between DRD and addictive behaviors. Published, peer-reviewed studies on addictive behaviors (alcohol, tobacco, cannabis, stimulants, opiates, and gambling) were identified via PubMed, MEDLINE, and PsycInfo. Studies were restricted to DRD measures of monetary gains. Random effects meta-analysis was conducted using Pearson's r as the effect size. Publication bias was evaluated using fail-safe N , Begg-Mazumdar and Egger's tests, meta-regression of publication year and effect size, and imputation of missing studies.

Results—The primary meta-analysis revealed a small magnitude effect size that was highly significant ($r = 0.14$, $p < 10^{-14}$). Significantly larger effect sizes were observed for studies examining severity compared with QF ($p = 0.01$), but not between the type of addictive behavior ($p = 0.30$) or DRD assessment ($p = 0.90$). Indices of publication bias suggested a modest impact of unpublished findings.

Conclusions—Delayed reward discounting is robustly associated with continuous measures of addiction severity and quantity-frequency. This relation is generally robust across type of addictive behavior and delayed reward discounting assessment modality.

Keywords

Addiction; delayed reward discounting; meta-analysis; quantity-frequency; severity; publication bias; behavioral economics

Introduction

Behavioral economics has been extensively applied to understand maladaptive decision-making in individuals with addictive disorders [1, 2]. One of the most widely studied behavioral economic indices is delayed reward discounting (DRD), which refers to the subjective devaluation of rewards based on their delay in time [3]. Although often considered a measure of impulsivity or self-control, DRD is generally uncorrelated with other measures of impulsivity [4–6]. It is typically measured using intertemporal choice tasks [7] or questionnaires [8] in which individuals make choices between smaller-sooner and larger-later rewards (e.g., “Would you rather have \$40 today or \$100 in one month?”). These measures involve systematically varying the magnitude of the immediate reward and delay to estimate indifference points corresponding to equal preference for immediate and delayed alternatives. Plotting the indifference points at each delay yields a DRD curve that is commonly modeled using a hyperbolic function, $V = A/(1+kd)$, where V is the value of the delayed reward, A is the amount of the delayed reward, d is the delay, and k is a derived parameter corresponding to the discount rate [9]. Larger k values correspond to steeper discounting. Two alternative approaches involve quantifying the area under the curve (AUC) [10] or calculating relative proportion of choices for immediate rewards (i.e., the impulsive choice ratio, or ICR) [11].

The literature suggests that individuals with addictive disorders consistently exhibit more precipitous DRD compared to healthy controls. This includes individuals with alcohol use disorders [e.g., 11], nicotine dependence [e.g., 12], cocaine dependence [e.g., 13], opiate dependence [e.g., 5], and gambling disorder [e.g., 14], but with the possible exception of marijuana dependence [16]. According to a meta-analysis of case-control studies [17], a highly-significant, medium magnitude effect size difference ($d = 0.62$, $p < 0.00001$) was present across studies examining categorical differences in DRD between individuals with addictive disorders and controls. Interestingly, studies including clinical samples were found to have significantly larger effect sizes than those using sub-threshold samples, suggesting this association scales to level of addiction severity. Finally, indices of publication bias (i.e., nonsignificant findings in small studies being less likely to be published relative to significant findings) suggested a modest influence from unpublished findings. Importantly, in addition to cross-sectional studies, prospective studies have found steep DRD to predict the development of addictive behavior [18–20] and post-treatment response [21–24], suggesting that it serves as an important etiological and maintaining factor in addiction.

To date, the extent to which DRD is associated with indices of engagement in addictive behaviors (i.e., quantity-frequency (QF) of drug or alcohol use, or gambling) or level of clinical severity across studies has not been examined. Several studies have reported significant correlations between steeper discounting and greater QF [15, 25–27], but not others [28–31]. Similarly, significant correlations between steeper DRD and higher addiction severity have been reported in some studies [32–35], but again with some inconsistency [36–38]. Therefore, to aggregate the diverse findings in the literature, the present meta-analysis had three aims. The first aim was to investigate continuous associations between DRD and addiction-related variables, including psychoactive drugs and gambling behavior. The second aim was to examine potential moderators of effects across studies, including category

of addictive behavior (alcohol, tobacco, stimulant, opiate, cannabis, gambling), addiction variable type (QF vs. severity), and task type (preconfigured item questionnaire vs. full task). The third aim was to examine the presence of publication bias on the aggregate findings.

Methods

Study Selection

Studies were identified via searches of PubMed, MEDLINE, and PsycInfo databases (through December 31, 2015) using the following Boolean search terms: discounting AND (alcohol OR alcoholics OR cigarette OR smoking OR tobacco OR crack OR cocaine OR methamphetamine OR THC OR marijuana OR opiate OR opioid OR heroin OR gambling). For inclusion, studies had to meet the following criteria: (i) published, peer-reviewed investigation on humans; (ii) inclusion of a DRD task of monetary gains; (iii) inclusion of a measure of addictive behavior; and (iv) inclusion of a correlation coefficient measuring the association between DRD and addictive behavior. Studies utilizing other measures (e.g., drug/health outcomes, probability discounting) were not included in order to focus on the most common methodology and minimize heterogeneity. Acute drug administration studies were excluded, unless the study reported correlations preceding drug administration. To avoid inferences based on a small number of associations, the following criteria were applied: (i) minimum of five effect sizes per category of addictive behavior; (ii) only associations pertaining to the most representative variable of interest rather than multiple, highly-redundant within-study measures (e.g., if a study reported associations with drinks/week and % binge drinking days, only the former was included); (iii) limit of four effect sizes per study per category; (iv) only inclusion of associations in the full sample if the sample was fractionated into subgroups; and (v) only inclusion of associations with the mean discounting rate for studies including multiple discounting indices (if reported). The final criterion applies to studies that reported associations between addiction variables and multiple DRD indices for a given participant (e.g., discounting rates at different reward magnitudes). If these studies also reported associations with a participant's overall mean DRD index, then only associations with the mean index were included. The study selection procedure is depicted in Figure 1 and followed preferred reporting items for systematic reviews and meta-analysis (PRISMA) standards [39].

Meta-analytic Sample Characteristics

Characteristics of the studies included are provided in Table 1; a comprehensive listing of associations included is provided in Table S1. Sixty-four unique studies met the inclusion criteria, yielding a total of 138 effect sizes. The aggregated sample size was 11,395, with an average sample size of 165 per study (range 12–1,778). The number of effect sizes per addictive behavior category was as follows: alcohol = 53, tobacco = 40, gambling = 21, cannabis = 12, stimulants = 9, and opiates = 3. Of note, due to the small number of studies in opiates, these studies were not included in the moderator analysis between addictive behavior types (see below), but were retained in all other analyses. Measures of QF and severity were equally represented (69 effect sizes each). Seventy-five associations were from studies using task-based DRD measures, while 63 associations were from studies using the

Monetary Choice Questionnaire (MCQ) [40], a questionnaire-based measure that estimates DRD rate via 27 items that are pre-configured to specific hyperbolic discounting functions.

