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Article type : Research Article

Reciprocal associations between implicit attitudes and drinking in emerging adulthood

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Role of Funding Source. Funding for this study was supported by a grant from the National Institute on Drug Abuse (NIDA) awarded to C. Colder (R01 DA020171), a grant from the National Institute on Alcohol Abuse and Alcoholism (NIAAA) awarded to K. Paige (F31AA028973), a grant from NIAAA awarded to F. Blow (T32 AA007477), and a grant from NIDA awarded to A. Weigard (K23 DA051561). The content of this study is solely the

responsibility of the authors and does not necessarily represent the official views of NIDA or NIAAA.

Abstract

Background: Implicit alcohol attitudes are considered important in the etiology of drinking, and theory posits reciprocal associations (Wiers & Stacy, 2006). Past research testing reciprocal associations between implicit attitudes (using the Implicit Association Task, IAT) and drinking is limited by a failure to consider multiple processes influencing performance on the IAT (Houben & Wiers, 2006a,b) and to disaggregate within- and between-person effects. The current study addressed these limitations by using a diffusion model to analyze IAT data and Latent Curve Models with Structured Residuals to test reciprocal associations (Curran et al., 2014).

Methods: The sample included 314 community emerging adults (52% female; predominantly non-Hispanic Caucasian (76 %) or African American (15%)) assessed annually for three years. Differences between IAT conditions in the drift rate parameter of the EZ-diffusion model ($v\Delta$; Wagenmakers et al., 2007) were used as an alternative to traditional response-time-based indices from the IAT (d-scores). Differences in drift rate have been found to effectively index implicit attitudes (Klauer et al., 2007; Rebar et al., 2015).

Results: Within-person reciprocal associations were supported, but between-person associations were not. Positive implicit alcohol attitudes ($v\Delta$) were prospectively associated with heavy drinking which was positively associated with subsequent positive implicit alcohol attitudes.

Conclusions: Findings suggest that positive implicit alcohol attitudes and heavy drinking reinforce each other in a negative cascade within individuals. Results highlight the importance of disaggregating within- and between-person prospective effects when testing dual process models and suggest that the diffusion model may be a fruitful approach to enhancing the construct validity of IAT assessed implicit attitudes.

Keywords: Dual process theory; Implicit attitudes; Heavy drinking; Response time measures; Emerging Adulthood

Introduction

Across the lifespan, alcohol use peaks in emerging adulthood (Chen & Kandel, 1995; Schulenberg et al., 2020). Prevalence rates of current alcohol use (past 30 days) rise sharply during emerging adulthood with 60%-70% of 18- to 24-year-olds reporting current drinking and

46% drinking heavily on one or more occasions in the past year (Chen et al., 2004). In 2020, the Monitoring the Future study reported that past month alcohol use increases markedly across ages 19 (46%) to 22 (68%) with current heavy drinking also increasing from 21% to 36% (Schulenberg et al., 2020). This is concerning because alcohol use, and heavy drinking in particular, has been associated with health risk behaviors including driving while impaired by alcohol (Naimi et al., 2003), risky sexual behaviors, and dating violence (Miller et al., 2007). Moreover, past year heavy drinking on one or more occasion has been identified as the major risk factor for meeting diagnostic criteria for Alcohol Use Disorder (Kranzler & Soyka, 2018). Therefore, better understanding risk and protective pathways to emerging adults' drinking is critical. Notably, implicit attitudes about alcohol have been identified as important in the etiology of alcohol use and maintenance of heavy drinking (Wiers & Stacy, 2006).

Implicit information processing is thought to operate spontaneously, without deliberation or awareness, and activated by drug-related cues (Stacy & Wiers, 2010). Dual process theories posit that implicit alcohol attitudes influence use behavior, such that positive implicit attitudes about alcohol precipitate drinking (Wiers & Stacy, 2006). Moreover, drinking may shape implicit attitudes; positive experiences with alcohol contribute to positive implicit alcohol attitudes (Wiers et al., 2007). When alcohol-related cues are encountered, these automatic processes are activated, triggering impulses to drink alcohol. Moreover, alcohol use becomes increasingly normative during emerging adulthood (Chen et al., 2004; Schulenberg et al., 2020), and the socially rewarding aspects of alcohol intensify as parental monitoring weakens and the importance of peer relationships increases (Borsari & Carey, 2001; White & Jackson, 2004). These changes in the context of emerging adult drinking likely facilitate increased learning opportunities about the positive aspects of alcohol, thereby strengthening positive implicit alcohol attitudes, as well as increased opportunities to encounter alcohol-related cues, strengthening the impact of implicit attitudes on drinking behavior. Bidirectional associations between positive implicit attitudes and heavy drinking may result in a problematic cascade, whereby each reciprocally exacerbates the other over time. Implicit attitudes likely also play a role in abstaining from drinking as it would be predicted that abstainers hold less positive implicit attitudes about alcohol (Wiers & Stacy, 2006). Accordingly, it is important to test dual process theories in a representative sample of emerging adults in order to better understand how implicit alcohol attitudes precipitate drinking and abstention. Importantly, the dual process literature faces two significant limitations: 1) poor construct validity in the measurement of implicit attitudes and, 2) the failure to disaggregate within- and between-person effects. The current study aims to address these concerns.

Measurement of Implicit Attitudes

The Implicit Association Task (IAT; Greenwald et al., 1998) is one of the most common tools for assessing implicit attitudes. It is a timed classification task in which two target opposing concepts are sorted in different combinations with two attribute categories (e.g. positive vs. negative valence). Many variants of the IAT have been developed, including a single-category IAT (SC-IAT) that includes only one target concept with two attribute categories (SC-IAT) and IATs with a single attribute category (unipolar IATs). Notably, the literature on alcohol implicit attitudes is mixed and this mixed picture does not seem to be systematically related to IAT version (Kwako & Lindgren, 2019). Several studies have found that positive implicit attitudes are associated with higher levels of drinking (Houben & Wiers, 2008; Ostafin & Palfai, 2006). In contrast, some studies have reported that implicit alcohol attitudes are not predictive of drinking behaviors (Houben & Wiers, 2009). These contradictory findings may be in part attributable to specific measurement issues of the IAT (Houben & Wiers, 2006a,b).

