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Hyperbolic discounting rates and risk for problematic alcohol use in youth enrolled in the Adolescent Brain and Cognitive Development study

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Abstract

Adolescence is the peak period for the emergence of substance use, which can lead to long-term psychosocial, occupational, and interpersonal complications. Ongoing large-scale, longitudinal, consortium initiatives, such as the Adolescent Brain and Cognitive Development (ABCD) study, offer unprecedented opportunities to elucidate key risk factors for problematic substance use in a well-powered sample, and to examine how changes in risk factors relate to symptoms across time. Delay discounting has been proposed as a putative risk marker for early substance-use initiation and other forms of psychopathology. However, the extent to which other factors (e.g., socioeconomic status, cognitive ability) influence discounting behavior in young adolescents is not well established. The present study leverages data from the ABCD study (n=11,045) to assess associations between core demographic and familial variables and delay discounting in youth—operationalized using hyperbolic discounting rates (*k*)—before the onset of significant psychopathology. Model estimates revealed significant effects of individual difference factors (e.g., sex, socioeconomic status) and alcohol risk status (based on family history) on delay discounting. No significant differences were observed in the primary sample when comparing the presence of parent drug problems or prenatal drug exposures. These effects will require replication in later waves of ABCD. Nonetheless, these results provide support for delay discounting as a potential risk marker for problematic alcohol use and demonstrate a relationship between key demographic variables and adolescent discounting behavior. Further, these results provide an empirical baseline from which developmental trajectories of delay discounting and substance use may be tracked throughout future waves of ABCD.

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Author Contributions

RJK and SWY generated the hypotheses and analysis plans for this manuscript. RJK performed all analyses and drafted the manuscript. SDL and SWY provided revisions, feedback, and guidance during development. All authors approved the manuscript for submission.

Conflict of Interest

No conflict declared

Keywords

computational modeling; reward; decision-making; addiction; development; initiation

Introduction

Adolescence is characterized by increases in risk taking and impulsivity, and this is theorized to contribute to the development of multiple disorders later in life[1]. Thus, measures of impulsivity are commonly utilized as surrogate markers of vulnerabilities for substance use initiation and other risk behaviors during adolescence[2–5]. In particular, individual differences in delay discounting—defined as the reduction in value of an outcome as a result of the delay until its receipt[6]—have been somewhat consistently associated with future substance use in adolescents[7, 8] and adults[9]. More generally, significant evidence indicates that delay discounting is a central transdiagnostic process that is altered across diverse psychiatric disorders[10]. However, multiple lines of evidence also indicate that delay discounting may differ as function of basic demographic factors—including family income and parental education[11, 12]. Thus, additional research is needed to determine the specific utility of delay discounting in predicting substance-use risk, as well as the sensitivity of delay discounting to other core demographic variables in a well-powered and large-scale sample.

The Adolescent Brain and Cognitive Development (ABCD) study provides an unprecedented opportunity to evaluate discounting behavior in >10,000 adolescents prior to the onset of problematic substance-use or significant psychopathology[13, 14]. The present study leverages this comprehensive dataset to characterize delay discounting behaviors—as operationalized via hyperbolic discounting rates (k)—in relation to key demographic and family history variables. In addition, we examine associations between delay discounting and clinical measures of inattention and impulsivity, which have also been linked to risk for substance use in adolescence[15, 16]. This initial assessment provides an empirical baseline from which developmental trajectories of delay discounting may be tracked throughout future waves of ABCD. Future data releases will allow assessment of how relationships between delay discounting and other variables change over time and as a function of risk for specific disorders (or clusters of disorders), and the extent to which discounting behaviors are stable within individuals over the course of development. This first empirical assessment provides a baseline for assessing such factors.

During delay discounting tasks participants are asked to choose between rewards of differing magnitudes with a varying delay between the response and the presentation of rewards (e.g., “Would you rather receive 500 dollars two days from now or 50 dollars now?”). Research suggests that human discounting behavior generally follows a hyperbolic function—such that people will discount larger delayed rewards in favor of rewards that are smaller but more immediate—and that there are significant individual differences in this hyperbolic function[17, 18]. A greater tendency to favor smaller immediate rewards over larger delayed rewards, reflected by a steeper discounting curve, is theorized to relate to risk for multiple disorders, including substance use[10].

To quantify discounting rates, we here apply hyperbolic modeling to compute individual participant discounting rates (*k*) using delay discounting data from 11,450 individuals aged ~10–11 from ABCD's Wave 1 baseline data release. While our modeling approach—i.e., calculation of k-estimates using hyperbolic modeling—is recommended by the ABCD study group, these data are not included in ABCD's data archive (which only includes indifference scores, details in Methods, below)[13]. Thus, as an additional contribution to the addiction and developmental research communities—and consistent with ABCD's 'open science' initiative—all of the code used to derive hyperbolic discounting rates and other analyses for this manuscript is provided in the Supplemental Materials, so that our approach may be easily adopted by other research groups and replicated using subsequent data releases of ABCD.

Methods

Adolescent Brain and Cognitive Development (ABCD) Study

The ABCD study is a longitudinal study of adolescent development across 21 sites in the United States with an enrollment of 11,875 youth. Participants are assessed annually, beginning at age 9–10 until age 19–20, on a multitude of clinical and psychosocial measures in order to facilitate understanding of adolescent neurodevelopment[14, 19]. Delay discounting scores are obtained on alternating years beginning at the one-year follow-up[13]. Therefore, only participants that completed the one-year follow-up are included in the present analyses (N=11,045). Data were downloaded under NIMH Data Use Agreement #7342.