Meta-analytic approach

The primary effect size of interest from individual studies was Pearson's r and Spearman's Rho (ρ), which were subsequently transformed to Fisher's Z . Since AUC values are inversely related to k , the sign for associations using AUC were reversed prior to inclusion in the analysis. Due to substantial heterogeneity in methods, the primary analysis used a random effects model. Two indices of effect size heterogeneity were calculated. Cochran's Q reflects the sum of squared differences between individual weighted study effects and the overall mean [41]. A second index, I^2 , captures the percentage of variation within study effect sizes that can be explained by heterogeneity [42]. To examine the influence of individual effect sizes, a sensitivity analysis was conducted by systematically omitting each association and re-estimating the aggregate effect sizes (e.g., 'jackknife' analysis [43]). In addition, to evaluate overrepresentation by studies contributing multiple effect sizes, the primary analysis was repeated after consolidation of studies with multiple associations into a single effect size. Moderator analyses examined systematic differences based on addictive behavior category (e.g., alcohol, tobacco, etc.), addiction variable type (QF vs. severity), and DRD measure type (questionnaire vs. task-based). Moderators were tested using the Q statistic associated with the between groups difference in a mixed effects analysis.

Presence of publication bias was based on consideration of five indices: Rosenthal's classic fail-safe N [44]; Orwin's fail-safe N [45]; examination of the funnel plots of sample size and effect size using the two-tailed Begg-Mazumdar test [46] and the one-tailed Egger's test [47]; and meta-regression between publication year and effect size. The classic fail-safe N reflects the number of unpublished studies needed to render the aggregate effect non-statistically-significant (i.e., $p > .05$). The Orwin fail-safe N estimates the number of studies needed to reduce the aggregate effect size to a specified critical value, which was defined as 50% of the aggregate effect size in this study. Adjusted estimates of effect size were generated based on imputed unpublished studies using Duval and Tweedie's trim and fill approach [48]. Analyses were conducted using Comprehensive Meta-Analysis Version 2 (Biostat; Englewood, NJ).

Results

Meta-analysis findings

Meta-analytic results are presented in Table 2 and the forest plot is in Figure S1. The random effects model revealed a highly-significant effect size that was of small magnitude ($r = 0.14$, $p < 10^{-14}$). The jackknife analysis indicated that systematically excluding each effect size included in the primary analysis generated similar results (Table 2), suggesting a limited influence of any single association. Finally, a similar effect size was also found after consolidating effect sizes from studies contributing multiple associations ($r = 0.15$, $p < 10^{-14}$). There was also substantial heterogeneity across studies ($Q = 443.35$, $p < 10^{-14}$; $I^2 = 69.10$).

Moderator analyses

Aggregated effect sizes for the moderators examined are presented in Table 2. First, systematic differences between types of addictive behavior were examined for alcohol, tobacco, gambling, cannabis, and stimulants. There was no statistically-significant difference in effect size across addiction types ($Q = 4.91, p = .30$). Second, a larger aggregated effect size was observed for measures of severity compared to QF ($r_s = 0.17$ and 0.11 , respectively), and this difference was statistically significant ($Q = 6.49, p = 0.01$). Finally, analysis of differences between type of DRD assessment revealed comparable effect sizes between questionnaire (MCQ) and task-based DRD measures ($r = .14$ in both cases; $Q = 0.01, p = 0.90$).

Publication bias

Rosenthal's classic fail-safe N indicated that there would need to be 2,652 unpublished studies to raise the p -value to above the threshold for statistical significance for the primary analysis. Orwin's modified fail-safe N indicated that 139 studies would be required to reduce the aggregate effect size by 50%. A significant Egger's test was found (intercept = $0.85, p = 0.002$), indicating the possibility of larger effect sizes in smaller studies. However, the Begg-Mazumdar test was non-significant (Kendall's $\tau = 0.08, p = 0.15$). The funnel plot depicting the association between effect size and standard error is presented in Figure S2. Duval and Tweedie's trim and fill method suggested the possibility of six unpublished studies (Figure S2). Imputation of these studies lowered the effect size from $r = 0.14$ to $r = 0.13$, suggesting minimal influence. Lastly, a meta-regression indicated a small magnitude but significant association between year of publication and effect size (slope = $-0.01, p < .01$), indicating larger effect sizes in earlier studies.

Discussion

The aims of this meta-analysis were to synthesize the literature on continuous relationships between DRD and diverse forms of addictive behavior, to examine the effects of three moderators, and to examine the presence of publication bias. The findings revealed a consistent association between DRD and addictive behavior overall, albeit of relatively small effect size magnitude [49] and high levels of heterogeneity. Larger effect sizes were present for severity measures compared to QF measures, but comparable effect sizes were found across addictive behavior categories and type of DRD assessment. The majority of publication bias indices examined did not suggest significant bias, but this was not uniformly the case. The Egger's test suggested that smaller studies had larger effect sizes, and meta-regression suggested that the effect sizes decreased over time. However, the magnitude of these effects was generally modest.

The findings of this meta-analysis align with and build upon the previous meta-analysis of categorical comparisons [17]. In particular, that meta-analysis found a larger effect size in individuals with a clinical diagnosis of addictive disorder compared to sub-threshold groups. This aligns with the present finding that steep DRD is robustly associated with greater addiction severity. Additionally, both studies found no significant differences by addictive behavior type, suggesting that steep DRD is a common across many forms of drug addiction

and gambling disorder. Finally, both meta-analyses found no differences in effect size magnitude between the MCQ and task-based DRD measures, suggesting that little measurement precision is lost with the MCQ. If this last finding is further substantiated, it may indicate that the MCQ can be used as a more pragmatic and efficient assessment than lengthier task-based DRD measures without sacrificing rigor (but see [50] for an example of an abbreviated 5-item adjusting DRD task). As discussed below, the MCQ also may be particularly useful in clinical applications of DRD in predicting addiction treatment outcomes (e.g., [23, 51, 52]).

Differences, however, are also present. Of note, the overall effect size in the present study was of smaller magnitude compared to the medium effect size reported in the previous meta-analysis of categorical differences. This finding is somewhat counter-intuitive as continuous designs putatively have higher power to detect associations between DRD and addictive behavior. There are a number of possible explanations for this difference. First, the present sample was comprised of a large number of studies in subclinical samples (e.g., young adult regular drinkers) that may have reduced the overall magnitude of the association and also contributed to the substantial heterogeneity in the primary analysis. The differences between subclinical and clinical samples in the previous meta-analysis would support this hypothesis. Second, the earlier categorical studies examined in the previous meta-analysis may have had, on average, larger effect sizes compared to more recent studies. This is supported to some extent by the present meta-regression results indicating that the magnitude of the effect size significantly decreased over time. Third, it is possible this difference reflects a true difference between categorical and continuous relationships. For example, the relationship between DRD and addictive behavior may actually be quasi- or semi-continuous. At lower levels of severity or QF the pattern may be linear, but once individuals traverse a clinically meaningful threshold to an addictive disorder they exhibit a disproportionately higher level of DRD. These are necessarily speculations, but the data are fairly unambiguous that the effect sizes are meaningfully different and understanding this difference is an important area for future research.

These results also have implications for understanding the clinical significance of DRD in addictive disorders. First, steeper DRD was more robustly associated with severity of addictive disorder than higher QF of use. Although QF and severity are certainly related, these results suggest that impulsive choice behavior is implicated to a greater extent in experiencing negative consequences or problems associated with substance use or gambling. A priority moving forward is to further disentangle the relative contributions of prolonged engagement in addictive behaviors versus severity of addictive disorder to the relationship with DRD. Second, steep DRD has been shown to predict worse treatment outcomes in nicotine and marijuana use disorder [23, 24, 51, 52]. Considered in the context of the present findings, an intriguing empirical question is whether the relation between DRD and treatment success varies as a function of clinical severity. Individuals with the greatest addiction severity may have the most difficulty maintaining abstinence, and the results this meta-analysis and others [17] suggest that this may be attributed, in part, to their increased preferences for immediate reinforcement. Therefore, specifically targeting DRD as supplement to traditional clinical interventions is a promising direction for the future. Indeed, several novel experimental manipulations have been shown to reduce rate of DRD in

healthy and addiction samples, such as episodic future thinking [54–57] and executive function training [58], among others.