Indeed, Response Time (RT) differences between the “compatible” and “incompatible” condition blocks form the basis of scoring algorithms commonly used in the IAT literature, which often also include corrections for error rates and scale mean RT differences by individuals’ RT variability (Greenwald et al., 2003). However, RTs are known to be influenced by multiple construct-irrelevant sources of variability, including measurement artifacts associated with participants’ level of response caution (e.g., speed/accuracy trade-offs) and motor response speed (Hedge et al., 2019; Stafford et al., 2020; Lerche & Voss, 2019). These additional sources of variability may threaten the validity of RT-based indices from the IAT. One aim of the current study is to demonstrate the utility of using a cognitive process model-based analytic approach to address these measurement concerns.

The diffusion decision model

The diffusion decision model (DDM: Ratcliff, et al., 2016; Ratcliff, 1978) is a widely used cognitive process model that describes performance on two-choice decision tasks. It offers a valuable tool for measuring experimental and individual differences in cognitive processing by precisely indexing efficiency of processing with the drift rate (v) parameter while simultaneously accounting for peripheral influences on RT and accuracy (e.g., response caution). The model posits that responses to cognitive tasks are the result of gradual accumulation of noisy evidence from the stimulus until a critical threshold of evidence is reached for one of the choices (Ratcliff, et al., 2016; Ratcliff, 1978). This idea of thresholds can be easily illustrated with a SC-IAT because of the simplicity of task. In the “compatible” condition SC-IAT trial in which an alcohol-related stimulus is presented (Figure 1), a participant would gather evidence informing the choice of whether to press the “alcohol/good” key or the “bad” key. The DDM assumes that the decision process drifts in a variable pattern between two boundaries which represent each possible choice (e.g., an upper “alcohol/good” boundary and a lower “bad” boundary). When the process intersects with one of the two boundaries, the corresponding choice is made. Although the process generally drifts towards, and most commonly terminates at, the boundary for the correct choice (the upper “alcohol/good” boundary in this example), errors occur when noise causes it to instead terminate at the alternate boundary (e.g., the lower “bad” boundary). In this framework, the drift rate (v parameter) quantifies the efficiency with which an individual gathers evidence in favor of the correct choice; higher drift rate would be represented in Figure 1 by a steeper arrow for the average v, which indicates more rapid evidence accumulation, on average, toward the upper boundary representing the correct choice and therefore causes faster and more consistent selection of the correct choice.

In case of the IAT, implicit associations may influence the efficiency of the evidence-gathering process and the drift rate, and hence, facilitate response choice in one condition or the other. Other parameters account for peripheral, and possibly confounding, influences on RT and accuracy; the boundary separation (a parameter) determines the level of response conservativeness (e.g., speed/accuracy trade-off settings) and nondecision time (Ter parameter) accounts for the timing of processes that occur before or after the primary decision process (e.g., motor response speed). By simultaneously accounting for all of these sources of variability, application of the DDM to empirical data allows for more specific, and statistically powerful, tests of effects in processes of interest (Stafford et al., 2020). In an alcohol IAT, the process of most interest is the degree to which implicit alcohol associations influence response choices, which is best indexed by the drift rate.

Klauer and colleagues (2007) applied the DDM to the IAT and found that the “compatible” condition (in which the target category of interest is paired with positive valance) was characterized by more efficient information processing (higher *v*), lower levels of response conservativeness (lower *a*), and faster nondecision time (lower *Ter*). However, variance associated with implicit attitude criterion variables was primarily concentrated in the drift rate (*v*) effect, suggesting that the *a* and *Ter* parameters instead account for construct-irrelevant variance. Drift rate represents efficiency of gathering evidence to make a choice, and high efficiency when, for example, alcohol is paired with positive valence relative to when alcohol is paired with negative valence would suggest a positive implicit attitude. The authors concluded that the DDM offers a valuable measurement method for distinguishing construct-specific variance in *v* from variance associated with individuals' response strategies (e.g., changes in conservativeness/*a*) and other construct-irrelevant factors that impact RT effects in the IAT (Klauer et al., 2007).

However, parameters from the standard DDM can be difficult to estimate when error rates are low and when the number of trials per condition is relatively sparse (e.g., <100), both of which are often true of IAT data. DDM parameter estimation procedures with simplifying assumptions, such as the "EZ diffusion model" method (EZDM; Wagenmakers et al., 2007), may therefore be best suited for these applications (Lerche et al., 2017). The EZDM is a simplification of the DDM that allows its main parameters (*v*, *a, Ter*) to be estimated using a closed form solution, rather than relying on maximum likelihood or another iterative fitting process that can be unstable at relatively low trial numbers. It provides an equation that outputs parameter estimates when only three pieces of information are entered for a given task condition: the accuracy rate, and the mean and variance of correct response times. Previous work (Lerche et al., 2017) has suggested that, likely because of its simplicity, EZDM may provide more accurate DDM parameter estimates than iterative fitting methods when trial numbers and error rates are relatively low, such as in the SC-IAT paradigm. Indeed, the EZDM method has recently been shown to allow for valid measurements of implicit associations in a SC-IAT focused on individuals' evaluation of physical activity (Rebar et al., 2015). In the current study, we similarly adopt the EZDM method for quantifying implicit alcohol associations in a SC-IAT paradigm.

