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Addressing methodological issues in a study of impulsivity and vulnerability for transition to alcohol use disorder

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Abstract

Background: Heightened behavioural impulsivity has been advocated as pre-existing risk factors for the development of alcohol use disorder (AUD). Nonetheless, studies investigating impulsivity in adolescent/young adult at-risk drinkers – who are at increased risk of developing AUD – report mixed findings. This may be due to methodological limitations related to definitions of at-risk drinking, the retrospective assessment of alcohol intake, and/or the relatively modest sample size of some studies.

Methods: Healthy individuals (N = 814, M_{age} = 22.50) completed online surveys and a measure of choice impulsivity. Of these, a number also undertook an online measure of response inhibition (n = 627, M_{age} = 22.66), and a further subgroup submitted real-time alcohol consumption information for a period of 21 days using an app (n = 543, M_{age} = 22.96). Differences in behavioural impulsivity were assessed as a function of various at-risk alcohol intake categories. Hierarchical multiple regression was employed to determine whether impulsivity predicted alcohol use in the form of a continuous index comprising variables related to intake and consequences of use.

Results: Significantly greater impulsivity was not evident in heavy, standard binge, high binge, harmful, or hazardous alcohol drinkers as compared to controls, regardless of the criteria employed to categorise these at-risk drinkers. Neither choice impulsivity nor reduced response inhibition significantly predicted the alcohol use index.

Conclusions: While results could be attributed to the online nature of this research, it is possible more sensitive measures of behavioural impulsivity are required when assessing non-dependent drinkers.

Key words: behavioural impulsivity, response inhibition, choice impulsivity, alcohol, alcohol use disorder

Introduction

Behaviourally, impulsivity is recognised as a multi-dimensional construct that refers to a propensity to act hastily and without adequate forethought or due consideration of outcomes (Daruna and Barnes, 1993). It is central to several prominent theories of addiction that emphasise the interplay between aspects of impulsivity that might explain a heightened tendency to misuse substances – such as choice impulsivity – and those that suggest a reduced ability to control this behaviour – such as response inhibition (Gullo et al., 2014). According to these models, dependent individuals make impulsive choices in order to satisfy

their desire for the short-term rewards associated with alcohol/drug taking, such as pleasure of intoxication and alleviation of craving/withdrawal; at the same time, there is an attenuated capacity to inhibit this impulsive decision-making, which leads to bingeing and compulsive intake (Bari and Robbins, 2013; De Wit and Richards, 2004; Goldstein and Volkow, 2011; Perry and Carroll, 2008; Potenza and Taylor, 2009; Zilverstand et al., 2018). Importantly, choice impulsivity and/or reduced response inhibition have been suggested as pre-existing risk factors for the development of alcohol use disorder (AUD; Poulton and Hester, 2020). Nonetheless, although individuals who engage in at-risk alcohol intake behaviour – that is, heavy or binge drinking – have an increased likelihood of developing AUD (Bonomo et al., 2004; Jennison, 2004), the extent to which impulsivity is evident in these non-dependent healthy individuals remains unclear.

Choice impulsivity – or the propensity to favor immediate reward regardless of delayed outcomes – is typically assessed using measures such as the Monetary Choice Questionnaire (MCQ; Bickel et al., 2012; Kirby et al., 1999). The MCQ examines the point at which people choose an immediate reward in preference to waiting for a larger one available after some delay; this point is known as the delay discounting rate (DDR; Kaplan et al., 2016). Individuals with clinically diagnosed dependence problems, including those involving alcohol, typically have high DDRs (MacKillop et al., 2011). DDRs have also been found to differentiate non-dependent problem and non-problem alcohol drinkers (Murphy and Garavan, 2011). Similarly, a significant association between weekly alcohol consumption and DDRs has been identified, such that non-dependent heavy drinkers have higher rates than light drinkers (Field et al., 2007). Thus, while research supports the notion that alcohol dependent individuals are characterized by high DDRs, there is also evidence choice impulsivity measures can distinguish between dependent users, non-dependent problematic users, and non-dependents. Critically, adolescents and young adults who discount future possible rewards in favour of more immediate ones appear more susceptible to prospective alcohol/drug use problems (Audrain-McGovern et al., 2009).

Response inhibition – or the ability to successfully inhibit a dominant behavioral or prepotent response – is commonly assessed using Stop-Signal and Go/No-Go Tasks (Bickel et al., 2012; Fernie et al., 2010). These tasks require participants to respond rapidly to specific frequently appearing stimuli, but to inhibit responses to others that are presented less often (Murphy and Garavan, 2011). Elevated commission errors, decreased successful inhibitions, and increased mean stop reaction times on these types of tasks typically signify poor response inhibition (Ahmadi et al., 2013; Lawrence et al., 2009). Impaired response

inhibition has been identified in individuals with a range of substance dependence problems, including AUD (Bickel et al., 2012; Verdejo-García et al., 2008). Investigations into the response inhibition of non-dependent at-risk drinkers have yielded variable results, however. While Smith and Mattick (2013) demonstrated female heavy drinkers had significantly longer stop-signal reaction times (SSRTs) than light drinkers, other studies utilising response inhibition measures have been unable to distinguish the performance of non-dependent at-risk drinkers from that of controls (Fernie et al., 2010; Liu et al., 2019; Murphy and Garavan, 2011). Importantly, pre-existing response inhibition deficits appear nonetheless to contribute to vulnerability for alcohol/substance use, misuse, and transition to dependence (Nigg et al., 2006; Verdejo-García et al., 2008). Thus, despite the mixed findings emanating from research concentrating on identifying response inhibition deficits in at-risk drinkers, there is evidence suggesting pre-existing impaired inhibitory control is associated with vulnerability for dependence.

Several methodological factors may account for the variable findings in the literature regarding the response inhibition of non-dependent at-risk drinkers. While both heavy and binge drinking are at-risk behaviours linked to the development of AUD (Bonomo et al., 2004; Jennison, 2004), questions remain regarding how best to describe and/or quantify heavy and binge drinking. There is a myriad of empirical definitions for these at-risk drinking behaviours. There are consequently inconsistencies across studies related to quantity of intake and ethanol content as well as issues pertaining to frequency, timeframe, and time period parameters (Courtney and Polich, 2009). There is also often a lack of clarity regarding how heavy and binge drinking are distinguished from each other, a tendency to rely on dichotomous methods of differentiating between at-risk individuals and controls, and a propensity to overlook distinctions within at-risk samples (Creswell et al., 2020; Patrick et al., 2013; Paul et al., 2011; Pearson et al., 2015). Furthermore, there is a reliance on retrospective summary measurement methods. As a result, information about volume and pattern of alcohol intake might not be sufficiently assessing behaviour. These definitional and assessment limitations may be undermining findings in the impulsivity literature.

An additional overarching concern regards statistical power. Some studies examining response inhibition in at-risk groups are characterised by relatively modest sample sizes. Authors of recent meta-analyses of studies in this area suggest non-significant results might reflect a lack of statistical power due to small sample size (<30 at-risk individuals) rather than a lack of response inhibition impairment (Liu et al., 2019; Smith et al., 2014). While moderate effects are reported in some meta-analytic investigations into the response

inhibition of AUD samples (g = 0.395-0.529; Smith et al., 2014; Stavro et al., 2013), effect sizes in non-dependent at-risk groups are likely to be smaller. Indeed, a meta-analytic review of 17 studies that focused on the SST and Go/No-Go performance of heavy drinkers (N = 856) reported a reasonably small weighted mean effect size for the former (g = 0.248) and no significant effect for the latter (Smith et al., 2014). Large samples are consequently required if small effects are to be detected. Although meta-analytic approaches provide a means of garnering a large sample, they are limited by the considerable heterogeneity across the literature regarding if/how individuals are classified as non-dependent at-risk – that is, heavy, binge or otherwise – drinkers.