These findings should be considered in the context of the study's strengths and limitations. Strengths of the study include the use of an extensive literature search strategy that included substance and non-substance based addictive behaviors, a large sample size (>11,000 individuals), and examination of multiple indices of small study bias. However, a limitation of the study concerns the correlational nature of the effects examined. As such, the causal relation between DRD and addiction cannot be ascertained from these data alone. Steep DRD may serve as a risk factor for engaging in addictive behaviors and the development of addictive disorders, it may be a consequence of prolonged use, or some combination of both (for additional discussion of these possibilities, see [59, 60]). Furthermore, due to the limited number of studies reporting continuous associations in opiate users (and also to a certain extent in stimulant users), these findings primarily apply to alcohol, tobacco, gambling, and cannabis. The studies included in this meta-analysis largely involved adult samples, with some exceptions [53, 61–63], which limits generalizability of these findings to other developmental periods such as adolescent substance use.

A final consideration that deserves particular attention is potentially high rates of polysubstance use across studies (i.e., participants concurrently engaging in multiple addictive behaviors such as drinking and gambling). Epidemiological data suggest that polysubstance use is highly prevalent (e.g., [64]), and polysubstance users exhibit steeper DRD relative to single substance users [15, 65]. In the case of the studies examined here, only 10% explicitly stated that participants were excluded for using substances other than the primary substance of interest. Therefore, the associations between DRD and individual addictive behavior types should be considered with the caveat that many participants may have been concurrently engaging in multiple forms of addictive behavior and the effect sizes may not reflect truly substance-specific relationships. Ultimately, additional research on DRD among polysubstance users is needed for a viable meta-analysis of these effects.

In sum, the present results provide a fairly comprehensive examination of DRD in cross-sectional addiction studies using continuous designs. The study indicates that steep DRD is robustly associated with severity and QF of addictive behaviors. Importantly, the magnitude of this relation did not significantly differ across the types of addictive behavior examined, offering further support for steep DRD as a trans-diagnostic process in addiction [66]. Additional research is needed to determine the causal relationship between impulsive discounting and addictive behavior and the potential for targeting DRD via behavioral economics-based interventions for addictive disorders.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

Funding Support: Dr. Amlung's role was partially supported by the Peter Boris Centre for Addictions Research at McMaster University/St. Joseph's Healthcare Hamilton. Dr. MacKillop's roles were partially supported by NIH grant P30 DA027827 and the Peter Boris Chair in Addictions Research.

References

1. Bickel WK, Johnson MW, Koffarnus MN, et al. The behavioral economics of substance use disorders: reinforcement pathologies and their repair. *Annu Rev Clin Psychol.* 2014; 10:641–77. DOI: 10.1146/annurev-clinpsy-032813-153724 [PubMed: 24679180]
2. Vuchinich, RE.; Heather, N. Choice, Behavioural Economics and Addiction. Elsevier; Amsterdam: 2003.
3. Madden, GJ.; Bickel, WK. Impulsivity: The Behavioral and Neurological Science of Discounting. American Psychological Association; Washington, D.C.: 2009.
4. Cyders MA, Coskunpinar A. Measurement of constructs using self-report and behavioral lab tasks: Is there overlap in nomothetic span and construct representation for impulsivity? *Clin Psychol Rev.* 2011; 31:965–82. DOI: 10.1016/j.cpr.2011.06.001 [PubMed: 21733491]
5. MacKillop J, Miller JD, Fortune E, et al. Multidimensional examination of impulsivity in relation to disordered gambling. *Exp Clin Psychopharmacol.* 2014; 22:176–85. DOI: 10.1037/a0035874 [PubMed: 24708148]
6. Stahl C, Voss A, Schmitz F, et al. Behavioral components of impulsivity. *J Exp Psychol Gen.* 2014; 143:850–10. 1037/a0033981. [PubMed: 23957282]
7. Madden GJ, Bickel WK, Jacobs EA. Discounting of delayed rewards in opioid-dependent outpatients: hyperbolic discounting functions? *Exp Clin Psychopharmacol.* 1999; 7:284–293. [PubMed: 10472517]
8. Kirby KN, Petry NM. Heroin and cocaine abusers have higher discount rates for delayed rewards than drug-using controls. *Addiction.* 2004; 99:461–471. ADD669 [pii]. DOI: 10.1111/j.1360-0443.2003.00669.x [PubMed: 15049746]
9. Mazur, JE. An adjusting procedure for studying delayed reinforcement. In: Mazur, JE.; Nevin, JA., editors. *Rachlin Anal Behav Vol 5 Eff Delay Interv Events Reinf Value.* Erlbaum; Hillsdale: 1987. p. 55-73.
10. Myerson J, Green L, Warusawitharana M. Area under the curve as a measure of discounting. *J Exp Anal.* 2001; :243.doi: 10.1901/jeab.2001.76-235
11. Mitchell JM, Fields HL, D'Esposito M, Boettiger CA. Impulsive responding in alcoholics. *Alcohol Clin.* 2005; 29:2158–2169. DOI: 10.1097/01.alc.0000191755.63639.4a
12. Petry NM. Delay discounting of money and alcohol in actively using alcoholics, currently abstinent controls. *Psychopharmacol.* 2001; 154:243–250. DOI: 10.1007/s002130000638
13. Baker F, Johnson MW, Bickel WK. Delay discounting in current and never-before cigarette smokers: differences across commodity, sign, and magnitude. *J Abnorm Psychol.* 2003; 112:382–392. [PubMed: 12943017]
14. Coffey SF, Gudleski GD, Saladin ME, Brady KT. Impulsivity and rapid discounting of delayed cocaine-dependent individuals. *Exp Clin Psychopharmacol.* 2003; 11:18–25. [PubMed: 12622340]
15. Petry NM. Pathological gamblers, with and without substance use disorders, discount delayed rewards. *Abnorm Psychol.* 2001; 110:482–487.
16. Johnson MW, Bickel WK, Baker F, et al. Delay discounting in current and former marijuana-dependent. *Clin Psychopharmacol.* 2010; 18:99–107. DOI: 10.1037/a0018333
17. MacKillop J, Amlung MT, Few LR, et al. Delayed reward discounting and addictive behavior: a meta-analysis. *Psychopharmacol.* 2011; 216:305–321. DOI: 10.1007/s00213-011-2229-0
18. Fernie G, Peeters M, Gullo MJ, et al. Multiple behavioural impulsivity tasks predict prospective alcohol involvement in adolescents. *Addiction.* 2013; 108:1916–23. DOI: 10.1111/add.12283 [PubMed: 23795646]