Disaggregating within- and between-person effects

In addition to measurement concerns with the IAT, the literature on implicit attitudes and drinking is limited with regard to study design. Indeed, the majority of past studies have utilized cross-sectional samples (e.g., Houben & Wiers, 2006a,b). This limits the ability to draw inferences regarding temporal precedence. Moreover, dual process theories suggest that relationships between implicit attitudes and drinking may operate bidirectionally (Wiers et al., 2007), and past cross-sectional studies fail to account for these reciprocal associations. Relatedly, little (or no) work that has tested dual process theories has examined differences across between- and within-person associations.

Disaggregating within- and between-person effects is important in this literature because dual process theories are models of individual differences, suggesting utility of considering both between- and within-person-level change over time. For example, theory posits that on average, individuals who have high levels of positive implicit alcohol attitudes tend to drink more heavily (e.g., between-person association). Additionally, it may be predicted that, for example, if an individual experiences higher positive implicit alcohol attitudes relative to their underlying typical level of positive implicit alcohol attitudes at one point in time, they are likely to drink more heavily relative to their average level of heavy drinking at a subsequent point in time (e.g., within-person association). Moreover, reciprocal associations between two constructs imply the disaggregation of between- and within-person effects, as earlier changes in one construct influence later changes in the other, and vice versa (Curran et al., 2014). This is a critical issue when testing dual process theories because they posit bidirectional effects, as noted above. The current study aims to address this gap by using a longitudinal sample and a Latent Curve Model with Structured Residuals (LCM-SR), which allows us to examine prospective reciprocal associations and distinguishes within- and between-person associations.

Hypotheses

The current study aims to clarify the association between implicit attitudes and heavy drinking. Notably, this is the first study to test these associations using the DDM's drift rate (v) parameter to operationalize implicit alcohol attitudes assessed by the IAT while accounting for construct-unrelated variance in other DDM parameters. Moreover, we expand upon work in this area by utilizing an LCM-SR model, which allows distinguishing associations at the between- and within-person levels. Three hypotheses are proposed:

1) On average, positive implicit attitudes (as indexed by the DDM drift rate) will be related to high levels of drinking (between-person level).
2) Positive implicit attitudes will prospectively predict high levels of drinking, accounting for average levels in both processes (within-person level).

3) High levels of drinking will prospectively predict more positive implicit attitudes, accounting for average levels in both processes (within-person level).

Materials and Methods

Sample

Recruitment. The community sample was recruited from [redacted for masked review]. Eligibility criteria included the child be 10-12 years old, fluent in English, without physical or mental impairments that would preclude completion of the interview, and a caregiver willing to participate. There were no eligibility criteria related to substance use risk. Recruitment began in April 2007 and was completed in February 2009. Only one child per household was recruited (for more details on recruitment see Authors, 2017).

Description. The final sample included 378 child and parent dyads that was evenly split on gender (52% female). The sample was largely White/non-Hispanic (76%), 15% were Black/African American, 3% were Hispanic/Latino, 2% were Asian/Pacific Islander, and 4% other (mostly mixed racial/ethnic background). Median family income was $60,000, and 7% received some sort of public assistance income. The current study utilized data from the last three of nine annual assessments when heavy drinking peaks (emerging adulthood; Waves 7-9). Average age at each of the annual assessments was 19.13 (0.99), 20.22 (1.05), and 21.26 (1.06) for Waves (W) 7 – 9, respectively.

Missing Data. Retention across W7-9 was 83% ($n = 314$), 78% ($n = 294$), and 71% ($n = 270$), respectively. Of W1 demographic (i.e. minority status, gender, income, parent education) and substance use (i.e. lifetime alcohol use without parental permission) variables, only parent education (Cohen's $d = 0.24$, $p < .05$) was associated with missingness. Lower parent education predicted higher attrition, but this was a small effect. Full-information maximum likelihood estimation was used to minimize the impact of missing data. This approach allows for inclusion of cases with missing data.

Procedure

Emerging adults completed the survey portion of W7-9 online via Qualtrics (Qualtrics, Provo, UT) and were given the choice to complete it at home or in our research offices. Computer tasks (e.g., SC-IAT) were completed at university research offices. Caregivers completed consent and permission for their child to participate if they were under the age of 18 before completing surveys. Emerging adults completed assent (if under 18 years of age) or consent (if over 18 years of age) before completing the surveys and computer tasks. Follow-up assessments were generally completed within a 2-month range of the anniversary of the prior assessment (90%). Similar procedures were used across W7-9 assessments. Families were compensated $125, $135, and $145 at W7-9, respectively, for completing surveys and tasks. All study procedures were approved by the university's Institutional Review Board.

Measures

Demographics. Emerging adult gender (0=male, 1=female) was assessed at W7. Caregivers reported on their child's minority status (0=Caucasian/non-Hispanic white, 1=Minority) at W1.

Alcohol SC-IAT. Young adults completed an alcohol SC-IAT. The SC-IAT (Karpinski & Steinman, 2006) is a modification of the IAT (Greenwald et al., 1998) that measures the strength of implicit evaluative associations with a single attitude object. The SC-IAT maintains bipolar, contrasting bivalent evaluative categories (e.g., positive vs. negative), allowing for a more ecologically valid assessment of substance-related attitudes since substance use is often associated with competing positive and negative cues. Additionally, the SC-IAT does not evaluate an implicit attitude relative to an opposing category as does the more common two category IAT. This is advantageous because alcohol does not have a naturally opposing attitude object. Indeed, non-alcoholic objects include other drugs, healthy drinks, soft drinks, household objects, food, etc. This raises concerns about the construct validity of an opposing alcohol category. For these reasons, the current study elected to use the SC-IAT.

The task requires participants to discriminate between an evaluative dimension (good and bad words) and an object category (pictures of alcoholic beverages). Participants were instructed to press the left-hand key (Z key) on the keyboard when they heard a good word (e.g., beautiful) and to press the right-hand key (?/ key) when they heard a bad word (e.g., sickness). The object category (alcohol) was paired with the response key for bad and then good words in two separate blocks (n=72 trials in each). Blocks were counterbalanced between participants and the ordering effects was controlled for in all analyses. More detail is provided below regarding computation of the EZ-diffusion model parameters.