These methodological limitations might be overcome by employing real-time alcohol intake assessment and online protocols. The real-time measure may provide a more accurate and nuanced understanding of consumption behaviour, while collecting data entirely online may elicit a larger, and potentially more representative, sample. App-based real-time measures of assessing alcohol consumption have been found to be reliable and valid, while online protocols appear to have the potential to garner large, diverse samples (Poulton et al., 2019b, 2018). As such, the aim of this study was to employ online protocols and an app designed to allow participants to record alcohol consumption in real-time, in order to investigate facets of behavioural impulsivity among at-risk alcohol drinkers. At-risk drinking was identified using a range of commonly cited criteria and was considered a categorical or continuous variable depending on the analyses adopted. In addition, measures of depression and anxiety were included as executive function has been shown to be negatively impacted by symptoms of depression and anxiety (Castaneda et al., 2008). Moreover, there is evidence to suggest individuals who misuse alcohol are characterised by increased anxiety and/or depression symptomatology (Ahmadi et al., 2013; Rubio et al., 2008).

It was hypothesised at-risk – specifically, heavy, standard binge, high binge, harmful, or hazardous – drinkers would have significantly greater impulsivity – in the form of heightened choice impulsivity and/or reduced response inhibition – than control groups, regardless of the specific criteria employed to categorise alcohol intake. Furthermore, it was anticipated greater impulsivity – that is, heightened choice impulsivity and/or reduced response inhibition – would predict elevated alcohol use in the form of an index comprising variables related to frequency of drinking, quantity of intake, rate of consumption, and alcohol use consequences.

Materials and Methods

Participants

Participants in this study form part of an ongoing project – entitled CheckMyControl – investigating the relationship between alcohol use and various social/cognitive factors in the healthy population. They were recruited through adverts, researcher networks, and social media posts. The University of Melbourne Human Ethics Committee approved the study in accordance with the National Health and Medical Research Council standards for ethical research.

The CheckMyControl project comprises three components: surveys (including the MCQ), SST, and CNLab-A app. Prior to exclusions being applied, 814 individuals (M = 22.50, SD = 6.59, range: 16-66, 68.4% female) completed the survey component; of these, 627 (M = 22.66, SD = 6.74, range: 16-59, 69.7% female) undertook the survey and SST components; and, of these, 543 (M = 22.96, SD = 6.93, range: 16-53, 70.2% female) finished the survey, SST, and app components. Participants were excluded if they did not consume alcohol or if they self-reported a history of alcohol or substance use disorder (SUD). Further participants were excluded because they did not meet cognitive task inclusion criteria. See Figure 1 for inclusion/exclusion details.

Classification of participants who completed all three components was initially based on criteria detailed by López-Caneda et al. (2012). Participants were designated as standard binge drinkers (n = 106) if (i) they consumed 6-11 standard alcoholic drinks per drinking occasion 3-6 times in 21 days, or (ii) if they consumed 6-11 standard drinks per drinking occasion 1-2 times in 21 days and drank >2 standard drinks per hour. Participants were denoted as high binge drinkers (n = 69) if (i) they consumed ≥12 standard drinks per drinking occasion 3-6 times in 21 days, or (ii) if they consumed ≥12 standard drinks per drinking occasion 1-2 times in 21 days and drank >2 standard drinks per hour. High binge drinkers thus consumed two or more times the intake of standard binge drinkers; these individuals have been found to experience significantly greater negative drinking outcomes than standard binge drinkers (Creswell et al., 2020). Controls (n = 265) consumed alcohol below the levels necessary for these criteria. Regular heavy drinkers (n = 9) consumed ≥6 standard drinks more than 6 times in 21 days; heavy drinkers were excluded from inferential analyses due to the small number of participants in this group.

Participants who completed all three components were also classified according to National Institute on Alcohol Abuse and Alcoholism (NIAAA) heavy and binge drinking criteria (NIAAA, 2018). NIAAA guidelines state heavy drinking occurs when ≥8 (women)/≥15 (men) drinks per week are consumed, while binge drinking occurs when ≥4 (women)/≥5 (men) drinks are consumed in 2 hours. In the United States, a standard drink

contains 14 g of alcohol, whereas in Australia it contains 10 g. Thus, to meet the NIAAA definition of heavy drinking (n = 43), ≥11.2 (women)/≥21 (men) Australian standard drinks must be consumed per week. To meet the NIAAA definition of binge drinking (n = 123), ≥5.6 (women)/≥7 (men) Australian standard drinks must be consumed in 2 hours. All other participants were categorised as controls (n = 283). Participants were, additionally, classified according to scores on the World Health Organisation Alcohol Use Disorders Identification Test (AUDIT; Babor et al., 2001) and Alcohol Use Questionnaire (AUQ; Townshend & Duka, 2002). Participants were designated as harmful (n = 47), hazardous (n = 190), or non-harmful (n = 212) drinkers based on AUDIT scores (≥16, 8-15, or <8 respectively). They were labelled binge (n = 157) or non-binge drinkers (n = 156) depending on their AUQ binge score (≥24 or ≤11 respectively).

Procedure

After reading a plain language statement and providing informed consent, participants answered an online researcher-devised demographic survey and undertook an abridged version of the Raven's Advanced Progressive Matrices (APM), the AUQ, AUDIT, Alcohol, Smoking and Substance Involvement Screening Test (ASSIST), Generalised Anxiety Disorder Scale (GAD-7), Patient Health Questionnaire (PHQ-9), and MCQ. They then followed a link to an online version of the SST. Finally, participants downloaded a smartphone app to record alcohol use over 21 days. Participants were compensated via course credit or received AU$10 for time spent completing online surveys and AU$0.50 each day information about alcohol consumption was submitted via the app (regardless of whether alcohol had been consumed or not). In the latter case, participants received a bonus AU$9.50 if app data were submitted on all 21 days. The maximum participants could be reimbursed was AU$30.

Materials

APM-6

This 6-item abridged version of the APM comprises a practice item plus matrices 4, 11, 18, 23, 30, and 35 of the APM Set II (Raven et al., 1998). The APM-6 forms half of the APM-12U, an abridged untimed 12-item version of the APM (Arthur et al., 1999). Test scores are operationalised as percentiles.

AUDIT

This 10-item screening measure requires participants respond to questions assessing alcohol intake, problems, and dependence with reference to the preceding six months (Babor

et al., 2001). Scores 8-15 suggest hazardous alcohol consumption; scores ≥16 indicate harmful alcohol use.

AUQ

This 15-item questionnaire asks quantity/frequency questions pertaining to alcohol consumption, speed of intake, and drunkenness over the preceding six months. Binge score can be derived from this measure: [(4 × intake speed) + number of drunkenness episodes + (0.2 × percentage of drunkenness episodes)] (Townshend and Duka, 2002). Tertile splits of the binge scores are used to assign binge and non-binge group membership (e.g., Townshend & Duka, 2005; non-binge ≤16, binge ≥24). As applied to this sample, scores ≤11 denote non-bingers while scores ≥24 suggest binge behaviour.