Delay Discounting Task

Adolescent discounting was measured via an adjusting-delay procedure[13, 20] encompassing 42 trials across 7 randomized blocks (6 trials per block). Each block corresponded to a delay interval (6 hours, 1 day, 1 week, 1 month, 3 months, 1 year, and 5 years) where a choice was offered between a hypothetical $100 reward in the future and an immediate reward of varying magnitudes. The value of the immediate reward was automatically adjusted between trials within a given block, depending on the participant's previous decision. For example, choosing the delayed reward resulted in an increase in immediate reward value for the subsequent trial. Indifference points were calculated for each delay (block) and represent the value at which the small immediate reward is equal to the larger but delayed alternative[6]. Variables used from ABCD's delay discounting data release included the seven indifference scores (e.g., ddis_scr_val_indiff_point_6h) and responses to validity check items (ddis_src_val_immedcho). Validity items are intended to identify non-systematic responding during the delay discounting task. The three validity questions, presented between blocks, ask the participant to choose between a rational (e.g., $100 now) vs. an irrational (e.g., $100 in 5 years) outcome and are designed to evaluate inattentive behavior during the task. Any irrational response is considered as evidence of inattention or irrational behavior during the task, as indicated in ABCD's data release variable notes.

In order to evaluate impulsive-like behavior during the delay discounting task, *k*-value estimates were obtained with hyperbolic modeling using the base nls function in R (4.0.3). These *k*-estimates are thought to reflect impulsive decision making [18] and their use is

recommended by the ABCD study group [13]. However, these data are not provided in ABCD's data archive[13]. Thus, we calculated *k* estimates ourselves, as follows:

$$V = A/1+kD$$

where V is the indifference point, A the large reward amount ($100), and D the delay. Delays in the present analyses were calculated as a proportion of a single month; e.g., the numerical value associated with the 6-hour delay was 0.008 and 0.033 for 1 day. Predicted subjective values were calculated by substituting *k* estimates back into the above equation and solving for V. Additional details and the code used for these analyses are provided in the Supplemental Materials.

Cash Choice Task

In addition to the delay discounting task, the cash choice task was selected as an alternative ABCD behavioral measure of discounting for comparison. Performance on this task is thought to reflect temporal discounting with high developmental stability[13, 21, 22]. This task involved a single trial in which participants were asked to decide between $75 dollars in 3 days or $115 in 3 months with a third option of "can't decide". Data from the cash choice task were collected at baseline whereas discounting data were collected during the one-year follow-up.

Demographic characteristics

Participant sex at birth was used to identify male and female adolescents. Household income was divided into three income brackets including less than $50,000 (<50k), between $50,000 and $100,000 (50k–100k), and greater than $100,000 a year (>100k). Parental marital status was classified into five levels: divorced, separated, married, never married, or lives with partner. The marital status "widowed" was removed due to low sample size. Parental education was separated into five levels based on terminal degree: <HS Diploma, high school or GED, some college, bachelor's degree, or post-graduate degree (master's, professional or doctorate).

Substance use history

The family history questionnaire was used to assess family substance use histories: Participants with at least one parent with a drug or alcohol problem were classified as having a positive family history of drug or alcohol use problems, respectively. In addition, familial alcohol and drug problem density variables were created by totaling the number of "yes problem" responses for each child's mother, father, and grandparents (maternal and paternal). A value of 6 indicates all included family members had problematic substance use. The developmental history questionnaire was utilized to assess for prenatal exposure to alcohol, tobacco, or marijuana. Participants exposed to any of these substances at any point during pregnancy were classified as having a positive history of prenatal substance exposure. Additionally, we also identified subjects whose mother continued to use substances after learning of their pregnancy, as this may reflect cases of more severe maternal substance use in the ABCD cohort[23].

Cognitive ability and self-reported impulsivity

To enable assessment of the relationship between hyperbolic discounting and other related dimensional constructs, cognitive ability[24, 25] and impulsivity assessments were also examined. Cognitive ability was measured by the Matrix Reasoning Task in the DEAP RDS file (3.0, #1042). The Behavioral Inhibition/Behavioral Activation System (BIS/BAS), Urgency-Premeditation-Perseverance-Sensation Seeking-Positive Urgency (UPPS-P), and Childhood Behavior Checklist (CBCL) were used to quantify inattention and impulsivity. BIS/BAS and UPPS-P sum scores were obtained from the mental health youth summary scores data file and CBCL t-scores (ADHD and attention) were obtained from the CBCL ASEBA data file. CBCL scores were based on parent/caregiver responses, while the BIS/BAS and UPPS-P were completed by adolescent participants.

Data analysis

All statistical analyses were performed in R (4.0.3). Several different approaches have been proposed to check for non-systematic responding during delay discounting tasks. Thus, we here used two such approaches and also adopted an inclusive data approach in which data from all participants with delay discounting data were analyzed. First, we used the ABCD delay discounting task validity check items. Of the entire delay discounting sample (n=11,045), only n=1,785 adolescents responded rationally on all 3 validity checks and would therefore meet criteria for inclusion based on ABCD recommendations (hereafter referred to as the “ABCD restricted” sample). Second, we considered an alternative systematic approach in which discounting data was evaluated using a previously validated algorithm[26] which aims to exclude participants that do not display monotonically decreasing indifference scores. This approach evaluates indifference scores based on two conditions: (1) indifference scores, beginning with the second delay (e.g., 1 day), must not be greater than the preceding delay’s indifference score by more than 20% of the larger reward (e.g., $20); (2) indifference scores for the last delay (e.g., 5-years) must be less than indifference scores of the first delay (e.g., 6 hours) by at least 10% of the larger reward (e.g., $10). Exclusion based on these criteria resulted in a sample size of n=4,357 (hereafter referred to as the primary sample; “Johnson & Bickel” sample).

Linear mixed-effect models (lmer package, R) were used to compare estimated values of k between groups of selected variables. Given the nested structure of ABCD, all mixed-effect models included random nested effects for family and site ID as recommended in the ABCD Data Exploration and Analysis Portal (DEAP). All “Refuse to Answer” responses from all included variables were removed from prior to modeling. Significant effects were followed up with tukey post-hoc analyses (emmeans package, R). Between group cohen’s d effect size estimates were calculated using the effect size function (eff_size) in the emmeans package, which uses model specific marginal means. A chi-square analysis (2×2) was performed on cash choice task data to assess for sex differences at baseline.