Past 90 Day Heavy Drinking and Past Year Alcohol Use. Alcohol use variables were assessed at W7-9 using items taken from the Monitoring the Future Study (Johnston et al., 2012) and the Daily Drinking Questionnaire (DDQ; Collins et al., 1985). Emerging adults were asked to reflect on typical activities during their heaviest drinking week in the past 90 days using timeline follow-back procedures. They were then asked on average how many drinks they consumed on drinking days during a heavy drinking week. This measure was used to calculate an index of drinks per drinking day during the heaviest alcohol use week. For descriptive purposes in the current study, we also examined past year alcohol use using one item: "In the past year, how often have you had a drink of beer, wine, wine cooler, or liquor?"

Data Analytic Strategy

EZ Diffusion Model

The EZDM method (Wagenmakers et al., 2007) offers a closed form algorithm for estimates of the *v*, *a* and *Ter* parameters of the DDM that are obtained from three input values: the accuracy rate and the mean and variance of RTs on correct choices. Following prior applications of the DDM to developmental data (Ratcliff et al., 2012), we excluded trials with RTs <300ms as fast guesses before estimating parameters. Although it is also common to use upper exclusion bounds (e.g., 3000ms: Ratcliff et al., 2012) to exclude long outlier RTs, the response window in the task had a 1500ms cutoff, which operated as a natural upper bound. We used the R code available from Wagenmakers et al. (2007) and the standard edge correction methods recommended by the authors (e.g., for participants with 100% accuracy) to separately estimate individuals' DDM parameters for the condition in which alcohol was paired with positively valanced words ("compatible" block) and the condition in which alcohol was paired with negatively valanced words ("incompatible" block). This led to estimates of *v*, *a*, and *Ter* for each of the two conditions at each wave for each individual. We note that, as the EZDM is a simplification of the standard DDM (with start point biases and between-trial variability parameters left out), these parameter estimates are interpreted similarly to the corresponding parameters in the standard model. Despite the EZDM's simplifying assumptions, both simulation-based (Lerche et al., 2017; van Ravenzwaaij Donkin & Vandekerckhove, 2016) and empirical (Dutilh et al., 2018) studies have demonstrated that inferences about the main DDM parameters (*v*, *a*, *Ter*), rarely differ between standard DDM analyses and EZDM analyses.

Cross-condition difference scores ($v\Delta$, $a\Delta$, and $Ter\Delta$) were then computed for each wave and individual by subtracting parameter estimates for the "incompatible" condition from those in the "compatible" condition. The main difference score of interest was that for drift rate ($v\Delta$), as this DDM parameter has been found in prior work to be the most closely related to implicit attitudes (Klauer et al., 2007; Rebar et al., 2015) and it represents efficiency of gathering evidence to make a choice. More efficient processing of information during the compatible condition would suggest a positive alcohol implicit attitude. Positive associations with alcohol were therefore expected to lead to positive values of $v\Delta$ while negative associations with alcohol were expected to lead to negative values.

Hypothesized Pathways

An LCM-SR model (Curran et al., 2014) was used to test hypotheses because it allowed us to disaggregate within- and between-person effects and test prospective cross-lags (see Figure 2). A major advantage of the LCM-SR framework is that it imposes a structure onto the time-specific residuals of the observed repeated measures for each construct. Therefore, the residuals are conceptualized as time-specific deviations between the observed repeated measure and the underlying growth curve. This time-specific residual structure represents the within-person portion of the model. The growth factors represent the between-person variance (Curran et al., 2014).

Model building occurred in several steps. First, univariate growth curves for implicit attitudes represented by difference in drift rate across conditions and heavy drinking were tested. Next, we imposed a structure on the time-specific residuals and specified autoregressive and cross-lagged parameters of this residual structure. We then compared the fit of a series of models resulting from imposing equality constraints on several model parameters (i.e., time-specific covariances, autoregressions, and cross-lags). Finally, covariates (between-condition changes in nondecision time, between-condition changes in response conservativeness, gender, and minority status) were added to the model. All models were specified using Full-information Maximum Likelihood estimation (FIML) in Mplus 8.2 (Muthén & Muthén, 1998–2018). Model fit was assessed using conventional absolute and incremental structural equation modeling fit indices. Since cutoffs for "good" fit can vary between models, ranges were used to determine acceptability of model fit (Hu & Bentler, 1999; Marsh et al., 2004). Fit indices and ranges included model chi-square (a significant chi-square indicates poor fit), the comparative fit index (CFI) and Tucker-Lewis index (TLI; for both <.90 is poor, .90 to .94 is acceptable, and $\geq$.95 is excellent), root mean square error approximation (RMSEA; >.08 is poor, .05 to .07 is acceptable, and $\leq$.05 is excellent), and standardized root mean square residual (SRMR; SRMR, >.09 is poor,

.06 to .09 is acceptable, and ≤.06 is excellent). Nested chi-square difference tests were used to assess equality constraints.

