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Delay discounting is associated with addiction and mental health measures while controlling for health behaviors and health barriers in a large US sample

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A R T I C L E I N F O

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A B S T R A C T

Background: Excessive discounting of future rewards [delay discounting (DD)] may be a transdiagnostic process and treatment target underlying behavioral health outcomes, including trauma, depression, anxiety, and problematic substance use. However, multiple health behaviors and barriers are also related to these outcomes, including social media usage, adverse childhood experiences (ACEs), sleep quality, healthcare access, housing status, and exercise. To extend research examining DD as transdiagnostic process, we recruited a large, heterogenous sample to examine the association between DD, problematic substance use, and mental health outcomes while controlling for certain health behaviors and health barriers.

Method: In a cross-sectional online survey of 3992 US residents, we administered validated measures of PTSD, depression, anxiety, and problematic alcohol, stimulant, and opioid use. Using linear or ordinal logistic models, scores for each outcome were regressed onto DD while controlling for demographics, health behaviors, and health barriers.

Results: Including only DD and demographics, DD was associated with each outcome at low effect sizes (f^2 = .013, *OR* range = 1.08–1.16). Except for opioid ASSIST scores, these relationships held when controlling for social media usage, sleep, housing status, healthcare access, ACEs, physical exercise, and demographic variables (f^2 = .002, *OR* range = 1.03–1.12), increasing confidence that DD concurrently and directly relates to four of these five clinical outcomes.

Discussion: These findings support the conceptualization of DD as a transdiagnostic process underlying certain psychopathologies and suggest targeting DD in co-occurring substance use disorder and/or mental health treatments may result in clinically significant outcomes.

1. Introduction

Health has been defined as "the ability to adapt and self-manage in the face of social, physical, and emotional challenges" (Huber et al., 2011, p. 1). Many everyday behaviors increase the risks of adverse health outcomes (e.g., substance use; Gandini et al., 2008; Pelucchi et al., 2008, 2011). By contrast, other behavioral patterns may protect against adverse health outcomes while promoting healthy physical and mental functioning (e.g., sleep quality, exercise; Hoevenaar-Blom et al., 2011; Pearce et al., 2022). Other behaviors (e.g., social media use) are known to affect health outcomes, but not in a clear direction (negative, neutral, or positive; Berryman et al., 2018; Schulte and Hser, 2013). Moreover, engaging in certain health-related behaviors is closely linked with the degree of engaging in other health-related behaviors (e.g., reduced sleep duration causing increased caloric consumption; Calvin et al., 2013).

Drivers of health-promoting and demoting behaviors result from interactions between psychological factors, behavior-environment contingencies, and the health-related behaviors themselves (Higgins et al., 2021; Kim-Spoon et al., 2019; Leventhal et al., 2019). However, there is growing evidence of shared processes that undergird co-occurring conditions, emphasizing the need for transdiagnostic research and intervention development (Dalgleish et al., 2020; Fusar-Poli et al., 2019). Delay discounting (DD), the tendency to devalue a reward as a function of delay to receipt (Odum, 2011a), has been proposed as one such transdiagnostic process contributing to multiple health behaviors,

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including substance use, physical activity engagement, and social media use (LeComte et al., 2020; Moody, Franck, & Bickel, 2016; Pancani et al., 2023). DD reflects a propensity to choose smaller sooner rewards over larger later rewards, which is associated with reduced access to net reinforcement over time and contributes to maladaptive health decision-making in multiple health domains (Moody, Franck, & Bickel, 2016). For example, overvaluation of immediate drug-related reinforcement (e.g., euphoria) at the expense of increased risk of negative future health outcomes is associated with persistent and elevated substance use consistent with conceptualizations of a "loss of control." Similarly, relationships between excessive DD and elevated anxiety, depression, and post-traumatic stress disorder symptoms (PTSD; Amlung et al., 2019) may be driven by avoidance of aversive stimuli derived at the expense of pursuing adaptive reinforcement in daily life or due to hopelessness about the future which drives devaluation of future rewards(Olin et al., 2022; Pulcu et al., 2014). Together with findings indicating that DD is both reliable over time within individuals and malleable in response to contextual factors or interventions (such as behavioral therapies), these findings suggest DD may be a core, malleable, and transdiagnostic treatment target (Miller et al., 2023; Odum, 2011b; Reyes-Huerta et al., 2023; Rung et al., 2019; Sofis et al., 2017; Strickland et al., 2023; Sze et al., 2017).

Despite evidence for the role of DD as a transdiagnostic indicator of problematic substance use and mental health symptoms, the existing evidence for this assertion is not without criticism (Bailey, Romeu, & Finn, 2021, 2023; cf. Stein et al., 2022). One limitation is that health behaviors and determinants of health known to increase or decrease risks for problematic substance use and adverse mental health outcomes are omitted from most studies exploring how DD relates to addiction and mental health outcomes. For example, adverse childhood experiences (Mersky et al., 2013), lack of healthcare access (Han et al., 2017; Knickman et al., 2016), houselessness (Dawson-Rose et al., 2020), poor sleep quality (Geoffroy et al., 2020), excessive social media use (Berryman et al., 2018), and infrequent physical activity (Ashdown-Franks et al., 2020) are each associated with increased risk of problematic substance use and elevated mental health symptomology, but no studies to our knowledge have examined the relationship between DD and either addiction or mental health outcomes while controlling for more than two of these health factors. Furthermore, homogenous sample recruitment (e.g., college students, individuals with substance use disorder) commonly used restrict variability observed in covariates and may fail to fully capture the independent contributions of DD. Moreover, relatively few studies have explored how DD relates to problematic alcohol, opioid, and stimulant use, despite the fact that alcohol use disorder (AUD) remains the most common substance use disorder in the U.S. and problematic opioid and stimulant use are overwhelmingly the largest contributors to preventable overdose deaths (O'Donnell, 2020; Tucker et al., 2020). Thus, more research (including large, heterogeneous samples and validated measures addressing a wide range of health behaviors, factors, and clinically significant addiction outcomes) is warranted to more rigorously test for the potential role of DD as a transdiagnostic process.

Therefore, in the current online survey study, we examined the relationship between DD and both problematic substance use (alcohol, opioids, stimulants) and mental health symptoms (anxiety, depression, PTSD) while controlling for diverse health-related behaviors and health outcomes. Our goal was to test the relationship between DD and health outcomes known to relate to DD (i.e., substance use disorders, anxiety, depression, post-traumatic stress disorder (PTSD); (Bryan & Bryan, 2021; Exum, Sutton, Bellitti, Yi, & Fazzino, 2023; Ho, Dang, Odum, DeHart, & Weiss, 2023; Moody, Franck, Hatz, et al., 2016; Olin et al., 2022; Stein & Madden, 2013) while controlling for the effects of other health-related behaviors and barriers that may be related to these health outcomes, allowing for more rigorous examination of the transdiagnostic, predictive utility of DD.