Spearman correlations between overall k estimates and clinical assessments were acquired with R’s cor.test() function as linear relationships were not assumed. Given the size of the present dataset, estimates of correlation and effect size are expected to be small. Recent literature utilizing data from large consortia studies, including ABCD, find this to be typical

and suggest that such small effects may be more representative of population estimates[27, 28]. Finally, datasets were combined for analyses utilizing the variable "src_subject_id" found in all ABCD files.

Results

Validity check

Discounting rates (k) were computed separately for each of the three datasets described above (full, ABCD restricted, Johnson & Bickel) and the residual mean squared error (RMSE) for each model was used to compare approaches. Exclusion based on the Johnson and Bickel (2008) algorithm resulted in the lowest RMSE (Johnson and Bickel=27.6; Full=36.6; Restricted=39.5). Results from this sample are therefore focused on as the primary sample (n=4,357) below. However, both the full (n=11,045) and ABCD restricted (n=1,785) datasets were also evaluated, and these findings are presented in the supplemental information for comparison. A total of n=611 adolescents were present in both the primary and restricted datasets.

Overall Discounting

Figure 1 displays the distribution of indifference scores at each delay interval for the primary (i.e., Johnson and Bickel algorithm) sample and Table 1 (a–b) displays sample characteristics for each variable in the primary sample (details on restricted and full samples are in the supplemental materials). For the primary dataset (n=4,357), median k was estimated to be 0.14. Estimates of k were positively skewed (γ=14.19) and were log-transformed (γ=0.66) (see Supplemental Figure 1a for distribution) for subsequent analyses. Interview age (months) was not correlated (spearman) with discounting rates (p=0.31, r=−0.02; p_{Full}=0.31, r_{Full}=−0.02; r=−0.02; $p_{Restricted}$=0.02, $r_{Restricted}$=−0.06) and thus was not included as a covariate. The overall discounting rate for the primary sample was ln(k)=−1.75 after controlling for the nested structure of site and family ID. Those who responded for the more immediate option on the cash choice task ($75 in three days; (ln($k$)=−2.38, σ=0.08, df=26.1) had significantly higher (p<0.0001, d=0.26; p_{Full}<0.001; $p_{\text{Restricted}}$=0.32) discounting rates than those who responded for the delayed option ($115 in 3 months; (ln($k$)=−1.51, σ=0.09, df=34.9), indicating relative concordance across tasks. See Figure 2a–c for total responses on the cash choice task separated by sex (as well as extension of findings in the full and restricted samples).

Demographic and participant characteristics

Males had significantly higher discounting rates comparted to females ($\ln(k)_{\text{Male}}$=−1.59, σ=0.07, df=31.1; $\ln(k)_{\text{Female}}$=−1.91, σ=0.08, df=36.7; p<0.0001, d=0.15, ci:[0.08,0.21]). Similarly, a 2×2 chi-square test revealed males and female adolescents differed significantly in their responses on the cash choice task, with a higher proportion of males selecting the more immediate choice option. ($\chi 2$=14.8, p<0.001; p_{Full}<0.001; $p_{\text{Restricted}}$=0.13). Figure 2d–f displays the predicted subjective value for each sex after substituting k back into the hyperbolic equation at each delay for the primary, restricted and full samples. For both tasks, sex differences were observed in the primary and full sample, but not in the restricted sample (see Supplemental Materials).

Estimates for ln(k) are displayed in Table 2a for all demographic variables in the primary analysis. Figure 3 displays the predicted subjective value at each delay for the primary, full and restricted samples. Effect size estimates for all significant pairwise comparisons in the primary analysis are displayed in Figure 4. See supplemental materials for effect size estimates for the restricted and full samples.

Children of parents who made a combined income between $50k–100k or >$100k had significantly lower discounting rates (p=0.0001, d=0.21 & p<0.0001, d=0.32 respectively) compared to children of parents who made <50k (Table 2a; Figure 3a–c). In addition, children whose parents made >$100k had significantly lower discounting rates than those whose parents made between $50k–100k ($p$=0.02, d=0.10). The size of the effect between the highest combined income (>$100k+, ln($k$)=−1.99, σ=0.06, df=41) and the lowest (<$50k, ln($k$)=−1.31, σ=0.09, df=144) was 0.32 (ci:[0.23, 0.41]). Similar effects of income were observed in the restricted and full samples for all comparisons except $50k–100k and >$100k (see Supplemental Materials).

Children of parents having received a bachelors or post graduate degree had the lowest ln(k) estimates ($\ln(k)_{\text{Post Graduate}}$=−2.00, σ=0.06, df=53.6; $\ln(k)_{\text{Bachelor's}}$=−1.91, σ=0.07, df=92.1) while those with a high school diploma or less had the highest ($\ln(k)_{\text{Diploma/GED}}$=−0.99, σ=0.15, df=1153.3; $\ln(k)_{\text{<High School Diploma}}$=−0.87, σ=0.22, df=1912.6) (Table 2a; Figure 3d–f). Adolescents of parents who obtained a post graduate degree had significantly lower discounting rates than those whose parents obtained <HS diploma (p<0.001, d=0.54, ci:[0.32,0.75]), HS diploma/GED (p<0.001, d=0.48, ci:[0.33,0.63]) or some college education (p=<0.001, d=0.29, ci:[0.28,0.38]). In addition, adolescents whose parents obtained a bachelor's degree had significantly lower discounting rates than those who had <HS diploma (p<0.001, d=0.49, ci:[0.28,0.71]), a HS diploma/GED (p=0.003, d=0.44, ci:[0.28,0.59]), and some college (p<0.001, d=0.25, ci:[0.15,0.34]). Similar effects of education were observed in the restricted and full samples except for the comparison between a bachelor's degree and some college in the restricted sample (see Supplemental Materials).