Results

Descriptive Statistics

Descriptive statistics for observed variables can be found in Table 1. Skewness and kurtosis for all study variables were within the acceptable range. The mean values for differences in drift rate between SC-IAT conditions in which alcohol was associated with positive versus negative valence ($v\Delta$) were negative, indicating that on average, emerging adults hold negative implicit attitudes about alcohol use. On average, difference scores in responsive conservativeness ($a\Delta$) and nondecision time ($Ter\Delta$) were negative and positive, respectively. Additionally, $a\Delta$ and $Ter\Delta$ were weakly to moderately correlated with $v\Delta$ (see Table 1). Therefore, $a\Delta$ and $Ter\Delta$ variables were entered as covariates in the LCM-SR model. The proportion of the sample that endorsed past year alcohol use ranged from 85%-90% across W7-9. Across Waves 7, 8, and 9, 36%, 37%, and 28% of our sample reported that they abstained from alcohol use in the past 90 days, respectively, and we set their frequency of heavy drinking to 0. Among participants who endorsed drinking in the past 90 days, men on average drank 5.28, 4.96, and 4.82 drinks and women on average drank 3.77, 3.62, and 3.40 drinks on heavy drinking days across Waves 7, 8, and 9, respectively. This suggests that heavy drinking in our sample was comparable to “binge drinking” for men and a bit lower than the threshold for “binge drinking” for women (e.g., 5/4 or more drinks on one drinking occasion for men/women; Wechsler et al., 1994). This distribution of heavy drinking is comparable to data from national samples (Schulenberg et al., 2020). Across our three repeated measures, White emerging adults endorsed higher levels of heavy drinking than their non-White counterparts. At W9, males endorsed heavier drinking than females.

Univariate growth models. Means and variances of slope factors were nonsignificant across a series of univariate growth curves (e.g., linear, quadratic, piecewise, etc.) for both implicit attitudes, as operationalized by $v\Delta$, and heavy drinking, indicating that there was no significant growth in either process across our three repeated measures. Accordingly, subsequent models included a latent random intercept, but no slope, for each construct (see Figure 2).

LCM-SR Model

The intercepts for implicit attitudes and heavy drinking (i.e., the between-person aspects of the model) were allowed to covary. Regarding the within-person portion of the model, equality constraints were supported for all autoregressive paths as well as within-time covariances between implicit attitudes and heavy drinking at Waves 7 and 9. Equality constraints were also supported for cross-lagged paths between the residuals for implicit attitudes and heavy drinking. The final LCM-SR model provided an excellent fit to the data (χ^2 (df) = 68.09 (66), p = .41, CFI = .99, TLI =.99, RMSEA =.01, 90%CI[0.000, 0.035], SRMR =.05). Parameter estimates are provided in Figure 2.

Regarding between-person associations, variances for the intercepts of implicit attitudes and heavy drinking were significant, indicating significant individual differences in initial levels of implicit attitudes and heavy drinking across individuals. The covariance between the intercepts was nonsignificant suggesting that at the between-person level, implicit attitudes and heavy drinking were unrelated. With respect to demographic covariates, $v\Delta$ was not related to gender or minority status. Males endorsed higher levels of heavy drinking. Minority status significantly predicted heavy drinking, such that White emerging adults reported higher levels of heavy drinking at the between-person level.

Within-person associations provided information distinct from the between-person component of the model. Autoregressive paths were nonsignificant for heavy drinking and implicit attitudes. This indicates, for example, that when an individual drank more heavily than usual at one wave of assessment, they did not tend to report heavier drinking than expected at the following assessment. The within-time covariance between implicit attitudes and heavy drinking was nonsignificant at W7. However, covariances at Waves 8 and 9 were significant and positive, such that individuals who had more positive implicit attitudes than usual also engaged in more heavy drinking than expected. Regarding the other parameters that were entered as covariates, nondecision time ($Ter\Delta$) was positively associated with implicit attitudes at W7 (β= 0.23, p < .01), W8 (β= 0.18, p < .05), and W9 (β= 0.26, p < .01). Pathways between responsive conservativeness ($a\Delta$) and implicit attitudes were nonsignificant across W7-9.

With respect to the cross-lags, the cross from implicit attitudes to heavy drinking was significant and positive. High positive implicit attitude than usual at one wave of assessment was associated with heavier drinking than expected (accounting for average levels of heavy drinking) at the following assessment. Additionally, prospective paths from heavy drinking to implicit attitudes were significant and positive. High levels of heavy drinking at one wave was associated with higher-than-expected levels of positive implicit alcohol attitudes one year later.

LCM-SR Model: D-scores

We also estimated an LCM-SR model with implicit attitudes represented by *D*-scores to examine differences between analyses utilizing the difference score for drift rate ($v\Delta$) and the traditional measure for the IAT (*D*-scores). More detail on these analyses are provided in Supplemental Material 1. There were some consistencies across the two models. Indeed, the covariance between the intercepts was nonsignificant, indicating that implicit attitudes and heavy drinking were not related at the between-person level. With respect to the hypothesized pathways, there were some notable differences from the primary model using drift rate. Cross-lagged associations between implicit attitudes and heavy drinking were significant and positive; however, standardized path coefficients were smaller in the model utilizing *D*-scores. Additionally, distinct from our primary model, prospective pathways between heavy drinking and implicit attitudes were nonsignificant ($p = 0.52$).

Discussion

Elucidating risk and protective pathways to emerging adult heavy drinking is a critical public health issue, and previous investigations have yielded inconsistent findings regarding whether implicit alcohol attitudes precipitate use (Kwako & Lindgren, 2019). Notably, there are concerns with construct validity of RT-based indices from the IAT (Klauer et al., 2007), which have been widely utilized to operationalize implicit attitudes. Poor construct validity may contribute to confusion regarding the role of implicit alcohol attitudes in the etiology and maintenance of heavy drinking. Associations between implicit alcohol attitudes and heavy drinking are further complicated by the fact that they may operate bidirectionally; indeed, dual process models posit that implicit alcohol attitudes precipitate drinking and that drinking shapes implicit alcohol attitudes (Wiers et al., 2007). Additionally, dual process models are theories of individual change (Stacy & Wiers, 2010), and past work in this area has often failed to distinguish between- and within-person effects. In this study, we attempted to address these limitations by using difference scores in the DDM's drift rate (v) parameter to operationalize implicit alcohol attitudes assessed by the IAT in a longitudinal sample, testing of bidirectional relationships, and distinguishing between- and within-person associations. Patterns of drinking in our sample represent normative use for the developmental stage of emerging adulthood (Schulenberg et al., 2020); therefore, our results are best understood in the context of typical emerging adult development.