2. Method

2.1. Participants

U.S. residents ($n = 8208$) from all 50 states were recruited in 2023 (June-July) using Cint's Survey Marketplace, which integrates hundreds of research panels containing access to at least 22 million U.S. residents, to complete a Qualtrics survey. The sample was demographically and geographically congruent with the general US population. Of those 8208, 1053 participants were excluded for missing a one-item attention check or a computer bot check. A further 2737 participants stopped responding partway through the survey; of the remaining 4418 participants who finished the survey, 426 did not provide complete answers to all variables included in the present analysis, leaving a final sample of 3992.

2.2. Procedure

Participants provided informed consent and the study was approved by the AHP IRB (protocol #7420.1). The survey included measures pertaining to health-related behaviors, barriers limiting one's ability to engage in health-related behaviors, DD, problematic substance use, mental health, and demographic information (e.g., age, education, family income, race, gender). We describe measures relevant to this report below; the complete survey is provided in the supplemental materials.

2.3. Measures

Health-related behaviors. This category included the following measures: sleep quality via the Pittsburgh Insomnia Rating Scale 20-item version (PIRS-20; Moul et al., 2007), hours spent per day during a typical week using social media, problematic substance use, and exercise frequency.

The PIRS-20 assesses sleep quality during the previous week (Cronbach's $\alpha = 0.93$). Summed responses are used to create an overall sleep quality score (0–60), wherein higher values denote worse sleep quality. Participants reported their daily time usage of social media in a typical week by selecting either "less than 30 min," "between 30 mins to 1 h," "1–2 h," "3–5 h," "6–8 h," "9–12 h," or "more than 12 h." We recoded responses to create four levels: one hour or less, 1–2 h, 3–5 h, and six or more hours. The Alcohol, Smoking, and Substance Involvement Screening Test – Lite (ASSIST-Lite; Ali et al., 2013) was used to assess problematic alcohol (Cronbach's $\alpha = 0.72$; scores ranged from 0 to 4 with moderate risk cutoff ≥ 2), non-prescribed opioid (Cronbach's $\alpha = 0.91$; scores ranged from 0 to 3 with moderate risk cutoff ≥ 1), and non-prescribed stimulant use (Cronbach's $\alpha = 0.90$; scores ranged from 0 to 3 with moderate risk cutoff ≥ 1). To measure exercise frequency, participants reported their frequency of any form of exercise; three levels of response options were scored: 1) "never," "less than once a year," and "several times per year" were recoded as "irregular exercise"; 2) "several times per month" and "once per week" were recoded as "semi-regular exercise"; 3) "several times per week" and "daily" were recoded as "regular exercise.".

Barriers to health-related behaviors. Barriers to health behaviors included ease of healthcare access, adverse childhood experiences (Felitti et al., 1998), and housing status (i.e., sleep location).

For healthcare access, participants reported how difficult it was for them to access healthcare services when needed. We recoded responses to create three levels: 1) "very difficult," "difficult," and "somewhat difficult" were recoded to "difficult"; 2) "somewhat easy," "easy," and "very easy" were recoded to "easy"; 3) "I did not access healthcare services within the past 12 months" was not recoded. To measure adverse childhood experiences, we used the 10-item Adverse Childhood Experiences (ACEs) questionnaire (Cronbach's $\alpha = 0.83$; Wingenfeld et al., 2011). We added the number of questions answered affirmatively to create a summed ACE score (0–10). To measure housing status, participants reported where they slept last night; response options were "in an emergency shelter, safe haven, or transitional housing project"; "in a facility (including hospital, jail, prison, juvenile detention facility, long-term care facility, or nursing home"; "in a place not meant for human habitation (including in a car, unsheltered on the street or under a bridge, etc."; "in housing you shared with others, but did not own"; "in a house or apartment you own or rent"; and "in a house or apartment or other safe housing that a friend or family owns or rents." We recoded responses to create two levels: the first three levels listed above were recoded as "transient, non-stable conditions," and the final three were recoded as "stable living conditions.".

Delay Discounting. We used the five-trial adjusting-delay task; participants indicated preferences between \$50 now or \$100 after a series of delays (Koffarnus & Bickel, 2014). As an attention check for participants who chose either the larger later or smaller sooner option across all trials, we presented an additional trial asking participants to indicate their preference between \$100 now or \$100 in 25 years or \$0 now or \$100 in one day, respectively. Participants who indicated either \$100 in 25 years or \$0 now when the alternative option was more advantageous were excluded from analysis ($n = 60$; Koffarnus, Rzeszutek, & Kaplan, 2021). Natural log transformed k values ($\ln[k]$) for all other participants were included in subsequent analyses.

2.4. Mental health

This category included measuring symptoms related to PTSD, depression, and generalized anxiety.

PTSD was assessed using the Short Post-Traumatic Stress Disorder Rating Interview (SPRINT; Cronbach's $\alpha = 0.94$; cutoff score = 14; Connor & Davidson, 2001), depression using the Patient Health Questionnaire-2 (PHQ-2; Cronbach's $\alpha = 0.88$; cutoff score = 3; Kroenke et al., 2003), and anxiety using the Generalized Anxiety Disorder-2 scale (GAD-2; Cronbach's $\alpha = 0.88$; cutoff score = 3; Kroenke et al., 2007).

2.5. Data analysis

We used multiple regression to predict scores on validated measures of mental health or health-related behaviors (SPRINT, PHQ-2, GAD-2, and ASSIST scores). We first modeled each outcome variable using only DD and demographic variables (age, income, gender, race, ethnicity, and education). In a hierarchical fashion, we then modeled each outcome variable by adding predictors related to health behaviors and health barriers (ACEs score, exercise frequency, time spent on social media, access to healthcare, and housing status) to the original variable set. We used linear regression to model PTSD scores via SPRINT and ordinal logistic regression to model ordinal variables (depression via PHQ-2; anxiety via GAD-2; and alcohol, stimulants, and opioid substance use via ASSIST).

Analyses were performed using R V.4.3.1 (R Core Team, 2022). The following packages were used: *tidyverse, beezdiscounting, gtsummary*, *summarytools*, *sensemakr, sjPlot*, and *MASS* (Cinelli et al., 2020; Comtois, 2022; Kaplan, 2023; Lüdecke et al., 2023; Sjoberg et al., 2021; Wickham et al., 2019; Venables & Ripley, 2002). Data and code to recreate these analyses are located here: https://osf.io/835gc/.

3. Results

Demographic characteristics included in analyses are depicted in Table 1. A third of participants met criteria for moderate or high-risk alcohol ($n = 1465$; 33.2 %), whereas only 10.4 % and 7.2 % met criteria for stimulants ($n = 459$) and opioid use ($n = 319$). Similarly, a little less than 30 % of the sample scored above the cutoff level for PTSD ($n = 1306$; 29.5 %), PHQ-2 ($n = 1203$; 27.2 %), and GAD-2 ($n = 1315$; 29.8 %).