ASSIST

Designed to identify harmful use of alcohol, tobacco and illicit drugs, the ASSIST comprises eight questions; it assesses frequency of use and associated problems over the preceding three months (WHO ASSIST Working Group, 2002). Given other measures in this study already index alcohol use/misuse, all ASSIST responses pertaining to alcohol were excluded from analyses. ASSIST total score in this study thus reflects global harmful drug use severity excluding alcohol.

PHQ-9

Standardised for use in the healthy population, this 9-item screener asks individuals how frequently – and to what extent – they have experienced depressive symptoms over the last two weeks (Kroenke et al., 2010). Scores ≥10 are indicative of moderate depression

GAD-7

Validated for use in the healthy population, this 7-item screener asks participants how often – and to what degree – they have experienced symptoms of anxiety over the last two weeks (Löwe et al., 2008). Scores ≥10 suggest moderate anxiety.

MCQ

This questionnaire requires participants make hypothetical choices between 27 small immediately available monetary rewards and larger ones obtainable only after some delay (Kirby et al., 1999). An individual's responses on this questionnaire can be expressed as a hyperbolic function. The DDR is measured by *k*, which denotes the slope of the function; larger k-values indicate greater discounting of the delayed reward (Kaplan et al., 2016). A consistency score can also be determined. This is indicative of how consistent an individual's

responses are with preceding/succeeding choices; participants are excluded if their consistency scores is less than 75% (Kaplan et al., 2016).

SST

The web-based SST (http://hesterlab.org/tasks/t1/ssd_task.html) was programmed using HTML and JavaScript client-side along with PHP and MySQL server-side for data storage and management. The task is run on Windows/Mac desktop/laptop computers and is supported by all major browsers. It consists of a practice block of 32 trials and 3 blocks of 64 experimental trials (Figure 2). Full details regarding instructions/prompts/feedback are provided in the Supplementary Material. Variables of interest include go accuracy, omissions and errors; average RT on unsuccessful stop trials; and SSRT. SSRT is derived when mean stop signal delay (SSD) is subtracted from average go RT; greater SSRTs indicate reduced inhibition ability (Logan et al., 1997). Participants are excluded if mean RT of either correct or incorrect failed stops is greater than mean go RT (Verbruggen et al., 2019). They are also excluded if stop accuracy is less than 25% or greater than 75%; go errors are greater than 10%; or, if SSRT is less than 50 ms (Congdon et al., 2012).

CNLab-A app

This freely available iOS/Android app can be used to record real-time alcohol intake over 21 days. App development and protocols have been described elsewhere (Poulton et al., 2019b). The app has previously been found to be a valid and reliable measure of alcohol intake, participant compliance has been identified as high, and reactivity to protocols over time low (Poulton et al., 2019b, 2018). Alcohol intake data can be submitted at any time, either in response to twice daily notifications or while drinking. Drinking indices derived from the app include number of days drinking; total standard drinks; standard drinks per days drinking; hourly rate of intake; and number of occasions where four or more (4/4+)/six or more (6/6+; etc.) drinks are consumed in one episode.

Data Analyses

Consistent with previous studies utilising the CNLab-A app, data related to the number of days drinking, total standard drinks, and occasions where 4/4+ (and so forth) drinks were consumed in one episode were aggregated across days for each individual (Poulton et al., 2019b, 2019a, 2018). Average drinks per day and per drinking day were calculated by dividing total standard drinks consumed by 21 and number of days drinking respectively. Where participants uploaded less than 21 days of app-based data, daily consumption was calculated as a function of the number of submission days. Each time drinking was submitted via the app, an hourly rate of consumption was computed based on

the start/end time recorded by participants. This allowed average hourly intake and highest intake in two hours to be computed.

Regarding the MCQ, hyperbolic *k*-values were log-transformed to correct for non-normal distribution. Untransformed values (three decimal places) are displayed in tables to assist with interpretation. With the SST, given possible variations in timing related to computer and browser/browser version utilised, the program was designed to capture timing information from the internal timing device, or real-time clock (RTC), of each computer. RTCs are known to be highly accurate (Marouani and Dagenais, 2008). Meta-SSD thus refers to RTC-derived SSD, as opposed to programmed SSD. There was a very strong correlation between meta-SDD ($M = 228.09$, $SD = 77.47$) and programmed SSD ($M = 224.88$, $SD = 77.47$), $r = .99$, $p < .001$. SSRT was calculated as meta-SSD subtracted from go RT (also timed via the RTC). SSRT was normally distributed.

One-way analyses of variance (ANOVAs) and post hoc tests corrected (Bonferroni) for multiple comparisons were conducted to determine whether alcohol intake behaviour groups were matched demographically and to investigate differences on drinking and cognitive measures. Effect sizes were computed using ω^2 values; they were interpreted according to Kirk's guidelines: 0.01 = small, 0.06 = moderate, and 0.14 = large effect (Kirk, 1996). Where only two alcohol intake behaviour groups were being compared, independent *t*-tests were employed. Adjusted *t*-values and associated degrees of freedom were reported where the assumption of homogeneity of variance was violated. Where multiple *t*-tests were employed, a critical *p*-value of .01 was adopted to control for multiple comparisons. Effect sizes were computed using Cohen's *d*; they were interpreted according to Cohen's guidelines: 0.20 = small, 0.50 = moderate, and 0.80 = large effect (Cohen, 1988). Bayesian analyses were additionally conducted on overall *k* and SSRT data to determine the probability of the alternative hypothesis. We adopted the default priors as set by JASP for the Bayesian analyses. In JASP, the prior distribution is defined by a Cauchy distribution centred on zero with width/scale of 0.707 for *t*-tests and width/scale of 0.5 for ANOVAs. Results are presented in terms of Bayes factor BF10, which represents the probability of the observed data given the alternative hypothesis (Wagenmakers et al., 2018). Bayes factors greater than one provide evidence for the alternative hypothesis (1-3 = anecdotal evidence, 3-10 = moderate evidence, 10-30 = strong evidence, and >30 = very strong evidence); Bayes factors less than one provide evidence for the null hypothesis (0.33-1 = anecdotal evidence, 0.10-0.33 = moderate evidence, 0.03-0.10 = strong evidence, and <0.03 = very strong evidence).

To reduce the chances of a Type 1 error and to avoid problems related to multicollinearity in the hierarchical multiple regression analysis, an alcohol use index was computed (Fernie et al., 2010). This was calculated using the mean of summed *z*-scores for percentage of days drinking, number of standard drinks consumed per drinking day, highest drink count in two hours, and AUDIT questions (4-10) related to alcohol problems and dependence. We conducted confirmatory factor analysis on the individual components of the alcohol use index to ensure they loaded onto a common dimension (Fernie et al., 2013). See Supplementary Materials for details. The alcohol use index was normally distributed. A hierarchical multiple regression analysis was employed to examine which measures explained unique variance in the alcohol use index. Regression diagnostics revealed 3 cases had standardised residuals greater than |3.00|; however, as Cook's Distance had a maximum value of 0.07, these outliers were not unduly influencing the model. There was no evidence assumptions of multicollinearity, homoscedasticity, or linearity were violated. Standardised residuals appeared normally distributed.

To achieve effects in the range reported in other studies (Smith et al., 2014), initial a priori power analyses using G*Power (Faul et al., 2009) suggested a total sample size of 432 was required for ANOVAs involving three groups when power was set at 80% and alpha at .05. A sample size of 398 was required for *t*-tests to detect similar types of effects. It was difficult to anticipate how many additional participants would be required to account for dropouts, non-compliance, and exclusions, however. In addition, we expected to categorise participants according to various criteria and aimed to run multiple inferential analyses. As such, as many participants as time/funds permitted were accepted into the study and post hoc analyses were conducted to examine power more fully.