Figure 3g–i displays predicted values based on k estimates grouped by parental marital status and table 2a displays ln(k) values all marital statuses. Children with married parents had the lowest ln(k) estimate (ln(k)=−1.89, σ=0.06, df=25.5) while those with parents that were never married had the largest (ln(k)=−0.99, σ=0.14, df=621.9). Children of parents who were married displayed significantly lower discounting rates than those whose parents were living with a partner (p=0.02; d=0.25, ci:[0.08, 0.41]), separated (p=0.01; d=0.32, ci:[0.12, 0.51]), or never married (p<0.001; d=0.44, ci:[0.31, 0.57]). In addition, children of divorced parents have significantly lower rates than those whose parents were never married (p=0.004; d=0.30, ci:[0.14,0.46]). Similar effects of family structure were observed in the full sample, whereas the only significant comparison in the restricted sample was between children whose parents were married and those whose parents were never married (see Supplemental Materials).

To account for dependence among these significant demographic variables, a single mixed-effect model including household income, marital status, parent education, and participant sex was analyzed. Results from this full model suggest parent education, parent marital

status and participant sex (p<0.001; d=0.15, ci:[0.08, 0.22]) contribute significantly to adolescent discounting rates. Pairwise comparisons revealed significant differences in parent education were between those whose parents obtained a post graduate degree and those whose parents received a HS diploma/GED (p=0.013; d=0.29, ci:[0.11, 0.47]), had some college education (p=0.003; d=0.20, ci:[0.09, 0.30]), or <HS diploma (p=0.028; d=0.39, ci:[0.13, 0.66]). Similar significant differences were found for those whose parents obtained a bachelor's degree (p=0.026; d=0.27, ci:[0.09, 0.45], p=0.010; d=0.17, ci:[0.07, 0.28], p=0.045; d=0.37, ci:[0.10, 0.63] respectively). For parent marital status, those whose parents were married had significantly lower discounting rates than those that were never married (p=0.022; d=0.23, ci:[0.08, 0.38]). Contrary to the individual models, household income was no longer associated with discounting rates. Using a stepwise approach, we found household income was significantly associated with discounting rates when parent marital status was excluded from the model. Pairwise comparisons for this model revealed a significant difference between parents with a combined income of >$100k and those whose combined income is <$50k ($p$<0.021; d=0.15, ci:[0.04, 0.26]).

Familial substance use

Figure 3j–r displays predicted values based on k estimates for family and developmental history subgroupings. Adolescents with either parent indicating an alcohol problem had significantly higher discounting rates than those whose parents did not endorse any alcohol problems ($\ln(k)_{\text{No Problems}}$=−1.78, σ=0.07, df=21.7; $\ln(k)_{\text{Either Parent Problems}}$=−1.35, σ=0.12, df=224.5; p<0.001, d=0.20, ci:[0.09,0.32];). This significant difference remained (p=0.02, d=0.14) after the inclusion of significant demographic variables described above (e.g., sex, household income, parent education, parent marital status, and race/ethnicity). Figure 3m–o displays predicted values for parent drug problems. No significant difference was observed for parent drug problems with (p=0.051) or without (p=0.25) the inclusion of additional covariates in the primary sample. No statistically significant differences were observed across calculated familial density variables for drug or alcohol problems. Similar significant findings were observed in the full sample for parental alcohol use. However, children of parents indicating a drug problem in the full sample had significantly lower discounting rates than those whose parents did not ($\ln(k)_{\text{No Problems}}$=−1.97, σ=0.08, df=24.2; $\ln(k)_{\text{Either Parent Problems}}$=−2.17, σ=0.10, df=50.5; p=0.02, d=0.06, ci:[0.01,0.11]) (Figure 3p–r). There were no significant differences based on parental drug use history in the restricted sample (see Supplemental Materials).

Youth with and without a history of prenatal substance exposure did not display significantly different discounting rates ($\ln(k)_{\text{None}}$=−1.77, σ=0.07, df=27.4; $\ln(k)_{\text{Any}}$=−1.67, σ=0.08, df=49.0, p=0.20) (Figure 3p–r). In addition, no difference was observed when including only adolescents whose mothers reported substance use after learning that they were pregnant ($\ln(k)_{\text{Had Knowledge}}$=−1.62, σ=0.14, df=505, p=0.34) in the primary sample. The same pattern of findings was observed in the restricted samples (see Supplemental Materials). However, youth with mothers who reported use after learning of the pregnancy did display significantly higher discounting rates in the full sample (p=0.008, d=0.1, ci:[0.02,0.18]).

Associations Between Cognitive Performance and Other Forms of Impulsivity

Spearman's rho was used to assess the association between individual *k* estimates and clinical measures including the UPPS-P, BIS/BAS, standardized t-scores from the CBCL and matrix reasoning task performance. Table 3 displays the correlations for all components of each clinical measure. UPPS-P measures including positive urgency (r=0.10, p<0.001) and negative urgency (r=0.05, p<0.001) were the only UPPS-P variables to survive multiple comparison corrections (p<0.0038). For the modified BIS/BAS, only BASm drive survived multiple comparison correction (r=0.05, p<0.001). CBCL DSM-V scales of attention (r=0.02 p= 0.21; r_{Full}=0.02, p_{Full}=0.08; $r_{Restricted}$=0.08, $p_{Restricted}$=0.001) and ADHD (r=0.03, p=0.06; r_{Full}=0.02, p_{Full}=0.01; $r_{Restricted}$=0.10, $p_{Restricted}$<0.001) symptoms were not significantly correlated with discounting rates in the primary analysis. Finally, estimates of ln(*k*) were negatively associated with cognitive performance as measured by the matrix reasoning task (r=−0.09, p<0.001; r_{Full}=−0.09, p_{Full}<0.001; $r_{Restricted}$=−0.15, $p_{Restricted}$<0.001). Results from the full and restricted samples were generally consistent with those from the primary sample. However, CBCL DSM-V scales for attention and ADHD were only significant in the primary and restricted samples. In addition, UPPS-P lack of planning and sensation seeking measures were significantly associated with discounting rates only in the restricted sample (see Supplemental Materials and Table 3).