The results of the models including only DD and demographics as predictors, and figures summarizing the distributions of each dependent and independent variables, are available in the supplemental materials.

PTSD. The multiple linear regression predicting PTSD scores as a function of all independent variables explained a statistically significant and substantial proportion of variance ($R^2 = 0.54$, $F(27, 3964) = 173.4$, $p < .001$, adj. $R^2 = 0.54$); the full model is depicted in Table 2. DD remained a significant predictor of PTSD scores after controlling for all covariates, although the effect size was small ($f^2 = .002$).

Depression, Anxiety, and Substance Use. The ordinal logistic regressions predicting PHQ-2, GAD-2, and ASSIST scores each accounted for a significant amount of variance in the outcomes compared to null models: $\chi2$ (27) = 1934.83, $p < .001$; $\chi2$ (27) = 1929.7, $p < .001$; $\chi2$ (27) = 559.86, $p < .001$; $\chi2$ (27) = 601.12, $p < .001$; and $\chi2$ (27) = 589.63, $p < .001$, respectively. Besides opioid ASSIST scores, DD remained a significant predictor of five out of six ordinal outcomes, although the effect sizes were small (*ORs*; 1.03–1.12). The full ordinal logistic models are depicted in Table 3.

Table 1
Demographics of participants included in analyses.

Characteristic	N = 3992[1]
Age	41 (29, 59)
Race	
American Indian, Native American, or Alaskan Native	53 (1.3 %)
Asian	150 (3.8 %)
Black or African American	584 (15 %)
More Than One Race	135 (3.4 %)
Native Hawaiian or other Pacific Islander	14 (0.4 %)
Other	151 (3.8 %)
White	2905 (73 %)
Gender	
Female	2688 (67 %)
Male	1211 (30 %)
Other	93 (2.3 %)
Education	
High school or less	1248 (31 %)
Trade school, some college, or Associate's degree	1456 (36 %)
Bachelor's degree or more	1288 (32 %)
Ethnicity	
Not Hispanic or Latino	3529 (88 %)
Hispanic or Latino	463 (12 %)
Family Income	
15k or less	731 (18 %)
25k−45k	1389 (35 %)
55k−65k	700 (18 %)
75k−95k	511 (13 %)
125k or more	661 (17 %)

[1]Median (IQR); n (%)

4. Discussion

The present study extends findings from previous cross-sectional studies showing that excessive DD is associated with elevated risks for mental health symptoms and clinically problematic substance use. We show that DD significantly predicted problematic substance use (alcohol, non-prescribed opioids, non-prescribed stimulants) even when accounting for the influence of diverse health behaviors and factors known to covary with DD, problematic substance use, and mental health symptomology. Consistent with previous cross-sectional studies, the effect sizes associated with DD and both problematic substance use and mental health outcomes found here were small (Dwyer et al., 2024; Levitt et al., 2023), which suggests that DD is unlikely to fully account for the presence or symptomology of these health conditions (Bailey et al., 2021). However, DD remained a significant predictor of

Table 2
Multiple Linear Regression Predicting SPRINT Scores.

	SPRINT score			
Predictors	*Estimates*	*CI*	*p*	f^2
(Intercept)	0.82	−0.30 to 1.95	0.153	0.001
ACE Score	0.89	0.82–0.97	<0.001	0.144
Exercise				
Irregular	*Reference*			
Semi-regular	−0.11	−0.60–0.38	0.653	0.000
Regular	−0.29	−0.75–0.16	0.204	0.000
Age	−0.02	−0.04 to −0.01	<0.001	0.004
Income				
15k or less	*Reference*			
25k−45k	−0.94	−1.48 to −0.41	0.001	0.003
55k−65k	−0.83	−1.46 to −0.21	0.009	0.002
75k−95k	−1.11	−1.80 to −0.42	0.002	0.002
125k or more	−0.88	−1.57 to −0.20	0.011	0.002
Ln*k*	0.11	0.03–0.18	0.006	0.002
Social Media Use				
1 h or less	*Reference*			
1–2 h	0.17	−0.33–0.66	0.510	0.000
3–5 h	0.46	−0.07–0.98	0.087	0.001
6 or more hours	1.63	1.07–2.20	<0.001	0.008
Healthcare Access				
None in past year	*Reference*			
Difficult	1.65	0.89–2.40	<0.001	0.005
Easy	0.04	−0.63 to 0.70	0.917	0.000
Race				
White	*Reference*			
American Indian, Native American, or Alaskan Native	−0.82	−2.41 to 0.77	0.311	0.000
Asian	−1.39	−2.36 to −0.43	0.005	0.002
Black or African American	−0.39	−0.93 to 0.15	0.157	0.001
Native Hawaiian or other Pacific Islander	0.52	−2.55 to 3.59	0.738	0.000
More Than One Race	−0.03	−1.05 to 0.99	0.956	0.000
Other	−0.15	−1.17 to 0.87	0.772	0.000
Ethnicity				
Not Hispanic or Latino	*Reference*			
Hispanic or Latino	−0.06	−0.68 to 0.56	0.848	0.000
Gender				
Female	*Reference*			
Male	0.39	−0.01 to 0.80	0.055	0.001
Other	0.70	−0.53 to 1.92	0.263	0.000
Education				
High school or less	*Reference*			
Trade school, some college, or Associate's degree	−0.19	−0.64 to 0.27	0.415	0.000
Bachelor's degree or more	0.65	0.14–1.16	0.012	0.002
PIRS-20	0.35	0.33–0.37	<0.001	0.385
Sleep Location				
Stable living conditions	*Reference*			
Transient, non-stable conditions	3.94	3.22–4.66	<0.001	0.029
Observations	3992			
R^2 / R^2 adjusted	0.542 / 0.538			

problematic alcohol and stimulant use, and anxiety, depression, and PTSD symptoms when controlling for health barriers (i.e., early childhood adversity, limited healthcare access), pro-health behaviors (i.e., physical exercise, sleep quality), and other non-substance related behaviors. Together, these findings provide additional evidence that DD functions as a transdiagnostic indicator of problematic substance use and mental health symptoms.