19. Khurana A, Romer D, Betancourt LM, et al. Working memory ability predicts trajectories of early alcohol use in adolescents: the mediational role of impulsivity. *Addiction*. 2013; 108:506–15. DOI: 10.1111/add.12001 [PubMed: 23033972]
20. Anokhin AP, Golosheykin S, Grant JD, Heath AC. Heritability of delay discounting in adolescence: a longitudinal twin study. *Behav Genet*. 2011; 41:175–83. DOI: 10.1007/s10519-010-9384-7 [PubMed: 20700643]
21. Krishnan-Sarin S, Reynolds B, Duhig AM, et al. Behavioral impulsivity predicts treatment outcome in a smoking cessation program for adolescent smokers. *Drug Alcohol Depend*. 2007; 88:79–82. DOI: 10.1016/j.drugalcdep.2006.09.006 [PubMed: 17049754]
22. MacKillop J, Murphy JG, Tidey JW, et al. Latent structure of facets of alcohol reinforcement from a behavioral economic demand curve. *Psychopharmacol*. 2009; 203:33–40. DOI: 10.1007/s00213-008-1367-5
23. Sheffer C, MacKillop J, McGeary J, et al. Delay discounting, locus of control, and cognitive impulsiveness independently predict tobacco dependence treatment outcomes in a highly dependent, lower socioeconomic group of smokers. *Am J Addict*. 2012; 21:221–232. DOI: 10.1111/j.1521-0391.2012.00224.x [PubMed: 22494224]
24. Stanger C, Ryan SR, Fu H, et al. Delay discounting predicts adolescent substance abuse treatment outcome. *Exp Clin Psychopharmacol*. 2012; 20:205–212. DOI: 10.1037/a0026543 [PubMed: 22182419]
25. Courtney KE, Arellano R, Barkley-Levenson E, et al. The relationship between measures of impulsivity and alcohol misuse: An integrative structural equation modeling approach. *Alcohol Clin Exp Res*. 2012; 36:923–931. DOI: 10.1111/j.1530-0277.2011.01635.x [PubMed: 22091877]
26. Mole TB, Irvine Ma, Worbe Y, et al. Impulsivity in disorders of food and drug misuse. *Psychol Med*. 2014; :1–12. DOI: 10.1017/S0033291714001834
27. Ohmura Y, Takahashi T, Kitamura N. Discounting delayed and probabilistic monetary gains and losses by smokers of cigarettes. *Psychopharmacology (Berl)*. 2005; 182:508–515. DOI: 10.1007/s00213-005-0110-8 [PubMed: 16167142]
28. Clewett D, Luo S, Hsu E, et al. Increased functional coupling between the left fronto-parietal network and anterior insula predicts steeper delay discounting in smokers. *Hum Brain Mapp*. 2014; 35:3774–3787. DOI: 10.1002/hbm.22436 [PubMed: 24523255]
29. Dennhardt AA, Murphy JG. Associations between depression, distress tolerance, delay discounting, and alcohol-related problems in European American and African American college students. *Psychol Addict Behav*. 2011; 25:595–604. DOI: 10.1037/a0025807 [PubMed: 21988480]
30. Wilson AG, Franck CT, Mueller ET, et al. Predictors of delay discounting among smokers: Education level and a Utility Measure of Cigarette Reinforcement Efficacy are better predictors than demographics, smoking characteristics, executive functioning, impulsivity, or time perception. *Addict Behav*. 2015; 45:124–133. DOI: 10.1016/j.addbeh.2015.01.027 [PubMed: 25661991]
31. MacKillop J, Mattson RE, Anderson Mackillop EJ, et al. Multidimensional assessment of impulsivity in undergraduate hazardous drinkers and controls. *J Stud Alcohol Drugs*. 2007; 68:785–788. [PubMed: 17960295]
32. Amlung M, MacKillop J. Understanding the Effects of Stress and Alcohol Cues on Motivation for Alcohol via Behavioral Economics. *Alcohol Clin Exp Res*. 2014; 38:1780–9. DOI: 10.1111/acer.12423 [PubMed: 24890323]
33. Andrade LF, Petry NM. White problem gamblers discount delayed rewards less steeply than their African American and Hispanic counterparts. *Psychol Addict Behav*. 2014; 28:599–606. DOI: 10.1037/a0036153 [PubMed: 24955678]
34. Christiansen P, Cole JC, Goudie AJ, Field M. Components of behavioural impulsivity and automatic cue approach predict unique variance in hazardous drinking. *Psychopharmacology (Berl)*. 2012; 219:501–10. DOI: 10.1007/s00213-011-2396-z [PubMed: 21735071]
35. Alessi SM, Petry NM. Pathological gambling severity is associated with impulsivity in a delay discounting procedure. *Behav Process*. 2003; 64:345–354. S0376635703001505 [pii].
36. Heyman GM, Gibb SP. Delay discounting in college cigarette chippers. *Behav Pharmacol*. 2006; 17:669–79. DOI: 10.1097/FBP.0b013e3280116cfe [PubMed: 17110793]

37. Madden GJ, Petry NM, Johnson PS. Pathological gamblers discount probabilistic rewards less steeply than matched controls. *Exp Clin Psychopharmacol.* 2009; 17:283–90. DOI: 10.1037/a0016806 [PubMed: 19803627]
38. Stojek MM, Fischer S, Murphy CM, MacKillop J. The role of impulsivity traits and delayed reward discounting in dysregulated eating and drinking among heavy drinkers. *Appetite.* 2014; 80:81–8. DOI: 10.1016/j.appet.2014.05.004 [PubMed: 24816318]
39. Stewart LA, Clarke M, Rovers M, et al. Preferred Reporting Items for Systematic Review and Meta-Analyses of individual participant data: the PRISMA-IPD Statement. *J Am Med Assoc.* 2015; 313:1657–65. DOI: 10.1001/jama.2015.3656
40. Kirby KN, Marakovic NN. Delay-discounting probabilistic rewards: Rates decrease as amounts increase. *Psychon Bull Rev.* 1996; 9:100–104.
41. Cochran WG. The combination of estimates from different experiments. *Biometrics.* 1954; 10:101–129.
42. Higgins JPT, Thompson SG. Quantifying heterogeneity in a meta-analysis. *Stat Med.* 2002; 21:1539–1558. DOI: 10.1002/sim.1186 [PubMed: 12111919]
43. Tukey JW. Bias and confidence in not quite large samples. *Ann Math Stat.* 1958; 29:614.
44. Rosenthal R. The file drawer problem and tolerance for null results. *Psychol Bull.* 1979; 86:638–641. DOI: 10.1037/0033-2909.86.3.638
45. Orwin RG. A fail-safe n for effect size in metaanalysis. 1983; 8:157–159.
46. Begg CB, Mazumdar M. Operating characteristics of a rank correlation test for publication bias. *Biometrics.* 1994; 50:1088–101. DOI: 10.2307/2533446 [PubMed: 7786990]
47. Egger M, Smith GD, Schneider M, Minder C. Bias in meta-analysis detected by a simple, graphical test. *BMJ.* 1997; 315:629–634. [PubMed: 9310563]
48. Duval S, Tweedie R. Trim and fill: A simple funnel-plot-based method of testing and adjusting for publication bias in meta-analysis. *Biometrics.* 2000; 56:455–63. [PubMed: 10877304]
49. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences.* Lawrence Erlbaum Associates; Hillsdale, NJ: 1988.
50. Koffarnus MN, Bickel WK. A 5-trial adjusting delay discounting task: Accurate discount rates in less than one minute. *Exp Clin Psychopharmacol.* 2014; 22:222–8. DOI: 10.1037/a0035973 [PubMed: 24708144]
51. MacKillop J, Kahler CW. Delayed reward discounting predicts treatment response for heavy drinkers receiving smoking cessation treatment. *Drug Alcohol Depend.* 2009; 104:197–203. DOI: 10.1016/j.drugalcdep.2009.04.020 [PubMed: 19570621]
52. Yoon JH, Higgins ST, Heil SH, et al. Delay discounting predicts postpartum relapse to cigarette smoking among pregnant women. *Exp Clin Psychopharmacol.* 2007; 15:176–186. DOI: 10.1037/1064-1297.15.2.186 [PubMed: 17469941]
53. Stanger C, Ryan SR, Fu H, et al. Delay discounting predicts adolescent substance abuse treatment outcome. *Exp Clin Psychopharmacol.* 2012; 20:205–212. DOI: 10.1037/a0026543 [PubMed: 22182419]
54. Peters J, Buchel C. Episodic future thinking reduces reward delay discounting through an enhancement of prefrontal-mediotemporal interactions. *Neuron.* 2010; 66:138–148. S0896-6273(10)00197-2 [pii]. DOI: 10.1016/j.neuron.2010.03.026 [PubMed: 20399735]
55. Kaplan BA, Reed DD, Jarmolowicz DP. Effects of episodic future thinking on discounting: Personalized age-progressed pictures improve risky long-term health decisions. *J Appl Behav Anal.* 2015; doi: 10.1002/jaba.277
56. Daniel TO, Stanton CM, Epstein LH. The future is now: reducing impulsivity and energy intake using episodic future thinking. *Psychol Sci.* 2013; 24:2339–42. DOI: 10.1177/0956797613488780 [PubMed: 24022653]
57. Snider SE, LaConte SM, Bickel WK. Episodic Future Thinking: Expansion of the Temporal Window in Individuals with Alcohol Dependence. *Alcohol Clin Exp Res.* 2016; 40:1558–1566. DOI: 10.1111/acer.13112 [PubMed: 27246691]
58. Bickel WK, Yi R, Landes RD, et al. Remember the future: working memory training decreases delay discounting among stimulant addicts. *Biol Psychiatry.* 2011; 69:260–265. DOI: 10.1016/j.biopsych.2010.08.017 [PubMed: 20965498]