Results

Sample Characteristics

Participant characteristics – as a function of CheckMyControl components completed and after exclusion criteria were applied – are provided in Table 1. Depending on components completed, almost 90% of participants were students. Approximately 41% were under the age of 20 years, 47% were aged 20-29, and 12% were 30 years or older. Australian census data shows 25% of the population is under 20 years, 14.4% are between 20 and 29 years, and 61% are over the age of 30 (Australian Bureau of Statistics [ABS], 2019). Most participants were born in Australia (68%), spoke English as a first language (81%), and resided in urban regions (89%). According to census data, 67% of Australians are born locally, 79% speak English, and 71% live in major cities (ABS, 2018).

On average, participants used the CNLab-A app 19.88 (*SD* = 2.25) days out of 21. As data submission was either event- or notification-contingent, there was no upper limit to the number of drinking sessions participants could report using the app. Participants received a maximum of 42 notifications asking them to record information about drinking. They submitted data, on average 2.01 (*SD* = 0.037) times per day. There were 24,471 total data points captured via the app. A repeated measures ANOVA showed significant differences between total average standard drinks recorded each week, $F(2, 896) = 8.04$, $p < .001$. Post hoc tests revealed average standard drinks recorded during the first week (*M* = 10.12, *SD* = 11.27) was significantly higher than that recorded in either of the subsequent weeks ($p < .05$); there was no difference between average standard drinks in the second (*M* = 8.57, *SD* = 9.91) and third (*M* = 8.42, *SD* = 10.18) weeks.

Investigating Differences in the Survey, SST, and CNLab-A Component Subgroup

Descriptive statistics and app-based alcohol use indices as a function of alcohol intake behaviour group – based on criteria developed by López-Caneda et al. (2012) – are displayed in Table 2. Cognitive task performance variables as a function of these groups are displayed in Table 3. Results of one-way ANOVA analyses conducted to investigate differences between the high binge, standard binge, and control groups are also shown in these tables. There were no significant differences between groups on any of the cognitive measures. Bayesian analyses showed that, as compared to the null hypothesis, the probability of the alternative was <1 for both overall *k* (0.04) and SSRT (0.03); in both cases, support for the null hypothesis was strong. See Supplementary Material for details regarding associations between biological sex and alcohol intake group membership.

Descriptive statistics and app-based alcohol use indices as a function of alcohol intake behaviour group based on NIAAA heavy and binge drinking criteria are displayed in Table 4. Cognitive task performance variables as a function of these groups are displayed in Table 5. The results of one-way ANOVA analyses conducted to investigate differences between the heavy, binge, and control groups are also shown in these tables. There were no significant differences between groups on any of the cognitive measures. Bayesian analyses showed that, as compared to the null hypothesis, the probability of the alternative was <1 for both overall *k* (0.09) and SSRT (0.15); this indicates strong and moderate support respectively for the null hypothesis.

Descriptive statistics and app-based alcohol use indices as a function of AUDIT harmful, hazardous, and non-harm classifications are displayed in Table S7. Cognitive task

performance variables as a function of these classifications are displayed in Table S8. The results of one-way ANOVA analyses conducted to investigate differences between groups are also shown in these tables. The harmful group displayed significantly greater delay discounting relative to the non-harm group (p = .029, ω^2 = 0.01), but not compared to the hazardous group (p = .089). There was no delay discounting difference between the hazardous and non-harm group. There were also no SSRT differences between groups. Bayesian analyses showed that, as compared to the null hypothesis, the probability of the alternative was <1 for both overall k (0.62) and SSRT (0.05); this indicates anecdotal and strong support respectively for the null hypothesis.

Descriptive statistics and app-based alcohol use indices as a function of alcohol intake behaviour group based on AUQ binge and non-binge categories are displayed in Table S9. Cognitive task performance variables as a function of these categories are displayed in Table S10. The results of independent t-tests conducted to investigate differences between groups are also shown in these tables. There were no significant differences between groups on any of the cognitive measures. Bayesian analyses showed that, as compared to the null hypothesis, the probability of the alternative was <1 for both overall k (0.03) and SSRT (0.03); in both cases, support for the null hypothesis was strong.

Investigating Differences in Survey Only and Survey Plus SST Component Subgroups

To investigate delay discounting utilising the maximum possible sample size, both AUDIT and AUQ classifications were also applied to the larger subgroup (n = 739) that completed only the survey component of this study. Regardless of which classification was applied, there were no significant differences between groups regarding delay discounting (see Tables S11-S12). Bayesian analyses showed that, as compared to the null hypotheses, the probability of the alternative was <1 for analyses conducted as a function of AUDIT (0.06) and AUQ (0.13) classifications; this indicates strong and moderate support respectively for the null hypotheses.

To explore SSRT utilising the greatest possible sample size, both AUDIT and AUQ classifications were additionally applied to the subgroup (n = 515) that undertook only the survey and SST components of this study. Regardless of which classification was applied, there were no significant SSRT differences between groups (see Tables S13-S14). Bayesian analyses showed that, as compared to the null hypotheses, the probability of the alternative was <1 for analyses conducted as a function of AUDIT (0.05) and AUQ (0.04) classifications; in both cases, support for the null hypotheses was strong.

Hierarchical Multiple Regression Analyses in the Survey, SST, and CNLab-A Component Subgroup

The alcohol use index (M = 0.34, SD = 0.70) was not significantly correlated with age, r = 0.08, p = .078, or the APM-6, r = 0.01, p = .821. The alcohol use index of males (M = 0.58, SD = 0.80) was significantly greater than that of females (M = 0.24, SD = 0.63), $t(447)$ = 4.76, $p < .001$, d = 0.47. With regard to the hierarchical multiple regression, biological sex was entered at step 1; this variable explained 4.8% of the variance in the alcohol use index, $F(1, 447) = 22.61$, $p < .001$. At step 2, drug use plus anxiety and depression symptomatology were entered into the model; this explained 11.9% of the variance in the alcohol use index, $F(4,444) = 14.96$, $p < .001$. These predictors explained an additional 7.1% of the variance in the alcohol use index, after controlling for sex, $\Delta R^2 = .07$, F change (3, 444) = 11.86, $p < .001$. At step 3, SSRT and overall k were entered into the model; this explained 12.3% of the variance in the alcohol use index, $F(6, 442) = 10.31$, $p < .001$. These variables explained an additional 0.4% of the variance in the alcohol use index, after controlling for sex, drug use, and anxiety and depression symptomatology; this was not a significant change to the model, $\Delta R^2 = .004$, F change (2, 442) = 1.01, p = .365. Finally, interaction items – each of anxiety and depression by each of SSRT and overall k – were included in the model. These items did not significantly improve the model, $\Delta R^2 = .01$, F change (4, 438) = 1.38, p = .245, and so were dropped from the final model. See Table 6 for coefficient details.

Discussion

Utilising online protocols and an app designed to allow participants to record alcohol consumption in real-time, this study attempted to garner a large, diverse sample to investigate the extent to which at-risk drinkers were characterised by facets of behavioural impulsivity. Contrary to expectations, significantly greater impulsivity – either in the form of increased choice impulsivity and/or reduced response inhibition – was not evident in heavy, standard binge, high binge, harmful, or hazardous alcohol drinkers as compared to controls, regardless of the criteria employed to categorise these at-risk drinkers. In all cases, Bayesian analyses revealed anecdotal to strong support for the null hypotheses. Neither choice impulsivity nor reduced response inhibition significantly predicted alcohol use in the form of an index that incorporated variables related to frequency of drinking, quantity of intake, rate of consumption, and alcohol use consequences.