The observed effect sizes in the full models were lower than those found when testing the direct relationships between DD and demographics with each outcome (see supplemental materials Tables 1-2); however, over half of those in the general population with at least one substance use disorder meet criteria for concurrent substance use disorders, in addition to meeting criteria for major depressive disorder or generalized anxiety disorder (GAD) (Center for Behavioral Health Statistics and Quality, 2023; Lai et al., 2015). The prevalent comorbidity of these conditions suggests that it may be fruitful for future research to examine how effectively targeting DD may result in effects across a range of psychopathologies, potentially leading to clinically significant cumulative improvements in mental health. Indeed, recent evidence suggests that higher rates of DD during developmental changes between childhood and adolescence predict the co-occurrence of several psychiatric disorders even when controlling for socioeconomic variables, emotional and behavior problems, and cognitive performance (DeRosa et al., 2024). Additional evidence suggests that DD more strongly predicts polysubstance use and accounts for more variance in co-occurring clinical outcomes (polysubstance use, comorbid mental health conditions), specifically in more clinically severe populations compared to individuals using a single substance (Moody, Franck, Hatz, et al., 2016). Taken together, these findings suggest that when developing treatments to target multiple SUDs or mental health disorders, DD may represent a clinically meaningful target despite the small effect sizes associated with each outcome given shared variance between DD and both problematic substance use and mental health outcomes. While there is much to be explored with respect to clinical relevance, these findings support the notion of DD as a transdiagnostic process.

Two strengths of this study provide additional evidence supporting DD as a transdiagnostic indicator. First, the current sample was large, diverse, and both demographically and geographically congruent with the U.S. population, which increases our confidence that these findings may generalize to other settings or populations for which DD might be used to identify risks of comorbid behavioral health conditions. Second, younger age, higher ACE scores, worse sleep quality, engaging in six or more hours of daily social media use, and currently experiencing transient or non-stable housing conditions significantly predicted each problematic substance use and mental health outcomes (Dawson-Rose et al., 2020; Geoffroy et al., 2020; Halladay et al., 2024; Levitt et al., 2021; Mersky et al., 2013). By replicating the anticipated relationships with problematic substance use and mental health symptoms found in previous studies while controlling for these health behaviors and barriers, increased confidence in each of the direct relationships between DD and these outcomes is obtained.

We note four limitations of this study. First, the cross-sectional design of this study does not inform the direction of the relationships between DD and the dependent measures. Second, we did not specify *a priori* hypotheses regarding model specification and results; as such, we did not employ type I error correction, nor did we conduct a power analysis to ensure adequate power to detect an effect for each predictor across multiple models. However, our large sample size of $n = 3992$ heterogeneous participants offset concern that we did not observe statistically significant effects in several predictors. Third, while we measured our dependent variables and DD using validated scales, not all predictors in the models were assessed using validated scales (e.g., exercise, healthcare access, social media usage). Several of these measures significantly predicted some of the outcome variables, but future research should use validated scales. Fourth, myriad barriers to health-related behaviors or cognitive patterns related to our outcomes of

Table 3
Ordinal Logistic Regressions Predicting PHQ-2, GAD-2, ASSIST – Alcohol, ASSIST – Stimulants, and ASSIST – Opioids Scores.

	PHQ-2			**GAD-2**			**ASSIST − Alcohol**			**ASSIST − Stimulants**			**ASSIST − Opioids**		
Predictors	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
0|1	2.72	1.86–3.97	<0.001	1.86	1.28–2.71	0.001	2.70	1.86–3.92	<0.001	43.33	19.52–96.16	<0.001	135.13	44.90–406.67	<0.001
1|2	5.85	3.99–8.58	<0.001	4.09	2.80–5.96	<0.001	9.29	6.37–13.54	<0.001	63.11	28.32–140.67	<0.001	202.05	66.76–611.52	<0.001
2|3	19.93	13.48–29.47	<0.001	14.93	10.17–21.92	<0.001	40.17	27.25–59.22	<0.001	121.91	54.12–274.64	<0.001	350.75	114.76–1072.07	<0.001
3|4	35.63	23.98–52.94	<0.001	27.25	18.47–40.18	<0.001	87.04	58.32–129.91	<0.001						
4|5	78.85	52.62–118.17	<0.001	55.97	37.69–83.11	<0.001									
5|6	148.22	97.99–224.21	<0.001	105.29	70.33–157.64	<0.001									
ACE Score	1.10	1.08–1.13	<0.001	1.10	1.07–1.12	<0.001	1.09	1.07–1.12	<0.001	1.20	1.15–1.25	<0.001	1.28	1.22–1.34	<0.001
Exercise															
Irregular	*Reference*														
Semi-regular	0.87	0.75–1.02	0.096	0.87	0.74–1.01	0.074	1.22	1.05–1.43	0.011	0.96	0.72–1.29	0.806	0.91	0.63–1.32	0.620
Regular	0.73	0.63–0.85	<0.001	0.81	0.70–0.94	0.005	1.29	1.11–1.49	0.001	0.97	0.73–1.29	0.826	1.12	0.79–1.59	0.516
Age	0.99	0.98–0.99	<0.001	0.98	0.98–0.99	<0.001	0.99	0.99–1.00	<0.001	0.98	0.97–0.99	<0.001	0.97	0.96–0.98	<0.001
Income															
15k or less	*Reference*														
25k−45k	1.08	0.91–1.29	0.366	1.18	0.99–1.41	0.059	1.68	1.41–2.02	<0.001	1.31	0.94–1.83	0.117	1.27	0.84–1.95	0.267
55k−65k	0.92	0.75–1.13	0.435	1.16	0.94–1.42	0.164	2.18	1.78–2.68	<0.001	1.18	0.79–1.75	0.425	1.38	0.85–2.25	0.195
75k−95k	0.94	0.75–1.18	0.579	1.01	0.80–1.26	0.954	2.32	1.85–2.90	<0.001	1.05	0.66–1.65	0.835	1.28	0.74–2.19	0.379
125k or more	0.91	0.72–1.14	0.404	1.04	0.83–1.30	0.712	2.68	2.15–3.35	<0.001	1.75	1.16–2.67	0.009	1.97	1.20–3.28	0.008
ln*k*	1.04	1.01–1.06	0.004	1.03	1.00–1.06	0.024	1.06	1.03–1.09	<0.001	1.12	1.08–1.18	<0.001	1.05	1.00–1.11	0.059
Social Media Use															
1 h or less	*Reference*														
1–2 h	1.13	0.96–1.34	0.152	1.28	1.09–1.51	0.003	1.26	1.08–1.47	0.004	1.12	0.79–1.60	0.529	0.75	0.47–1.20	0.236
3–5 h	1.28	1.08–1.51	0.005	1.35	1.14–1.59	0.001	1.35	1.15–1.60	<0.001	1.25	0.89–1.77	0.204	1.26	0.83–1.93	0.277
6 or more hours	1.34	1.11–1.62	0.002	1.33	1.11–1.60	0.002	1.60	1.34–1.92	<0.001	1.85	1.32–2.61	<0.001	1.84	1.22–2.81	0.004
Healthcare Access															
None in past year	*Reference*														
Difficult	1.08	0.84–1.39	0.557	1.17	0.91–1.50	0.213	1.26	0.98–1.62	0.072	1.44	0.88–2.48	0.166	2.37	1.12–5.81	0.037
Easy	0.91	0.72–1.14	0.388	1.02	0.82–1.27	0.877	1.41	1.14–1.76	0.002	1.23	0.77–2.08	0.413	2.43	1.18–5.90	0.028
Race															
White	*Reference*														
American Indian, Native American, or Alaskan Native	1.02	0.60–1.71	0.950	0.73	0.43–1.22	0.227	1.65	1.00–2.73	0.050	1.09	0.42–2.45	0.845	1.09	0.35–2.79	0.866
Asian	0.81	0.59–1.11	0.197	0.59	0.44–0.80	0.001	0.80	0.59–1.09	0.158	0.46	0.20–0.93	0.045	0.51	0.20–1.11	0.116
Black or African American	0.83	0.69–0.99	0.034	0.71	0.59–0.84	<0.001	1.27	1.07–1.52	0.006	0.98	0.72–1.32	0.883	1.02	0.71–1.46	0.903
Native Hawaiian or other Pacific Islander	0.82	0.26–2.37	0.715	0.50	0.18–1.34	0.177	0.39	0.12–1.15	0.094	1.20	0.18–4.69	0.815	1.02	0.05–5.56	0.985
More Than One Race	0.91	0.65–1.27	0.582	0.75	0.54–1.03	0.079	0.53	0.37–0.74	<0.001	0.65	0.34–1.16	0.164	0.42	0.17–0.91	0.042
Other	0.83	0.59–1.16	0.282	0.98	0.71–1.35	0.916	0.73	0.52–1.03	0.071	0.56	0.27–1.08	0.101	0.63	0.26–1.35	0.267
Ethnicity															
Not Hispanic or Latino	*Reference*														