59. De Wit H. Impulsivity as a determinant and consequence of drug use: a review of underlying processes. *Addict Biol.* 2009; 14:22–31. DOI: 10.1111/j.1369-1600.2008.00129.x [PubMed: 18855805]
60. Weafer J, Mitchell SH, de Wit H. Recent Translational Findings on Impulsivity in Relation to Drug Abuse. *Curr Addict reports.* 2014; 1:289–300. DOI: 10.1007/s40429-014-0035-6
61. Canale N, Vieno A, Griffiths MD, et al. Trait urgency and gambling problems in young people by age: The mediating role of decision-making processes. *Addict Behav.* 2015; 46:39–44. DOI: 10.1016/j.addbeh.2015.02.020 [PubMed: 25796006]
62. Castellanos-Ryan N, Struve M, Whelan R, et al. Neural and cognitive correlates of the common and specific variance across externalizing problems in young adolescence. *Am J Psychiatry.* 2014; 171:1310–1319. DOI: 10.1176/appi.ajp.2014.13111499 [PubMed: 25073448]
63. Kim-Spoon J, Mccullough ME, Bickel WK, et al. Longitudinal associations among religiousness, delay discounting, and substance use initiation in early adolescence. *J Res Adolesc.* 2015; 25:36–43. DOI: 10.1111/jora.12104 [PubMed: 25750491]
64. Grant BF, Goldstein RB, Saha TD, et al. Epidemiology of DSM-5 Alcohol Use Disorder: Results From the National Epidemiologic Survey on Alcohol and Related Conditions III. *JAMA psychiatry.* 2015; 72:757–766. DOI: 10.1001/jamapsychiatry.2015.0584 [PubMed: 26039070]
65. Moody L, Franck C, Hatz L, Bickel WK. Impulsivity and Polysubstance Use: A Systematic Comparison of Delay Discounting in Mono-, Dual-, and Trisubstance Use. *Exp Clin Psychopharmacol.* 2015; doi: 10.1037/pha0000059
66. Bickel WK, Jarmolowicz DP, Mueller ET, et al. Excessive discounting of delayed reinforcers as a trans-disease process contributing to addiction and other disease-related vulnerabilities: emerging evidence. *Pharmacol Ther.* 2012; 134:287–97. DOI: 10.1016/j.pharmthera.2012.02.004 [PubMed: 22387232]
67. Acker J, Amlung M, Stojek M, et al. Individual variation in behavioral economic indices of the relative value of alcohol: Incremental validity in relation to impulsivity, craving, and intellectual functioning. *J Exp Psychopathol.* 2012; 3:423–436. DOI: 10.5127/jep.021411
68. Albein-Urios N, Martinez-González JM, Lozano Ó, Verdejo-Garcia A. Monetary delay discounting in gambling and cocaine dependence with personality comorbidities. *Addict Behav.* 2014; 39:1658–1662. DOI: 10.1016/j.addbeh.2014.06.001 [PubMed: 25047890]
69. Amlung M, MacKillop J. Clarifying the relationship between impulsive delay discounting and nicotine dependence. *Psychol Addict Behav.* 2014; 28:761–768. [PubMed: 24841186]
70. Amlung M, Sweet LH, Acker J, et al. Dissociable brain signatures of choice conflict and immediate reward preferences in alcohol use disorders. *Addict Biol.* 2012; doi: 10.1111/adb.12017
71. Amlung M, Few LR, Howland J, et al. Impulsivity and alcohol demand in relation to combined alcohol and caffeine use. *Exp Clin Psychopharmacol.* 2013; 21:467–74. DOI: 10.1037/a0034214 [PubMed: 24364537]
72. Arantes J, Berg ME, Lawlor D, Grace RC. Offenders have higher delay-discounting rates than non-offenders after controlling for differences in drug and alcohol abuse. *Leg Criminol Psychol.* 2013; 18:240–253. DOI: 10.1111/j.2044-8333.2012.02052.x
73. Ballard ME, Mandelkern Ma, Monterosso JR, et al. Low Dopamine D2/D3 Receptor Availability is Associated with Steep Discounting of Delayed Rewards in Methamphetamine Dependence. *Int J Neuropsychopharmacol.* 2015; :1–10. DOI: 10.1093/ijnp/pyu119
74. Banca P, Lange I, Worbe Y, et al. Reflection impulsivity in binge drinking: Behavioural and volumetric correlates. *Addict Biol.* 2015; doi: 10.1111/adb.12227
75. Bobova L, Finn PR, Rickert ME, Lucas J. Disinhibitory psychopathology and delay discounting in alcohol dependence: personality and cognitive correlates. *Exp Clin Psychopharmacol.* 2009; 17:51–61. 2009-01082-006 [pii]. DOI: 10.1037/a0014503 [PubMed: 19186934]
76. Callan MJ, Shead NW, Olson JM. Personal relative deprivation, delay discounting, and gambling. *J Pers Soc Psychol.* 2011; 101:955–973. doi: <http://dx.doi.org/10.1037/a0024778>. [PubMed: 21875231]
77. Castellanos-Ryan N, Struve M, Whelan R, et al. Neural and cognitive correlates of the common and specific variance across externalizing problems in young adolescence. *Am J Psychiatry.* 2014; 171:1310–1319. DOI: 10.1176/appi.ajp.2014.13111499 [PubMed: 25073448]