Between-Person Associations

Our hypothesis that positive implicit attitudes would be related to high levels of heavy drinking at the between-person level was not supported. To our knowledge, only one previous study in this literature disaggregated between- and within-person effects (Meisel et al., 2018), and similarly did not find associations between implicit alcohol attitudes and alcohol use at the between-person level. On the other hand, several past studies that did not distinguish between and within-person associations have reported significant associations between positive implicit attitudes and alcohol use (Houben & Wiers, 2008; Ostafin & Palfai, 2006). Notably, substantially less of the variance in implicit attitudes was accounted for in the between-person portion of our model. It may be that reciprocal relationships between implicit attitudes and heavy drinking operate more strongly at the level of individual change, and studies that do not disaggregate between- and within-person effects may be missing this nuance. Moreover, no prior work has examined associations between implicit attitudes and heavy drinking using difference scores in the DDM's drift rate (v) parameter from the IAT, which has been shown to provide a less contaminated index of implicit attitudes by accounting for construct-irrelevant influences on IAT experimental performance differences (Klauer et al., 2007; Rebar et al., 2015). Our novel measurement of implicit attitudes may be another reason that null results at the between-person level diverge from past work.

Within-Person Associations

Our hypothesis that positive implicit attitudes would prospectively predict high levels of heavy drinking, accounting for average levels in both processes, was supported. When an individual had a more positive implicit attitude than usual at one wave of assessment, they tended to engage in heavier drinking than expected (given their average levels of heavy drinking) at the following assessment. This supports dual process conceptualizations of implicit alcohol attitudes as a critical pathway to drinking (Stacy & Wiers, 2010) and corroborates past longitudinal studies which have reported that positive implicit attitudes are associated with increased alcohol use (Lindgren et al., 2018; Peeters et al., 2013). Moreover, this finding, we believe, demonstrates for the first time the importance of implicit alcohol attitudes in escalating heavy drinking risk over time at the level of individual change.

Our hypothesis that high levels of heavy drinking would prospectively predict more positive implicit attitudes, accounting for average levels in both processes, was also supported.

When an individual drank more heavily than expected at one wave, their implicit attitude was more positive than usual at the following assessment. This is also consistent with dual process models which posit that experiences with substance use shape implicit attitudes about the substance within individuals over time (Wiers et al., 2007). Indeed, alcohol use becomes increasingly normative during emerging adulthood (Chen et al., 2004; Schulenberg et al., 2020), and the socially rewarding aspects of alcohol intensify as parental monitoring weakens and the importance of peer relationships increases (Borsari & Carey, 2001; White & Jackson, 2004). The context of emerging adult drinking likely facilitate increased learning opportunities about the positive aspects of alcohol, thereby, strengthening positive implicit alcohol attitudes and weakening negative ones. Overall, our pattern of findings suggest that heavy drinking and positive implicit alcohol attitudes may operate in a problematic developmental cascade, reciprocally exacerbating each other over time.

The diffusion decision model

To our knowledge, the current study is the first to apply the DDM to an alcohol SC-IAT. Results suggest that the DDM offers a useful method of indexing emerging adults' implicit alcohol attitudes assessed with SC-IATs. Additionally, there were notable differences with respect to hypothesized associations across our primary model using drift rate and the supplementary model using the traditional *D*-score to measure implicit alcohol attitudes. The drift rate parameter provided stronger support for the hypothesized reciprocal associations between implicit alcohol attitudes and heavy drinking, and this is likely attributable to the methodological advantages of the drift model. The drift model uses a process model that links a mechanistic process to explain responses on the IAT. In contrast, *D*-scores are response time-based measurements with a heuristic correction for accuracy rates without an underlying model to explain how responses are generated. The lack of a model undergirding computation of *D*-scores is problematic because accumulation of empirical evidence suggests that *D*-scores are influenced by multiple construct-irrelevant sources of variability, which threaten their construct validity. Taken together, drift rates and DDM approaches likely represent a more valid measure of implicit attitudes due to the models' ability to account for additional sources of variability (e.g., response caution, perceptual encoding speed) within a well-validated model-based framework.

Notably, the current study is the first to examine differences in associations between implicit attitudes and behavior across models using drift rates and *D*-scores for an alcohol SC-IAT at the within-person level. Using an exercise SC-IAT, one previous study found that drift rate, but not the traditional *D*-score, was positively related to physical activity behavior (Rebar et al., 2015). Therefore, the current findings extend past work by illustrating that methodological advantages of the drift model may enhance construct validity of an alcohol SC-IAT in measuring implicit alcohol attitudes.

Limitations

It is important to consider limitations of the current study. First, our study utilized a difference score for the drift rate (v) parameter of the DDM to operationalize implicit alcohol attitudes. Any difference-score-based measure, regardless of whether it uses RT or a formal measurement model, is susceptible to possible problems with reliability and interpretability (Draheim et al., 2019; Edwards, 2001). A useful direction for future work is to integrate the DDM with modeling methods designed to mitigate the limitations of difference scores (e.g., latent difference score models as used in Meisel et al., 2019). Second, the current study used a bipolar SC-IAT, and therefore, we were unable to consider the possibility of individuals simultaneously holding positive and negative implicit alcohol attitudes. A useful future direction would be to investigate our hypotheses utilizing a unipolar alcohol IAT.

Finally, our community sample provided an opportunity to test dual process models within a normative developmental context. Our study is best characterized as a one of normative use. Although few studies have used the IAT to examine how associations between implicit alcohol attitudes and drinking may differ between heavy and light drinkers, it is possible that these reciprocal associations operate differently in heavy using or clinical samples. Relatedly, our sample was limited by homogeneity with respect to ethnicity and there was a small effect of attrition associated with parental education. It would be informative for future research to test our hypotheses using more ethnically representative and clinical or heavy using samples.