Discussion

Our application of hyperbolic modeling to discounting data from a cohort of >10,000 youth —i.e., ABCD—enabled characterization of discounting rates in relation to core demographic and family history variables in youth prior to the onset of significant psychopathology on an unprecedented scale. Our findings largely converge with prior work demonstrating significant effects of both basic individual difference factors (e.g., sex, socioeconomic status) and alcohol risk (here, defined based on family history) status on discounting rates, although anticipated associations with illicit substance use risk were not observed in the primary sample[11, 15, 29, 30].

Across two separate monetary choice tasks, presented a year apart, males and females displayed significant differences in immediate choice responding in the primary (n=4,357) and full samples (n=11,045). These results are consistent with prior work in healthy control adolescents[31], but for the first time provide evidence of significant sex differences in delay discounting behaviors at a young age (~10 years) and in a well-powered sample. These data provide an important baseline from which sex-specific developmental trajectories may be tracked in future waves of ABCD's data releases. To facilitate this process, and consistent with ABCD's 'open science' initiative, all of the code used to derive hyperbolic discounting rates and other analyses for this manuscript is provided in the Supplemental Materials.

There was a significant effect of combined parent income on discounting rates, such that hyperbolic discounting rates decreased as a function of increased income. Our findings are consistent with some literature in adult and adolescent populations[15, 32] and provide additional evidence for the significant effect of socioeconomic status on early adolescent monetary decision-making behavior. Other effect estimates in the present study, including parent marital status and education, provide additional support for the impact of family

environment on discounting behavior more generally. Adolescents whose parents were never married displayed the highest rates of discounting whereas adolescents whose parents were married displayed the lowest. Discounting rates were also significantly higher in adolescents whose parents only had some high school education or a GED/Diploma when compared to those whose parents had a bachelor's degree or post graduate education. These results support the few available studies that have found significant effects of family environmental variables on adolescent discounting[11, 29] and demonstrate the importance of considering familial demographic variables in large-scale studies of delay discounting and other reward-related behaviors.

A large number of studies have consistently demonstrated higher rates of delay discounting among individuals with addictions[17, 33, 34]. However, given the current low rates of alcohol and other substance use in the ABCD sample, it is not yet feasible to examine how hyperbolic discounting rates might differ as a function of substance use initiation. For example, only 21 adolescents denoted any alcohol use other than 'taking a sip' at baseline. Thus—as a proxy measure of alcohol and substance use risk—we examined the relationship between familial substance use histories and delay discounting. Consistent with prior literature[29, 35, 36], youth with a positive parental history of alcohol problems exhibited significantly higher discounting rates when compared to youth without a positive parental history of alcohol problems. Critically, this significant difference remained after the inclusion of additional demographic variables found to be significant in the present study (e.g., family income). In contrast, we observed no significant effect of parental drug use problems on hyperbolic discounting rates in the primary sample, raising the possibility that previously observed negative associations between substance use risk[11, 29, 30] and delay discounting may emerge later in adolescence. However, it is nonetheless important to note that significant effects of familial substance-use risk were found in the full sample (i.e., all participants included). Thus, future work using later data releases from ABCD should carefully consider the method of data validation employed, as this may significantly impact results. This initial assessment provides a critical 'baseline' from which the relationship between discounting rates and substance-use risk may be tracked in future waves of ABCD.

Contrary to expectations, there was no significant difference in discounting rates between youth with and without prenatal substance exposure in the primary sample. However, a significant difference was observed in the full sample when including only youth whose mothers engaged in substance use after knowledge of pregnancy. As above, this finding should be considered as preliminary and again underscores the importance of carefully considering different individual-participant data validation methods and their potential impact on group-level findings.

As anticipated, there were significant associations between hyperbolic discounting rates and self-report indices of impulsivity[37, 38], however the effect sizes observed were relatively modest. These modest effect size estimates are consistent with results from a meta-analysis[39] suggesting that associations between self-report and behavioral measures of impulsivity are in fact modest. Of the measures assessed, positive urgency had the largest effect size in both the primary and full samples in the present study. Taken together, these

results provide further evidence for the importance of taking a multidimensional approach to quantifying impulsive behaviors.

Several limitations exist in the present manuscript. First, adolescent responding during the delay discounting validation questions did not appear to reflect the ABCD group's intended use, which was to identify individuals who may have responded irrationally during experimental trials. For example, adolescents with 3 rational responses on the validity questions were expected to have lower discounting rates than those who responded irrationally at least once. Contrary to this, increases in the number of rational choices made were associated with *steeper* discounting rates during the test questions. Critically, using this exclusion criteria resulted in almost 10,000 samples being removed from the dataset (supplemental material includes full and restricted sample). In contrast, adoption of a systematic approach preserved ~2.5 times the amount of participant data relative to the ABCD recommended approach. These results suggest that use of ABCD's three 'validity check' items with a stringent cutoff of 100% 'rational' responses may be overly conservative. While some of our findings differed as a function of sample size, analyses of the primary (i.e., Johnson & Bickel systematic validity approach) and full datasets yielded largely similar results, with a few notable exceptions (discussed above; full details in the Supplemental Materials).

Second, interpretation of discounting behaviors in young adolescents is complex: Younger adolescents orient less towards the future than older adolescents (16+) and prior studies have interpreted this as evidence that discounting in younger adolescents may be more indicative of planning ability rather than impulsivity, per se[40]. However, results from clinical associations in the present study did not find any significant association between lack of planning (UPPS-P subscale) and discounting rates. In addition, interview age was not associated with discounting rates in the primary or full samples and parent income may not be independently related to discounting rates as demonstrated by our full and stepwise models. These data nonetheless are important because they identify relationships between demographic factors in the context of discounting rates. Given that we chose to only evaluate hyperbolic discounting rates, future work should include additional measures, such as area under the curve and exponential modeling, to determine whether alternative approaches reveal similar findings. Finally, while large sample sizes may provide more accurate measures of true population estimates, multi-site data collection is prone to higher variability due to increased experimental error and between-participant heterogeneity[41, 42]. This limitation is inherent to all large-scale data collection initiatives, such as ABCD. Recent literature has suggested the ABCD sample may not be nationally representative[43] and population-level interpretations should be taken with caution.