(*continued on next page*)

Table 3 (*continued*)

Predictors	PHQ-2			GAD-2			ASSIST — Alcohol			ASSIST — Stimulants			ASSIST — Opioids		
	Odds Ratios	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
Hispanic or Latino	0.91	0.74–1.11	0.332	0.78	0.64–0.95	0.016	1.11	0.91–1.35	0.307	1.11	0.79–1.55	0.541	1.07	0.71–1.58	0.744
Gender															
Female	*Reference*														
Male	1.05	0.92–1.20	0.456	0.81	0.71–0.92	0.001	1.58	1.39–1.80	<0.001	2.55	2.01–3.23	<0.001	2.85	2.14–3.80	<0.001
Other	0.81	0.54–1.19	0.285	0.62	0.42–0.91	0.016	0.59	0.39–0.88	0.011	0.79	0.35–1.59	0.538	0.75	0.28–1.70	0.525
Education															
High school or less	*Reference*														
Trade school, some college, or Associate's degree	0.96	0.83–1.12	0.631	1.07	0.92–1.24	0.382	1.16	1.00–1.35	0.045	1.04	0.79–1.38	0.785	0.72	0.51–1.03	0.070
Bachelor's degree or more	1.01	0.85–1.20	0.907	1.22	1.04–1.45	0.017	1.31	1.11–1.54	0.001	1.23	0.89–1.71	0.209	1.21	0.83–1.77	0.326
PIRS-20	1.11	1.10–1.11	<0.001	1.10	1.10–1.11	<0.001	1.01	1.01–1.02	<0.001	1.03	1.02–1.04	<0.001	1.03	1.01–1.04	<0.001
Sleep Location															
Stable living conditions	*Reference*														
Transient, non-stable conditions	1.82	1.46–2.27	<0.001	1.77	1.42–2.20	<0.001	1.87	1.45–2.40	<0.001	4.41	3.28–5.90	<0.001	5.13	3.68–7.14	<0.001
Observations	3992			3992			3992			3992			3992		
R^2 Nagelkerke	0.398			0.395			0.139			0.239			0.285		

Note: 0|1, 1|2, 2|3, etc. indicate the odds of being at least in that category or lower given all other covariates at their reference levels (i.e., intercepts).

interest were not assessed – we chose to include measures across diverse health dimensions, including pro-health behaviors (e.g., exercise), non-substance-related addictive outcomes (e.g., social media), health barriers (e.g., housing status and healthcare access), and supplemental health outcomes (e.g., sleep quality), while also weighing participant burden. Future research should include additional measures spanning an even wider gamut of health-related measures.

The present study extends previous work highlighting the empirical connectedness between DD and both problematic substance use and mental health symptoms by accounting for current and previous health-related behaviors, environmental factors, and health outcomes (Finlay et al., 2022; Guidi et al., 2021; Leventhal et al., 2019; Martinez et al., 2022; Suvarna et al., 2020). By measuring diverse factors relevant to multiple health-related behaviors in a large, heterogenous sample, we provide additional support for the role of DD as a transdiagnostic process underlying multiple psychopathologies and health-demoting behaviors. In summary, our results suggest targeting the transdiagnostic functioning of DD may meaningfully contribute to the understanding of and treatment success for co-occurring substance use disorders and/or mental health diagnoses.

CRediT authorship contribution statement

Jeremiah M. Brown: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation. **Michael Sofis:** Writing – review & editing, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Sara Zimmer:** Writing – review & editing, Software, Resources, Methodology, Investigation, Conceptualization. **Brent A. Kaplan:** Writing – review & editing, Visualization, Supervision, Project administration, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Deidentified data, analysis code, and supplementary materials can be found in the following Open Science Framework project: https://osf.io/835gc/.

References

Ali, R., Meena, S., Eastwood, B., Richards, I., & Marsden, J. (2013). Ultra-rapid screening for substance-use disorders: The Alcohol, Smoking and Substance Involvement Screening Test (ASSIST-Lite). *Drug and Alcohol Dependence, 132*(1–2), 352–361. https://doi.org/10.1016/j.drugalcdep.2013.03.001

Amlung, M., Marsden, E., Holshausen, K., Morris, V., Patel, H., Vedelago, L., Naish, K. R., Reed, D. D., & McCabe, R. E. (2019). Delay discounting as a transdiagnostic process in psychiatric disorders: A meta-analysis. *JAMA Psychiatry, 76*(11), 1176–1186. https://doi.org/10.1001/jamapsychiatry.2019.2102

Ashdown-Franks, G., Firth, J., Carney, R., Carvalho, A. F., Hallgren, M., Koyanagi, A., Rosenbaum, S., Schuch, F. B., Smith, L., Solmi, M., Vancampfort, D., & Stubbs, B. (2020). Exercise as medicine for mental and substance use disorders: A meta-review of the benefits for neuropsychiatric and cognitive outcomes. *Sports Medicine, 50*(1), 151–170. https://doi.org/10.1007/s40279-019-01187-6

Bailey, A. J., Romeu, R. J., & Finn, P. R. (2021). The problems with delay discounting: A critical review of current practices and clinical applications. *Psychological Medicine, 1–8*. https://doi.org/10.1017/S0033291721002282