Conclusions

Findings from the current study demonstrate that positive implicit alcohol attitudes and heavy drinking reinforce each other in a negative developmental cascade within individuals; higher-than-usual levels of positive implicit alcohol attitudes predict higher levels of heavy drinking than expected (given an individual's average levels of heavy drinking), and increased heavy drinking predicts further increases in positive implicit alcohol attitudes across emerging adulthood. Strong evidence for these reciprocal relationships supports the importance of interventions that target implicit alcohol attitudes (Houben et al., 2010). Moreover, results emphasize the importance of disaggregating within- and between-person prospective effects. This is consistent with calls for clinical science research to more carefully test theoretical models which posit individual change across time (Curran et al., 2014). Finally, our findings suggest that the application of the DDM model to SC-IATs may be a fruitful approach in enhancing construct validity in the measurement of implicit attitudes.

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Figure 1. Schematic of the decision process assumed by the EZ diffusion model for a "compatible" condition SC-IAT trial in which an alcohol stimulus is presented.

Note. v = drift rate, or efficiency with which an individual gathers evidence in favor of the correct choice. a = boundary separation; response conservativeness (e.g., speed/accuracy trade-off settings). *Ter* = nondecision time (e.g., motor response speed). The model assumes that, on a given trial, an evidence accumulation process drifts between a boundary for the correct choice, set at parameter a, and a boundary for the incorrect choice, set at 0. The process begins at a start point (in the simplified EZ diffusion model framework, always assumed to be $a/2$) and drifts toward the correct choice boundary with an average rate of v. The *Ter* parameter is a constant that accounts for the time taken up by other processes peripheral to the decision process (e.g., perceptual encoding, motor responses). The evidence accumulation process typically terminates at the upper, correct choice boundary (for this trial, the "alcohol"/"good" choice boundary), but errors occur when noise causes the process to terminate at the lower boundary (for this trial, the "bad" choice boundary). Gray traces represent simulated decision processes on individual trials. Gray density plots represent the density of response times at the respective boundaries that are predicted by the model.

Figure 2. Latent Curve Model with Structured Residuals for Implicit Attitudes and Heavy Drinking.

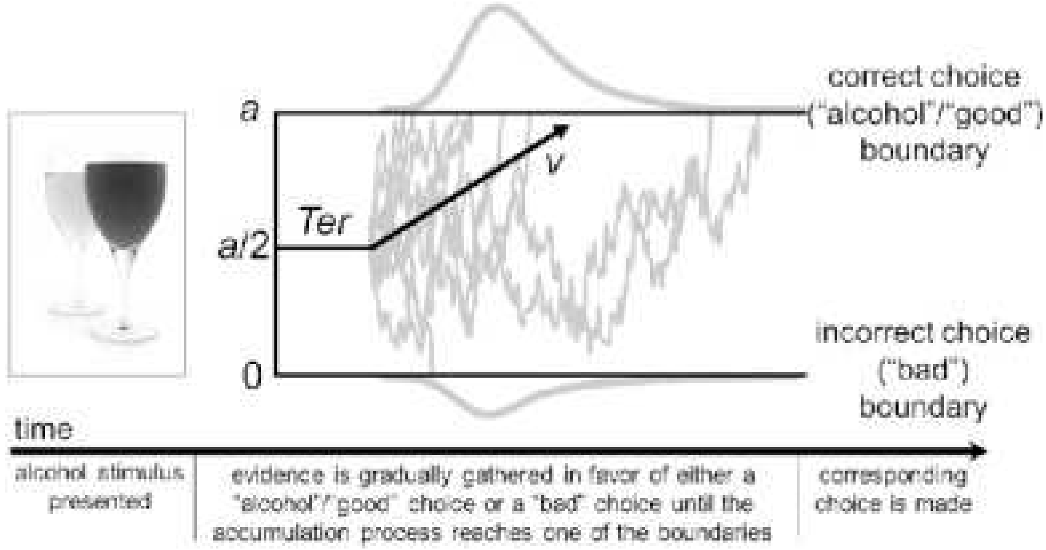
Note. Solid black lines are significant and dotted grey lines are non-significant pathways. Betas are reported next to significant associations and standard errors are reported in parentheses. Levels of significance were based on unstandardized regression estimates. For simplicity, the covariates of between-condition changes in nondecision time and between-condition changes in response conservativeness across Waves 7-9 are not depicted. RI = Random Intercept. W = Wave. $p < .05$ = * $p < .01$ = ** $p < .001$ = ***.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Wave 7														
1. Gender	-													
2. Minority Status	-0.01	-												
3. Heavy Drinking	-0.11	**-0.24**	-											
4. Drift Rate change ($v\Delta$)	-0.02	0.01	0.00	-										
5. Nondecision time change (ΔTer)	0.08	0.03	-0.08	**0.21**	-									
6. Conservativeness change ($a\Delta$)	0.06	-0.01	0.06	-0.10	**-0.44**	-								
Wave 8														
7. Heavy Drinking	-0.08	**-0.23**	**0.58**	0.11	0.05	0.06	-							
8. Drift Rate change ($v\Delta$)	0.04	0.03	0.05	**0.29**	0.04	0.07	0.09	-						
9. Nondecision time change (ΔTer)	0.07	0.004	-0.08	0.01	0.01	0.13*	-0.12	0.20**	-					
10. Conservativeness change ($a\Delta$)	-0.02	0.01	0.07	-0.12	-0.00	-0.04	0.05	-0.15*	**-0.54**	-				
Wave 9														
11. Heavy Drinking	-0.14*	-0.16**	**0.55**	-0.02	-0.06	-0.001	**0.56**	0.11	-0.05	-0.03	-			
12. Drift Rate change ($v\Delta$)	-0.001	0.07	-0.11	**0.23**	0.01	0.05	0.04	0.21**	0.17*	-0.16*	-0.04	-		
13. Nondecision time change (ΔTer)	-0.11	0.06	0.01	-0.005	0.12	-0.13	0.12	0.03	0.13	0.05	-0.03	0.19**	-	
14. Conservativeness change ($a\Delta$)	0.15*	-0.01	-0.04	-0.02	-0.002	0.08	-0.01	-0.03	0.03	-0.06	-0.02	-0.07	**-0.56**	-
Mean	0.52	0.24	3.21	-0.04	0.01	-0.02	3.13	-0.03	0.01	-0.02	3.31	-0.02	0.005	-0.02
SD	0.50	0.43	3.69	0.61	0.04	0.17	3.48	0.66	0.04	0.17	3.40	0.62	0.04	0.18