These data nonetheless provide some of the first ever large-scale assessments of delay discounting behavior in youth and provide an empirical baseline from which trajectories of discounting behavior may be tracked over time in ABCD. The robust effect size estimates identified between familial demographic variables suggests that they may be important for future studies delineating adolescent discounting behaviors. Subsequent ABCD releases will help determine whether these demographic variables are strongly associated with discounting rates at different stages of adolescent development. The significantly heightened

discounting rates in children with parents endorsing an alcohol problem highlights the potential importance of value-based decision-making as a clinical assessment of risk for problematic use during early adolescence. Given that heightened discounting rates among individuals with a family history of alcohol problems persist through adulthood[35]—and are sensitive to clinical interventions in adolescents [44]—early interventions targeting discounting behavior may be critical for preventing problematic alcohol behaviors later in life.

Data Use

Data used in this manuscript were obtained from the Adolescent Brain and Cognitive Development (ABCD; https://abcdstudy.org) study and can be found in the National Institute of Mental Health Data Archive. Data access can be obtained through a request at the following link https://nda.nih.gov/abcd/request-access. Data use for the present manuscript were accessed under use agree #7342 (NIMH Data Use Agreement #).

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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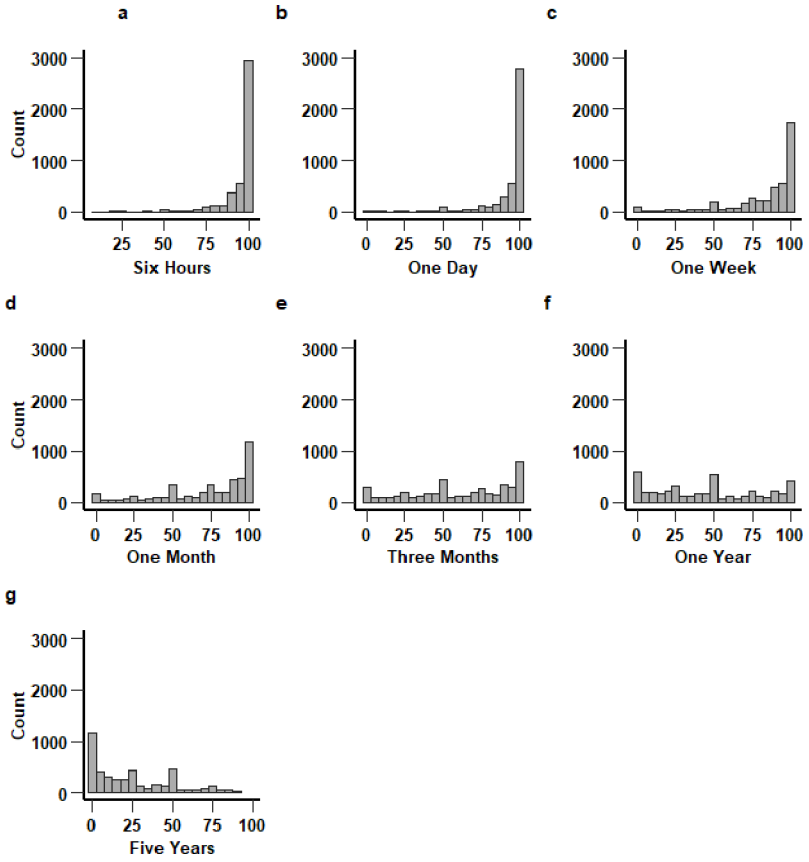