Choice impulsivity and reduced response inhibition differences were examined as a function of several commonly employed classifications. In the first instance, participants who

had completed all study components were categorised according to a widely cited researcher-determined definition of binge drinking that enables heavy drinkers to be differentiated from bingers (López-Caneda et al., 2012). Binge drinkers were further segregated into standard and high binge groups as high bingers – that is, those that consume two or more times the standard binge threshold – have been found to experience significantly greater negative drinking outcomes than standard binge drinkers (Creswell et al., 2020). While the binge and control groups differed significantly on app-based alcohol use indices, binge score, alcohol-related harm/hazard, and adverse alcohol use consequences, there were no group differences for choice impulsivity or response inhibition performance. Participants who had completed all study components were additionally classified as a function of NIAAA heavy and binge drinking guidelines (NIAAA, 2018). Again, there were significant differences between the at-risk groups and controls on app-based alcohol use indices, alcohol-related harm/hazard, and adverse alcohol use consequences; unsurprisingly, the binge group had significantly greater binge scores relative to both the heavy and control groups. Regardless, there were no choice impulsivity or response inhibition distinctions between groups.

Rather than using researcher-determined empirical definitions of at-risk drinking, or those based on national guidelines, some studies take advantage of well-validated surveys to identify those at risk. In this study, choice impulsivity and response inhibition were consequently also examined as a function of AUQ and AUDIT scores. In accordance with other research (Townshend and Duka, 2005), individuals who had completed all study components were classified as binge or non-binge based on a tertile split of AUQ binge scores. Compared to non-bingers, binge drinkers were characterised by significantly greater app-based alcohol use indices (apart from percentage of days drinking), binge scores, alcohol-related harms/hazards, drug use, and adverse alcohol use consequences. There were, however, no differences between groups on measures of choice impulsivity or response inhibition. There were also no differences pertaining to choice impulsivity or response inhibition when comparisons were made using larger samples that had only completed the survey (including delay discounting) component of the study or the survey (including delay discounting) and SST components. Regarding the AUDIT, harmful/hazardous and non-harm groups differed significantly on measures of app-based alcohol use indices (apart from hourly rate of intake), binge scores, alcohol-related harms/hazards, drug use, and adverse alcohol use consequences. While there were no differences between groups pertaining to response inhibition, the harmful group demonstrated greater choice impulsivity relative to the non-harm group, though the effect size was small ($\omega^2 = 0.01$). Given this small effect size, it was

unsurprising that this finding was not replicated in the larger sample that had only completed the survey (including delay discounting) component of the study. There was also no response inhibition difference between groups in a larger sample that had completed only the survey (including delay discounting) and SST components. When a continuous index of at-risk alcohol use – incorporating quantity, frequency, rate, and consequences parameters – was adopted, neither choice impulsivity nor response inhibition was a predictive variable.

Online measures and real-time alcohol intake assessment were utilised to secure a large sample representative of the wider Australian population in terms of country of birth and first language. As the study was advertised in and around the University of Melbourne, most participants were students; participant age was thus positively skewed, and a large number resided in urban areas. Nonetheless, more than 10% of the sample comprised individuals 30 years or over. A substantial percentage (11%) heralded from rural or remote regions. The use of an app to assess alcohol consumption facilitated the collection of reliable and valid real-time drinking data, with compliance and reactivity in keeping with previous studies (Poulton et al., 2019b, 2018). Various common definitions of at-risk drinking were utilised and, where possible, heavy drinkers were differentiated from bingers and distinctions were made between standard and high binge drinkers. There were significant and largely consistent differences between at-risk and control groups on app-derived alcohol indices. Thus, the at-risk and control groups were all meaningfully different from each other in terms of alcohol intake behaviour. There were also appreciable differences across at-risk and control groups in terms of severity of alcohol-related harms/hazards and adverse alcohol use outcomes. The AUDIT scores of both at-risk drinkers and controls accord with those reported in other studies where significant choice impulsivity or response inhibition differences have been identified (Field et al., 2007; Murphy and Garavan, 2011; Smith and Mattick, 2013). Similarly, AUQ scores of binge drinkers were in keeping with those detailed in other studies (Fernie et al., 2010; Mayhew et al., 2020). Nevertheless, despite these methodological strengths, no response inhibition or choice impulsivity differences – either between any at-risk group and controls or between the various at-risk groups – were evident and these facets of impulsivity did not predict the alcohol use index.

Given the mixed findings pertaining to response inhibition and choice impulsivity in at-risk drinkers, further consideration regarding the nature and sensitivity of the cognitive tasks employed when assessing these behaviours is warranted. It is possible only short-term fluctuations in response inhibition are related to alcohol intake in sub-clinical users. Response inhibition has been demonstrated to change as a function of environmental conditions (Jones

et al., 2013), and manipulations designed to momentarily reduce inhibitory control in non-dependent samples have been shown to increase subsequent ad libitum drinking (Jones et al., 2011). Potentially, daily – or momentary – fluctuations in response inhibition performance are more closely linked to real-time at-risk alcohol intake. Few studies have examined this prospect, although Jones and colleagues found deterioration in response inhibition across the day predicted alcohol consumption on that day (Jones et al., 2018). Real-time momentary assessments of both response inhibition and alcohol intake might facilitate a more detailed exploration of the cognitive antecedents and consequences of drinking behaviour. With regard to choice impulsivity, inconsistent findings across studies have previously been explained in terms of both the validity of the MCQ and the age of participants (Banca et al., 2016; Caswell et al., 2016). The MCQ employs hypothetical rewards. Although the results of several studies have found individuals discount hypothetical and actual monetary rewards to the same extent, these studies typically only make one actual monetary reward available to participants (Madden et al., 2004, 2003). Delay discounting has additionally more consistently been identified in adolescent at-risk drinkers (Field et al., 2007; Whelan et al., 2014), but not young adult student samples (Banca et al., 2016; Caswell et al., 2016). Using real rewards throughout the whole task, especially when assessing the choice impulsivity of a sample comprising mainly young adult students, might increase sensitivity to discounting.

It is, of course, possible other measures of response inhibition – to do with premature responding or waiting – and choice impulsivity – such as reflection/interference or risk-taking tasks – may better capture deficits in these areas or that impulsivity alone does not distinguish at-risk drinkers from control participants. Other factors may play a role. Affect has, for instance, been linked to alcohol intake, alcohol-related problems, and AUD (Lannoy et al., 2021). Moreover, impulsivity has been shown to moderate this association (Dvorak et al., 2016; Stevenson et al., 2015). In this study, consistent mood differences, particularly related to depression, were evident when at-risk drinkers were categorised according to NIAAA, AUDIT, and AUQ criteria. However, the regression analysis found neither anxiety nor depression – nor interactions between each of these variables and each of choice impulsivity and response inhibition –were significant predictors of the alcohol use index.

While this study sought to minimise methodological shortcomings identified in other research focusing on behavioural impulsivity in at-risk drinkers, other limitations might have impacted the results. Several commentators have suggested statistical power may be an issue and have consequently advocated for larger sample sizes, particularly in the area of response inhibition research (Liu et al., 2019; Smith et al., 2014). While large numbers of individuals

completed the first (survey) component of this study, 23% did not undertake the SST and 33% neglected to download the app. In addition, 17% of those who completed all study components were excluded. To determine whether non-significant results were due to a lack of statistical power, we conducted post hoc power analyses using G*Power (Faul et al., 2009), with power set at 80% and an alpha of .05. Sample sizes were found to be sufficiently large enough (n = 440-449 for ANOVAs; n = 313 for t-test) to detect effect sizes in the small to medium range (f = 0.15 in the ANOVAs; d = 0.28 in the t-test). To detect smaller effects, even larger samples will be required. It is worth noting that samples utilised in supplementary analyses were large enough (n = 515-739 for ANOVA; n = 346-739 for t-tests) to detect smaller effects (f = 0.11-0.14; d = 0.22-0.27), yet no differences between groups on cognitive measures were evident.