Bailey, A. J., Romeu, R. J., & Finn, P. R. (2023). The fundamental questions left unanswered: Response to commentary on the 'problems with delay discounting'. *Psychological Medicine, 53(4), 1660-1661*. https://doi.org/10.1017/S0033291721005572

Berryman, C., Ferguson, C. J., & Negy, C. (2018). Social media use and mental health among young adults. *The Psychiatric Quarterly, 89*(2), 307–314. https://doi.org/10.1007/s11126-017-9535-6

Bryan, C. J., & Bryan, A. O. (2021). Delayed reward discounting and increased risk for suicide attempts among U.S. adults with probable PTSD. *Journal of Anxiety Disorders, 81*, Article 102414. https://doi.org/10.1016/j.janxdis.2021.102414

Calvin, A. D., Carter, R. E., Adachi, T., Macedo, P. G., Albuquerque, F. N., van der Walt, C., Bukartyk, J., Davison, D. E., Levine, J. A., & Somers, V. K. (2013). Effects of experimental sleep restriction on caloric intake and activity energy expenditure. *Chest, 144*(1), 79–86. https://doi.org/10.1378/chest.12-2829

Center for Behavioral Health Statistics and Quality. (2023). *Results from the 2022 National Survey on Drug Use and Health: Detailed tables*. Substance Abuse and Mental Health Services Administration. https://www.samhsa.gov/data/report/2022-nsduh-detailed-tables.

Cinelli, C., Ferwerda, J., & Hazlett, C. (2020). *sensemakr: Sensitivity Analysis Tools for OLS in R and Stata*.

Comtois, D. (2022). *summarytools: Tools to Quickly and Neatly Summarize Data* (1.0.1) [Computer software]. https://cran.r-project.org/web/packages/summarytools/index.html.

Connor, K. M., & Davidson, J. R. (2001). SPRINT: A brief global assessment of post-traumatic stress disorder. *International Clinical Psychopharmacology, 16*(5), 279–284. https://doi.org/10.1097/00004850-200109000-00005

Dalgleish, T., Black, M., Johnston, D., & Bevan, A. (2020). Transdiagnostic approaches to mental health problems: Current status and future directions. *Journal of Consulting and Clinical Psychology, 88*(3), 179–195. https://doi.org/10.1037/ccp0000482

Dawson-Rose, C., Shehadeh, D., Hao, J., Barnard, J., Khoddam-Khorasani, L. (Ladi), Leonard, A., Clark, K., Kersey, E., Mousseau, H., Frank, J., Miller, A., Carrico, A., Schustack, A., & Cuca, Y. P. (2020). Trauma, substance use, and mental health symptoms in transitional age youth experiencing homelessness. *Public Health Nursing, 37*(3), 363–370. doi:10.1111/phn.12727.

DeRosa, J., Rosch, K. S., Mostofsky, S. H., & Nikolaidis, A. (2024). Developmental deviation in delay discounting as a transdiagnostic indicator of risk for child psychopathology. *Journal of Child Psychology and Psychiatry, 65*(2), 148–164. https://doi.org/10.1111/jcpp.13870

Dwyer, C. L., Craft, W. H., Tomlinson, D. C., Tegge, A. N., Kim-Spoon, J., & Bickel, W. K. (2024). Latent profiles of regulatory flexibility in alcohol use disorder: Associations with delay discounting and symptoms of depression, anxiety, and stress. *Alcohol, Clinical and Experimental Research, 48*(1), 188–198. https://doi.org/10.1111/acer.15235

Exum, A. C., Sutton, C. A., Bellitti, J. S., Yi, R., & Fazzino, T. L. (2023). Delay discounting and substance use treatment outcomes: A systematic review focused on treatment outcomes and discounting methodology. *Journal of Substance Use and Addiction Treatment, 149*, 209037. https://doi.org/10.1016/j.josat.2023.209037

Felitti, V. J., Anda, R. F., Nordenberg, D., Williamson, D. F., Spitz, A. M., Edwards, V., Koss, M. P., & Marks, J. S. (1998). Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults: The Adverse Childhood Experiences (ACE) Study. *American Journal of Preventive Medicine, 14*(4), 245–258. https://doi.org/10.1016/S0749-3797(98)00017-8

Finlay, S., Roth, C., Zimsen, T., Bridson, T. L., Sarnyai, Z., & McDermott, B. (2022). Adverse childhood experiences and allostatic load: A systematic review. *Neuroscience & Biobehavioral Reviews, 136*, Article 104605. https://doi.org/10.1016/j.neubiorev.2022.104605

Fusar-Poli, P., Solmi, M., Brondino, N., Davies, C., Chae, C., Politi, P., Borgwardt, S., Lawrie, S. M., Parnas, J., & McGuire, P. (2019). Transdiagnostic psychiatry: A systematic review. *World Psychiatry, 18*(2), 192–207. https://doi.org/10.1002/wps.20631

Gandini, S., Botteri, E., Iodice, S., Boniol, M., Lowenfels, A. B., Maisonneuve, P., & Boyle, P. (2008). Tobacco smoking and cancer: A meta-analysis. *International Journal of Cancer, 122*(1), 155–164. https://doi.org/10.1002/ijc.23033

Geoffroy, P. A., Tebeka, S., Blanco, C., Dubertret, C., & Le Strat, Y. (2020). Shorter and longer durations of sleep are associated with an increased twelve-month prevalence of psychiatric and substance use disorders: Findings from a nationally representative survey of US adults (NESARC-III). *Journal of Psychiatric Research, 124*, 34–41. https://doi.org/10.1016/j.jpsychires.2020.02.018

Guidi, J., Lucente, M., Sonino, N., & Fava, G. A. (2021). Allostatic Load and Its Impact on Health: A Systematic Review. *Psychotherapy and Psychosomatics, 90*(1), 11–27. https://doi.org/10.1159/000510696

Halladay, J., Sunderland, M., Chapman, C., Teesson, M., & Slade, T. (2024). The InterSECT framework: A proposed model for explaining population-level trends in substance use and emotional concerns. *American Journal of Epidemiology.* , Article kwae013. https://doi.org/10.1093/aje/kwae013

Han, B., Compton, W. M., Blanco, C., & Colpe, L. J. (2017). Prevalence, treatment, and unmet treatment needs of US Adults with mental health and substance use disorders. *Health Affairs, 36*(10), 1739–1747. https://doi.org/10.1377/hlthaff.2017.0584

Higgins, S. T., DeSarno, M., Bunn, J. Y., Gaalema, D. E., Leventhal, A. M., Davis, D. R., … Hughes, J. R. (2021). Cumulative vulnerabilities as a potential moderator of response to reduced nicotine content cigarettes. *Preventive Medicine, 152*, Article 106714. https://doi.org/10.1016/j.ypmed.2021.106714