Figure 1. Indifference Score Distributions in Primary Sample

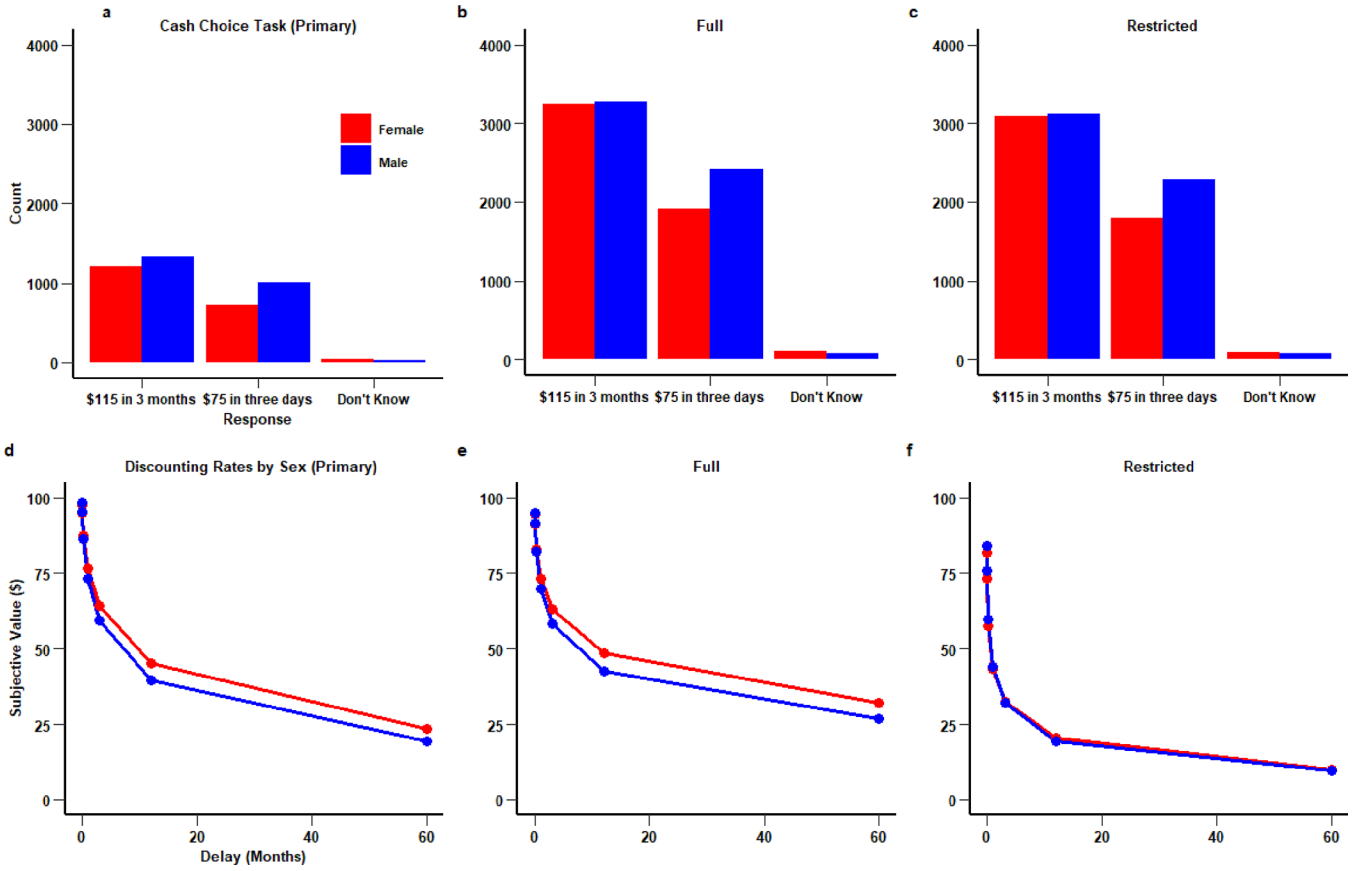

Figure 2. Sex Comparisons for Cash Choice Task and Discounting Rates (k)