Table Legends.

Table 1. Bivariate Correlations and Descriptive Statistics for Observed Variables.

Note. * = $p < .05$; ** = $p < .01$, Bolded = $p < .001$.



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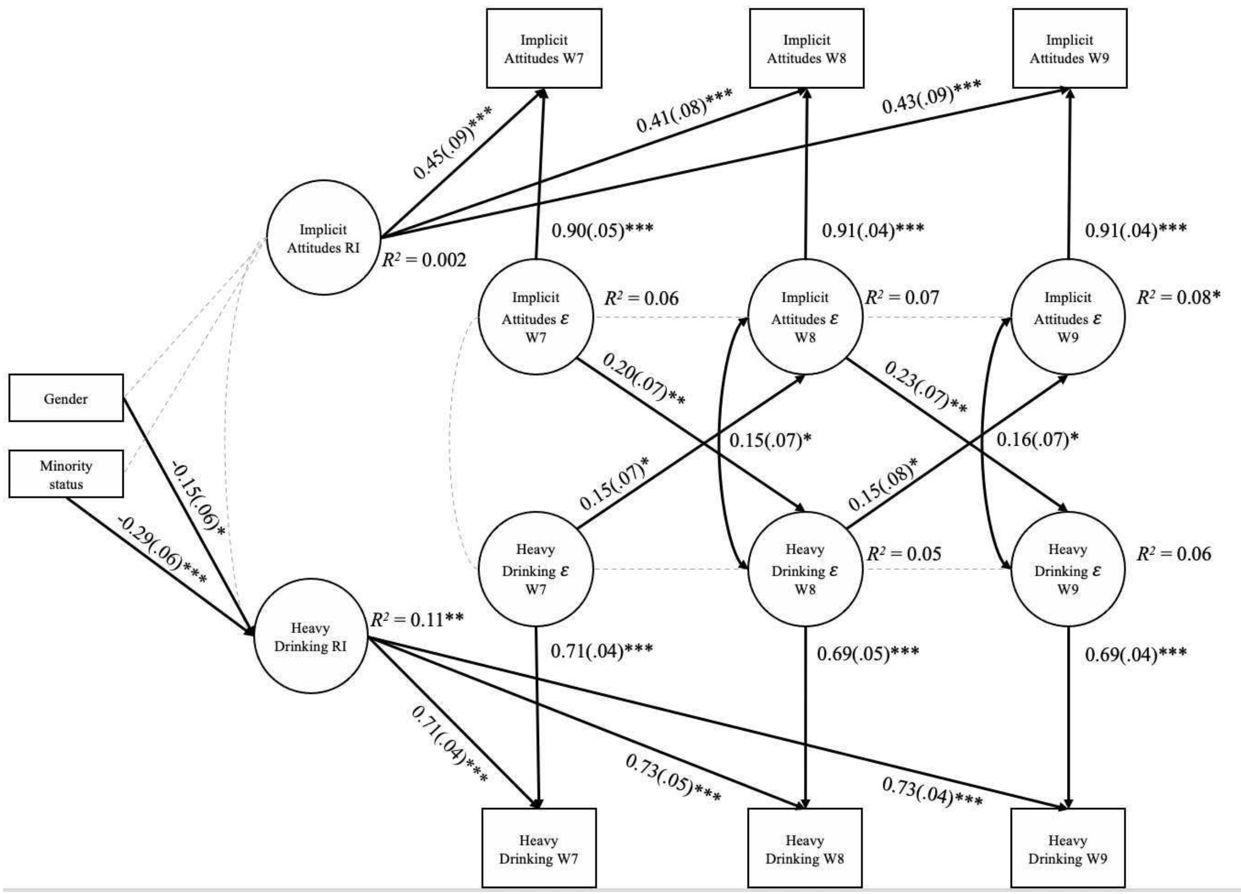
Implicit Attitudes W7
Implicit Attitudes W8
Implicit Attitudes W9
0.45(.09)***
0.41(.08)***
0.43(.09)***
Implicit Attitudes RI
$R^2 = 0.002$
0.90(.05)***
0.91(.04)***
0.91(.04)***
Implicit Attitudes ε W7
$R^2 = 0.06$
Implicit Attitudes ε W8
$R^2 = 0.07$
Implicit Attitudes ε W9
$R^2 = 0.08$*
0.20(.07)**
0.23(.07)**
0.15(.07)*
0.16(.07)*
0.15(.07)*
0.15(.08)*
Gender
Minority status
-0.15(.06)*
-0.29(.06)***
Heavy Drinking ε W7
Heavy Drinking ε W8
$R^2 = 0.05$
Heavy Drinking ε W9
$R^2 = 0.06$
Heavy Drinking RI
$R^2 = 0.11$**
0.71(.04)***
0.69(.05)***
0.69(.04)***
0.71(.04)***
0.73(.05)***
0.73(.04)***
Heavy Drinking W7
Heavy Drinking W8
Heavy Drinking W9