78. Claus ED, Kiehl KA, Hutchison KE. Neural and Behavioral Mechanisms of Impulsive Choice in Alcohol Use Disorder. *Alcohol Clin Exp Res*. 2011; 35:1209–1219. DOI: 10.1111/j.1530-0277.2011.01455.x [PubMed: 21676001]
79. Dai Z, Harrow S-E, Song X, et al. Gambling, Delay, and Probability Discounting in Adults With and Without ADHD. *J Atten Disord*. 2013; doi: 10.1177/1087054713496461
80. De Wilde B, Goudriaan A, Sabbe B, et al. Relapse in pathological gamblers: A pilot study on the predictive value of different impulsivity measures. *J Behav Addict*. 2013; 2:23–30. DOI: 10.1556/JBA.2.2013.1.4 [PubMed: 26165768]
81. Dennhardt, Aa; Yurasek, AM.; Murphy, JG. Change in delay discounting and substance reward value following a brief alcohol and drug use intervention. *J Exp Anal Behav*. 2015; 103:125–140. DOI: 10.1002/jeab.121 [PubMed: 25533393]
82. Epstein LH, Richards JB, Saad FG, et al. Comparison between two measures of delay discounting in smokers. *Exp Clin Psychopharmacol*. 2003; 11:131–138. DOI: 10.1037/1064-1297.11.2.131 [PubMed: 12755457]
83. Fernie G, Cole JC, Goudie AJ, Field M. Risk-taking but not response inhibition or delay discounting predict alcohol consumption in social drinkers. *Drug Alcohol Depend*. 2010; 112:54–61. DOI: 10.1016/j.drugalcdep.2010.05.011 [PubMed: 20580495]
84. Field M, Christiansen P, Cole J, Goudie A. Delay discounting and the alcohol Stroop in heavy drinking adolescents. *Addiction*. 2007; 102:579–586. ADD1743 [pii]. DOI: 10.1111/j.1360-0443.2007.01743.x [PubMed: 17309540]
85. Finn PR, Gunn RL, Gerst KR. The Effects of a Working Memory Load on Delay Discounting in Those With Externalizing Psychopathology. *Clin Psychol Sci*. 2014; 3:202–214. DOI: 10.1177/2167702614542279
86. Gonzalez VM, Reynolds B, Skewes MC. Role of impulsivity in the relationship between depression and alcohol problems among emerging adult college drinkers. *Exp Clin Psychopharmacol*. 2011; 19:303–313. DOI: 10.1037/a0022720 [PubMed: 21480733]
87. Gray JC, MacKillop J. Genetic basis of delay discounting in frequent gamblers: examination of a priori candidates and exploration of a panel of dopamine-related loci. *Brain Behav*. 2014; doi: 10.1002/brb3.284
88. Heinz AJ, Peters EN, Boden MT, Bonn-Miller MO. A comprehensive examination of delay discounting in a clinical sample of Cannabis-dependent military veterans making a self-guided quit attempt. *Exp Clin Psychopharmacol*. 2013; 21:55–65. DOI: 10.1037/a0031192 [PubMed: 23379614]
89. Johnson MW, Bickel WK, Baker F. Moderate drug use and delay discounting: a comparison of heavy, light, and never smokers. *Exp Clin Psychopharmacol*. 2007; 15:187–194. 2007-05127-007 [pii]. DOI: 10.1037/1064-1297.15.2.187 [PubMed: 17469942]
90. Jouts J, Voon V, Johansson J, et al. Dopaminergic function and intertemporal choice. *Transl Psychiatry*. 2015; 5:e491.doi: 10.1038/tp.2014.133 [PubMed: 25562841]
91. MacKillop J, Tidey JW. Cigarette demand and delayed reward discounting in nicotine-dependent individuals with schizophrenia and controls: An initial study. *Psychopharmacology (Berl)*. 2011; 216:91–99. DOI: 10.1007/s00213-011-2185-8 [PubMed: 21327760]
92. MacKillop J, Miranda R, Monti PM, et al. Alcohol demand, delayed reward discounting, and craving in relation to drinking and alcohol use disorders. *J Abnorm Psychol*. 2010; 119:106–114. DOI: 10.1037/a0017513 [PubMed: 20141247]
93. MacKillop J, Celio Ma, Mastroleo NR, et al. Behavioral Economic Decision Making and Alcohol-related Sexual Risk Behavior. *AIDS Behav*. 2015; 19:450–458. DOI: 10.1007/s10461-014-0909-6 [PubMed: 25267115]
94. Monterosso J, Ehrman R, Napier KL, et al. Three decision-making tasks in cocaine-dependent patients: do they measure the same construct? *Addiction*. 2001; 96:1825–1837. DOI: 10.1080/09652140120089571 [PubMed: 11784475]
95. Ohmura Y, Takahashi T, Kitamura N. Discounting delayed and probabilistic monetary gains and losses by smokers of cigarettes. *Psychopharmacology (Berl)*. 2005; 182:508–515. DOI: 10.1007/s00213-005-0110-8 [PubMed: 16167142]

96. Petry NM. Pathological gamblers, with and without substance use disorders, discount delayed rewards at high rates. *J Abnorm Psychol.* 2001; 110:482–487. DOI: 10.1037//0021-843X [PubMed: 11502091]
97. Petry NM. Discounting of probabilistic rewards is associated with gambling abstinence in treatment-seeking pathological gamblers. *J Abnorm Psychol.* 2012; 121:151–159. DOI: 10.1037/a0024782 [PubMed: 21842965]
98. Reynolds B, Fields S. Delay discounting by adolescents experimenting with cigarette smoking. *Addiction.* 2012; 107:417–24. DOI: 10.1111/j.1360-0443.2011.03644.x [PubMed: 21906199]
99. Reynolds B. Do high rates of cigarette consumption increase delay discounting? A cross-sectional comparison of adolescent smokers and young-adult smokers and nonsmokers. *Behav Process.* 2004; 67:545–549. DOI: 10.1016/j.beproc.2004.08.006
100. Reynolds B. The Experiential Discounting Task is sensitive to cigarette-smoking status and correlates with a measure of delay discounting. *Behav Pharmacol.* 2006; 17:133–142. DOI: 10.1097/01.fbp.0000190684.77360.c0 [PubMed: 16495721]
101. Rezvanfard M, Ekhtiari H, Mokri A, et al. Psychological and behavioral traits in smokers and their relationship with nicotine dependence level. *Arch Iran Med.* 2010; 13:395–405. 010135/AIM.006. [PubMed: 20804306]
102. Schmaal L, Goudriaan AE, Joos L, et al. Neural substrates of impulsive decision making modulated by modafinil in alcohol-dependent patients. *Psychol Med.* 2014; 44:2787–98. DOI: 10.1017/S0033291714000312 [PubMed: 25066449]
103. Shibata Y. Sex differences in the effects of disinhibition, perceived peer drinking, and delay discounting on drinking among Japanese college students. *Pers Individ Dif.* 2013; 55:766–770. DOI: 10.1016/j.paid.2013.06.011
104. Stea JN, Hodgins DC, Lambert MJ. Relations between delay discounting and low to moderate gambling, cannabis, and alcohol problems among university students. *Behav Processes.* 2011; 88:202–205. DOI: 10.1016/j.beproc.2011.09.002 [PubMed: 21946096]
105. Stevens L, Roeyers H, Dom G, et al. Impulsivity in cocaine-dependent individuals with and without attention-deficit/hyperactivity disorder. *Eur Addict Res.* 2015; 21:131–143. DOI: 10.1159/000369008 [PubMed: 25675959]
106. Sweitzer MM, Donny EC, Dierker LC, et al. Delay discounting and smoking: association with the Fagerström Test for Nicotine Dependence but not cigarettes smoked per day. *Nicotine Tob Res.* 2008; 10:1571–1575. DOI: 10.1080/14622200802323274 [PubMed: 18946776]
107. Teeters JB, Murphy JG. The behavioral economics of driving after drinking among college drinkers. *Alcohol Clin Exp Res.* 2015; 39:896–904. DOI: 10.1111/acer.12695 [PubMed: 25871945]
108. Thomas KB, Derenne A, Weatherly JN. Delay and probability discounting in the context of gambling function and expectancies. 2015:35–56.
109. White TJ, Redner R, Skelly JM, Higgins ST. Examining educational attainment, prepregnancy smoking rate, and delay discounting as predictors of spontaneous quitting among pregnant smokers. *Exp Clin Psychopharmacol.* 2014; 22:384–391. DOI: 10.1037/a0037492 [PubMed: 25069014]

Figure 1.
Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) inclusion flow diagram.