The online behavioural testing protocols may have introduced a degree of variability. Participants might not have attended to cognitive tasks as required given they undertook this study in uncontrolled testing environments. While this is likely to have been randomised across the whole sample, it would be interesting in future to determine if more impulsive individuals are more susceptible to this phenomenon. Although participants in a study involving multiple app-based assessments of response inhibition reported being distracted about 30% of the time, analysis of data showed that when these data points were included, findings were unaffected (Jones et al., 2018). Moreover, as response inhibition assessments were conducted twice daily for 14 days in that study, there may have been a greater degree of participant burden and thus an increased tendency to satisfice. Variability might also emerge due to the use of different computers and browsers, as well as internet speed (Feenstra et al., 2018), though other studies examining the relationship between online and in-person cognitive testing report strong positive correlations between conditions (.52-.92; Haworth et al., 2007).

A further consideration is the method used to calculate SSRT. Here, we utilised the mean method, which involves subtracting mean SSD from average go RT. This is a widely used technique for determining SSRT but has recently been reported as being less reliable than the integration method and tends to underestimate SSRT (Verbruggen et al., 2019). Nevertheless, simulations show the correlation between SSRT calculated using each method is high. Moreover, utilising the mean method is in keeping with how SSRT has been calculated in similar previous studies. In this study, the DDRs of at-risk drinkers were not dissimilar to those reported in other alcohol-related papers (0.02-0.03), though our controls tended to have higher rates than detailed elsewhere (0.01; Kirby & Petry, 2004; Murphy &

Garavan, 2011). Likewise, SSRTs were slightly longer than the typical 200-250 ms (Smith et al., 2014). Nonetheless, both DDR and SSRT values were in keeping with those described in a recent psychometric analysis involving only healthy participants (Caswell et al., 2015).

In sum, this study sought to determine if choice impulsivity and/or response inhibition deficits were evident in at-risk alcohol drinkers. Online testing protocols and an app designed to allow participants to record alcohol consumption in real-time helped secure a large sample. Various empirical definitions of at-risk drinking were applied to app-derived alcohol intake data. Definitions based on well-validated surveys were also utilised. Drinking data was analysed both in terms of distinct cut-offs and as a continuous variable. Regardless, there was little evidence to suggest at-risk drinkers were distinguished by increased choice impulsivity or reduced response inhibition, and neither variable predicted the alcohol use index. While this result might be related to the online nature of this research, it is possible more sensitive measures of behavioural impulsivity are required when assessing non-dependent drinkers.

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Figure 1 Legend

MCQ = Monetary Choice Questionnaire; SST = Stop-Signal Task.

Figure 2 Legend

Practice trials have an inter-trial interval (ITI) of 4250ms and comprise a blank screen (1000ms), fixation cross (250ms), stimulus presentation (1000ms), and feedback screen (2000ms). Experimental trials have an ITI of 2250ms and comprise a blank screen (1000ms), fixation cross (250ms), and stimulus presentation (1000ms). Trial-by-trial feedback is provided during the practice block while block-based feedback is given during experimental

trials. Go stimuli comprise random presentation of letters (X/O) that map to corresponding keyboard letters. A stop signal in the form of a white box surrounding the go stimuli appears on 25% of randomly selected trials. Stop signals are not presented on consecutive trials. The initial stop-signal delay (SSD) is set at 250 ms and adjusts dynamically as a function of participant response; successful inhibitions result in a 50 ms increase in the SSD, while it decreases by 50 ms following an unsuccessful inhibition. This staircase design ensures the probability of successful inhibition approaches 50%.

Table 1

Characteristics of Participants as a Function of CheckMyControl Study Components Completed After Applying Exclusion Criteria

	Survey only (n = 739)	Survey & SST (n = 515)	Survey, SST, & CNLab-A (n = 449)
	M (SD)	*M (SD)*	*M (SD)*
Age	22.45 (6.42)	22.67 (6.59)	22.93 (6.70)
APM-6	50.75 (28.02)	52.24 (27.81)	52.48 (27.73)
AUQ binge	22.27 (20.30)	22.07 (20.05)	21.96 (20.45)
AUDIT	8.63 (5.48)	8.61 (5.35)	8.63 (5.26)
ASSIST (less alcohol)	8.44 (14.96)	8.08 (14.81)	8.31 (15.22)
GAD-7	5.27 (5.20)	4.98 (5.10)	4.95 (5.12)
PHQ-9	6.40 (5.40)	6.08 (5.30)	5.96 (5.30)
	%	%	%

Assigned birth sex (M:F)	30:70	30:70	29:71
Country of birth			
Australia	66.8	67.2	68.6
Other	33.2	32.8	31.4
First language			
English	79.8	81.2	82.4
Other	20.2	18.8	17.6
Residence			
Capital city	57.0	60.2	60.8
Other metropolitan	31.9	29.1	28.5
Rural or remote	11.1	10.7	10.7
Highest Education			
Part/All secondary	37.0	37.7	36.7
Trade	1.5	1.6	1.8
Part bachelor's degree	36.4	33.8	32.3
Bachelor's degree	15.3	16.5	18.0
Postgraduate	9.8	10.4	11.2

Note. APM-6 = Abridged 6-item version of Raven's Advanced Progressive Matrices; AUQ = Alcohol Use Questionnaire; AUDIT = Alcohol Use Disorders Identification Test; ASSIST (less alcohol) = Alcohol, Smoking and Substance Involvement Screen; GAD-7 = Generalised Anxiety Disorder Scale; PHQ-9 = Patient Health Questionnaire.

Table 2

Demographics and App-based Alcohol Use Indices for the Survey, SST and CNLab-A Subgroup (n = 449) as a Function of Alcohol Intake Behaviour Group Based on Criteria Developed by López-Caneda and Colleagues