Ho, H., Dang, H.-M., Odum, A. L., DeHart, W. B., & Weiss, B. (2023). Sooner is better: Longitudinal relations between delay discounting, and depression and anxiety symptoms among vietnamese adolescents. *Research on Child and Adolescent Psychopathology, 51*, 133–147. https://doi.org/10.1007/s10802-022-00959-5

Hoevenaar-Blom, M. P., Spijkerman, A. M. W., Kromhout, D., van den Berg, J. F., & Verschuren, W. M. M. (2011). Sleep Duration and Sleep Quality in Relation to 12-Year Cardiovascular Disease Incidence: The MORGEN Study. *Sleep, 34*(11), 1487–1492. https://doi.org/10.5665/sleep.1382

Huber, M., Knottnerus, J. A., Green, L., van der Horst, H., Jadad, A. R., Kromhout, D., Leonard, B., Lorig, K., Loureiro, M. I., van der Meer, J. W. M., Schnabel, P., Smith, R., van Weel, C., & Smid, H. (2011). How should we define health? *BMJ, 343*, Article d4163. https://doi.org/10.1136/bmj.d4163

Kim-Spoon, J., Lauharatanahirun, N., Peviani, K., Brieant, A., Deater-Deckard, K., Bickel, W. K., & King-Casas, B. (2019). Longitudinal pathways linking family risk, neural risk processing, delay discounting, and adolescent substance use. *Journal of Child Psychology and Psychiatry, 60*(6), 655–664. https://doi.org/10.1111/jcpp.13015

Knickman, J., Krishnan, R., & Pincus, H. (2016). Improving access to effective care for people with mental health and substance use disorders. *Journal of the American Medical Association, 316*(16), 1647–1648. https://doi.org/10.1001/jama.2016.13639

Koffarnus, M. N., & Bickel, W. K. (2014). A 5-trial adjusting delay discounting task: Accurate discount rates in less than 60 seconds. *Experimental and Clinical Psychopharmacology, 22*(3), 222–228. https://doi.org/10.1037/a0035973

Kaplan, B. A.. *beezdiscounting: Behavioral Economic Easy Discounting* (0.3.1) [R package version 0.3.1]. https://cran.r-project.org/web/packages/beezdiscounting/index.html.

Koffarnus, M. N., Rzeszutek, M., & Kaplan, B. A. (2021). *Additional Discounting Rates in Less Than One Minute: Task Variants for Probability and a Wider Range of Delays*. https://doi.org/10.13140/RG.2.2.31281.92000

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2003). The Patient Health Questionnaire-2: Validity of a two-item depression screener. *Medical Care, 41*(11), 1284–1292. https://doi.org/10.1097/01.MLR.0000093487.78664.3C

Kroenke, K., Spitzer, R. L., Williams, J. B. W., Monahan, P. O., & Löwe, B. (2007). Anxiety disorders in primary care: Prevalence, impairment, comorbidity, and detection. *Annals of Internal Medicine, 146*(5), 317–325. https://doi.org/10.7326/0003-4819-146-5-200703060-00004

Lai, H. M. X., Cleary, M., Sitharthan, T., & Hunt, G. E. (2015). Prevalence of comorbid substance use, anxiety and mood disorders in epidemiological surveys, 1990–2014: A systematic review and meta-analysis. *Drug and Alcohol Dependence, 154*, 1–13. https://doi.org/10.1016/j.drugalcdep.2015.05.031

LeComte, R. S., Sofis, M. J., & Jarmolowicz, D. P. (2020). Independent effects of ideal body image valuation and delay discounting on proximal and typical levels of physical activity. *The Psychological Record, 70*(1), 75–82. https://doi.org/10.1007/s40732-019-00369-y

Leventhal, A. M., Bello, M. S., Galstyan, E., Higgins, S. T., & Barrington-Trimis, J. L. (2019). Association of Cumulative Socioeconomic and Health-Related Disadvantage With Disparities in Smoking Prevalence in the United States, 2008 to 2017. *JAMA Internal Medicine, 179*(6), 777–785. https://doi.org/10.1001/jamainternmed.2019.0192

Levitt, E. E., Amlung, M. T., Gonzalez, A., Oshri, A., & MacKillop, J. (2021). Consistent evidence of indirect effects of impulsive delay discounting and negative urgency between childhood adversity and adult substance use in two samples. *Psychopharmacology (Berl), 238*(7), 2011–2020. https://doi.org/10.1007/s00213-021-05827-6

Levitt, E. E., Oshri, A., Amlung, M., Ray, L. A., Sanchez-Roige, S., Palmer, A. A., & MacKillop, J. (2023). Evaluation of delay discounting as a transdiagnostic research domain criteria indicator in 1388 general community adults. *Psychological Medicine, 53*(4), 1649–1657. https://doi.org/10.1017/S0033291721005110

Lüdecke, D., Bartel, A., Schwemmer, C., Powell, C., Djalovski, A., & Titz, J. (2023). *sjPlot: Data Visualization for Statistics in Social Science* (2.8.15) [Computer software]. https://cran.r-project.org/web/packages/sjPlot/index.html.

Martinez, J. L., Hasty, C., Morabito, D., Maranges, H. M., Schmidt, N. B., & Maner, J. K. (2022). Perceptions of childhood unpredictability, delay discounting, risk-taking, and adult externalizing behaviors: A life-history approach. *Development and Psychopathology, 34*(2), 705–717. https://doi.org/10.1017/S0954579421001607

Mersky, J. P., Topitzes, J., & Reynolds, A. J. (2013). Impacts of adverse childhood experiences on health, mental health, and substance use in early adulthood: A cohort study of an urban, minority sample in the U.S. *Child Abuse & Neglect, 37*(11), 917–925. https://doi.org/10.1016/j.chiabu.2013.07.011

Miller, B. P., Reed, D. D., & Amlung, M. (2023). Reliability and validity of behavioral-economic measures: A review and synthesis of discounting and demand. *Journal of the Experimental Analysis of Behavior, 120*(2), 263–280. https://doi.org/10.1002/jeab.860

Moody, L., Franck, C., & Bickel, W. K. (2016). Comorbid depression, antisocial personality, and substance dependence: Relationship with delay discounting. *Drug and Alcohol Dependence, 160*, 190–196. https://doi.org/10.1016/j.drugalcdep.2016.01.009

Moody, L., Franck, C., Hatz, L., & Bickel, W. K. (2016). Impulsivity and polysubstance use: A systematic comparison of delay discounting in mono-, dual-, and trisubstance use. *Experimental and Clinical Psychopharmacology, 24*(1), 30–37. https://doi.org/10.1037/pha0000059

Moul, D., Mai, E., Miewald, J., Shablesky, M., Pilkonis, P., & Buysse, D. (2007). Psychometric study of the Pittsburgh Insomnia Rating Scale (PIRS) in an initial calibration sample. *Sleep, 30*, A343–A.