Table 1

Studies Included in Meta-Analysis

Study	Groups	N	DRD Index	Task Type	Delayed Amount(s)	DV's
Acker et al., 2012 [67]	Heavy Drinkers	61	Log(k)	MCQ	\$55 (M)	AUDIT; Drinks/week
Albein-Urios et al., 2012 [68]	Cocaine-dependent Individuals, Pathological Gamblers, Controls	67	AUC	MCQ	\$55 (M)	Cocaine and tobacco use/month
Alessi & Petry, 2003 [35]	Pathological Gamblers	62	Log(k)	MICT	\$1000	Gambling Symptoms; Dollars/month
Amlung & MacKillop, 2014 [69]	Daily Smokers	933	Sqrt(k)	MCQ	\$204 (M)	AUDIT-QF; AUDIT-HZD; FTND; Frequency of marijuana, stimulant, opiate use
Amlung et al., 2012 [70]	Heavy Drinking Males	25	Log(k)	MICT	\$100	AUDIT
Amlung et al., 2013 [71]	Undergraduate Monthly Drinkers	273	ICR	MCQ	\$55 (M)	AUDIT
Andrade & Petry, 2014 [33]	Problem gamblers	315	Log(k)	MCQ	\$55 (M)	ASI-Alcohol; ASI-Gambling
Arantes et al., 2013 [72]	Incarcerated offenders and control non-offenders	133	Log(k)	MICT	Variable	MAST
Ballard et al., 2015 [73]	Methamphetamine-dependent Adults	41	Ln(k)	MCQ	\$55 (M)	QF of methamphetamine use; FTND; Cigarettes/day
Banca et al., 2015 [74]	Binge drinkers, Controls	60	Log(k)	MCQ	\$55 (M)	AUDIT
Bobova et al., 2009 [75]	Alcohol Dependence w/ and w/o Childhood Conduct Disorder, Individuals w/ Conduct Disorder, Controls	393	Log(k)	MICT	\$50	SSAGA-II Alcohol, Cannabis; Frequency of alcohol, cannabis, stimulant, opiate use; Quantity of alcohol use
Callan et al., 2011 [76]	Regular Gamblers	83	AUC	MICT	\$1000	PGSI
Canale et al., 2015 [61]	Healthy Adolescents/Young Adults	986	ICR	MCQ	\$55 (M)	SOGS-RA
Castellanos-Ryan et al., 2014 [77]	European adolescents	1778	k	MCQ	\$55 (M)	AUDIT; ESPAD (QF); ESPAD (Lifetime occasions of being drunk)
Christiansen et al., 2012 [34]	Social Drinkers	97	AUC	MICT	£100	AUDIT; Drinks/week
Claus et al., 2011 [78]	Heavy Drinkers	151	Log(k)	MICT	\$517 (M)	AUDIT
Clewett et al., 2014 [28]	Nicotine-dependent Smokers	39	Ln(k)	MCQ	\$55 (M)	FTND; Cigarettes/day
Courtney et al., 2012 [25]	Problem Drinkers	139	k	MCQ	\$55 (M)	Alcohol Use and Problems Composite Scores
Dai et al., 2013 [79]	Adults with ADHD, Controls	60	AUC	MICT	\$50, \$5000	SOGS
De Wilde et al., 2013 [80]	Pathological Gamblers; Controls	53	Log(k)	MICT	10€100€	SOGS
Dennhardt & Murphy, 2011 [29]	College Drinkers	190	Log(k)	MCQ	\$55 (M)	YAACQ; Drinks/week
Dennhardt et al., 2015 [81]	Heavy drinkers	97	k	MICT	\$100	YAACQ; Drinks/week; MPS; Marijuana frequency
Epstein et al., 2003 [82]	Current Smokers	78	Log(k)	MCQ; MICT	\$55 (M)	Cigarettes/day
Fernie et al., 2010 [83]	Social Drinkers	68	AUC	MICT	£500	AUDIT; Drinks/week

Study	Groups	N	DRD Index	Task Type	Delayed Amount(s)	DVs
Field et al., 2007 [84]	Heavy Drinkers, Light Drinkers	90	AUC	MICT	£500	AUDIT; Drinks/week
Finn et al., 2015 [85]	Individuals with alcohol, marijuana, or other drug dependence, or conduct disorder	542	Log(k)	MICT	\$50	Alcohol and marijuana problems
Gonzalez et al., 2011 [86]	College Drinkers	143	AUC	MICT	\$10	B-YAACQ; Drinks/month
Gray & MacKillop, 2014 [87]	Weekly Gamblers	175	Log(k)	MCQ	\$55 (M)	SCI-PG
Heinz et al., 2013 [88]	Treatment-seeking Cannabis Dependent Veterans	75	Ln(k)	MICT	\$1000	AUDIT; FTND; MPS
Heyman & Gibb, 2006 [36]	Current Smokers, Chippers, Non-Smokers	40	Log(k)	MICT	\$17 (M), \$1000	FTND; Cigarettes/week
Johnson et al., 2007 [89]	Heavy & Light Smokers	30	Log(k)	MICT	\$100	Cigarettes/day
Joutsa et al., 2015 [90]	Male pathological gamblers	12	k	MCQ	\$55 (M)	SOGS
Kim-Spoon et al., 2015 [63]	Healthy adolescents	106	Log(k)	MCQ	\$55 (M)	Alcohol, cigarette, marijuana frequency
Kirby & Petry, 2004 [8]	Alcohol, Heroin, or Cocaine Abusers, Controls	145	Ln(k)	MCQ	\$55 (M)	ASI-Alcohol, Cocaine, and Opiates
MacKillop & Kahler, 2009 [51]	Heavy Drinking Treatment-seeking Smokers	57	k	MCQ	\$55 (M)	FTND; Drinks/day
MacKillop & Tidey, 2011 [91]	Smokers w/ Schizophrenia or Schizoaffective Disorder, Control Smokers	47	Log(k)	MCQ	\$55 (M)	FTND; Cigarettes/day
MacKillop et al., 2007 [31]	Hazardous Drinkers, Social Drinkers	83	Log(k)	MICT	\$1000	AUDIT
MacKillop et al., 2010 [92]	Heavy Drinkers	60	Log(k)	MCQ	\$55 (M)	DSM-IV AUD Symptoms; Drinks/week
MacKillop et al., 2014 [5]	Frequent Gamblers	353	k	MCQ	\$55 (M)	SCI-PG
MacKillop et al., 2015 [93]	Hazardous Drinkers	127	Log(k)	MCQ	\$55 (M)	% Drinking days/month; Average drinks/day
Madden et al., 2009 [37]	Treatment-seeking Male Gamblers, Controls	38	Ln(k)	MCQ	\$55 (M)	SOGS
Mitchell et al., 2005 [11]	Abstinent Alcoholics, Controls	28	ICR	MICT	\$23 (M)	AUDIT; DUSI; SOGS
Mole et al., 2015 [26]	Abstinent Alcoholics	30	Sqrt(k)	MCQ	£55	Drinks/day
Monterosso, et al., 2001 [94]	Treatment-seeking Cocaine Dependent Individuals	32	Exp(k)	MCQ	\$55 (M)	Cocaine days/month; Amount/day
Ohmura et al., 2005 [95]	Habitual Smokers	27	AUC	MICT	100000 Yen	Cigarettes/day
Petry, 2001 [96]	Treatment-seeking Pathological Gamblers w/ and w/o Substance Use Disorders, Controls	60	Log(k)	MICT	\$1,000	Gambling frequency (last 3 months)
Petry, 2012 [97]	Treatment-seeking Gamblers	226	Log(k)	MCQ	\$55 (M)	SOGS; Dollars/month
Reynolds & Fields, 2012 [98]	Smokers, Experimenters, Non-Smokers	141	AUC	MICT	\$10	Alcohol / marijuana use (last 6 months)
Reynolds, 2004 [99]	Adult and Adolescent Smokers	44	Log(k)	MICT	\$10	Cigarettes/day
Reynolds, 2006 [100]	Smokers	30	k	MICT	\$10	Cigarettes/day; Drinks/day
Rezvafard et al., 2010 [101]	Light Dependent Smokers, Heavily Dependent Smokers, Non-Smokers	89	k	MICT	\$100	FTQ
Schmaal et al., 2014 [102]	Alcohol-dependent Males; Controls	32	AUC	MICT	€500 (M)	Cigarettes/week