	Heavy (n = 9)	High Binge (n = 69)	Standard Binge (n = 106)	Controls (n = 265)			
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	*F*	*p*	ω^2
Age	28.89 (10.12)	21.03 (4.78)	22.56 (6.87)	23.37 (6.78)	3.62	.028	0.01
APM-6	71.83 (22.08)	52.17 (24.57)	53.16 (28.69)	51.63 (28.17)	0.11	.896	<0.01
AUQ binge	37.13 (48.51)	38.56 (28.52)	28.04 (18.53)	14.70 (12.04)	62.12	<.001	0.22
AUDIT	13.89 (5.82)	12.74 (5.03)	10.61 (4.84)	6.58 (4.36)	63.91	<.001	0.22
ASSIST (less alcohol)	15.56 (11.34)	11.01 (13.23)	9.83 (16.66)	6.74 (15.04)	3.01	.050	0.01
GAD-7	5.44 (6.21)	3.99 (4.92)	5.19 (5.75)	5.09 (4.86)	1.46	.234	<0.01
PHQ-9	8.44 (8.63)	5.70 (5.51)	6.57 (5.61)	5.71 (4.97)	1.09	.336	<0.01
App drinking indices							
Days drinking (%)	69.84 (19.49)	34.48 (16.14)	35.31 (19.97)	23.37 (19.03)	20.08	<.001	0.08
Total drinks	112.10 (44.11)	53.82 (25.91)	35.83 (18.87)	13.77 (12.55)	180.84	<.001	0.45
Drinks/day	5.33 (2.10)	2.62 (1.24)	1.79 (1.01)	0.69 (0.63)	168.75	<.001	0.43
Drinks/drinking day	7.78 (2.46)	8.05 (2.70)	5.51 (3.36)	2.85 (1.96)	175.21	<.001	0.44
Hourly intake	1.77 (0.37)	3.76 (2.93)	2.91 (2.06)	2.00 (2.03)	19.74	<.001	0.08
Highest drinks/2hrs	6.72 (2.44)	9.34 (4.26)	6.06 (1.92)	2.94 (1.54)	244.08	<.001	0.52
4/4+ intake	11.56 (3.68)	4.25 (2.34)	3.75 (2.38)	1.07 (1.39)	131.39	<.001	0.37
6/6+ intake	9.56 (3.09)	3.28 (1.80)	2.43 (1.40)	0.36 (0.63)	263.68	<.001	0.54
12/12+ intake	1.33 (2.65)	1.70 (1.03)	0.18 (0.51)	0.05 (0.25)	284.88	<.001	0.56

20/20+ intake	0.22 (0.67)	0.36 (0.64)	0.04 (0.24)	0.004 (0.06)	45.02	<.001	0.17

Note. Classification of participants was based on criteria detailed by López-Caneda and colleagues (López-Caneda et al., 2013, 2012). Heavy drinkers were excluded from inferential analyses due to the small number of participants in this group. APM-6 = Abridged 6-item version of Raven's Advanced Progressive Matrices; AUQ = Alcohol Use Questionnaire; AUDIT = Alcohol Use Disorders Identification Test; ASSIST (less alcohol) = Alcohol, Smoking and Substance Involvement Screen; GAD-7 = Generalised Anxiety Disorder Scale; PHQ-9 = Patient Health Questionnaire. Drinks refer to self-reported alcohol consumption in Australian standard drinks (1 drink = 10 g alcohol); 4/4+ (and so forth) intake refers to occasions where four or more drinks were consumed in one episode.

Table 3

Cognitive Task Performance Variables for the Survey, SST and CNLab-A Subgroup (n = 449) as a Function of Alcohol Intake Behaviour Group Based on Criteria Developed by López-Caneda and Colleagues

	Heavy (n = 9)	High Binge (n = 69)	Standard Binge (n = 106)	Controls (n = 265)			
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	*F*	*p*	ω^2
MCQ							
Overall *k*	0.013 (0.020)	0.016 (0.023)	0.019 (0.026)	0.016 (0.027)	0.72	.485	<0.01
SST							
Go accuracy (%)	97.84 (1.28)	97.21 (2.37)	97.01 (2.49)	97.04 (2.39)	0.17	.847	<0.01
Go RT (ms)	485.61 (36.96)	485.59 (65.49)	484.18 (66.93)	498.43 (71.37)	2.06	.129	<0.01
Go omissions (%)	0.62 (1.12)	0.41 (0.84)	0.53 (1.27)	0.59 (1.29)	0.58	.561	<0.01
Go errors (%)	1.54 (1.09)	2.37 (2.16)	2.46 (2.33)	2.37 (2.21)	0.06	.941	<0.01
Go errors RT (ms)	395.37 (58.98)	417.26 (112.15)	421.75 (83.17)	418.72 (100.74)	0.05	.956	<0.01

Stop accuracy (%)	49.07 (3.31)	49.06 (2.71)	48.80 (3.60)	49.47 (3.16)	1.75	.176	<0.01
Failed (correct key) stop RT (ms)	434.70 (31.25)	443.87 (58.84)	441.07 (54.88)	456.73 (63.08)	3.06	.048	0.01
Failed (incorrect key) stop RT (ms)	356.48 (64.61)	344.00 (77.97)	363.84 (70.10)	359.83 (69.15)	0.87	.421	<0.01
Meta SSD (ms)	228.67 (62.62)	218.77 (76.29)	216.50 (72.10)	233.64 (80.40)	2.31	.100	0.01
SSRT (ms)	256.93 (42.28)	266.81 (38.12)	267.69 (41.42)	264.79 (36.62)	0.25	.781	<0.01

Note. Classification of participants was partially based on criteria detailed by López-Caneda and colleagues (López-Caneda et al., 2013, 2012). Heavy drinkers were excluded from inferential analyses due to the small number of participants in this group. MCQ = Monetary Choice Questionnaire; k = the slope of the function describing how an individual discounts future reward. SST = Stop-Signal Task; Meta SDD = stop-signal delay as timed by computer; SSRT = stop-signal reaction time (Go RT – meta SSD).

Table 4

Demographics and App-based Alcohol Use Indices for the Survey, SST and CNLab-A Subgroup (n = 449) as a Function of Alcohol Intake Behaviour Group Based on NIAAA Guidelines

	Heavy (n = 43)	Binge (n = 123)	Controls (n = 283)			
	M (SD)	*M (SD)*	*M (SD)*	*F*	*p*	ω^2
Age	28.00 (10.63)	21.33 (4.92)	22.85 (6.24)	16.97	<.001	0.07
APM-6	51.45 (29.21)	51.80 (26.82)	52.93 (27.97)	0.13	.875	<0.01
AUQ binge	19.59 (16.62)	34.87 (27.77)	16.72 (13.73)	40.04	<.001	0.15
AUDIT	10.60 (4.40)	12.14 (5.39)	6.80 (4.38)	60.01	<.001	0.21
ASSIST (less alcohol)	10.23 (12.79)	10.04 (15.80)	7.26 (15.24)	1.82	.163	<0.01
GAD-7	4.91 (6.04)	5.13 (5.68)	4.88 (4.72)	0.10	.904	<0.01
PHQ-9	4.72 (5.20)	6.90 (5.95)	5.75 (4.96)	3.38	.035	0.01
App drinking indices						

Days drinking (%)	62.57 (21.54)	33.44 (15.89)	21.69 (15.94)	120.65	<.001	0.35
Total drinks	59.65 (26.91)	45.49 (28.61)	14.17 (12.62)	171.20	<.001	0.43
Drinks/day	2.97 (1.32)	2.22 (1.39)	0.71 (0.63)	171.42	<.001	0.43
Drinks/drinking day	5.02 (1.87)	6.94 (2.97)	3.17 (2.28)	103.01	<.001	0.31
Hourly intake	1.73 (0.45)	3.51 (2.80)	2.15 (2.03)	19.56	<.001	0.08
Highest drinks/2 hours	4.54 (0.79)	8.81 (3.24)	2.99 (1.50)	332.68	<.001	0.60
4/4+ intake	6.05 (3.82)	4.07 (2.50)	1.12 (1.30)	165.93	<.001	0.42
6/6+ intake	3.35 (3.14)	2.95 (2.10)	0.56 (0.91)	123.04	<.001	0.35
12/12+ intake	0.51 (1.03)	0.94 (1.25)	0.08 (0.36)	52.06	<.001	0.19
20/20+ intake	0.02 (0.15)	0.24 (0.56)	0.01 (0.08)	24.91	<.001	0.10

Note. Heavy and binge groups determined using NIAAA guidelines adapted for the alcohol content of an Australian standard drink. APM-6 = Abridged 6-item version of Raven's Advanced Progressive Matrices; AUQ = Alcohol Use Questionnaire; AUDIT = Alcohol Use Disorders Identification Test; ASSIST (less alcohol) = Alcohol, Smoking and Substance Involvement Screen; GAD-7 = Generalised Anxiety Disorder Scale; PHQ-9 = Patient Health Questionnaire. Drinks refer to self-reported alcohol consumption in Australian standard drinks (1 drink = 10 g alcohol); 4/4+ (and so forth) intake refers to occasions where four or more drinks were consumed in one episode.