O'Donnell, J. (2020). Vital Signs: Characteristics of Drug Overdose Deaths Involving Opioids and Stimulants — 24 States and the District of Columbia, January–June 2019. *MMWR. Morbidity and Mortality Weekly Report, 69*. https://doi.org/10.15585/mmwr.mm6935a1

Odum, A. L. (2011a). Delay Discounting: I'm a k, You're a k. *Journal of the Experimental Analysis of Behavior, 96*(3), 427–439. https://doi.org/10.1901/jeab.2011.96-423

Odum, A. L. (2011b). Delay discounting: Trait variable? *Behavioural Processes, 87*(1), 1–9. https://doi.org/10.1016/j.beproc.2011.02.007

Olin, C. C., McDevitt-Murphy, M. E., Murphy, J. G., Zakarian, R. J., Roache, J. D., Young-McCaughan, S., & , … Peterson, A. L., for the C. to A. (2022). The associations between posttraumatic stress disorder and delay discounting, future orientation, and reward availability: A behavioral economic model. *Journal of Traumatic Stress, 35*(4), 1252–1262. https://doi.org/10.1002/jts.22820

Pancani, L., Petilli, M. A., Riva, P., & Rusconi, P. (2023). I can't live without you: Delay discounting in smartphone usage. *Journal of Cognitive Psychology, 35*(4), 441–455. https://doi.org/10.1080/20445911.2023.2195031

Pearce, M., Garcia, L., Abbas, A., Strain, T., Schuch, F. B., Golubic, R., Kelly, P., Khan, S., Utukuri, M., Laird, Y., Mok, A., Smith, A., Tainio, M., Brage, S., & Woodcock, J. (2022). Association between physical activity and risk of depression: A systematic review and meta-analysis. *JAMA Psychiatry, 79*(6), 550–559. https://doi.org/10.1001/jamapsychiatry.2022.0609

Pelucchi, C., Gallus, S., Garavello, W., Bosetti, C., & La Vecchia, C. (2008). Alcohol and tobacco use, and cancer risk for upper aerodigestive tract and liver. *European Journal of Cancer Prevention, 17*(4), 340–344.

Pelucchi, C., Tramacere, I., Boffetta, P., Negri, E., & Vecchia, C. L. (2011). Alcohol Consumption and Cancer Risk. *Nutrition and Cancer, 63*(7), 983–990. https://doi.org/10.1080/01635581.2011.596642

Pulcu, E., Trotter, P. D., Thomas, E. J., McFarquhar, M., Juhasz, G., Sahakian, B. J., Deakin, J. F. W., Zahn, R., Anderson, I. M., & Elliott, R. (2014). Temporal discounting in major depressive disorder. *Psychological Medicine, 44*(9), 1825–1834. https://doi.org/10.1017/S0033291713002584

R Core Team. (2022). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. https://www.R-project.org/.

Reyes-Huerta, H. E., Robles, E., & dos Santos, C. V. (2023). Valuing the future at different temporal points: The role of time framing on discounting. *Journal of the Experimental Analysis of Behavior, 120*(2), 1–14. https://doi.org/10.1002/jeab.871

Rung, J. M., Peck, S., Hinnenkamp, J. E., Preston, E., & Madden, G. J. (2019). Changing delay discounting and impulsive choice: Implications for addictions, prevention, and human health. *Perspectives on Behavior Science, 42*(3), 397–417. https://doi.org/10.1007/s40614-019-00200-7

Schulte, M. T., & Hser, Y.-I. (2013). Substance use and associated health conditions throughout the lifespan. *Public Health Reviews, 35*(2), Article 2. https://doi.org/10.1007/BF03391702

Sjoberg, D. D., Whiting, K., Curry, M., Lavery, J. A., & Larmarange, J. (2021). Reproducible Summary Tables with the gtsummary Package. *The R Journal, 13*(1), 570–580. https://doi.org/10.32614/RJ-2021-053

Sofis, M. J., Carrillo, A., & Jarmolowicz, D. P. (2017). Maintained physical activity induced changes in delay discounting. *Behavior Modification, 41*(4), 499–528. https://doi.org/10.1177/0145445516685047

Stein, J. S., MacKillop, J., McClure, S. M., & Bickel, W. K. (2022). Overstate the 'problems with delay discounting'. *Psychological Medicine*, 1–2. https://doi.org/10.1017/S0033291721005286

Stein, J. S., & Madden, G. J. (2013). Delay discounting and drug abuse: Empirical, conceptual, and methodological considerations. In *The Wiley-Blackwell handbook of addiction psychopharmacology* (pp. 165–208). Wiley Blackwell. https://doi.org/10.1002/9781118384404.ch7.

Strickland, J. C., Gelino, B. W., Rabinowitz, J. A., Ford, M. R., Dayton, L., Latkin, C., & Reed, D. D. (2023). Temporal reliability and stability of delay discounting: A 2-year repeated assessments study of the Monetary Choice Questionnaire. *Experimental and Clinical Psychopharmacology, 31(5), 902-907*. https://doi.org/10.1037/pha0000651

Suvarna, B., Suvarna, A., Phillips, R., Juster, R.-P., McDermott, B., & Sarnyai, Z. (2020). Health risk behaviours and allostatic load: A systematic review. *Neuroscience & Biobehavioral Reviews, 108*, 694–711. https://doi.org/10.1016/j.neubiorev.2019.12.020

Sze, Y. Y., Stein, J. S., Bickel, W. K., Paluch, R. A., & Epstein, L. H. (2017). Bleak present, bright future: Online episodic future thinking, scarcity, delay discounting, and food demand. *Clinical Psychological Science, 5*(4), 683–697. https://doi.org/10.1177/2167702617696511

Tucker, J. A., Chandler, S. D., & Witkiewitz, K. (2020). Epidemiology of recovery from alcohol use disorder. *Alcohol Research: Current Reviews, 40*(3), 02. https://doi.org/10.35946/arcr.v40.3.02

Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S* (Fourth edition). New York: Springer. https://www.stats.ox.ac.uk/pub/MASS4/.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., … Yutani, H. (2019). Welcome to the Tidyverse. *Journal of Open Source Software, 4*(43), 1686. https://doi.org/10.21105/joss.01686

Wingenfeld, K., Schäfer, I., Terfehr, K., Grabski, H., Driessen, M., Grabe, H., Löwe, B., & Spitzer, C. (2011). The reliable, valid and economic assessment of early traumatization: First psychometric characteristics of the German version of the Adverse Childhood Experiences Questionnaire (ACE). *Psychotherapie, Psychosomatik, medizinische Psychologie, 61*(1), e10–e14. https://doi.org/10.1055/s-0030-1263161