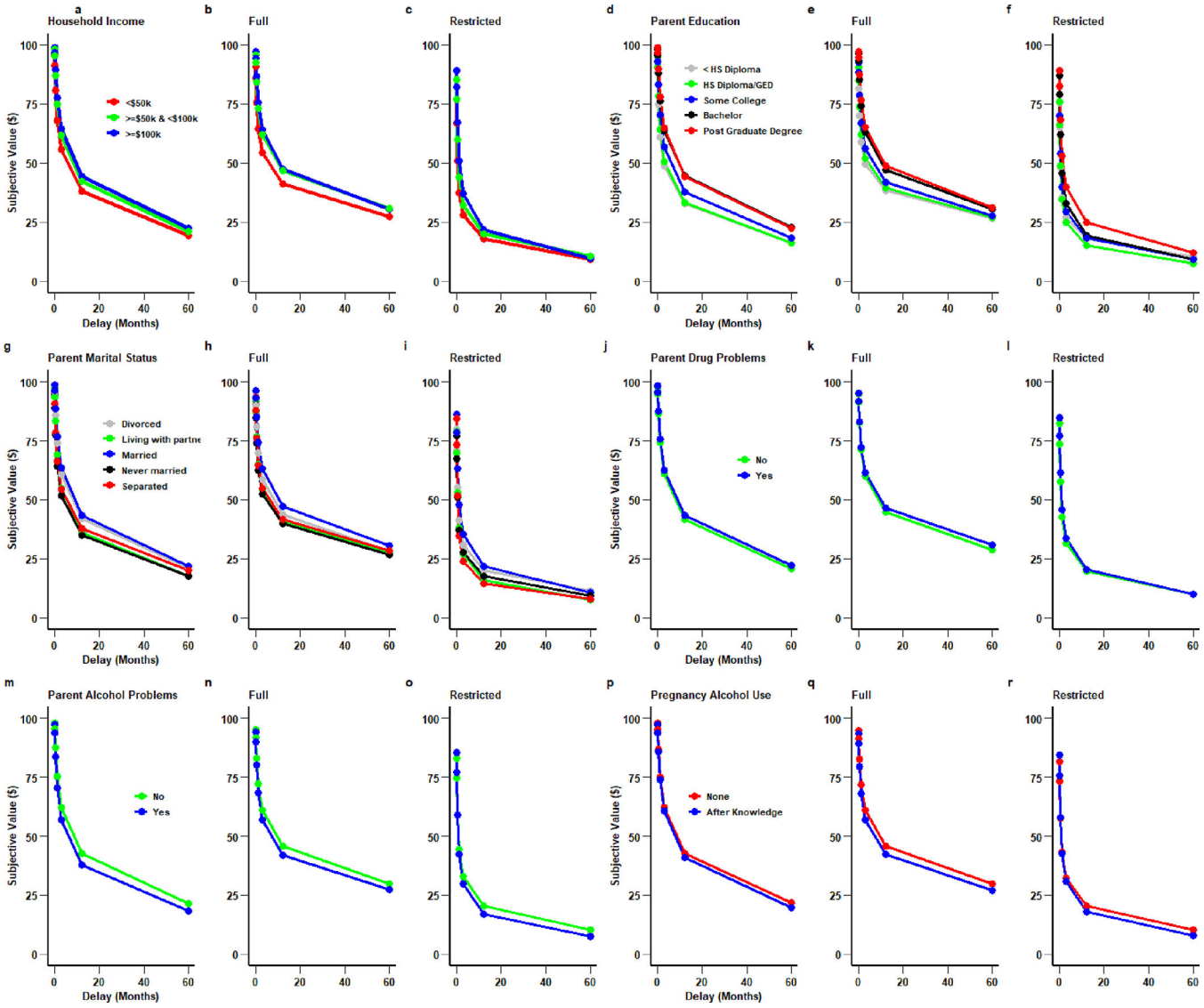

Figure 3. Discounting Rates (k) Across All Variables

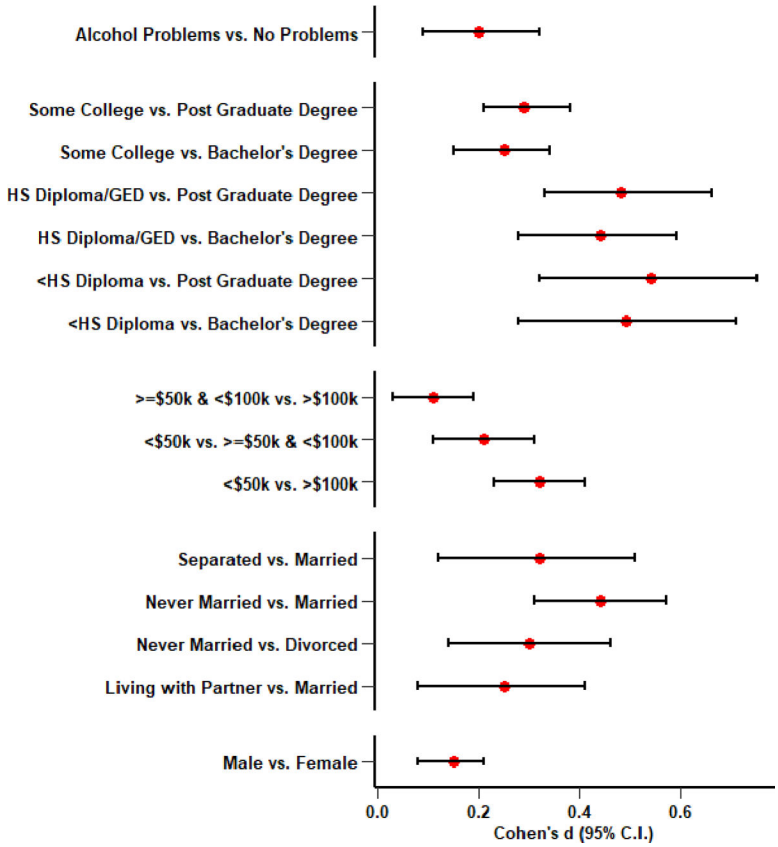

Figure 4. Significant Effect Sizes (Primary)

Table 1.

Table 1 displays sample size characteristics for each variable in the primary sample (n=4,357). (a) includes all child (e.g., sex and overall discounting) and parent demographic variables. (b) includes familial substance use variables. Values in the right column reflect sample size and the variables sample size percentage relative to other levels of the same variable.

a. Demographic Characteristics

Variable (n=)	**N = 4,357**
Sex	
F	1,975
M	2,382
Household Income	
[<50K]	837
[>=100K]	2,050
[>=50K & <100K]	1,166
N/A	304
Parent Education	
< HS Diploma	113
Bachelor	1,246
HS Diploma/GED	243
Post Graduate Degree	1,834
Some College	919
N/A	2
Parent Marital Status	
Divorced	389
Living with partner	198
Married	3,260
Never married	326
Refused to answer	13
Separated	139
Widowed	31
N/A	1

b. Substance Use Characteristics

Variable (n=)	**N = 4,357**
Parent Alcohol Problem	
N/A	133
No	3,654
Yes	570
Parent Drug Problem	
N/A	216
No	2,908

Yes	1,233
Prenatal Substance Use	
N/A	203
No	2,680
Yes	1,474
After Knowledge of Pregnancy	
N/A	1,386
No	2,680
Yes	291
Familial Drug Problem Density	
0	2,232
1	844
2	403
3	159
4	70
5	23
6	15
N/A	611
Familial Alcohol Problem Density	
0	2,807
1	806
2	266
3	77
4	33
5	10
6	1
N/A	357

Table 2.

Table 2 displays estimates of ln(*k*) calculated from hyperbolic modeling of indifference scores in the primary sample (n=4,357). (a) displays ln(k) for overall discounting, sex, and parental demographic variables. (b) displays ln(*k*) estimates for familial substance use variables.

a: Demographic ln(*k*) Estimates	
	ln(k)
Overall	
All Adolescents	**−1.75**
Sex	
Male	**−1.59**
Female	**−1.91**
Household Income	
<$50k	**−1.31**
>=$50k – <$100k	**−1.76**
>$100k	**−1.99**
Education	
<HS Diploma	**−0.87**
HS Diploma/GED	**−0.99**
Some College	**−1.39**
Bachelor's Degree	**−1.91**
Post Graduate Degree	**−2.00**
Marital Status	
Married	**−1.89**
Never Married	**−0.99**
Lives with Partner	**−1.37**
Divorced	**−1.67**
Separated	**−1.28**
b: Substance Use ln(*k*) Estimates	
	ln(k)
Family Substance Use History	
Parent Alcohol Problems	**−1.35**
No Parent Alcohol Problems	**−1.78**
Parent Drug Problems	**−1.80**
No Parent Drug Problems	**−1.70**
Any Prenatal Substance Use Exposure	**−1.67**
Prenatal Exposure After Pregnancy Knowledge	**−1.62**
No Prenatal Substance Use Exposure	**−1.77**

Table 3:

Table 3 displays spearman rho correlation statistics for associations between clinical measures and individual *k* estimates for the primary (n=4,357), full (n=11,045), and restricted samples (n=1,785). Significance threshold was Bonferroni-corrected to account for the total number of comparisons.

Clinical Assessment Associations with ln(*k*)			
	Primary	**Full**	**Restricted**
UPPS-P			
Negative Urgency	**0.05** *	**0.05** *	**0.02**
Lack of Planning	**<0.00**	**<0.00**	**−0.06**
Sensation Seeking	**−0.03**	**−0.03** *	**−0.08** *
Positive Urgency	**0.10** *	**0.08** *	**0.05**
Lack of Perseverance	**0.04**	**0.03** *	**0.02**
BIS/BAS			
BAS FS	**0.03**	**0.03** *	**−0.02**
BISm Sum	**0.03**	**0.01**	**0.03**
BASm RR	**0.04**	**0.03** *	**0.04**
BASm Drive	**0.05** *	**0.04** *	**0.04**
CBCL			
Attention	**0.01**	**0.02**	**0.07** *
ADHD	**0.01**	**0.02**	**0.09** *
Cognitive Performance			
Matrix Reasoning	**−0.09** *	**−0.09** *	**−0.15** *

* indicates a significant association ($p < 0.003$).