Table 5

Cognitive Task Performance Variables for the Survey, SST and CNLab-A Subgroup (n = 449) as a Function of Alcohol Intake Behaviour Group Based on NIAAA Guidelines

	Heavy (n = 43)	Binge (n = 123)	Controls (n = 283)			
	M (SD)	*M (SD)*	*M (SD)*	*F*	*p*	ω^2
MCQ						
Overall *k*	0.013 (0.021)	0.016 (0.026)	0.017 (0.027)	0.97	.382	<0.01
SST						
Go accuracy (%)	97.43 (2.41)	96.90 (2.47)	97.10 (2.35)	0.82	.440	<0.01
Go RT (ms)	505.37 (76.64)	482.69 (58.73)	495.35 (71.69)	2.23	.108	0.01
Go omissions (%)	0.66 (1.50)	0.41 (0.97)	0.59 (1.28)	1.12	.328	<0.01
Go errors (%)	1.91 (2.19)	2.69 (2.37)	2.31 (2.14)	2.33	.099	0.01
Go errors RT (ms)	409.84 (75.93)	421.90 (97.83)	418.44 (100.67)	0.19	.826	<0.01
Stop accuracy (%)	49.71 (3.00)	48.87 (3.32)	49.33 (3.19)	1.41	.245	<0.01

Failed (correct key) stop RT (ms)	460.49 (68.43)	440.61 (47.29)	453.42 (63.75)	2.57	.078	0.01
Failed (incorrect key) stop RT (ms)	373.54 (44.23)	352.44 (82.50)	358.49 (67.29)	0.57	.565	<0.01
Meta SSD (ms)	242.26 (100.38)	211.89 (67.17)	231.58 (77.41)	3.69	.026	0.01
SSRT (ms)	263.11 (44.88)	270.80 (39.02)	263.76 (36.41)	1.58	.208	<0.01

Note. Heavy and binge groups determined using NIAAA guidelines adapted for the alcohol content of an Australian standard drink. MCQ = Monetary Choice Questionnaire; *k* = the slope of the function describing how an individual discounts future reward. SST = Stop-Signal Task; Meta SDD = stop-signal delay as timed by computer; SSRT = stop-signal reaction time (Go RT – meta SSD).

Table 6

Unstandardised and Standardised Beta Values for the Hierarchical Multiple Regression Predicting the Alcohol Use Index From Gender, Drug Use, Anxiety, Depression, Choice Impulsivity, and Response Inhibition

	Unstandardised		Standardised		
	B	*SE*	*β*	*p*	CI 95%
Model 1					
Constant	0.58	0.06			

Sex	-0.34	0.71	-.22	<.001	[-0.48, -0.20]
Model 2					
Constant	0.40	0.07			
Sex	-0.31	0.07	-.20	<.001	[-0.45, -0.17]
ASSIST (less alcohol)	0.01	0.002	.23	<.001	[0.01, 0.02]
PHQ-9	0.02	0.01	.11	.117	[-0.004, 0.03]
GAD-7	-0.004	0.01	-.03	.651	[-0.02, 0.01]
Model 3					
Constant	0.23	0.25			
Sex	-0.31	0.07	-.20	<.001	[-0.45, -0.17]
ASSIST (less alcohol)	0.01	0.002	.23	<.001	[0.01, 0.02]
PHQ-9	0.01	0.01	.11	.124	[-0.004, 0.03]
GAD-7	-0.004	0.01	-.03	.654	[-0.02, 0.01]
Overall *k*	0.04	0.05	.05	.424	[-0.05, 0.13]
SSRT	0.001	0.001	.04	.232	[-0.001, 0.003]

Note. ASSIST = Alcohol, Smoking and Substance Involvement Screen; GAD-7 = Generalised Anxiety Disorder Scale; PHQ-9 = Patient Health Questionnaire; *k* = the slope of the function describing how an individual discounts future rewards; SSRT = stop-signal reaction time (Go RT – meta SSD).

Figure 1

Study Component Participation Inclusion and Exclusion Criteria

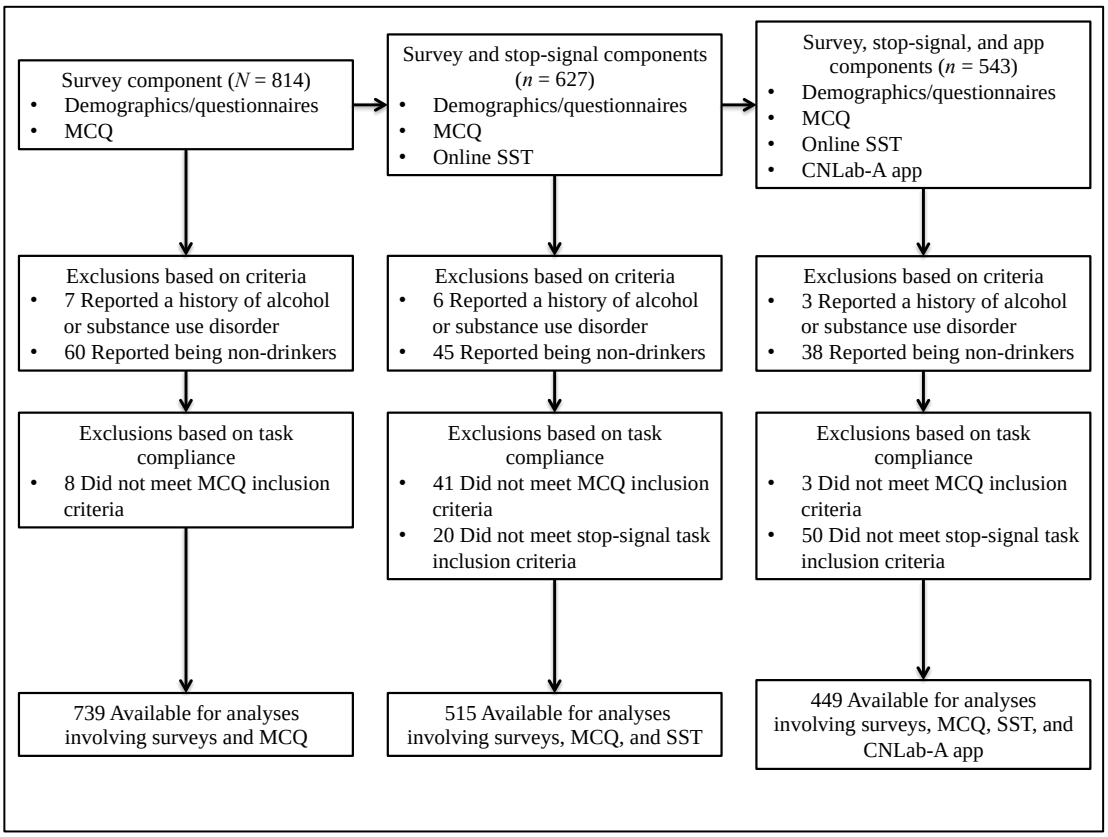

Figure 2

Schematic of Go and Stop Trials in the Practice and Experimental Blocks of the Online Stop-Signal Task