Study	Groups	N	DRD Index	Task Type	Delayed Amount(s)	DVs
Sheffer et al., 2012 [23]	Treatment-seeking Nicotine Dependent Smokers	97	Ln(k)	MICT	\$1000, \$100	FTND
Shibata, 2013 [103]	Japanese college students	258	Ln(k)	MCQ	¥5500 (M)	Drinking frequency
Stanger et al., 2012 [24]	Treatment-seeking Adolescent Marijuana Users	165	Ln(k)	MICT	\$100, \$1000	FTND; Marijuana days/month
Stea et al., 2011 [104]	Gamblers, Cannabis Users, Controls	217	AUC	MICT	\$1,000	AUDIT; ASSIST-Cannabis; PGSI
Stevens et al., 2015 [105]	Cocaine-Dependent Individuals	59	Ln(k)	MICT	\$504 (M)	Past month cocaine use
Stojek et al., 2014 [38]	Heavy Drinkers	108	Log(k)	MCQ	\$55 (M)	AUDIT; Drinks/week
Sweitzer et al., 2008 [106]	Current Smokers, "Triers," Ex-Smokers, Never-Smokers	237	Log(k)	MICT	\$100	FTND; Cigarettes/day
Teeters & Murphy, 2015 [107]	College Drinkers	419	Sqrt(k)	MICT	\$100	Drinks/week
Thomas et al., 2015 [108]	Undergraduate students	272	AUC	MICT	\$1000, \$100000	SOGS
White et al., 2014 [109]	Pregnant Smokers and Recent Quitters	349	Log(k)	MICT	\$1000	Cigarettes/day
Wilson et al., 2015 [30]	Nicotine-dependent Smokers	94	Ln(k)	MICT	\$1000, \$10	FTND; Cigarettes/day
Yoon et al., 2007 [52]	Treatment-seeking Pregnant Former Smokers	48	Log(k)	MICT	\$1000	Cigarettes/day

Notes: Studies are presented in alphabetical order by first author last name. Sample sizes reflect largest sample size analyzed in each study; individual sample sizes for each effect size are provided in Supplementary Materials. *Abbreviations:* DRD Index = Delayed Reward Discounting indices; k = discounting rate; AUC = Area Under the Curve; ICR = Impulsive Choice Ratio; Ln = natural log transform; Log = logarithmic transform; Sqrt = square root transform; Exp = exponential transform. DRD Task = Delayed Reward Discounting task type; MCQ = Monetary Choice Questionnaire; MICT = Multi-item Choice Task. *Addiction Variables:* ASI = Addiction Severity Index; ASSIST = Alcohol, Smoking, and Substance Involvement Screening Test; AUD = Alcohol Use Disorder Symptoms; AUDIT = Alcohol Use Disorders Identification Test; AUDIT-HZD = Alcohol Use Disorders Identification Test – Hazardous Alcohol Use subscale; AUDIT-QF = Alcohol Use Disorders Identification Test – Quantity/Frequency of Alcohol Consumption subscale; B-YAACQ = Brief Young Adult Alcohol Consequences Questionnaire; DSM-IV = Diagnostic and Statistical Manual of Mental Disorders – 4th Edition, Text Revision; DUSI = Drug Use Screening Inventory; ESPAD = European School Survey Project on Alcohol and Drugs; FTND = Fagerstrom Test for Nicotine Dependence; FTQ = Fagerstrom Tolerance Questionnaire; MAST = Michigan Alcoholism Screening Test; MPS = Marijuana Problems Scale; PGSI = Problem Gambling Severity Index; SCI-PG = Structured Clinical Interview for Pathological Gambling; SOGS = South Oaks Gambling Screen; SOGS-RA = South Oaks Gambling Screen – Revised Adolescent; SSAGA-II = Semi-Structured Assessment for the Genetics of Alcoholism; YAACQ = Young Adult Alcohol Consequences Questionnaire.

Table 2

Meta-Analytic Findings for Associations between Delay Discounting and Type of Addictive Behavior, Type of Dependent Variable, and Discounting Measure

Variable	# ES	N	r	pr	r _{OSR}	Q	p _Q	I ²
I. Overall Effect Size	138	11,395	.14	<10 ⁻¹⁴	.14-.14	443.35	<10 ⁻¹⁴	69.10
II. Addictive Behavior Type								
Alcohol	53	7,365	.14	<10 ⁻¹⁴	.13-.15	143.04	<10 ⁻⁹	63.65
Tobacco	40	2,714	.17	<10 ⁻¹¹	.16-.17	61.07	.01	36.13
Gambling	21	2,940	.16	<10 ⁻⁵	.15-.18	75.39	<10 ⁻⁷	73.47
Cannabis	12	2,654	.10	.04	.08-.13	69.67	<10 ⁻⁹	84.21
Stimulants	9	1,649	.05	.48	.01-.09	29.87	<001	73.22
Between Category Difference	-	-	-	-	-	4.92	.30	-
III. Dependent Variable Type								
Severity	69	9,492	.17	<10 ⁻¹⁴	.16-.17	191.11	<10 ⁻¹⁴	64.42
Quantity-Frequency (QF)	69	7,100	.11	<10 ⁻⁹	.10-.11	193.00	<10 ⁻¹⁴	64.77
Between Category Difference	-	-	-	-	-	6.49	.01	-
IV. Discounting Measures								
MCQ	63	6,954	.14	<10 ⁻¹³	.13-.15	263.19	<10 ⁻¹⁴	76.44
Task-Based	75	4,571	.14	<10 ⁻¹⁴	.14-.15	172.36	<10 ⁻¹⁴	57.07
Between Category Difference	-	-	-	-	-	0.01	.90	-

Note. # ES = number of effect sizes included in each category; N = total number of unique individuals represented in each category; r = Pearson's r effect size statistic; pr = significance value corresponding to Fisher's Z transformation of the r statistic; r_{OSR} = range of effect sizes obtained from one-study-removed analysis; Q = Cochran's Q test of homogeneity; p_Q = p value corresponding to Cochran's Q; I² = proportion of variability due to heterogeneity; MCQ = 27-item monetary choice task.